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CONCEPTUALISING THE MATURITY OF CITIZENS FOR CONSUMER HEALTH INFORMATICS IN LOW AND MIDDLE-INCOME COUNTRIES

EMPIRICAL ANALYSIS OF CHILE, GHANA, IRAQ, KOSOVO, TURKEY, AND UKRAINE

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DEDICATION

To my dearest father, Sapielga Alusuba Yakubu, your seed will forever thrive on earth.

To the citizens of LMICs who need these tools to access healthcare, may the professed solutions of Consumer Health Informatics (ConsHI) meet your expectations.

To our Ukrainian citizens, our hearts and prayers go out to you in these tormentous times.

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CHAPTER ONE: INTRODUCTION

The pervasive adoption of Information Technology (IT) such as the Internet and mobile phones, is a pathway to significantly reducing cost and improving the safety and timeliness of healthcare services delivery. Mobile health (mHealth) is an umbrella term for medical services conveyed using mobile devices. The appropriate use of technologies such as mHealth, electronic health (eHealth) and Health Information Technology (HIT) have improved current healthcare services and designs (Hameed, 2003; Lester *et al.*, 2008; Kayser *et al.*, 2019). Remarkably, the diffusion of consumer technology, such as mobile phones, has enhanced the role of consumers as partners in healthcare delivery (Middleton *et al.*, 2013; Featherall *et al.*, 2018). Accordingly, a surge in consumer quest for information about their health results in a cultural shift within healthcare systems. For instance, where there are options to consider a course of treatment to follow, collective decision-making helps assure consumers that clinical decisions are evidence-based and founded on inpatient and family preferences (Eysenbach, 2000).

The plethora of literature (Carey *et al.*, 2016; Inal *et al.*, 2020; Krasuska *et al.*, 2020) has enormously reported opportunities to improve consumers' health using technology. For example, there are smartphones to inform patients of the need to manage diet, reminders of routine exercise and mobile applications that support keeping track of progression in daily health activities. Also, smartphones support applications for medication adherence and patient-doctor appointment reminders, which has positive results (Al-shorbaji *et al.*, 2017). Therefore, the appropriate use of technology such as mHealth may result in significant advances in expanding health care coverage, increasing decision-making speeds, managing chronic conditions, and providing proper health care in emergencies.

Furthermore, engaging consumers in integrating technology into healthcare suggests a reliable solution to solving the demand-supply gap in healthcare services (World Health Organization, 2011; Ben-Zeev *et al.*, 2014). Particularly, in the wake of increasing population that is worsening the healthcare services' demand-supply gap in many countries, predominantly developing countries (World Health Organization, 2018). The complexities of healthcare demands associated with the growing population exert pressure on the existing healthcare systems globally. For instance, the Novel Coronavirus (Covid-19) pandemic in 2019 devastated many healthcare systems and ravaged healthcare delivery operations (Sutherland *et al.*, 2020; Yordanov *et al.*, 2020). Thus, calling for innovative approaches to sustain the ailing healthcare systems.

The recent efforts to use technology to support consumers in healthcare have resulted in several concepts, such as Consumer Health Informatics (ConsHI), derived from Medical Informatics and Nursing Informatics (Houston *et al.*, 2001; Demiris, 2016). ConsHI (Houston *et al.*, 2001; Demiris,

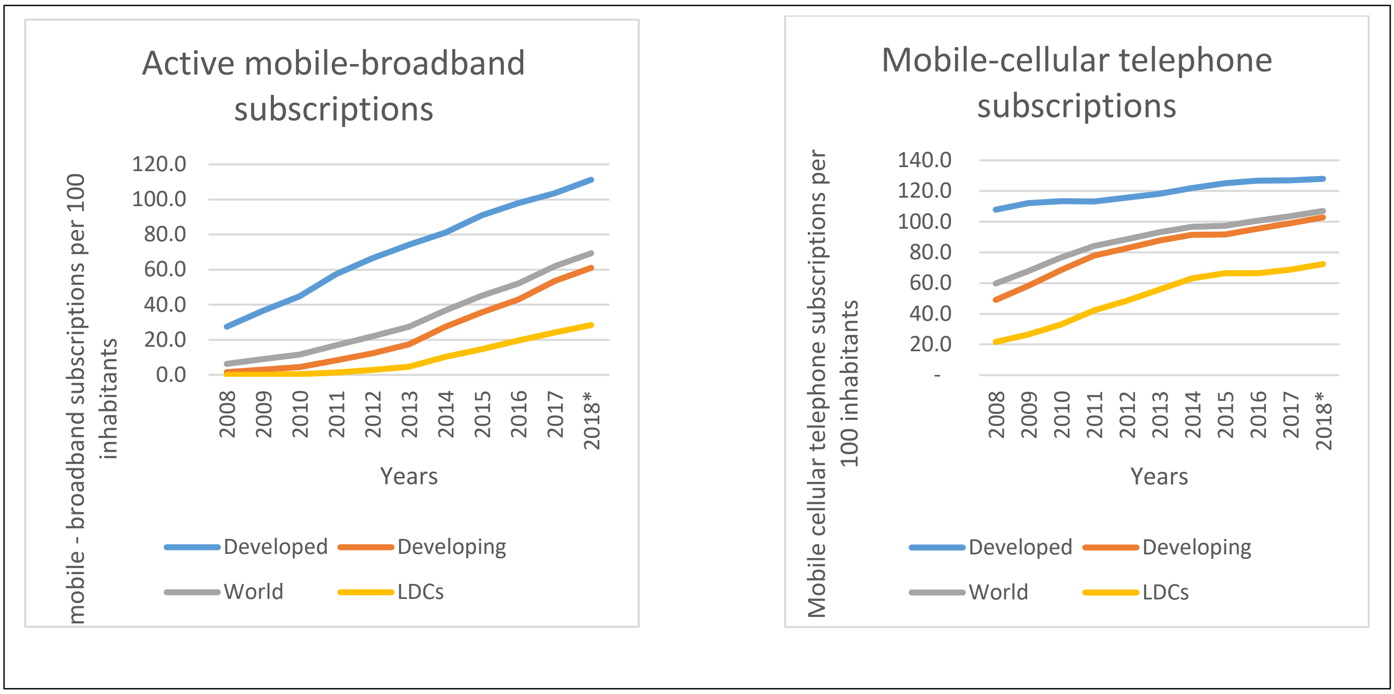
2016) is a game-changer offering to curb the myriads of issues plaguing healthcare systems by shifting the paradigm of existing healthcare systems from producer centred to consumer-centred.

1.1 THE OPPORTUNITY OF INFORMATION AND COMMUNICATION TECHNOLOGY (ICT)

Advances in the frontiers of mobile devices and the quest for personalised technology have catalysed evolutions in Information and Communication Technology (ICT). The International Telecommunication Union (ITU) reports a pervasive increase in mobile technology and the potential to bridge the digital inequalities regardless of location, population size and infrastructure (International Telecommunication Union, 2015; Union, 2018). The ITU (International Telecommunication Union, 2015; Union, 2018) revealed that by the end of 2018, global access to the Internet would have passed a critical point. More than half the world's population would have been using the Internet via mobile phones and other personalised devices for the first time. The swell in the consumerism of technology offers enormous potential for various consumer-centred services such as healthcare.

Further, the ITU data reveals a consistent improvement in the ICT infrastructure in developing countries. Current literature shows the shrinking gap between developed and developing countries due to increased access to mobile devices and essential telecommunication services.

The consistency of these findings across various studies (Pelletier *et al.*, 2011; Lluch and Abadie, 2013; Mertz, 2016) explains the relentless calls on healthcare producers and consumers alike to embrace the usage of ICT in providing Universal Health Coverage (UHC). Furthermore, there is massive potential in mHealth apps for meeting the challenges in reaching UHC, provided the apps are evidence-based (Inal *et al.*, 2020). It involves scrutinising the benefits, harms, acceptability, feasibility, resource use, and equity considerations (Inal *et al.*, 2020).



***NB:** LDCs means Least Developed Countries.*

Fig 1. 1: Trend of mobile -broadband and mobile-cellular phone subscriptions (International Telecommunication Union, 2018)

These (Fig 1.1) reports (International Telecommunication Union, 2018) show that broadband access continues to demonstrate sustained growth, with mobile broadband penetration increasing from 4 subscriptions per 100 inhabitants in 2007 to close to 70 subscriptions per 100 inhabitants in 2018 globally. This trend (International Telecommunication Union, 2018) has translated into increased investment in ICT infrastructure and enhanced the quality of services since most people worldwide can now access the Internet through a 4G, 5G or higher-speed network.

The result is the increased availability of mobile signals that promotes numerous social activities. Notably, the entire world population (97%) lives within a mobile cellular signal (Alqahtani and Atkins, 2017). Alqahtani and Atkins (2017) affirmed this position and reported that globally there are over 7.6 billion mobile connections (4.7 billion subscribers). Also, with more than one billion 4G connections in 150 countries, there is an estimated global subscriber base of 5.6 billion by 2020, representing over 70% of the world's population, thus offering an enormous opportunity for the application of mobile phone services using these technologies.

An additional opportunity to bolster this trend is the affordability of services provided by network operators in recent years. With a global drop in mobile-cellular, mobile-broadband and fixed-broadband prices, more than 50% of the world's population now subscribe to mobile phone and Internet services (International Telecommunication Union, 2018). Hence, mobile devices have become an essential part of human activities and growing directly proportionally to the global population (Srivastava, 2005).

Among the primary beneficiaries of this proliferation and reach of ICT are the Low- and Middle-Income Countries (LMICs). The global trend of increased Internet access and mobile phone ownership offers low-cost and scalable opportunities for ConsHI to empower individuals (Huh *et al.*, 2018). Practically, eHealth and mHealth are widely accessible through mobile devices such as tablets and mobile phones.

Conceivably, mobile services have offered unlimited opportunities to improve the health of citizens globally (Khatun *et al.*, 2015; Kutun *et al.*, 2015; Mogoba *et al.*, 2019), resulting in the proliferation of eHealth and its attendant innovations such as mHealth. Also, the multifaceted development of ICT and associated opportunities abound in both developed and developing countries. The potential of technology in health can be maximised, provided consumers play an active role in using mobile devices in the healthcare supply chain.

1.2 HEALTH CHALLENGES OF LMICs

There has been significant progress in managing epidemics such as Human Immunodeficiency Virus infection and acquired immunodeficiency syndrome (HIV/AIDS), Tuberculosis (TB) and Malaria since 2006 (Juma *et al.*, 2018; Ridgeway *et al.*, 2018). For example, in 2006, the incidence of HIV/AIDS decreased by 20% globally, while the mortality rate declined by 53% due to 16.4 million people from LMICs on antiretroviral therapy (ART) (Juma *et al.*, 2018; Ridgeway *et al.*, 2018). Reducing epidemics is good news because it will increase life expectancy and decrease spending on health, resulting in a more productive society and transforming countries' economic fortune (World Health Organization, 2021).

However, LMICs remain the leaders regarding people living with HIV/AIDS, and their combined spending to address HIV/AIDS lags far behind higher-income countries (World Health Organization, 2018). The global healthcare challenges remain a concern, because most developing countries lagged in the health-related Sustainable Development Goals (SDGs) and Targets index for 2017 (United Nations, 2017). Reports show that healthcare delivery in LMICs suffers from many problems (Abaza and Marschollek, 2017).

Globally, there has never been adequate human resources in the healthcare sector, spanning clinical to non-clinical staff (World Health Organization, 2021). The disparate global distribution of health workers due to brain drain motivated by unbalanced incentives offered to them in different countries remains a critical impediment to healthcare provision (Plange-Rhule *et al.*, 2005). A situation that is precarious in developing countries, particularly, the shortage of essential health professionals such as physicians, nurses, and skilled birth attendants worsens the burden of diseases in most LMICs (Plange-Rhule *et al.*, 2005).

The World Health Organisation (WHO) precisely reported that, the African region endures more than 22% of the global disease burden but has access to only 3% of the worldwide health workforce (World Health Organization, 2019). Furthermore, more than 40% of WHO member states have less than ten medical doctors per 10 000 population (Plange-Rhule *et al.*, 2005). For instance, from 2013–to 2018, statistics reveal that almost 40% of WHO member countries have fewer than ten medical doctors per 10 000 people: 90% of low-income countries suffer from such shortages, whereas only 5% of high-income countries (World Health Organization, 2019). The average global density of medical doctors in 2017 was 15 per 10 000. Up to 93% of low-income countries have fewer than 40 nursing and midwifery personnel per 10 000 people, compared to 19% of high-income countries.

The WHO African region reports that 64% of countries have fewer than five per 10 000 people a dentist (World Health Organization, 2019). Also, for pharmacists, 60% of countries have fewer than five per 10 000 people (World Health Organization, 2019). In 2016 and 2017, Ghana reported 1.27 and 1.36 doctors per 10 000 population. Similarly, the nursing and midwifery categories recorded increases in two consecutive years. Remarkably, the numbers increased from 21.16 to 23.52 per 1000 people in 2016 and 2017, respectively. In 2019, the WHO reported that Ghana's density of medical doctors was 1.1 per 10 000, while the nursing and midwifery personnel combined was 27.1 per 10 000 (World Health Organization, 2021). These figures show an increase in the nurses and midwifery ratio but a decrease in the medical doctor ratio. The fluctuation in the statistics of healthcare professionals' points to the need for alternatives to support healthcare delivery in LMICs, particularly in the WHO African region. While the WHO African regions have a higher responsibility for diseases, they have a relatively lower density of health workforce which compounds their woes. Also, a positive correlation exists between the number of health workers available to a population and a country's income. The health sector budget is low for lower-income countries, so healthcare professionals have a lower density (World Health Organization, 2019).

Furthermore, the WHO African regions have access to less than 1% of the world's budget to finance healthcare. Financial access shortage exacerbates the non-availability of essential infrastructures such as hospitals (for inpatient beds), rural population access roads, and necessary drugs for chronic diseases like HIV/TB and diabetes (Peters *et al.*, 2008). The correlation between healthcare financing and inadequate healthcare infrastructure to support healthcare services is positive in LMICs, as less funding has hampered infrastructure development and, consequently, a consistent reduction in healthcare quality. Worrying is the challenge of travelling from one location to another for healthcare. As a result of the uneven distribution of healthcare services, many people seek primary care in remote areas. Mainly, the poor roads and geographical access have remained challenging in these countries for some time. Also, travelling difficulties affect distant patients' ability to fulfil appointments with service providers.

Lack of health care financing in LMICs is a theming challenge. Globally in 2016, the mean proportion of total government expenditure from domestic sources devoted to health was 10.6%, varying from less than 2% in some countries to over 20% in others. The proportion was lowest in low-income countries (around 6.6%) and highest in high-income countries (above 14%). External aid represents less than 1% of global health expenditure. Remarkably, there is decreasing national spending on health and, consequently, inadequate infrastructure to support services in LMICs and pressure on the individual to spend out-of-pocket on their health (World Bank Group, 2017).

Recent statistics show that middle-income countries have the highest proportion of the population spending a large share of the household budget on health out-of-pocket. For instance, in 2019, the WHO reported that in 2010 an estimated 808 million people (11.7% of the world's population) spent at least 10% of their household budget paying out of their pocket for healthcare services. For 179 million people, these payments exceeded a quarter of their household budget (World Health Organization, 2019). The rising health care needs and costs exacerbate the disease burden in LMICs.

Furthermore, adherence rates to drugs and treatment of diseases such as HIV and TB remain low mainly due to a lack of awareness. Similarly, LMICs account for 99% of maternal deaths worldwide due to the lack of knowledge on reproductive health, making it one of the broadest health gaps between the developed and the developing world (World Health Organization, 2019). In most (99%) LMICs, deaths due to maternal health occurred, with almost two-thirds (64%) occurring in the WHO African Region. For instance, to reduce maternal mortality, ensuring that women have access to quality care before, during and after childbirth is crucial [48]. The same report has fallen short in achieving the Sustainable Development Goals (SDG); notably, SDG 3 seeks to ensure healthy living and promote well-being.

1.3 JUSTIFICATION FOR LMICS

The WHO asserts that ICT for health is "recognised as one of the most rapidly growing areas in health today" (World Health Organization, 2016). Universal Health Coverage (UHC) is possible with the beneficial diffusion of eHealth globally (World Health Organization, 2016, p. 5).

Adopting health technology offers eHealth an opportunity to support a wide-range and coherent approach to healthcare and support integrated people-centred services (Oliveira and Martins, 2011; Bloomfield *et al.*, 2014; Toefy, Skinner and Thomsen, 2016). That will facilitate SDG 3 to "Ensure healthy lives and promote well-being for all ages" (United Nations, 2017; World Health Organization, 2019). The eighth target is to "Achieve universal health coverage" for all people to receive high-quality health services without financial hardship.

Mobile phones seem to offer near-perfect solutions to achieving Goal 3 and Target 8 of the SDG (World Health Organization, 2016). More importantly, mobile phones benefit developing countries as challenges of infrastructure, power, and skills are pronounced in these areas (Velez *et al.*, 2014; Forrest *et al.*, 2015; Tilahun *et al.*, 2018). Also, LMICs will be the most significant potential healthcare technology beneficiaries since they have recorded high mobile phone penetration rates over the last decade (Källander *et al.*, 2013).

This study focused on selected LMICs, based on a convenience sample. It depended on the countries of origin of the research team members: Chile, Ghana, Ukraine, Kosovo, Iraq, and Turkey. In these home countries, the project team members could quickly secure approval for the required protocols and access the population to collect data.

Specifically, this study seeks to establish the fertile ground for the facilitation of mobile technology as a service to provide healthcare in LMICs. This study hypothesised that LMICs would gain more from the power of technology by promoting facilitating factors for the mass adoption of mobile technology (Hartzler and Wetter, 2014). Thus, the need to assess the maturity of citizens of LMICS for ConsHI is well-timed since the myriad of problems relating to the growing population, reducing budgetary allocation, and timely delivery of healthcare is eminent.

1.4 DIRECTIONS OF RESEARCH AND RESEARCH QUESTIONS

Understanding the success factors for adopting technology is essential (Kaba and Osei-Bryson, 2009). Lessons from implementing mobile services in developed countries could serve as a good foundation for developing countries to leapfrog in managing the myriad of persistent health challenges (Deglise, Suggs and Odermatt, 2012; Peprah *et al.*, 2020). There is enough evidence that health service providers can reduce the pressure on their resources, reduce cost and stress on healthcare workers as well as create a flexible environment to engage their consumers using mHealth (Venkatesh, Thong and Xu, 2012; Chaiyachati *et al.*, 2013; Zurovac *et al.*, 2013; O'Brien *et al.*, 2018). Developing countries have achieved little success adopting mHealth (Greenhalgh *et al.*, 2017; Lundin, Dumont and Ng, 2017). Lundin, Dumont and Ng (2017) mention the unfavourable Ghana and Zambia situations resulting in some developing countries like Uganda refusing to embark on new mHealth initiatives.

Arguably, most of these mHealth initiatives have positioned the consumer as a passive entity who only responds when the service provider initiates a request (Evans *et al.*, 2014; Chatzipavlou, Christoforidou and Vlachopoulou, 2016; Rossi and Bigi, 2017). This research shifts our focus from inactive patients in healthcare delivery to active patients (consumers) (Hartzler and Wetter, 2014). Since we also cover healthy behaviour and prevention, it makes sense to use the term citizen.

For instance, Peprah *et al.* (2020) posed some relevant questions in assessing the use of mHealth in Ghana, such as whether patients would feel comfortable having a consultation with a healthcare provider over the phone. Would patients want a self-care intervention delivered via phone? Would health care providers be willing to care for patients over the phone?

While we found these direct questions relevant to the adoption of mHealth, the maturity of citizens as a state of mind has many facets, and it remains a salient question to be answered in the adoption of mHealth.

Another claim by Edmunds and Hass (2019) is that there remains more to learn about people's preferences for technology use, considering personal differences in age, gender, race/ethnicity, cultural background, and health beliefs. They asserted that people would share their data readily if they believed it would help others and trust the custodians of the data.
These varying opinions on what factors drive the use of technology in healthcare motivated this study. The present study attempts to address multiple gaps and, in doing, addresses salient questions. Hence, the argument for researching the maturity of citizens of LMICS for ConsHI by assessing available models, factors (both facilitators and barriers) to the maturity of ConsHI and assessing methods used to evaluate technology use.

1. Hartzler and Wetter (2014) reported in their survey of demonstrator services showing a breadth of achievements and future opportunities for harnessing mobile technology to promote consumer health informatics in LMIC. Their report confirmed improvements of mHealth interventions as services in the poorest countries (LMICs) which inspires a future of leveraging mobile phones in the hands of citizens for empowerment through ConsHI (Hartzler and Wetter, 2014). Hartzler and Wetter (2014) pointed out that ConsHI has far-reaching benefits to all communication segments and cost-effectively facilitates better health and wellness. However, researchers should investigate the barriers to the maturity of LMICs.
   However, they contended that there were no universal success factors but a range of diverse and well-considered examples as evidence for mHealth outcomes in LMIC.
   Thus, no identified success factors to support the mass adoption of the concepts of ConsHI in LMICs. Despite the high mobile phone penetration in LMICs, the application of ConsHI concepts has rarely been successfully reported. The burgeoning issues hindering large-scale adoption of ConsHI relates to the maturity of the citizen of LMICs to employ mobile devices

in their routine healthcare activities (Mauco, Scott and Mars, 2019). Also, they specifically reported that gaps remain in research and practice to fight poverty and disease in LMICs (Hartzler and Wetter, 2014).

Researchers (Wang *et al.*, 2013; Hartzler and Wetter, 2014; Akhlaq, Sheikh and Pagliari, 2015; Nilmini Wickramasinghe, 2019) identified several barriers and facilitators of ConsHI as a solution to the myriads of health inequalities which will also challenge Universal Health Coverage (UHC).

Huh *et al.* (2018), in their extensive review of ConsHI amongst underserved populations between 2012 and 2017, identified several barriers and facilitators to the adoption of ConsHI amongst the underserved population in the US. Nonetheless, there is not much research on facilitators and barriers to ConsHI. Huh *et al.* (2018) suggested that future research should revise and broaden its inclusion and exclusion criteria to cover non-US contexts and underserved populations.

Furthermore, Huh *et al.* (2018) recommended that future studies consider testing barriers and facilitators in ConsHI adoption using a confirmatory technique. Their research elicited facilitators of scalability and generalizability of ConsHI amongst underserved populations. They showed that, in addition to usability methods, user-centred design techniques result in reliable methods for tailoring facilitators of ConsHI (Huh *et al.*, 2018). Such practices include common scenarios of use, case studies, and participatory critique. Their study extends the limited research on the understanding of factors that determine the maturity of the citizens of LMICs for ConsHI. Finally, a digital divide is one of the barriers to securing equal involvement in technology-based health management results, specifically among underserved population groups that unduly experience difficulty accessing care owing to social, economic, geographic, racial, or ethnicity (Huh *et al.*, 2018). The facilitators and barriers to ConsHI are embedded in theoretical models, hence the need to assess theories that support the adoption and use of ConsHI. Our study is one of the first to consider ConsHI maturity as an essential antecedent for improving healthcare in LMICs, and this results in our first research question:

Research question 1: What factors will predict the maturity of ConsHI in LMIC?

2. Venkatesh *et al.* (2003) have long tried to identify factors influencing users' acceptance of information technology by aggregating various technology-related models. Their effort resulted in the Unified Theory of Acceptance and Use of Technology (UTAUT). Notably, the initial assessed adoption in the context of members in an organisation. Subsequently, they considered individuals outside the organisational environment using their UTAUT. Their

results showed variations in technology adoption in a different context and thus the formulated Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh, Thong and Xu, 2012). Subsequently, Venkatesh, Thong and Xu (2012) suggested that future research should test UTAUT2 in different countries, other age groups, and various technologies. They argued that their model was limited to Hong Kong, with a very high mobile phone penetration rate; the findings may not apply to less technologically advanced countries like LMICs. Although they had improved on UTAUT to UTAUT2, there was room for future research to identify other relevant factors that may help increase the applicability of UTAUT to a wide range of consumer technology use contexts.

Jewer (2018) asserted that, despite the application of UTAUT to study acceptance and use in a wide variety of settings, there is limited application of UTAUT in healthcare. A literature review of 174 studies that applied UTAUT identified only ten studies in healthcare, of which only three focused on patient use of IT. Only one of those three studies (Demiris, 2016) collected and analysed data. A google scholar search for UTAUT and patients revealed four more studies that used UTAUT to study patients' intention to use health IT with conflicting findings (Jewer, 2018). Jewer (2018) concluded that UTAUT is essential by examining the model in the context of patient use. If used in its generic form, UTAUT may not capture, but rather may contradict, some of the contextual features of using such systems. Also, knowledge about UTAUT in the patient context is insufficient. To supplement these findings, we sought other models to identify factors for the maturity of the citizens of LMICs for ConsHI.

Hence, based on the UTAUT model, the study intends to ascertain the importance of ConsHI maturity in LMICs. The study would add to the theoretical development by integrating the UTAUT model with other theories and models that support ConsHI maturity in LMICs. Resulting in our next research question:

> ***Research question 2: What models and theories are used to assess citizens' maturity in LMICs for ConsHI?***

3. We now investigate elements of the above models, such as taking action, behavioural intention, habit, et cetera. Redesigning systems based on IT capabilities may further isolate underserved populations due to limited access to resources, widening the gap. There is a need to include more faciliators of use, such as those related to users and tasks, to examine the explanatory power of behavioural intention and habit. Demiris (2016) states that the predictive power of habit may increase relative to that of behavioural intention when users' daily tasks are included in the measurement of use, as daily routine tasks are more subject to the influence

of habit. There is, however, a gap in research on structural elements of use, such as those related to users and tasks, to examine the explanatory power of behavioural intention and habit. Kaba and Osei-Bryson (2009) argued that behavioural models do not universally hold across cultures, so cultural differences between countries could impact the acceptance and use of technology. Similarly, economic differences are a significant factor in determining the use of models for health and IT. Later studies (Chaiyachati *et al.*, 2013) unequivocally supported lessons learned from developed countries. However, they argued that behavioural models are not cast-in-stone, eliciting the need for models that work in LMICs. While quantitative approaches support more generalisable population findings, technology adoption issues enormously vary with socio-economic factors between developed and developing countries (Deglise, Suggs and Odermatt, 2012). Precisely, there is a need to assess the elements of actual models in improving interventions for LMICs.

The present study investigates the elements of three theoretical models (i.e., UTAUT, Patients Activation Measure (PAM) and ConsHI). The study extends the research concerning elements of technology adoptions, citizens activation and ConsHI levels to ConsHI maturity in LMICs by investigating the distinct constructions from these theories to formulate an instrument of study and assess the citizens' maturity of LMICs for ConsHI. These models and their elements help in predicting the maturity of the citizens, thus our questions:

Research question 3: What is the predictive relationship between factors in these models and the maturity of citizens of LMICs for ConsHI?

Research question 4: What other factors moderate the predictive power of the factors that influence the maturity of the citizens of LMICs for ConsHI?

In summary, existing literature points to gaps in models for technology adoption in developed versus developing countries, the inconsistent use of models to assess technology adoption, and the variation in adoption based on different methods of research points to a colossal gap in the literature. Notably, there is a need to rigorously test existing models using multidimensional datasets from different countries and quantitative techniques to identify enablers and barriers to ConsHI.

We find a growing number of endeavours and success stories (Hartzler and Wetter, 2014). However, to the best of our knowledge, there is a paucity of comprehensive models to assess the maturity of health care consumers of LMICs for ConsHI. Conclusively, LMICs are at the crux of opportunities for ConsHI and will benefit enormously from research that seeks to answer the above questions; hence in the following sub-section, our objectives are formulated based on these theming questions from literature.

1.5 RESEARCH OBJECTIVES

The research goal was to develop a model to assess the maturity of citizens of LMICS for ConsHI. The derivatives of the objectives from the research questions are:

1. To assess supportive models and theories for assessing the maturity of the citizens of ConsHI in LMICs.
2. To create a survey instrument to assess the maturity of citizens of LMICS for ConsHI.
3. To identify factors that facilitate the maturity of citizens of LMICs for ConsHI.
4. To propound a model for predicting the maturity of citizens of LMICs for ConsHI.
5. To elicit potential modifiers of the relationship between maturity factors and citizens' maturity for ConsHI in LMICs.

1.6 SCOPE AND DELIMITATION OF THE STUDY

The current study considers Internet and mobile application to healthcare as measures of ConsHI. To assess the maturity of citizens for ConsHI, we design instruments based on theories intended for both technology adoption and patient activation.

We surveyed six countries: Chile, Ghana, Kosovo, Iraq, Ukraine, and Turkey. We collected quantitative data from all six countries using the same instrument in its translations to the local languages from January 2018 to December 2018. The respondents were people in busy areas such as markets and bus stations. We also selected health facilities and clinics to collect data from respondents seeking medical care.

1.7 STRUCTURE OF THE MONOGRAPH FOR THE RESEARCH

The report is in seven parts, and chapter one introduces the entire study covering the objectives and research questions. Chapter two discusses the literature on theories, models, and concepts relevant to this study to conceptualise our maturity model. Chapter three describes the demographic characteristics of the study sites and salient factors regarding ConsHI. In chapter four, we elaborate on the materials and methods for the study, such as the sampling techniques, size, and ethical considerations from all countries. In chapter five we present the results, and the statistical methods model the ConsHI. Subsequently, we discuss the results thoroughly in chapter six, and then conclusions and recommendations in chapter seven. The penultimate chapter is eight, summarising our study in English and Germany.

1.8 TERMINOLOGY

Healthcare consumers: *A healthcare consumer* is any individual who assesses healthcare services (both patients and individuals who are not ill) for information for personal health needs (Abaidoo and Larweh, 2014). Similarly, Huh *et al.* (2018) defined Consumers as patients, caregivers, or healthy individuals with prevention needs. In a similar fashion, Ramaprasad and Syn (2016) described the consumer as the patients, caretakers, families, citizens, and communities. We note that, there are three main categories of healthcare consumers: a) healthy citizens with an interest in personal health and prevention, b) citizens with a non-persistent disease, i.e., patients, and c) chronically ill patients (Wiesner *et al.*, 2016). Interestingly, accordint to Zeng and Tse (2006) synonyms for citizen include lay people or layperson.

Lewis, Chang and Friedman (2005) offer some notably perspectives like, healthcare consumers seek information about health promotion, disease prevention, treatment of specific conditions, and managing various health conditions and chronic illnesses. Consumers of health information consisted of persons with particular health conditions, their friends and family, and the public concerned about promoting optimal health (Lewis, Chang and Friedman, 2005). For our study, *the consumer is a user of healthcare services by citizens (see all three categories)*

Mobile phone: *A mobile phone is a cellular phone, cell phone, cellphone, handphone, handphone or pocket phone; also, a mobile, cell, or just phone,* is a handy telephone for calls over a radio frequency link while the user is in motion within a telephone service area. Radiofrequency establish connections to mobile phone operators' switching systems, providing an avenue for a public switched telephone network (PSTN). Mobile phones offer only feature phones; smartphones are mobile phones with advanced computing capabilities (Little *et al.*, 2012).

Mobile Health (mHealth): is the medical and public health practice supported by mobile technology, like mobile phones, personal digital assistants, and many wireless devices (Hartzler and Wetter, 2014). We define *mHealth as using mobile devices and the Internet for healthcare activities, including preventive, curative and rehabilitative.*

A provider is a healthcare professional or facility providing healthcare needs to the consumer (Kaplan and Brennan, 2001).

For thi study, we define **access to a mobile phone or Internet** as ownership or use of another person's devices.

Facilitators: this is a factor that influences the pair-wise relations of elements, supporting corresponding relationships in a positive ("facilitator") direction (Wiesner *et al.*, 2016).

Barriers: is a factor that influences the pair-wise relations of elements, hindering elements, and factors corresponding to a relationship in a negative ("barrier") direction (Wiesner *et al.*, 2016).

Consumer Health Informatics (ConsHI): Eysenbach (1998) delivers information to patients through other media. Eysenbach (1998) coined ConsHI out of the broad heading of medical informatics and defined it as a branch of medical informatics that analyses consumers' needs for information. While Eysenbach offered to put the patient (consumer) in a recipient (passive) position in his definition of ConsHI, Wetter (2016) posited *Consumer Health Informatics as a discipline of:*

> *"Information and communication technology-based methods, services and equipment to enable the lay citizen to safely play an* ***active role*** *in his health and preventive care." (My emphasis)*

For our research, we adopt the definition that ConsHI involves patients in healthcare through ICT, making patients actively play a safe role in their health (M. Christopher Gibbons; *et al.*, 2009). *Thus, ConsHI uses mobile devices and the Internet for healthcare (mHealth), involving patients through mobile devices such as mobile phones, smartphones, and personal digital assistants* (Hartzler and Wetter, 2014).

Digital maturity: is the extent to which digital technologies are used as enablers to deliver a high-quality health service (Flott *et al.*, 2016). Also, empirically digital maturity is linked to better outcomes and is an antecedent to a well-performing organisation (individual for micro level) (Khanbhai *et al.*, 2019)

ConsHI maturity: Analogously, ConsHI maturity is the extent to which ConsHI concepts facilitate the delivery of healthcare services. Thus, the maturity of the citizens for ConsHI is the capability of consumers to use ICT, particularly mHealth (mobile devices), to perform well in the health care delivery process (Kaplan and Brennan, 2001).

CHAPTER TWO: LITERATURE REVIEW

In this chapter we use a mix of narrative and theoretical review approaches to assess and synthesise extant research in ConsHI. The rationale is to chronicle emperical evidence to produce an account of the evolving state of ConsHI while specifically identifying and commenting on applicable theoretical models. The study focuses on the context and substance of the author's overall argument (Grant and Booth, 2009). We start with the fundamentals of ConsHI, the framework and its relationship with mHealth. We proceed to discuss the facilitators and barriers to the maturity of citizens for ConsHI. Considering several theoretical frameworks, we discuss identified independent variables that support the formation of our model, touching on methods that lend support to some of these variables. We consider the maturity of citizens for ConsHI as an outcome of certain factors and deduce a conceptual model for this research.

2.1 CONSUMER HEALTH INFORMATICS (ConsHI)

Professionals in academic medical centres and health systems have used the term consumer health informatics since the year 2000 to refer to the study of people's ability to access information, participate in evidence-based care, and control their health through partnerships supported by ICT (Jadad and Eysenbach, 2001; Kaplan and Brennan, 2001). In 2001 ConsHI was explicitly distinguished to the needs and perspectives of consumers using emerging electronic tools from healthcare providers as "medical tools" developed (Gibbons *et al.*, 2009).

Notably, informatics is a growing and thriving field, incorporating artificial intelligence and consumer technology advances while evolving medical understanding and improving health (Roberts *et al.*, 2017). ConsHI provides an exciting evolution that creates new challenges and opportunities in the medical and healthcare landscape. Undoubtedly, the benefits of these new technologies in healthcare can be optimised while preserving the human side of healthcare.

Kutun, Föller-Nord and Wetter (2015) noted that ConsHI offers an active role to the consumer in preventive and curative medical services, thus emphasising healthy and ill-healthy citizens. Hence, calling them consumers is more appropriate than patients. The essence of ConsHI is consumer empowerment; therefore, using personal technologies is essential to the success of ConsHI. For this research, we adopt the definition that ConsHI involves patients in healthcare through ICT, making patients actively play a safe role in their health (Gibbons *et al.*, 2009). ConsHI uses mobile devices and the Internet for healthcare, involving patients through mobile devices such as mobile phones, smartphones, and personal digital assistants (Hartzler and Wetter, 2014).

Several authors emphasise the aspect of technology and its development. Currently, ConsHI solutions are mainly electronic tools, technology, or application designed to assist consumers, with or without the support of qualified healthcare personnel (Edmunds, Hass and Holve, 2019). The history of ConsHI reveals many consumer informatics tools used for health purposes, and most of these technologies have been reviewed elsewhere (Edmunds, Hass and Holve, 2019). The specific categories include mobile health (i.e., smartphones and wearable devices with wireless connections). These tools are mainly technology types and perspectives that have received comparatively little discussion, although essential. ConsHI tools are relevant because (1) they are known to impact the health of consumers significantly; or (2) because they are already being used by most consumers and therefore offer the potential for being able to reach everyone for health purposes (Edmunds, Hass and Holve, 2019). Earlier Gibbons *et al.* (2009) enumerated ConsHI applications to include electronic tools, technology, or system that is:

1) mainly designed to interact with health information consumers
2) interface directly with the consumer who provides personal health information to the ConsHI system and receives personalised health information from the application; and
3) the information or other benefits delivered to the consumer are not dependent on healthcare professionals.

Though not exhaustive, this classification espouses what new technologies can be used depending on the activities of consumers and the expected outcomes. Recently, wearable devices have permeated the electronic markets, which help monitor the vital signs of consumers. In addition, Gibbons *et al.* (2009) identified applications such as patient kiosks, personalised health risk assessment tools, interactive consumer websites, disease risk calculators, and electronic medication reminder systems.

Technologies, including devices, software, and networks, must work symbiotically with non-technological features such as processes, people, and policies for ConsHI to be effective. However, the technological elements become the dominant focus of design to exclude the non-technological aspects. Also, a provider's access policies and processes limit the potential of a smartphone. The design has to address the socio-technical challenges (Ancker *et al.*, 2014). The method of ConsHI using a smartphone, for example, has to encompass the creation of associated policies and processes (Ramaprasad and Syn, 2016). Remarkably, the possibilities for ConsHI to improve health and health equity are transformational. Since smartphones with enhanced audio features that quickly increase font size will deliver medication reminders for those with limited vision and hearing, new start-ups will provide home delivery for prescriptions in neighbourhoods.

Furthermore, the ontology of ConsHI helps specify the precise achievable outcomes (Ramaprasad and Syn, 2016). Convincingly, these applications and their functions employ mobile devices to provide the needed services. Consumer devices such as smartphones can collect physical activity, and affordable biometric sensors that compile and disseminate weight, blood pressure, heart rate, temperature, and blood glucose information from patients to their healthcare providers are speeding the adoption of ConsHI. Recently, the ability for consumers to increase their participation in their healthcare by recording and to distribute health data using sensors has inextricably tied together with the topics of ConsHI. They are mainly focusing on mobile devices and services such as mHealth, which have become the pivotal point for the success of ConsHI.

The applications of informatics range from cutting-edge medical research in genomics to helping consumers find necessary health information (Lai *et al.*, 2017). Notably, informatics advances in one area often benefit other areas. For example, a machine learning method for clinical research informatics might be usable in clinical decision support. A clinical decision support algorithm might be helpful as a consumer mobile health application. Also, a consumer engagement tool might provide insights into developing improved interoperability standards.

Gibbons *et al.* (2009) asserted that ConsHI tools and technologies applications include but are not limited to:

1. Applications and technologies that promote the comprehension of clinical parameters (disease management);
2. Also, comprehending observations of daily living (ODLs) and similar technologies enhancing calendaring (lifestyle management assistance);
3. Applications and technologies that enable prevention and health promotion;
4. Applications and technologies that facilitate self-care; and
5. Applications and technologies that help care and caregiving.

A systematic review (Or and Karsh, 2009) that looked at what ConsHI applications had emerged over a decade organised them into five categories: *information aids* – which offer consumers ways to access, store, control, and distribute their personal health information; *verdict aids* – which are computer-based tools that consider individual health information to help people make informed choices about their healthcare decisions; *education aids* – these generally promote health literacy for the consumer; *management aids* – these support the consumer in the long-term management of their health and best exemplified by support group services and subscription messaging services; and *rating services* – allow consumers to rank and share information about the quality of health providers, treatments and interventions, consumer health informatics apps or websites, or any other aspect of healthcare that is of interest (Or and Karsh, 2009). While they offer insight into the classification of applications, they also elicit the functions of ConsHI. Some identified functions include assessing the risk of disease and current health status, knowledge building such as education, self-management such as behaviour/lifestyle, stress, and decision-making. The functions of ConsHI should connect to the expected outcomes of the applications in the current healthcare systems.

Eysenbach (1998) is one of the early proponents of a precise definition to provide a framework for ConsHI. He posited that in ConsHI, the consumer could play a critical role in healthcare delivery (Eysenbach, 1998). While he (Eysenbach, 1998) offered the consumer a passive role in his definition of ConsHI, Wetter (2016) affirmed ConsHI as a discipline and suggested that the consumers play an active role in delivering healthcare. The multidisciplinary nature of ConsHI has increased to devices that support healthcare consumers. Consequently, the increasing case of affordable consumer devices such as smartphones, wearables, and sensors and the use of technologies such as patient portals and personal health records have fast-tracked the quest to make the consumer an active player in healthcare. Also, we emphasise the service nature over the technological nature of ConsHI and demands as a necessary criterion that consumers – healthy or patient – play an active role.

ConsHI also uses personalised information and provides the consumer tailored support to manage better their health or health care (Gibbons *et al.*, 2009). ConsHI focuses on prevention, self-management, and providing consumers with the technologies and information they need better to manage their health and wellness (Wickramasinghe, 2019).

2.2 MOBILE HEALTH (mHEALTH)

mHealth uses smartphones, tablets, wearable devices, and sensor technologies in healthcare. mHealth is fundamental to healthcare transformation since it can collect data anywhere, anytime, and integrate it into our lives (Lai *et al.*, 2017). mHealth allows for a gradual shift of healthcare closer to the patient's daily life and away from the traditional clinical environment. Some applications of mHealth include monitoring chronic disease and the potential for enhancing self-management of chronic disease. Chronic diseases are at the centre of mHealth developments. They require the continuous and active involvement of healthcare professionals and patients, all of whom can be empowered. mHealth applications in developing countries have shown effectiveness in many areas of medical care: patient follow-up, uptake of counselling and testing, and improved patient adherence and response to treatment (Arnhold, Quade and Kirch, 2014; Seçkin *et al.*, 2016). In practice, mHealth aids in transmitting electronic medical records between medical staff and patients, monitors patients remotely, sends automatic alerts for disease control, and provides practical applications, information, and functionality to health consumers (Lai *et al.*, 2017).

ConsHI represents a drastic shift in focus from traditional medical informatics based on industrial-age concepts (e.g., provider-driven) to consumers based on the ubiquity of information (Lai *et al.*, 2017). Consumers use the various applications of mHealth for activities such as finding health advice, medical treatment compliance and adherence. Also, consumers staying connected with their healthcare providers enhance personal health and chronic disease management activities (Rai *et al.*, 2013). The use of mHealth to broaden access to health care in developing countries remains pronounced in practice and research.

Considering ConsHI and mHealth, evidence (Lai *et al.*, 2017) shows there is an overlap between mHealth when it is mobile and has an active patient. Nevertheless, we have disjoint parts, e.g., active consumers in non-mobile landline internet-based, ConsHI but not mHealth, and passive patients in motion (the 24-hour ECG is an example), which is mHealth but not ConsHI.

2.3 MATURITY CONCEPT

Maturity is a broad concept that includes biological, psychological, legal, and cultural aspects of nature. Notably, biological maturity is a readiness to reproduce; psychological is stability in mindset. At the same time, the legal is responsible for crimes on the one hand and the capacity to close contracts. On the other hand, cultures share immaterial assets and values of a society. It is noteworthy that the maturity of ICT has all these components except biological. Since our study has more social and psychological connotations, we are inclined to this perspective of maturity.

The preponderant investigation of Caspi, Roberts and Shiner (2005) into maturity using the maturity principle, is a good starting point for our consideration of the maturity concept. Particularly, they argued that the graduation to maturity, reveals that, most people become more dominant, agreeable, conscientious, and emotionally stable over the course of their lives. They classify this form of maturity into two: first, the **humanistic** persepctive, equating maturity to self-actualisation and personal growth, becoming less defensive and rigid and more creative and open to feelings. Notably, they argued that emperical evidence, does not second this developmental progression; and that, people do not grow increasingly open to experience toward old age; after young adulthood, they exhibit declines in traits related to Openness-to-Experience. Secondly, they profess the **functional** definition, equating maturity to the capacity to become a productive and involved contributor to society, becoming more planful, deliberate, and decisive, but also more considerate and charitable. Evidently, most people seem to become more functionally mature with age, and those who develop the critical ability of psychological maturity earliest are more effective in their love, work, and health.

We find their functional definitions of maturity more appealing to our objectives. It is fair to align with the functional definition since it points to productivity towards work, love, and health, which are cardinal constructs of our theoretical models (Marsh, Nagengast and Morin, 2013). Consequently, we define maturity as capacity to become productive in the application of ConsHI. Consequently, the maturity of populations is an aggregation of the maturity of individuals in the sample of interest.

The maturity of the citizens for ConsHI is the capability of consumers to use ICT, particularly mHealth (mobile devices), to perform well in the health care delivery process (Kaplan and Brennan, 2001). While we are aware of infrastructure to support mHealth becoming available, we investigate the willingness and capacity of citizens in LMICS to actively adopt and maximise the use of their mobile devices in healthcare services.

As more interactive, consumer-facing applications appear, consumers are now playing a more active role in their health management and the shaping of services. The shift of responsibility and power from the institution to the individual has vast implications for worldwide healthcare systems. Patient-centred innovations will influence and be influenced by the organisation's changes and healthcare funding. The adoption of information technology (IT) suggests that consumer characteristics (e.g., socio-economic characteristics), individual differences (e.g., personal innovativeness), and situational factors (e.g., access to and utilisation of health care services) significantly impact IT preferences (Rai *et al.*, 2013).

2.4 FACILITATORS TO ConsHI ADOPTION

Kutun, Foller-Nord and Wetter (2015) investigated the involvement of patients in health care through ICT in LMICs. Their descriptive statistics of studies on ConsHI attributed the successes and failures to apparent factors. They reported a lack of common success factors to support the service-to-context fit for ConsHI (Kutun *et al.*, 2015). ConsHI, like many concepts, will thrive or diminish based on notable factors (Wiesner *et al.*, 2016). Such factors can influence the corresponding relation in a positive ("facilitator") or negative ("barrier") direction (Wiesner *et al.*, 2016). Comparably, successful technology implementation requires understanding how various factors like the individual, human-technology interaction, organisational, social, task, and environment affect acceptance (Or and Karsh, 2009).

While the application of advances in informatics benefits other areas, researchers still ask for the facilitating and hindering factors to the success of these technologies as socio-technical systems in healthcare delivery (Edmunds, Hass and Holve, 2019). These intriguing puzzles pose the question of facilitators and barriers to adopting these mobile technologies in developing new information tools and services for LMICs (Kaplan and Brennan, 2001).

The factors that facilitate the adoption of technology (ConsHI) depend on the settings. The settings for technology adoption have been classified into Macro (global/national), Meso (Corporate, Organization, Regional) and Micro (Individual, personal, citizen)(Venkatesh *et al.*, 2016). The provision for Macro settings in most jurisdictions is policy direction like the Ghana Electronic Transaction act, the Legal status of the International Telecommunication Union (ITU) and many other global and national protocols to ensure the safety and security of users.

Similarly, Meso (Corporate, Organization, Community, Group) settings offer systems that require organised technology usage. For instance, workers/ employees must use the technology and services provided in their work environment in the contemporary workplace since corporate demands and goals exist. The first two (macro and meso) settings are mandatory (involuntary, obliged, or compulsory).

While these settings may facilitate technology adoption, the ultimate driver is the micro (individual, personal) user.

When micro (individual) users drive technology (ConsHI) adoption, they are intrinsically motivated, so factors that support their drive should be established and promoted. Consequently, facilitating factors will differ for the involuntary and voluntary technology users (Šumak *et al.*, 2017). Also, organisational use of technology that creates a quasi-compulsory environment will reveal different facilitating factors (Bawack and Kamdjoug, 2018).

Wickramasinghe (2019) identified enablers and barriers to ConsHI in developing countries (Macro factors). Facilitators included socio-political support through proper administration, practical strategies, and substantial political goodwill. These will prevent incompetence and inconveniences that would cause ConsHI to fail. Cost-effectiveness of a solution, such as affordable Information Technology (IT) infrastructure, a practical business model that drives growth, and consistent investment, were financial enablers of ConsHI. The development and adoption of mobile phone services, IT hardware, reliable power supply, and protection against data loss and damage to hardware are enabling infrastructure for the success of ConsHI (Wickramasinghe, 2019). These are typical macro facilitators of ConsHI.

Meso factors that facilitate the adoption of ConsHI include dissatisfaction with medical care services and one's health plan. Also, dissatisfaction with transportation and the amount of disease treatment-related information given by a physician. Positive attributes like internet skill training promote ConsHI adoption in the macro context. The plethora of factors reported in the literature consider all categories (Macro, Meso, and Micro), however since this study focuses on citizens (micro), less attention will be given to Macro and Meso factors that facilitate the adoption of ConsHI (Šumak *et al.*, 2017).

The adoption of ConsHI emphasises active citizens, proposing a more voluntary (non-organisational) user context. Personal motivation becomes one of the many drivers, leading us to assess facilitating factors contextually. Again, Hartzler and Wetter (2014) enumerated three factors that can facilitate the maturity of Citizens for the health-related use of the Internet and Mobile phones in LMICs. Their study emphasises the personal level; the first factor is *instincts and emotions*, comprising trust, privacy, and confidence directly related to ConsHI concepts (Hartzler and Wetter, 2014). The second individual factor encompasses the *acquired skills, knowledge, and cultural beliefs,* extended to include literacy, and personal motivation, which mandates cultural appropriateness as an essential theme beyond general usability principles. Thus, cultural appropriateness may technically mean availability in multiple languages (Hartzler and Wetter, 2014).

Finally, (Hartzler and Wetter, 2014) identify community factors conveyed through *societal influence* as the third factor in facilitating the adoption of ConsHI. They posit that material possessions that connote the ability to acquire and sustain the running cost of mobile services are enablers. Also, religious beliefs and practices affect the context of ConsHI differently. Mostly in LMICs, religion plays a significant role in the communities; hence, a source of information on moral support from religion will facilitate the adoption of ConsHI.

Besides, Huh *et al.* (2018) enumerated facilitators for individuals, such as (1) *early user engagement through iterative user-centred design;* (2) *engaging users throughout the design and development process and identifying their health information needs; and finally,* (3) *involving proxies, such as caregivers or family members*, who are more familiar with technology and use ConsHI on behalf of the users.

Imperatively, the particular user context is somewhat motivated by individual demographic variables like age, sex, education, marital status, and residential status. Or and Karsh (2009) examined age in 39 publications and found inconsistency. Twenty-six (67%) of the studies reported a significant effect of age, while 13 reported insignificant results. Similarly, the review of gender revealed that gender was the second most considered variable; however, the majority (84%) reported a negligible effect of gender in affecting the use context of technology. Lastly, they reviewed 28 publications and reported education as another revealing variable in the adoption context. More than half (68%) posited that adoption positively correlates with educational levels (higher education connoted faster adoption of technology.

Previous exposure to computer/health technology is an antecedent to ease of acceptance. In two studies to assess the different perspectives of exposure to computer/health technology (i.e., computer ownership, previous usage of computers, past Internet usage, and past experiences of health Web sites or health technology and accessing the Internet at home). More than half (15) found that previous experience was associated with increased acceptance. The rest of the sociodemographic variables were examined in too few studies to draw conclusions or mixed results.

These variables are moderators that can influence the dependent and independent variables. This study uses moderators to assess the relationship between constructs and factors that predict the maturity of the citizens for ConsHI.

2.5 BARRIERS TO CONSHI ADOPTION

Analogous to our classification of facilitators, barriers to adopting ConsHI include macro, meso (Organization, structured, compulsory) and micro (individual, unstructured, voluntary). Houston *et al.* (2001) enumerated the following as macro and meso-level barriers to ConsHI: (1) lack of funding for ConsHI, (2) lack of a standard definition for ConsHI, (3) lack of access due to some digital divide, (4) lack of quality control /research evidence (5) lack of cooperation, user-involvement, and support, and

(6) lack of consumer privacy. Some of these factors were reported in 2001 by Eysenbach and Jadad (2001).

Considering the particular context of barriers, they (Huh *et al.*, 2018) found barriers to ConsHI adoption at the micro level, particularly among underserved populations such as LMICs, to include: (1) little health literacy; (2) challenges in accepting the present information technology systems; (3) poor usability and clarity of content; and (4) lack of involvement with information technology usage. Other barriers identified in a 2010 report to the Office of the National Coordinator for Health Information Technology (ONC) (NORC, 2010) showed that (1) low levels of health and technological knowledge, (2) culture and language barriers, (3) lack of ease in relating with the healthcare system, and (4) the digital divide were barriers of ConsHI adoption. Gibbons (Gibbons, 2011) further enumerated barriers to ConsHI in underserved populations, such as the lack of trust, technical challenges, technology fears, and cognitive and physical disabilities as persistent barriers to ConsHI adoption. These barriers reflect the insufficiency of user motivation and barriers to technology access rather than the design of ConsHI systems.

Discussing barriers at the Macro level, Demiris (2016) repeated the critical concern of privacy and security, considering the surge of cybersecurity challenges that could compromise patient privacy. The lack of access to infrastructures like computers and the Internet and user behaviour compounds these barriers. Demiris (2016) identifies additional barriers like ethical, practical, and legal concerns in multi-country engagement for mHealth. Other restrictions include installation, maintenance, and training costs, which could be high on average.

While these factors are not exhaustive, it is paramount to consider some as salient and feeding into adoption theories. Šumak and Šorgo (2016) asserted that there are several theories on information systems and the application of technology to human activities(Šumak and Šorgo, 2016). Previous approaches serve as springboards for discussing inputs to develop a theoretically grounded model. In the following sub-section, we discuss selected and relevant theories to build a model for the maturity of citizens for ConsHI in LMICs.

2.6 THEORETICAL MODELS

Technological adoption studies such as ConsHI are in various denominations, such as intentions, technology acceptance, technology adoption, technology resistance and others, by theorists from many fields, including health, information technology, psychology, and sociology (Macedo, 2017; Margulis, Boeck and Laroche, 2019). Most technology and health adoption research is rooted in theoretical models like the Technology Acceptance Model (TAM) (Chuttur, 2009; Ma and Liu, 2011), the Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2) (Venkatesh *et al.*, 2003, 2016; Venkatesh, Thong and Xu, 2012), the diffusion of innovations theory (Walker and Whetton, 2003) and the Patient Activation Model (PAM 32 and 13) (Hibbard *et al.*, 2004, 2005; Hibbard and Gilburt, 2014). Studies investigating the adoption and acceptance of information systems in healthcare are numerous and cover various technologies (Khechine, Lakhal and Ndjambou, 2016).

Leveraging constructs from research in technology acceptance, technology assimilation, consumer behaviour, and health informatics, we developed a cross-sectional survey to study determinants of consumers' mHealth usage intentions, uptake, and channel preferences. The study uses selected relevant models, such as UTAUT, PAM and ConsHI.

2.6.1 Unified Theory of Acceptance and Use of Technology (UTAUT)

This theory advanced through reviews and merging of constructs from eight models used by earlier researchers to explain information system usage behaviour (Venkatesh *et al.*, 2003; Šumak and Šorgo, 2016). UTAUT summarises 32 variables from eight extant models, namely 1. Theory of Reasoned Action(TRA), 2. Theory of Planned Behavior (TPB), 3. Technology Acceptance Model (TAM), 4. Motivational Model (MM), 5. Combined Theory of Planned Behavior and Technology Acceptance Model (C-TPB-TAM), 6. Model of PC Utilisation (MPCU), 7. Diffusion of Innovation Theory (DIT) and 8. Social Cognitive Theory (SCT) into four measurement and moderating factors (Im, Hong and Kang, 2011; Khechine, Lakhal and Ndjambou, 2016). The blends of the measurement constructs and moderating variables have increased the predictive efficiency to 70%. Succinctly, UTAUT aims to explain user intentions to use an information system and subsequent usage behaviour (Venkatesh *et al.*, 2016).

Oye, Iahad and Rahim (2014) reported that the UTAUT model elicits the critical factors in the acceptance of ICT as measured by behavioural intention to use the technology and actual usage. In doing this, Venkatesh *et al.* (2003) defined the four measurement constructs in the context of the consumer as follows:

- *Performance expectancy is defined as the amount to which using technology will deliver benefits to consumers in performing certain activities* (Venkatesh *et al.*, 2003; Venkatesh, Thong and Xu, 2012)
- *Effort expectancy is the degree of ease linked with consumers' use of technology* (Venkatesh *et al.*, 2003; Venkatesh, Thong and Xu, 2012)
- *Social influence is the extent to which clients recognise that vital others (e.g., family and friends) believe they would use a specific technology* (Venkatesh *et al.*, 2003; Venkatesh, Thong and Xu, 2012)
- *Facilitating conditions refer to consumers' recognition perceptions of the resources and support available to perform a behaviour* (Venkatesh *et al.*, 2003; Venkatesh, Thong and Xu, 2012)

UTAUT was initially used in organisational (Meso) contexts, and the primary constructs were performance expectancy, effort expectancy, social influence, and facilitating conditions. While the first three impact usage intention, the facilitating conditions directly determine user behaviour. Age, Gender, Voluntariness, and Use experience are defined to moderate the impact of the four critical constructs on usage intention and behaviour (Figure 2.1).

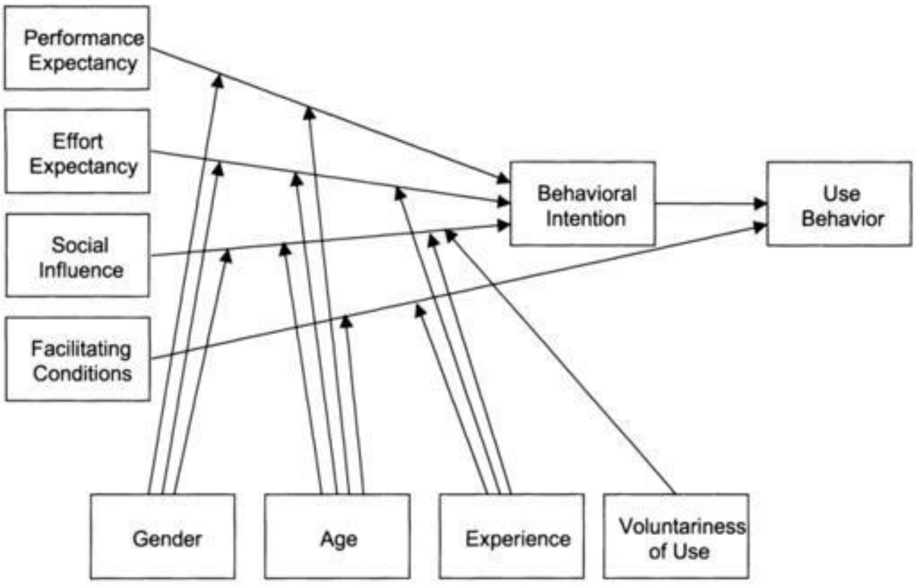


Fig 2. 1: Theoretical Model of UTAUT (adopted from Venkatesh *et al.* (2003)

2.6.2 Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

In 2012, (Venkatesh, Thong and Xu, 2012) revised their earlier version of UTAUT, paid more attention to the context of consumer (micro) use, and developed UTAUT2. Subsequently, they added three vital constructs from prior research on general adoption, consumer adoption and use of technologies. They modified some of the existing relationships in UTAUT and included new links (see Fig 2.2). Venkatesh, Thong and Xu (2012) considered the behaviour in the use and acceptance of technologies when users are responsible for their costs. They included three constructs (Hedonic motivation, Price value and Habit) into UTAUT, resulting in UTAUT2. Hedonic motivation was defined *"as the fun or pleasure consequential in using technology"*, and it plays a significant role in determining technology acceptance and uses, mainly in the consumer context. The second construct, Price value, is defined as *"a consumer's coherent exchange amongst the professed benefits of the applications and the cost-effective price for using them"*. Finally, Habit is *"the extent to which people tend to perform behaviours repeatedly because of learning"* (Venkatesh, Thong and Xu, 2012, p. 161).

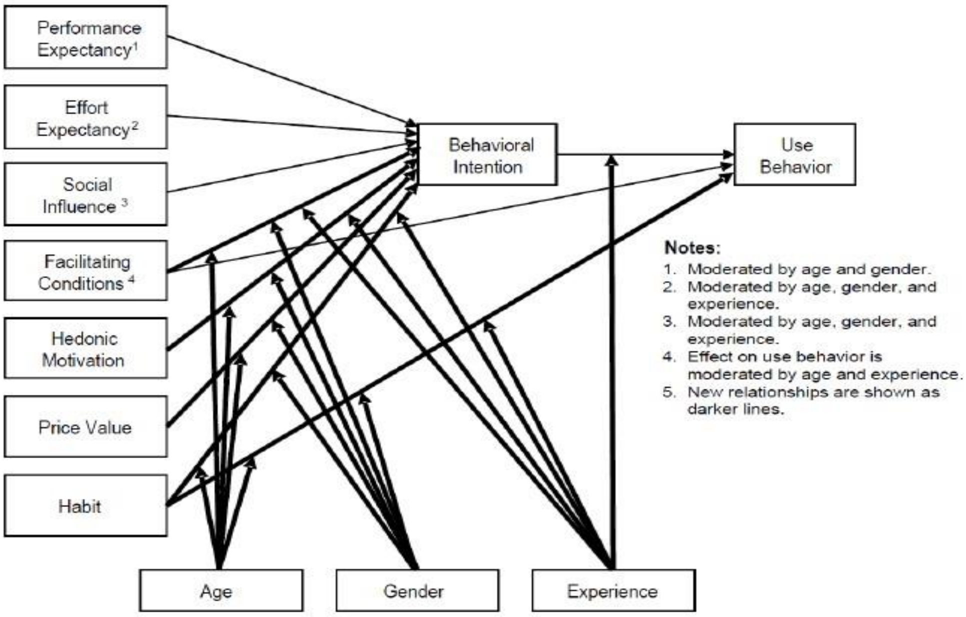


Fig 2. 2: Theoretical Model of UTAUT2 (Source Venkatesh, Thong and Xu, 2012)

2.6.3 Extension of UTAUT (UTAUTe)

Venkatesh *et al.* (2016) synthesised the applications of their model in various publications. They suggested that UTAUT extension is when an empirical study includes part of or the complete UTAUT as the baseline model and identified 37 extensions of UTAUT in various publications.

In 2017, Hoque and Sorwar (2017) extended the UTAUT model because they wanted to understand the elderly's acceptance and adoption of mHealth services in developing countries. They fashioned a questionnaire and collected data from 300 participants aged 60 and above from Bangladesh. Compared to UTAUT, new questions addressed the presumed factors of technology anxiety and resistance to change. In their study, their questionnaire was divided into two parts. Part A contained demographic information (age, gender, educational qualifications, chronic disease, and mobile phone usage experience). Part B included questions for the different constructs presented in UTAUT and the new items, all using a 5-point Likert scale, starting from "strongly disagree" to "strongly agree" (Hoque and Sorwar, 2017).

2.6.4 Applications of UTAUT and UTAUT2

Bawack and Kala Kamdjoug (2018) used clinicians to assess factors influencing adoption of health information systems in Cameroon. They modified the UTAUT and used structural equation modelling (SEM) by collecting structured questionnaires from doctors in public hospitals in Cameroon. Answers from the 228 respondents revealed that UTAUT explained only 12% of the variance in clinicians' intention to use IT. Besides, age was the only significant moderating factor, improving the model to 46%. Self-efficacy and cost-effectiveness have no substantial direct effect on HIS adoption in the context of this study. They concluded that UTAUT is not robust in identifying factors that contribute to the approval of IT by clinicians. Age was a moderator and revealed that younger clinicians are more likely and ready to adopt IT than older clinicians. The settings of UTAUT applications increase the explanatory power in a different context.

For example, Jewer (2018) examined UTAUT in a quasi-experiment setting using patients, which is very interesting to this study since her research offered a mix of structured and unstructured environments. The study's objective was to adapt UTAUT to the context of consumer acceptance of an Emergency Department (ED) wait-times website to ascertain the modified model and compare the results to the original UTAUT model. This study revealed that the modified UTAUT improved variance explained behavioural intention compared to UTAUT (66% versus 46%). The modified-UTAUT model showed significant effects in constructs such as performance expectancy and facilitating conditions on behavioural purpose to use the website. The study provides evidence for the modified-UTAUT in patients' choice to use an ED wait times website.

In another study, an extended UTAUT was used to test a model for predicting the factors affecting older users' acceptance of Home Telehealth Services (HTS) using a survey methodology (Cimperman, Makovec Brenčič and Trkman, 2016). They administered to 400 participants aged 50 years and above from rural and urban Slovenia environments. Structural equation modelling is used to examine the causal effect of seven hypothesised predicting factors. The results also indicate that Social Influence as an irrelevant predictor of acceptable behaviour. The model of six predictors yielded 77% of the total variance explained in the final measured Behavioral Intention to Use HTS by older adults. In their conclusion, the level at which HTS are perceived as easy to use and manage is the leading predictor of older users' HTS acceptance. Together with Perceived Usefulness and Perceived Security, these three factors influence older people's HTS acceptance behaviour.

Other research (Palau-Saumell, Forgas-Coll and Javier, 2019) examined the adoption of mobile applications for restaurant searches and reservations (MARSR) by users as part of their experiential quality. Following an extended and expanded version of UTAUT2, their research proposed eight predictors of intentions: performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, price-saving orientation, Habit, social influence, and perceived credibility. They found the need to extend and expand UTAUT2 by including perceived credibility and the social norm approach. According to their study, the intentions to use MARSR include Habit, perceived credibility, hedonic motivation, price-saving orientation, effort expectancy, performance expectancy, social influence, and facilitating conditions. Habit, facilitating needs, and intentions to use is significantly related to use. Also, the moderating effects of gender, age, and experience were tested. Users' experience moderated the relationships hypothesised in the model, while gender and age were insignificant (Palau-Saumell, Forgas-Coll and Javier, 2019).

2.6.5 Patient Activation Measure (PAM)

Emerging policy directions that promote consumer-centric care are vital in healthcare quality and cost management. Hence, consumer-directed health plans rely on conversant choices to manage costs and improve the quality of care. Consumer participation in healthcare decision-making is a laudable approach to improving healthcare, reducing cost and offering the best services amid alternatives. Notably, no existing measure includes the broad range of elements involved in consumer activation, including the knowledge, skills, beliefs, and behaviours that patients need to manage their healthcare (Hibbard *et al.*, 2004).

Hibbard *et al.* (2004a) argued that there was no single measure for assessing patient engagement in developing PAM's healthcare process. Further, they asserted a consensus that engaging patients to be an active part of the care process is a critical element of healthcare quality. Improving this aspect of care will require three pertinent steps: (1) composing a measure to evaluate activation; (2) identifying and using practical interventions to accelerate activation; and (3) a system for accountability for providers for supporting and increasing activation (Hibbard *et al.*, 2004).

Consequently, they proposed a measure that can assess the readiness of patients to participate in the healthcare process by activation. This measurement is called the Patient Activation Measure (PAM), where patients progress through four stages as they become activated. PAM has solid psychometric properties and seems to tap into the developmental nature of activation. It is highly versatile at the personal level and reasonable to diagnose activation and individualise healthcare plans. Predictably, the measure maintains accuracy across diverse demographic and consumer groups and is usable at the aggregate level to compare the efficacy of different interventions and healthcare delivery systems.

The first version of PAM developed in 2004 consisted of 22 – unidimensional items (earlier a Likert scale but later converted Guttman-like scale) measuring patients' performance from 0 – to 100 (Hibbard *et al.*, 2004). PAM is attuned from 0 to 100 and determines how ‘activated’ a person is in four stages (Level 1–4, where one is least activated). They defined the four stages as follows:

1. *Believes Active Role Important: patients believe they can play a role in their healthcare*
2. *Confidence and knowledge to act: patients with self–confidence and the knowledge to take action.*
3. *Taking Action; these are patients who are sure able and take action*
4. *Staying the Course under Stress: patients who can endure to the end of the care delivery process* (Hibbard *et al.*, 2004).

2.6.6 Patient Activation Measure revised (PAM2/PAM - 13)

Subsequently, they (Hibbard *et al.*, 2004, 2005) revised the 22 items in the first version to 13 items in 2005 but still used the Likert scales. Their revised PAM is designed to assess an individual's knowledge, skill, and confidence concerning managing their health. Interchangeably we call it Patient Activation Meausre 2 (PAM2) or PAM-13. For conformity to UTAUT in this research, we will contact the PAM-13 PAM2. The new 13 – item PAM2 has similar psychometric properties as the original 22 – items. However, PAM2 resulted in slightly lower reliability for some consumer groups, such as chronic illness or 85 + years of age. Similarly, trends were observed among those with self-rated poor health and those with lower income and education (Hibbard *et al.*, 2004, 2005; Roberts *et al.*, 2016).

2.6.7 Application of PAM and PAM2

However, international evidence demonstrates that PAM2 has been used to evaluate various self-management interventions across different long-term conditions, countries, and cultures (Fowles *et al.*, 2009; Roberts *et al.*, 2016). Thus, PAM2 has become a validly accepted measure of consumer activation and contribution to healthcare. PAM2 was was validated in different settings for both inpatient and outpatient (Hibbard *et al.*, 2005; Roberts *et al.*, 2016; Tiase *et al.*, 2018). For instance, Barello *et al.* (2016) asserted that PAM2 is a reliable and valid measure to be used in the inpatient setting. Therefore, by measuring patient activation with PAM2, clinicians and researchers could precisely understand their patients and provide personalised communication and care plans to meet patients' needs.

2.6.6 Consumer Health Informatics (ConsHI): Levels of service

Wetter (2016) described ConsHI from the perspective of services and defined four Levels in which individuals safely play an active part in their health care using technology. So "level" is used synonymously in the PAM and the ConsHI discourse. However, while PAM's levels are about a patient's initiative regarding their medical condition, ConsHI levels are about how ICT is used and is instrumental in health-related behaviour. In the following, we explain the four levels of ConsHI with illustrated examples.

Level 0: this is the first stage in the ConsHI adoption levels. The main characteristic of this level is that services include citizens initiating and searching the Internet, finding, trusting, and eventually acting based on the information. The search leads to content that enables decision-making. Based on estimates, one-third of Internet searches have a medical range (Gibbons, 2011; Li *et al.*, 2015, 2020). Internet users need to be able to describe their medical problems precisely. Most information on the Internet is knowledge about medicine and health care in general, and this knowledge is usually simplified to be understandable for laypeople.

However, Wetter (2016) demonstrated that using conventional search engines does not guarantee valid or reproducible results. Wetter (2016) reported that Wikipedia and the pharmaceutical industry are not independent, and Wikipedia articles often underreport adverse drug events. Another fact known by Wetter (2016) is that people often use the Internet for self-diagnosis. In one follow-up investigation about the opportunities and perils of such self-diagnosis, only ~40% of the self-diagnoses were confirmed (Kuehn, 2013). So, 60% of the self-diagnosed citizens risked unwanted consequences from inappropriate behaviours.

Level 1: at this level, the physician and patient enhance their face-to-face visits through intermittent synchronous and asynchronous exchange of information. It extends into an ICT-enhanced relationship where the exchange of medical information between clients and their providers allows the patients to modify their health-related behaviours actively. Providers can be physicians, physical therapists, dieticians, et cetera. On ConsHI Level 1, new media, such as social networks, e-Mail, or electronic health records, are used. However, identification, authentication and privacy can contain some risks. Electronic health records can collect all client and physicians' data into a client's health history. At level 1, ConsHI services exist for various chronic conditions, including asthma, diabetes, hypertension, depression, rheumatism, and pain. However, we must still find better solutions to manage this data and take advantage of it (Wetter, 2016).

Level 2: here, services are without in-person contact between provider and client, primary preventive and promoting positive health behaviours through technology. They can show benefits when used for prevention and well-being, such as nutrition, physical fitness, or the control of medications. At level 2, some critical applications include child health promotion, sexually transmitted disease prevention, mental disorders, and addiction management. For these diseases, communication is essential and virtual reality therapies or virtual group therapies are under development. Somatic diseases are harder to manage virtually, but some services try to give behavioural advice without making the patient feel embarrassed (Wetter, 2016). Wetter (2016) draws attention to health services legislation and ethics. According to the prohibition of remote treatment ("Fernbehandlungsverbot"), it is imperative (with very few exceptions) that medicine is not practised through such services while prevention and behavioural advice are primarily legal.

Level 3: Comparable to level 0, the client willingly provides services based on a wealth of knowledge and experiences acquired over a period. Clients offer to share real-life experiences and practices that seek to support others in a similar situation through ICT. The exchange of such knowledge occurs at three stages: individual (person – person) through ICT. Next is the group stage, coordinated efforts mainly to support groups of similar needs. The final step is the crowdsourcing level. Here, people work collectively to discover and build knowledge. Again, level 3 offers a similar hand as PAM, where the consumer initiates support for others.

Considering the previous discussions of the technology theory (UTAUT, UTAUT2, and UTAUTe) and consumer participation in health (PAM and ConsHI), we profess a conceptual model derived from these theories. Using a survey approach to include items appropriate to assess the adoption of mobile services as a measure of citizens' maturity for ConsHI, we aggregated items from UTAUT2, PAM, and ConsHI levels.

2.7 CONCEPTUAL FRAMEWORK

This study aggregates construct, namely UTAUT, UTAUT2, UTAUTe, PAM, PAM2 and ConsHI, from various studies (Venkatesh *et al.*, 2003; Hibbard *et al.*, 2004, 2005; Venkatesh, Thong and Xu, 2012; Wetter, 2016; Hoque and Sorwar, 2017) to formulate a novel conceptual framework that postulates patients engagement to support ConsHI. Since, these factors including the ones from section 2.4 (Hartzler and Wetter, 2014; Huh *et al.*, 2018) are adopted from theoretical models, for the purposes of our study we call them theoretical factors (**t – factors**).

The study seeks to assess active participation in healthcare using the Internet or mobile device, which connotes a blend of technology and services (i.e. UTAUT, UTAUT2, UTAUTe and ConsHI, respectively) (Carlsson *et al.*, 2006). Also, PAM will elicit health awareness and psychological responses. At the same time, this research's extension of UTAUT (UTAUTe) will assess the technology anxiety and resistance to change (Hoque and Sorwar, 2017). Below (Fig 2.3) is our high-level conceptual framework.

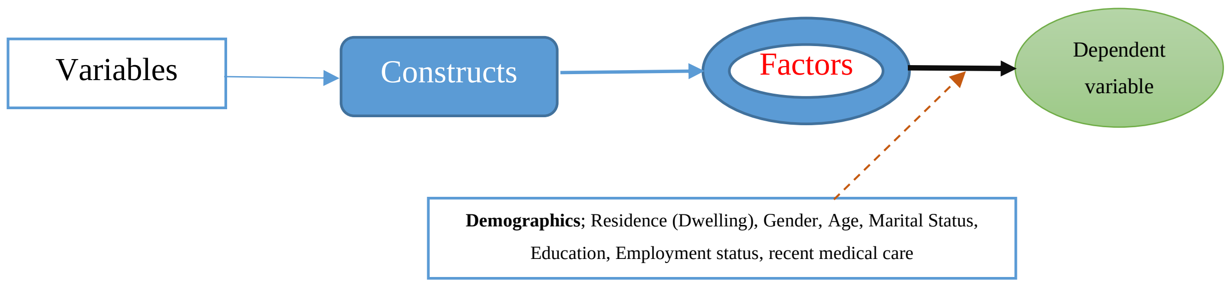


Fig 2. 3: High-level conceptual framework for assessing the maturity of the citizens of LMICs

2.7.1 Dependent variable

The output of the system is dependent variable. In this study, the dependent (outcome) variable is the maturity of citizens for ConsHI. The citizens' maturity for ConsHI is consumers' ability to use ICT, particularly mHealth (mobile devices), to access healthcare delivery (Ben-Zeev *et al.*, 2014; Price *et al.*, 2014; Abaza and Marschollek, 2017). Also, the willingness and ability to use mobile phones and the Internet for healthcare purposes, be it preventive or curative, is regarded as maturity. Arguably, using the mobile phone and the Internet for appointments and discussing medical conditions with a medical professional will require a higher level of willingness and ability. Hence consistent with Hibbard *et al.* (2004a), progression is assessed using the various levels of ConsHI. Notably, ConsHI levels connote multiple stages of maturity.

2.7.2 Independent variables

Conceptually we compose our maturity predictors from the t – factors like performance expectancy, effort expectancy, social influence, and facilitating conditions in the context of ConsHI. These can be called **Attitudes,** which are positive attitudes that determine how the Internet is used (e.g., Level 0 Services). Similarly, we propose **Confidence** as a trust factor in one's ability to handle technology and take action. Constructs such as the Habit of using a mobile phone or the Internet (e.g., Level 0, 1 or 2 ConsHI services), the following factor anchors on skills and affinity for the technology and services, which is an **Aptitude,** consisting of the constructs behavioural intention and taking action. These individuals have the necessary ability to see the potential in ConsHI and be skilled in ConsHI Level 2. Lastly, **Motivation** consists of hedonic motivation, actual behaviour usage and the ability to stay under stress. To distinguish the various conceptual factors, we will label the maturity factors **m – factors**. Emperically, these are composites of the t – factors that will be used to predict the outcome variable ConsHI maturity.

Notably, gaming has become an integral part of managing mobile applications. Thus, assessing the individual fun level using the mobile phone or the Internet would enhance the adoption. On Level 3 ConsHI services, we assume fun will motivate the consumers to use ConsHI services for an extended period. Conversely, technological anxiety and resistance to change are negative attitudes towards technology. Also, a lack of confidence would be associated with a lack of knowledge about caring for oneself.

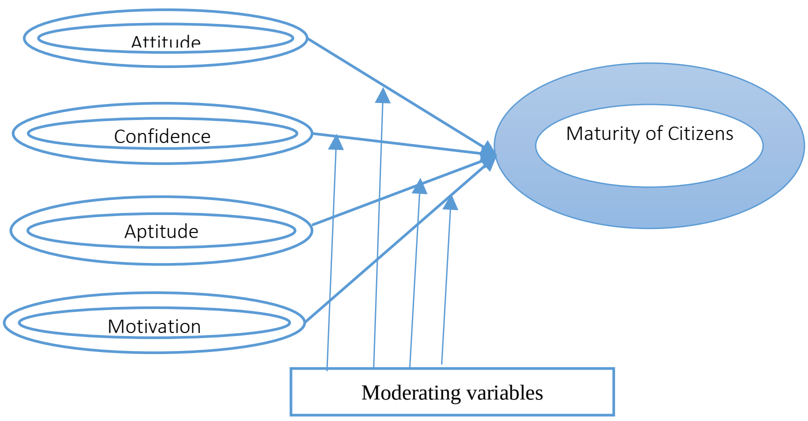


Fig 2. 4: Third (m - factors) order model for predicting the maturity of citizens of LMICs for ConsHI

The figure depicts how the four (Attitude, Confidence, Aptitude and Motivation) factors can predict the maturity of citizens of LMICs.

Decomposing the factors into constructs produces our conceptual framework consisting of t – factors from the various theories and models (Venkatesh *et al.*, 2003; Hibbard *et al.*, 2004, 2005; Venkatesh, Thong and Xu, 2012; Wetter, 2016; Hoque and Sorwar, 2017) adopted for this research work.

2.7.3 Moderating Effects

Moderator is a third variable that modifies the strength or direction of a causal relationship (Rose *et al.*, 2004). A moderator is an innate attribute (i.e., gender or ethnicity), a relatively stable trait (i.e., personality types or disposition), or a relatively unchangeable background, environmental or contextual variable (i.e., parents' education level or neighbourhood)(Zumbo, Gadermann and Zeisser, 2007; Wu and Zumbo, 2008).

Demographic variables such as age, experience and voluntariness are moderators in UTAUT (Fig 2.5). Undoubtedly, additional variables could influence the relationship between the constructs and the factors of the maturity of citizens for ConsHI. Some studies have considered geographical location, age, and environmental settings (hospital or outside) (Venkatesh *et al.*, 2016; Liddell *et al.*, 2018; Tan and Ooi, 2018). To moderate the effect of demographic variables, we choose more micro-level variables to assess how they will affect the maturity of citizens for ConsHI. Demographic items such as age, education, and gender could moderate the effect of some of these constructs, as posited in UTAUT and UTAUT2. We, therefore, include relevant items in this model.

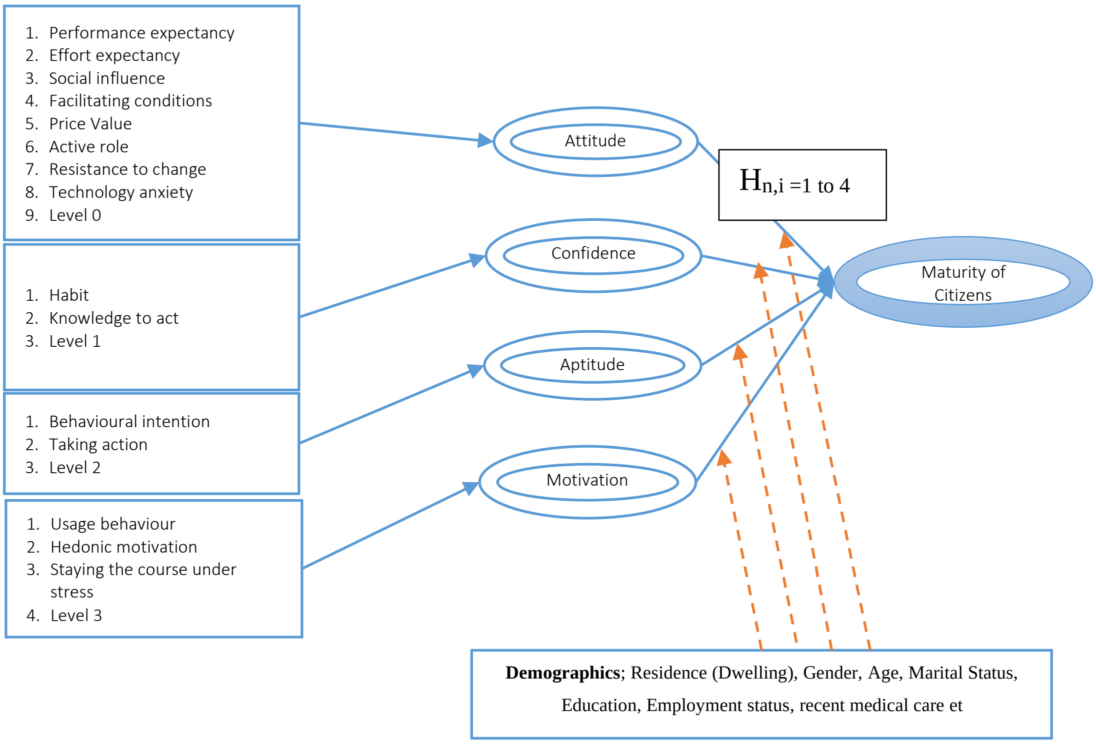


Fig 2. 5: Second (t – factors) order conceptual a model for predicting citizens' maturity for ConsHI in LMICs

2.7.4 Lower Order Constructs (First Order)

The hypothesis of the Dependent Variable (maturity of citizens):

HA: There is a positive relationship between APTITUDE and the maturity of citizens for ConsHI

HB: There is a positive relationship between ATTITUDE and the maturity of citizens for ConsHI

HC: There is a positive relationship between CONFIDENCE and the maturity of citizens for ConsHI

HD: There is a positive relationship between MOTIVATION and the maturity of citizens for ConsHI

In summary, the study draws on theoretical models to propose a concept for assessing the maturity of citizens for ConsHI using mHealth and the Internet (Fig 2.5). Our 78-item conceptual model consists of 26 items from UTAUT2, 21 from PAM, and five from UTAUTe. Also, we created 12 new items for ConsHI levels and 14 demographic variables. The conceptual framework shows second-order dependent variables that assess the study's objective.

Table 2. 1: Conceptual hypothesis of research objective five

Hypothesis Number	**Statements**
	First Order Hypothesis
H1a	There is a positive relationship between constructs (lower (first) order components (LOCs) and factors (higher (second) order components; HOCs).
	Second Order Constructs
HA	There is a significant categorical moderating effect of demographic variables (Residence, Gender, Age, Marital Status, Education, Employment status, recent medical care) on the relationship between factors (explanatory variables; HOCs) and ConsHI MATURITY of the citizens of LMICS (outcome variable)

In Fig 2.6 we make a graphical representation of the first order models without the moderation or intereactoin effects. This is the first step to developing our research model.

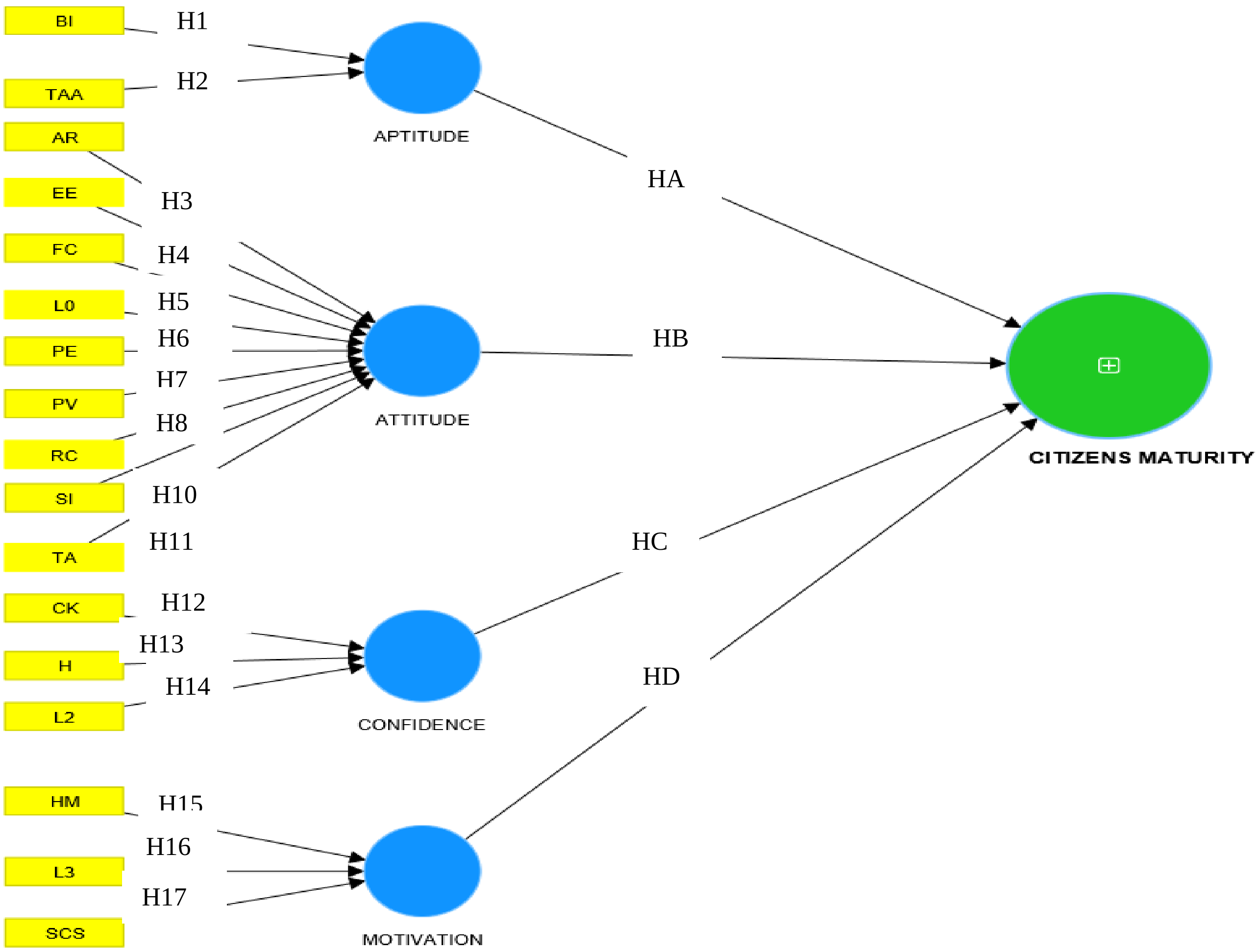


Fig 2. 6: Graphical representation of the conceptual model in SmartPLS 4.0

CHAPTER THREE: DEMOGRAPHIC ANALYSIS OF STUDY SITES

In this chapter, we profile the six countries where survey data will be collected. The choice of these countries is for two primary reasons. The first is classification adopted from Hartzler and Wetter (2014, p. 183), who used Inequality-adjusted Human Development Index (IHDI); Life expectancy (LE); Per Capita Gross Domestic Product (GDP); and Economic development to classify LMICs. In this study, we only ranked using the GDP of the various countries. The second reason was the availability and willingness of a researcher to administer the question in a particular country that satisfied our classification of LMICs per GDP. Country profiling considers a limited number of issues like demographics, religion, languages, education, health, the economy, and internet use.

ICT has been vital in helping maintain continuity in business activity, employment, education, provision of essential services, entertainment, and socialising (International Telecommunication Union, 2020). While the world battles the pandemic and attempts to revive economies to support the achievement of the Sustainable Development Goals (SDGs), ICT has proven to be the panacea to myriads of human activities. An estimated 4.9 billion people were using the Internet in 2021. That means roughly 63% of the world's population was online (17%), with almost 800 million people estimated to have come online since 2019. Internet penetration increased more than 20% in Africa, Asia, the Pacific, and the UN-designated Least Developed Countries (LDCs). Also, the Internet has long been a source of countless personal fulfilment opportunities, professional development, and value creation. More importantly, in the wake of the COVID-19 pandemic, the Internet has become a vital necessity for working, learning, accessing essential services, and keeping in touch (Li *et al.*, 2021). The latest ITU data show that uptake of the Internet has accelerated.

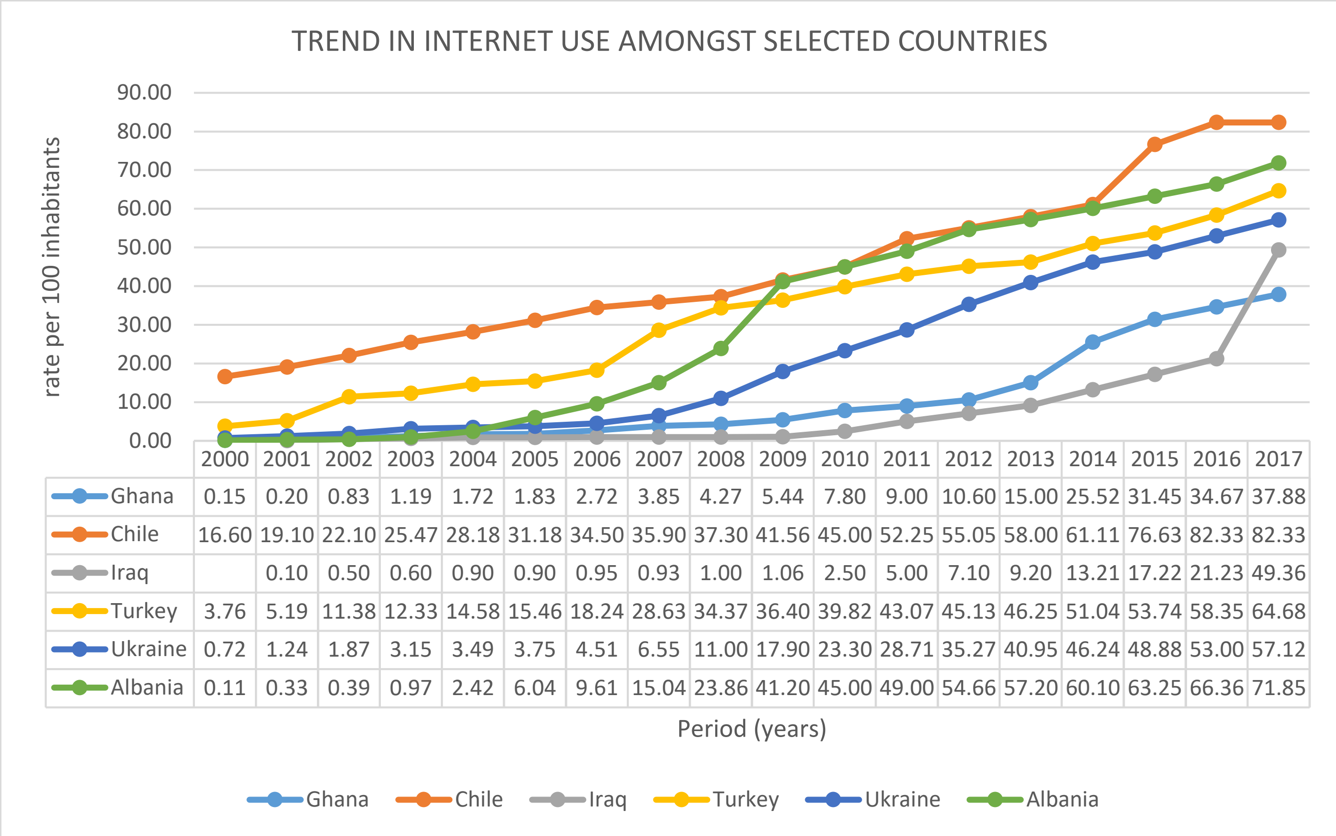


Fig 3. 1: Trend in Internet use amongst selected countries (Source: ITU, 2018)

Table 3.1 shows the countries where we conducted our study. It is imperative to report that Chile's transition into a High-Income country is recent. It could still exhibit the characteristics of Middle-income countries, especially for the field of ConsHI, where the large size of the country and respective low population density in many regions impact healthcare delivery. Also, Albania is a proxy for Kosovo, where data on Kosovo is unavailable.

Table 3. 1: Countries and their economic classification using GDP growth (annual %)

	Gross domestic product per capita, current prices ($)										
Country	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Chile	**15,306.9**	15,786.5	14,644.7	13,469.6	13,576.0	14,314.8	14,274.4	14,757.2	15,293.3	15,881.5	16,522.8
Ghana	**1,682.6**	1,870.2	1,479.0	1,372.2	1,551.4	1,607.7	1,697.4	1,777.4	1,849.5	1,932.4	2,030.0
Iraq	**6,692.6**	7,021.4	6,517.3	4,869.2	4,532.7	4,958.1	5,091.2	5,193.8	5,361.9	5,569.0	5,806.0
Kosovo	**3,598.4**	3,898.1	4,016.5	3,505.8	3,601.7	3,580.6	3,697.6	3,835.8	3,997.3	4,162.4	4,323.7
Turkey	**11,552.6**	12,395.4	12,022.2	10,914.9	10,817.4	10,434.0	11,124.7	11,706.9	12,282.2	12,841.7	13,408.7
Ukraine	**3,872.5**	3,968.8	3,095.1	2,135.2	2,198.8	2,458.6	2,597.2	2,818.2	3,049.9	3,319.3	3,594.9

Source: International Monetary Fund (2022) and World Bank Group (2017); Bold (2012) is the benchmark values for subsequent years

3.1 CHILE

3.1.1 Demographics

Chile's 2017 population census reports indicated a population of 17,574,003 and a projected figure of 19,116,208 for 2020 (Fig 3.2). Its population growth rate has decreased since 1990 due to a declining birth rate. About 87.6 % of the country's population lives in urban areas, while 12.3% lives in rural areas per 2020 estimates (Agency, 2016; Baten and Llorca-Jaña, 2021). According to the 2002 census, the most significant clusters are Greater Santiago with 5.6 million people, Greater Concepción with 861,000 and Greater Valparaíso with 824,000. The population density in Chile is 26 per Km^2 (67 people per meter square), with a gross land area of 743,532 Km^2 (287,079 sq. miles).

Moreover, 84.8 % of the population is urban (16,205,574 people in 2020), and the median age in Chile is 35.3 years. The gender spread in the population pyramid shows a good balance between males and females in Chile since the UN reports the sex ratio to be 97.3 (*World Population Prospects - Population Division - United Nations*, no date). Remarkably, the graph shows Chile still has a robust working population. Also, the pyramid base points to decreasing population growth which could negatively affect the country's future. Hence, the shallow one in Chile (25) indicates that mHealth and ConsHI are good for Chile.

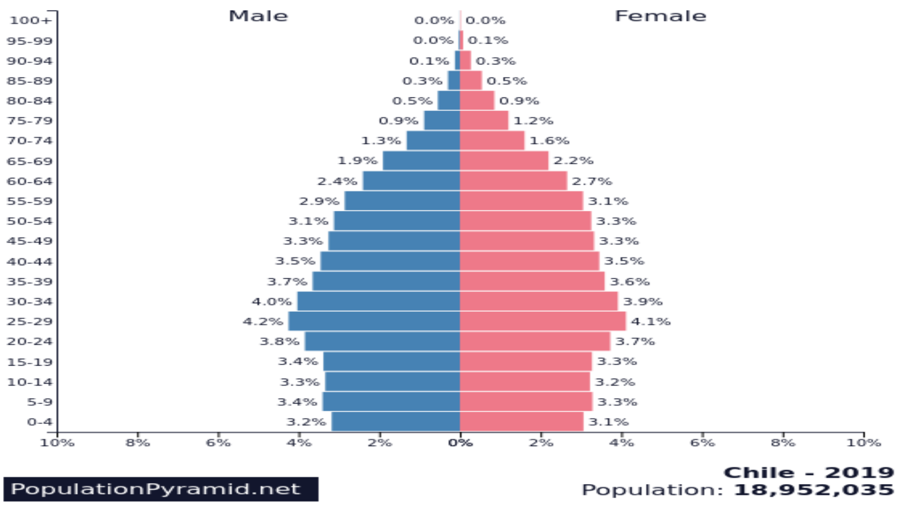


Fig 3. 2: Population Pyramid of Chile (source:

3.1.2 Religion

By 2015, the major religious groups in Chile are Christianity (68%), consisting of about 55% Roman Catholics, 13% of various evangelicals, and 7% other religions. Estimates show that about 25% of the population are agnostics and atheists. Further, Chile has a Bahá'í religious community and is home to the Bahá'í mother temple, or continental House of Worship, for Latin America.

The Chilean constitution assures the right to freedom of religion; laws and policies also contribute to the general freedom of religion. The law at all levels fully protects right against abuse by any actor. Notably, the Church and the state are formally separate in Chile. The Chilean government treats Christmas, Good Friday, the Festivals like the Virgin of Carmen, the Saints Peter and Paul, the Ascension, the Immaculate Conception, and All Saints' Day as national holidays.

3.1.3 Languages

Most Chileans speak Spanish as their primary language. It is distinctively accented and unlike neighbouring South American countries because they omit the final syllables, and some consonants have a soft pronunciation. The accent varies only slightly from north to south; there are apparent differences in accent based on various social classes in the country.

Also, Chileans speak indigenous languages like the Mapudungun, Aymara, Rapa Nui, Chilean Sign Language and (barely surviving) Qawasqar and Yaghan, and non-aboriginal German, Italian, English, Greek and Quechua. Spanish became the lingua franca post the Spanish invasion; later, their original languages became minority languages, with most extinction.

In larger cities or small countryside, Chileans in the southern part of Chile still speak German as a second language to Spanish. Also, the government made English mandatory for students in fifth grade and above in public schools. Most private schools in Chile started teaching English from kindergarten, mainly retaining used English words appropriated into everyday Spanish speech.

3.1.4 Education

The educational system in Chile starts with pre-school until the age of 5. next, primary school is provided from age six to thirteen. Students then attend secondary school until graduation by seventeen years. Secondary education is in two parts: Students receive a general education during the first two years. Then, they choose a branch: scientific education, humanistic education, artistic education, or technical and professional education. Secondary school ends two years later, acquiring a certificate (Licencia de enseñanza media). Successful graduates from the secondary level may continue into the traditional Chilean Universities in either a private or a public institution.

3.1.5 Health

World Health Organization (2021) reports that by 2019, Life expectancy at birth (years) for Chileans was 80.7 and 70.0 years for healthy life expectancy (disability-free life expectancy). Also, maternal mortality was 13 in every 100,000 live births. In 2017 the UHC index for Chileans was 70, and the population with household expenditures on health>10% of total household expenditure or income (%) was 14.6 between 2011 – 2018. Notably, the proportion of health facilities with a core set of relevant essential medicines available and affordable on a sustainable basis was 36.4%. Also, the density of medical and nursing and midwifery personnel (per 10 000 population) was 51.8 and 133.2, respectively, in 2019 (World Health Organization, 2021).

WHO further reports that the domestic general government health expenditure (GGHE-D) as a percentage of public government expenditure (GGE) (%) was 18.3% in 2018 [45]. The Ministry of Health (*Minsal*) serves as the highest administrative arm of government regarding health matters. Minsal plans direct, coordinate, execute, control, and inform the public about the Chilean President's health policies and programs. Notably, Fonasa is the national health fund established in 1979, and the finance department is responsible for collecting, managing, and distributing national resources for the healthcare of Chileans. The public funds and all employees pay the fund 7% of their monthly income.

3.1.6 Economy

Chile has been one of Latin America's fastest-growing economies in recent decades, enabling the country to reduce poverty significantly. Notably, the unemployment rate in 2020, a percent of the total labour force, stood at 10.77% (Agency, 2016). An estimate of employment as a conjugate of unemployment shows 89% of Chileans will be employed in some form in 2020. Also, from 2000 to 2015, the population living in poverty (on US$ 4 or less per day) decreased from 26 % to 7.9 % (Agency, 2016). Nevertheless, GDP growth fell from a high of 6.1% in 2011 to 1.6% in 2016 because of declining copper prices. Since July 2013, Chile has been considered a "high-income economy" by the World Bank. Chile, as of 2020, had a GDP of 252.92 billion dollars. Chile has the highest degree of economic freedom in South America (ranking seventh worldwide). In 2006, Chile had the highest nominal GDP per capita in Latin America. As of 2020, Chile ranks third in Latin America (behind Uruguay and Panama) in nominal GDP per capita. Copper mining makes up 20% of Chilean GDP and 60% of exports in Chile.

3.1.7 Internet Usage and Mobile Phones

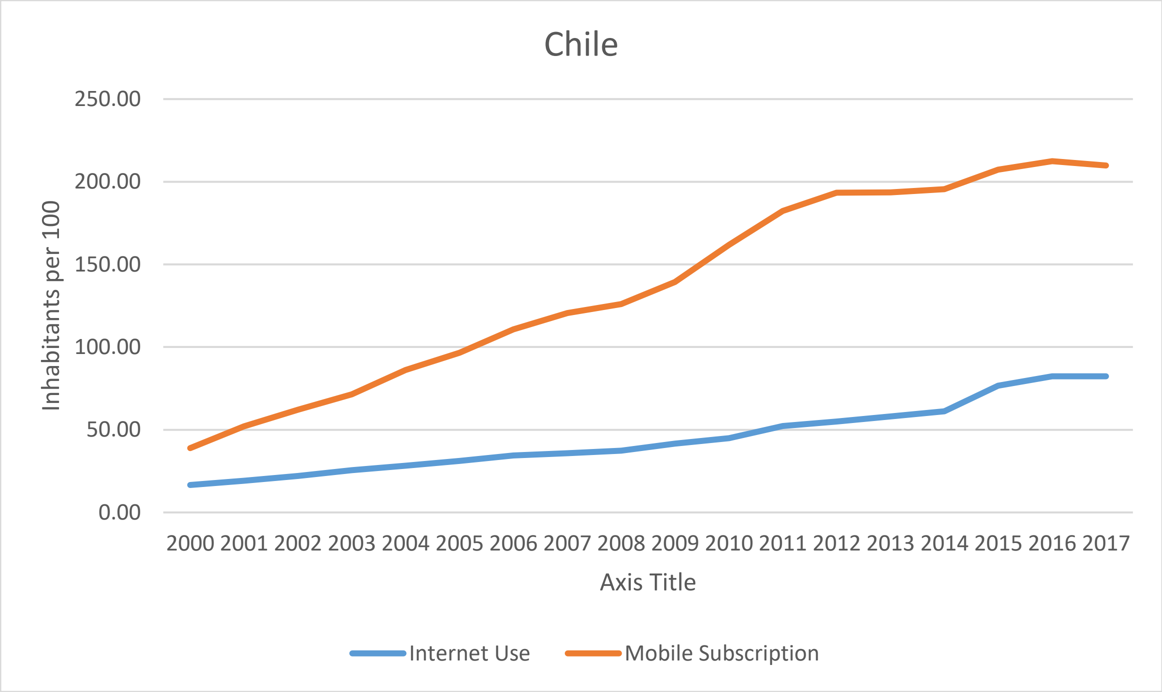


Fig 3. 3: Landline Internet usage and Mobile phones in Chile (Source: ITU, 2018)

ITU (International Telecommunication Union, 2020) reports that though a vast majority of the world's people can access the Internet through mobile broadband, less than two-thirds currently do (Fig 3.3). Also, while access to mobile networks has increased over time, the same speed cannot be said about internet use. The ITU facts show the increasing rate of mobile subscriptions. It is noteworthy that demographic factors such as urban and rural dwellings, gender, age and education play essential roles in the uptake of mobile phones and the use of the Internet globally (International Telecommunication Union, 2020).

3.2 GHANA

3.2.1 Demographics

Ghana's draft 2021 census report shows that the de facto Population in Ghana on Census Night was 30,792,608, of which females make up 50.7% (15,610,149) and males 49.3% (15,182,459), thus 97 per 100 inhabitants as the national sex ratio (Fig 3.4). Therefore, a slight increase in the sex ratio of 95 above the 2010 figure. The population density at the national level increased by 26 persons per square kilometre over the 103 recorded in 2010. The Ghanaian median age is 30, and the average household size is 3.6. Ghana still has an aggressively growing population looking at the median age and the population pyramid typical of a growing economy. Also, about 57.4 % of the country's population lives in urban areas, while 42.6% lives in rural areas as of 2020 estimates (*Rural population (% of the total population) - Ghana | Data*, no date).

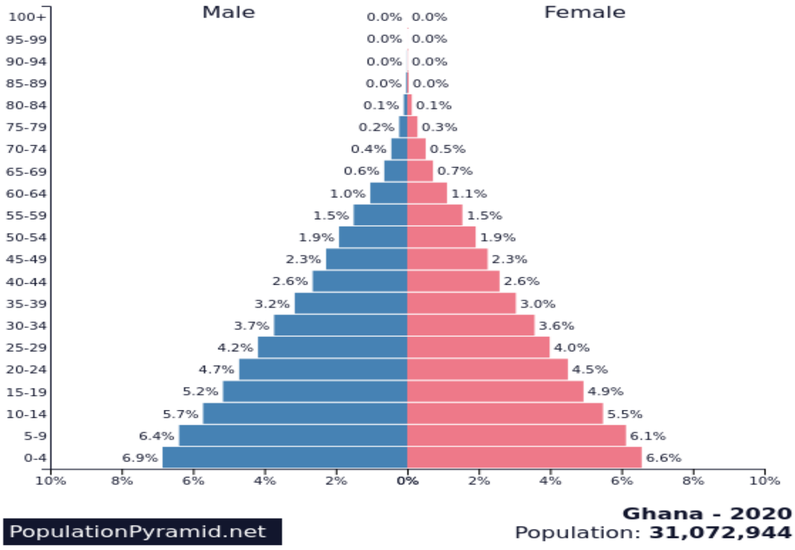


Fig 3. 4: Population Pyramid of Ghana (source

3.2.2 Religion

Ghana is predominantly Christian, although a sizable Muslim minority exists and practices traditional beliefs as well. In 2010, the Population of Ghana was 72.2% Christian. Approximately 18.6% of the Population of Ghana is Muslim, and the remaining 9.2% is a mix of the traditional African religion and other religious groups such as the Hindus and Bahais. Notably, more than 10,000 Ghanaians practise Hinduism, primarily converts. Also, the Bahá'í established their religion in 1951 in Ghana; currently, they have more than 100 communities and more than 50 local Bahá'í administrative councils.

3.2.3 Languages

Ghana is a multi-ethnic country. Although the official language of Ghana is English, and the majority (67.1%) of Ghanaians speak English, eleven languages are government-sponsored. These are Akan, Dangme, Ewe, Ga, Guan, Kasem, and Mole-Dagbani. Also, because French-speaking countries surround Ghana, French is widely taught in schools and used for commercial and international economic exchanges.

3.2.4 Education

The Ghanaian educational system is divided into pre-primary, primary, secondary, and tertiary. The duration of primary school (comprising kindergarten and primary) is 11 years. Next is Junior High (3 years), which ends with the Basic Education Certificate Examination (BECE). Once the BECE is attained, the pupil can proceed to the second cycle. Hence, the pupil chooses between general education (offered by the Senior High School) and vocational education (provided by the Technical and Vocational Institutes). Senior High School (SHS) lasts three years and leads to the West African Secondary School Certificate Examination (WASSCE), a prerequisite for tertiary education. Polytechnics are open to vocational students from SHS or Technical and Vocational Institutes (TVI).

Ghana has public and private tertiary institutions offering various programs of study to support the economy's growth. Tertiary students can obtain terminal degrees such as PhDs in Ghana. The duration of programs differs from one institution to the other, and generally, it spans two to 6 six years maximum for any tertiary qualifications. The education system in Ghana also encourages professional pursuits as career paths. Ghana has over 95% of children in schooling, making it one of Africa's highest school enrolment countries. The total education system's ratio of females to males was 0.98 in 2014.

3.2.5 Health

Recently, the World Health Organization (2021) reports that by 2019, Life expectancy at birth (in years) for Ghanaians was 66.3 and 58.0 years for healthy life expectancy. Also, maternal mortality was 308 in every 100,000 live births, while the proportion of births attended by skilled health personnel was 79%. The report also revealed that under-five, and neonatal mortality rates were 46 and 23 per 1000 live births in 2019. In 2017, the UHC index for Ghanaians was 47, and the population with household expenditures on health>10% of total household expenditure or income (%) was 1.1 % between 2011 – 2018 since the national health insurance scheme covers most of the out-patient services. Notably, the proportion of health facilities with a core set of relevant essential medicines available and affordable on a sustainable basis was 12.5%. Also, the density of medical and nursing and midwifery personnel (per 10 000 population) was 1.1 and 27.1, respectively, in 2019 (World Health Organization, 2021).

Reports also indicate that the domestic general government health expenditure (GGHE-D) percentage of public government expenditure (GGE) was 6.4% in 2018. Ghana operates a state-financed insurance scheme called the National Health Insurance Scheme (NHIS). In 2012, over 12 million Ghanaian residents were covered by the Scheme (NHIS). in Ghana, more than 70% of health infrastructure is situated in urban centres with well-resourced hospitals, clinics, and pharmacies.

3.2.6 Economy

Ghana is a lower-middle-income country with a GDP per capita of US$ 1,849.52 in 2020. The services sector has the largest economy share, accounting for more than 50% of GDP, manufacturing is 24.1%, extractive industries is 5%, and taxes are 20.9%. Notably, Ghana is an average natural resource-enriched country possessing industrial minerals, hydrocarbons, and precious metals. It is an emerging digital economy with mixed economy hybridisation and an emerging market.

Employment is working-age persons who produce goods or provide services for pay or profit during a reference period. Usually, people 15 years and older are considered the working-age population. The employment rate in Ghana was 65.02% in 2019 and declined to 63.3% in 2020.

3.2.7 Internet Usage and Mobile Phones

The difference in landline and mobile internet use follows a similar pattern as in Chile, and Figure 3.5 shows the trend for Ghana.

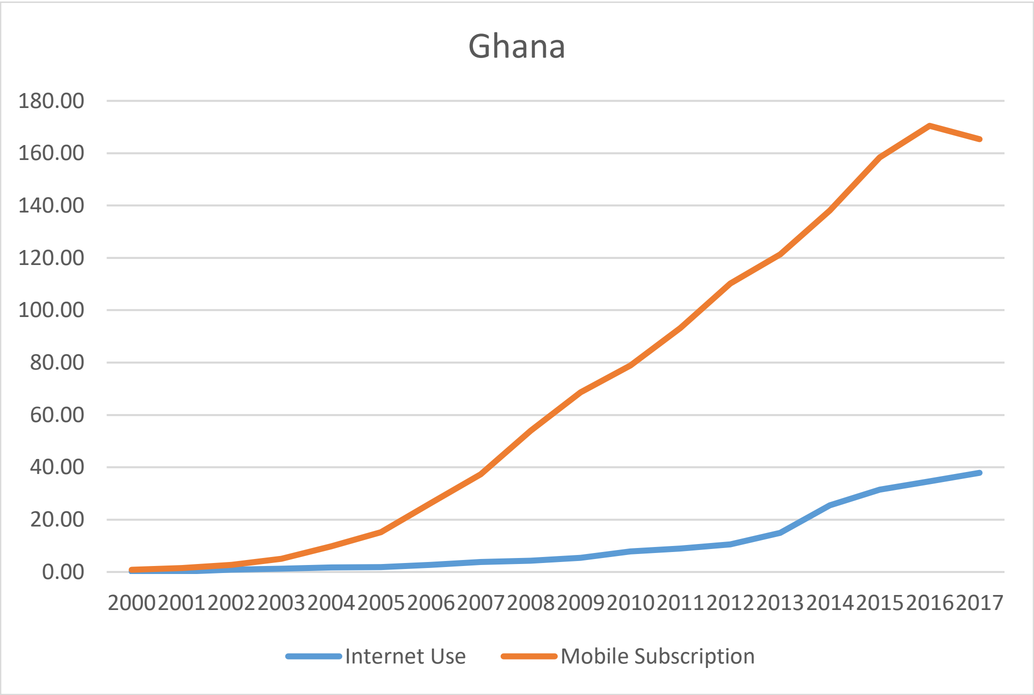


Fig 3. 5: Internet usage and Mobile phones in Ghana (Source: ITU, 2018)

3.3. IRAQ

3.3.1 Demographics

In 2018, Iraq'sIraq's total population was estimated at 38,433,600. However, the United Nations projected Iraq's population to be 40,222,503 and a sex ratio of 102.5 in 2020 (Fig 3. 6). Notably, there are more males in Iraq than females, as reported. An estimated 70.9 % of the country's population lives in urban areas, while 29.1% live in rural areas as of 2020. Iraq's native population is predominantly Arab and includes other ethnic groups such Kurds, Turkmens, Assyrians Yazidis, Shabaks, Armenians, Sabian-Mandaeans, Circassians, and Kawliya.

The Chechen and Armenian communities in Iraq are 2,500 and 20,000, respectively. The legacy of the slave trade includes a community of African descent in southern Iraq, who practised the Islamic Caliphate before the Zanj Rebellion of the 9th century (*Population of Iraq 2019 - PopulationPyramid.net*, no date; Al-Zahery *et al.*, 2011).

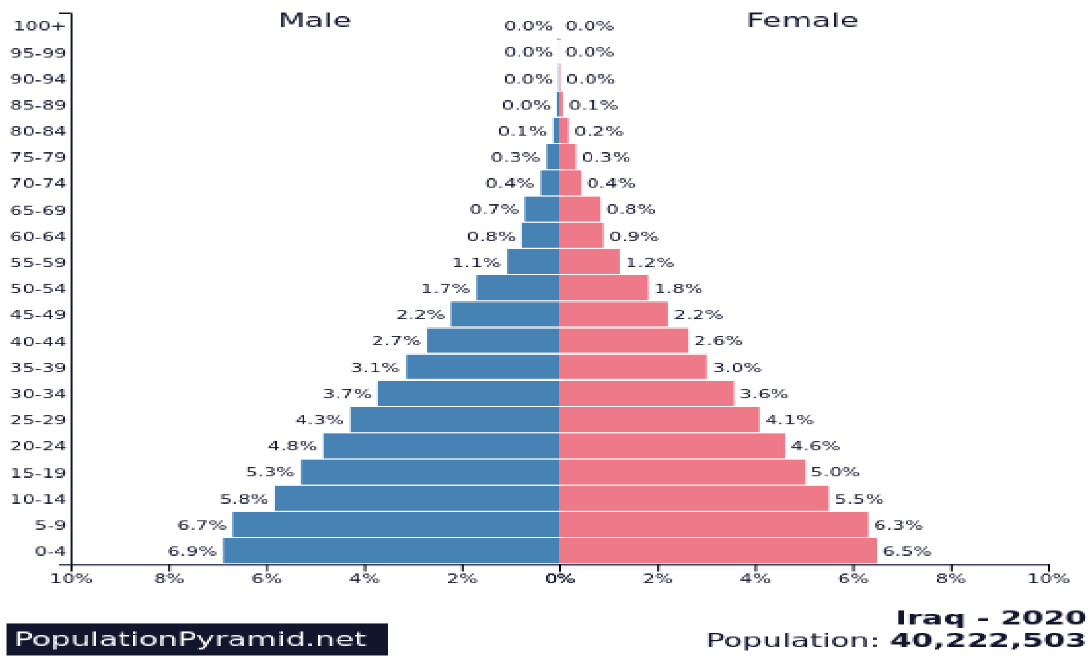


Fig 3. 6: Population Pyramid of Iraq

3.3.2 Religion

Mainly, Iraq has a mixed Shia and Sunni populations. Abrahamic religions are the majority in Iraq, primarily comprising (95–98%) Muslim and a few others like Christian, Yazidi, Sabian-Mandaean, Bahá'í, Zoroastrian, Hindu, Buddhist, Jewish, folk religion, unaffiliated, and others all <0.1% according to a Central Intelligence Agency (CIA) World Factbook (2021).

3.3.3 Languages

Mesopotamian is the dominant language in Iraq, and others are Arabic, Kurdish, Turkmen/Turkoman dialect of Turkish and the Neo-Aramaic language. Arabic scripts are used to write Arabic and Kurdish mostly. In 2005, the Turkmen/Turkoman changed from the Arabic script to the Turkish alphabet. Also, the Neo-Aramaic languages use the Syriac script. Other minor minority languages include Mandaic, Shabaki, Armenian, Circassian and Persian.

After the approval of the new constitution of Iraq in 2005, both Arabic and Kurdish are recognised (Article 4) as official languages, while three other languages: Turkmen, Syriac and Armenian, are minority languages.

3.3.4 Education

Iraq has a successful Arab education system, which is complex to categorise like other global educational schemes before the economic sanctions from the UN. Some say that the sanctions hurt the education system because they affected the children, whether intentionally or not.

Although the numbers suggest a dramatic increase in enrollment rates for primary education, many children remain out of the education system. With the overall rise in enrollment rates, there continues to be a significant strain on educational resources. United Nations International Children's Emergency Fund (UNICEF) notes that academic quality will continue to plummet without an increase in education expenditures.

The United Nations Educational, Scientific and Cultural Organization (UNESCO) reports that the educational system in Iraq had issues with standard-built school buildings, textbooks, and technologies to reach its educational goals in the early 2000s. However, the reports said they had enough teachers to implement a standardised curriculum. In 2000, the adult literacy rate was higher (84%) amongst males than females (64%), according to the CIA World Factbook reports. Meanwhile, the UN figures suggest a slight decline in the literacy of Iraqis aged 15–24 between 2000 and 2008, from 84.8% to 82.4%.

3.3.5 Health

The World Health Organization (2021) reports that by 2019, Life expectancy at birth (years) for Iraqis was 72.4 and 62.7 years for healthy life expectancy. Also, maternal mortality was 79 in every 100,000 live births — the proportion of births attended by skilled health personnel was 96%. The report also revealed that under-five, and neonatal mortality rates were 26 and 15 per 1000 live births in 2019. In 2017 the UHC index for Iraqis was 61, and the population with household expenditures on health >10% of total household expenditure or income (%) was 3.3 between 2011 – 2018. The density of medical, nursing and midwifery personnel (per 10 000 population) was 7.1 and 20.4, respectively, in

2019 (World Health Organization, 2021). Also, the report was silent on the proportion of health facilities with a core set of relevant essential medicines on an affordable and sustainable basis.

Reports also indicate that the domestic general government health expenditure (GGHE-D) percentage of public government expenditure (GGE) was 6.2% in 2018. Also, in 2010, spending on healthcare accounted for 6.84% of the country's GDP. Iraq had a well-established centralised free health care system in the 1970s using a hospital-based, capital-intensive medical care system. Iraq imports large-scale medicines, medical equipment and health workers paid for with oil income, according to a joint by the UNICEF and the WHO in July 2003. Iraq has sophisticated medical systems comparable to westernised hospitals with advanced medical procedures provided by specialist physicians. In early 1990, most (97%) of the urban dwellers and most (71%) of the rural dwellers accessed free primary health care. According to joint UNICEF and WHO reports, only 2% of hospital beds were privately owned.

3.3.6 Economy

The oil sector dominates (95%) of Iraq's economy, providing high foreign exchange earnings. Other sectors are underdeveloped, resulting in an estimated 18%–30% unemployed and a per capita GDP of $4,869.21 in 2015, which is the least since 2012 (Table 3.1). In 2011, nearly 60% of full-time employment was in the public sector. Also, a modest (22%) percentage of women participate in the labour force.

Employment is working-age persons who produce goods or provide services for pay or profit during a reference period. Ages 15 and older are the working-age population was 37.49% in 2019 and declined to 35.66% in 2020.

3.3.7 Internet Usage and Mobile Phones

The difference in landline and mobile internet use follows a similar pattern as in Chile. Figure 3.7 has the precise trend for Iraq(International Telecommunication Union, 2020).

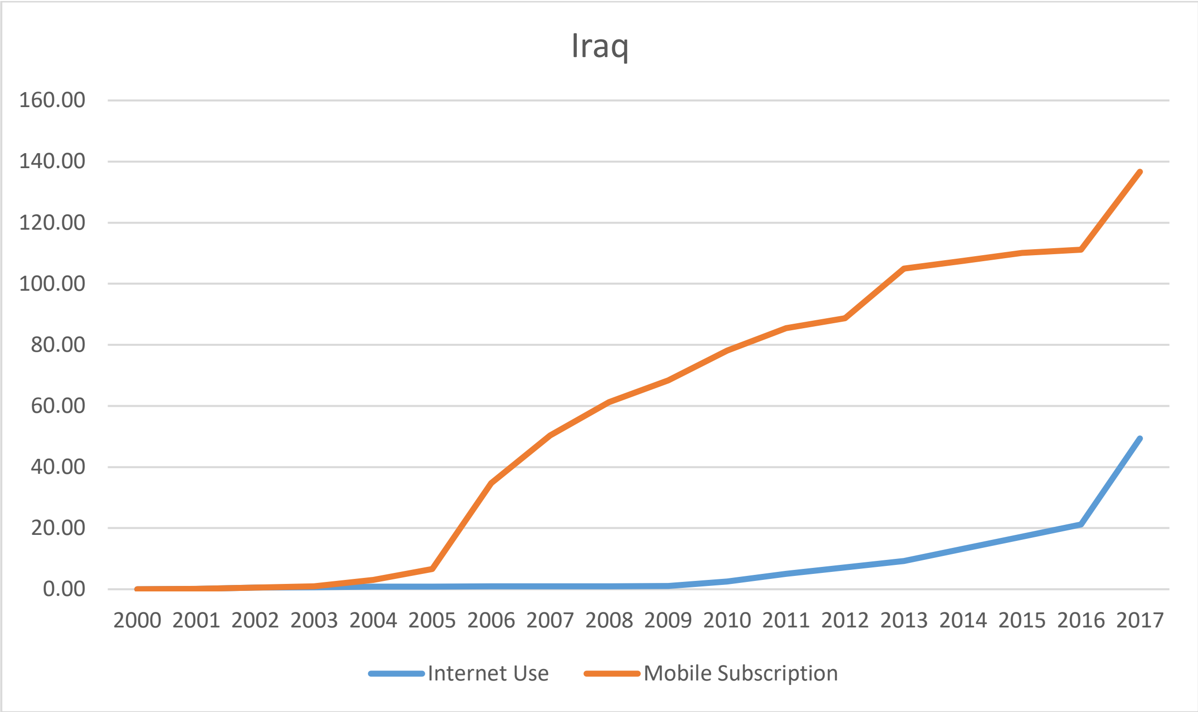


Fig 3. 7: Internet Usage and Mobile phones in Iraq (Source: ITU, 2018)

3.4 KOSOVO

3.4.1 Demographics: Religion, Language and Education

Kosovo is in the South-Eastern part of Europe, and the neighbouring countries are Albania, Montenegro, Serbia, and Macedonia. The Population of Kosovo is around 1.895.250 million. The Population's average age was 27.1 years in 2012, and the population pyramid (Fig. 3.8) shows that the beam is most comprehensive in the age group 30 – 34. The Kosovo Population and Housing Census reported that the Population aged ≥ 65 years was 6.7% in 2011. Comparatively, in Europe, Kosovo has a young population, a high emigration rate, and a fragile democratic system. In 2011, the number of people living in rural areas was 61.7%, and 38.3% of the population dwelled in urban areas.

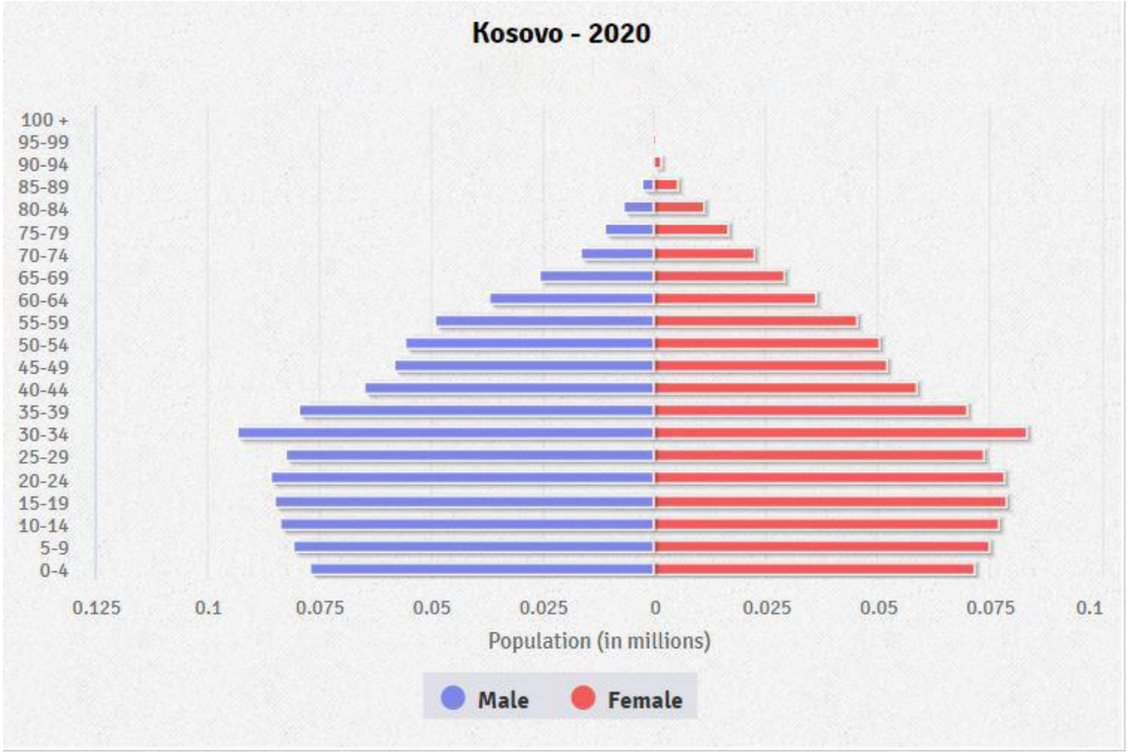


Fig 3. 8: Population Pyramid of Kosovo

3.4.2 Religion

Kosovo is a civil state with no state religion; freedom of belief, conscience and religion is a fundamental right in the Constitution of Kosovo. Kosovan society is highly civilised and ranks first in Southern Europe and ninth globally for religious tolerance. In the 2011 census, the majority (95.6%) were Muslim, while the minority (3.7%) were Christian, comprising 2.2% Roman Catholic and 1.5% eastern orthodox. The rest (0.3%) of the population either did not have a religious affiliation or did not provide an answer.

3.4.3 language

There are two (Albanian and Serbian) official languages in Kosovo, and the institutions are committed to ensuring the equal use of both languages. While at the municipal level, Turkish, Bosnian and Roma are the official languages when they represent at least 5% of the municipality's total population. Notably, 95% speak Albanian as a first language, while Bosnian and Serbian are 1.7% and 1.6%, respectively. Municipal civil servants are required to talk about anyone with Albanian or Serbian as an official language.

3.4.4 Education

Predominantly, education is publicly supported by the state. There are two major stages, namely primary and secondary education, and higher education. Primary and secondary, the first stage is categorised into four pre-schools, primary and low secondary, high secondary school, and the particular school. Mainly, pre-school is for children aged one to five years.

The early phase (primary education) includes grades one to five, and the second phase (low secondary education) covers grades six to nine. The third phase (high secondary education) covers general and professional education, focusing on different fields. It lasts four years; however, pupils can apply for higher or University studies. Also, pupils who cannot get a general education get an exceptional education (fifth phase), according to the ministry of education. Higher educational institutions offer studies for Bachelor's, Master, and PhD degrees.

3.4.5 Health

Kosovo's life expectancy at birth was 70.0 years in 2011, as reported by the Kosovo Human Development Report (2012). Among Kosovo's public health, indicators were 7.2 maternal deaths in 100.000 births. There is no health care system with health insurance in Kosovo, as in high-income countries such as Germany, half of the health-related costs are paid out-of-pocket. The number of physicians per 100.000 population was 146, and the number of nurses per 100.000 population was 412 in 2011. A person visits a doctor 2.8 times per year. Public health spending was 2.3% of the GDP, and the public expenditure on health of total government expenditure was 7.6% in 2009. Kosovo still must overcome some difficulties to build a stable health care system.

3.4.6 Economy

Kosovo is a small country with few inhabitants, and its economy is mainly agriculture. With a gross domestic product (GDP) per capita of $3,997.25 in 2020. The GDP was $3,598.39 in 2012, according to the IMF. The percentage of the poor in Kosovo was around 34%, and for the extremely poor, it was about 12% in 2009.

3.4.7 Internet Usage and Mobile Phones

The difference in landline and mobile internet use follows a similar pattern as the previous countries. Figure 3.9 reveals the accurate trend of Kosovo.

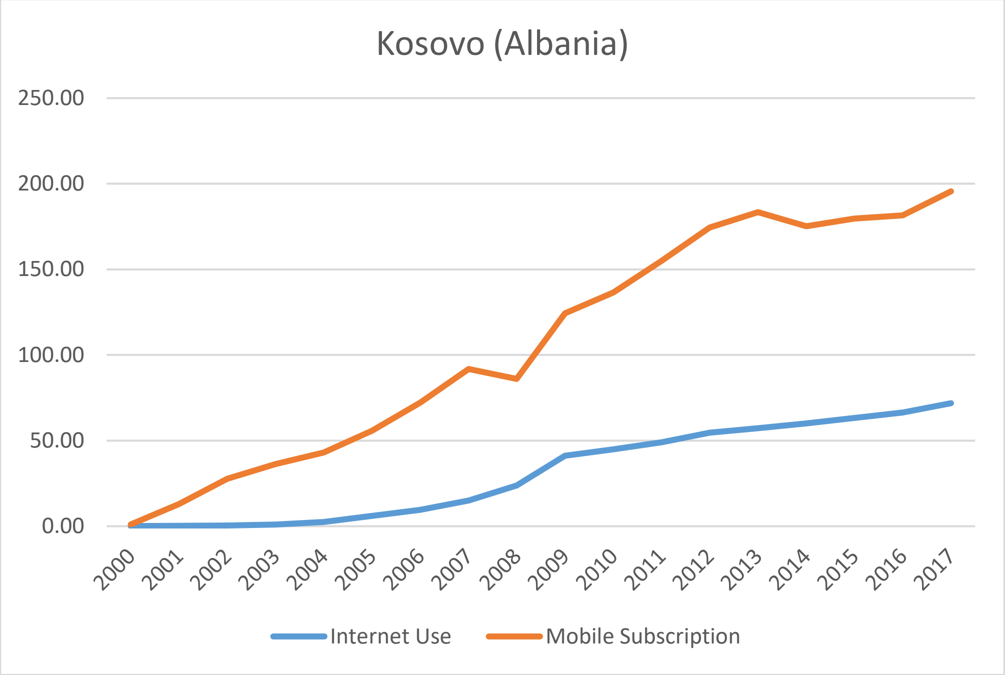


Fig 3. 9: Internet usage and Mobile phones in Kosovo (Source: ITU, 2018)

NB: Albania was used as a proxy for Kosovo since the ITU data did not provide for Kosovo as a sovereign state.

3.5 TURKEY

3.5.1 Demographics

In 2019, the population of Turkey was 83,429,607, according to world bank reports (Fig 3.10). Remarkably, Article 66 of the Turkish Constitution defines a "Turk" as "a person bound to the Turkish state through the bond of citizenship", distinguishing the legal use of the term "Turkish" as a citizen from the ethnic definition. Turkey is home to a Muslim community of Megleno-Romanians. The sex ratio was 97.5% in 2019, with 70.9% of the population in urban areas and the remaining 29.1% in rural.

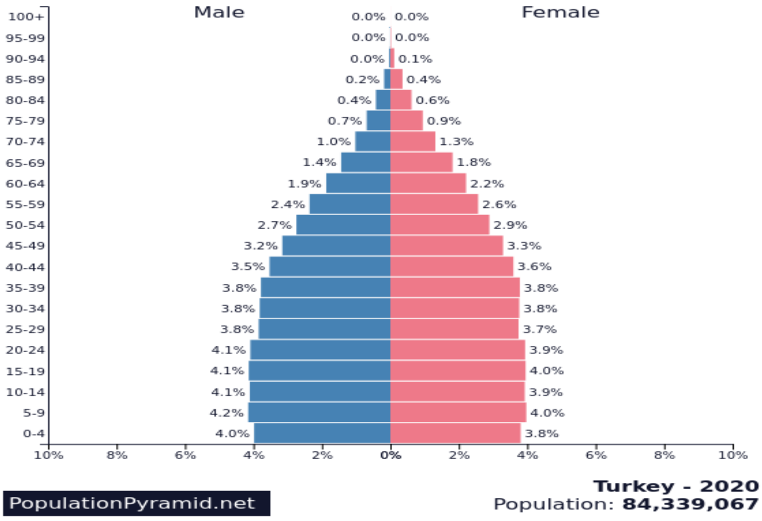


Fig 3. 10: Population Pyramid of Turkey

3.5.2 Languages

The official language is Turkish, spoken by 85.54% of the population as a first language, while the Kurmanji dialect of Kurdish is spoken by 11.97% as their mother tongue. A minority of 2.4% speak Arabic and Zaza as their mother tongues, and various minority groups in small parts of Turkey speak several other languages as their mother tongues.

3.5.3 Religion

Turkey is a civil state with no official religion; the constitution provides freedom of religion and conscience. A 2016 survey of 17,180 adults across 22 regions reported Islam as the dominant (82%) religion. In comparison, religiously unaffiliated and Christians were 13% and 2%, respectively. In 2019, a religiosity poll reported by OPTİMAR showed an increase of 7.5% (89.5%) for Islam. A decrease of 8.5% (4.5%) for the religiously unaffiliated but believed in God. the rest were 2.7% agnostics, 1.7% atheists, and 1.7% did not answer.

3.5.4 Education

The ministry of education superintends a compulsory pre-tertiary education that lasts twelve years (four years of each primary school, middle school and high school). Turkey's primary education lags other OECD countries, with significant differences between high and low performers. Access to high-quality schools heavily depends on the performance in the secondary school entrance exams.

As of 2017, there were 190 universities in Turkey. Excluding the Open Education Faculties (AÖF) at Anadolu, Istanbul and Atatürk University, the National Student Selection and Placement System (ÖSYS) examination regulates entrance to University according to the performance of high school graduates. Also, the Higher Education Board (YÖK) holds state and private universities. Since 2016, the President has appointed the head of YÖK and all rectors of state and private universities in Turkey.

3.5.5 Health

The World Health Organization (2021) reports that by 2019, Life expectancy at birth (years) for Turkish was 78.6 and 68.4 years for healthy life expectancy. Also, maternal mortality was 17 in every 100,000 live births—the proportion of births attended by skilled health personnel was 99%. The report also revealed that under-five and neonatal mortality rates were 10 and 5 per 1000 live births in 2019. In 2017 the UHC index for Turkish was 74, and the population with household expenditures on health>10% of total household expenditure or income (%) was 3.2 between 2011 – 2018. Notably, the proportion of health facilities with a core set of relevant essential medicines available and affordable on a sustainable basis was 12.5%. Also, the density of medical, nursing and midwifery personnel (per 10 000 population) was 18.1 and 30.0, respectively, in 2019 (World Health Organization, 2021).

Reports also indicate that the domestic general government health expenditure (GGHE-D) percentage of public government expenditure (GGE) was 9.3% in 2018. The health ministry of health has run a universal public healthcare system since 2003, and universal Health Insurance (*Genel Sağlık Sigortası*), funded by a tax surcharge on employers, is currently at 5%. Approximately 75.2% of health expenditures and many private hospitals are public-sector funding. Turkey has benefited from medical tourism in recent years, and health tourism earned above $1B in Turkey in 2019. mostly (60%) of the income is obtained from plastic surgery, and 662,087 health tourists patronised healthcare services in Turkey in 2020.

3.5.6 Economy

Turkey is a newly industrialised country with an upper-middle-income economy, the twentieth-largest in the world by nominal GDP and the eleventh-largest. World Bank estimates that Turkey's GDP per capita will be $32,278 in 2021 and estimates that about 11.7% of Turks are at risk of poverty or social exclusion as of 2019. The World Bank reports that unemployment in Turkey was at 13.6% in 2019. The middle-class population rose from 18% to 41% between 1993 and 2010.

3.5.7 Internet Usage and Mobile Phones

The difference in landline and mobile internet use follows a similar pattern as the preceding countries. Figure 3.11 depicts the exact trend of the statistics for Turkey.

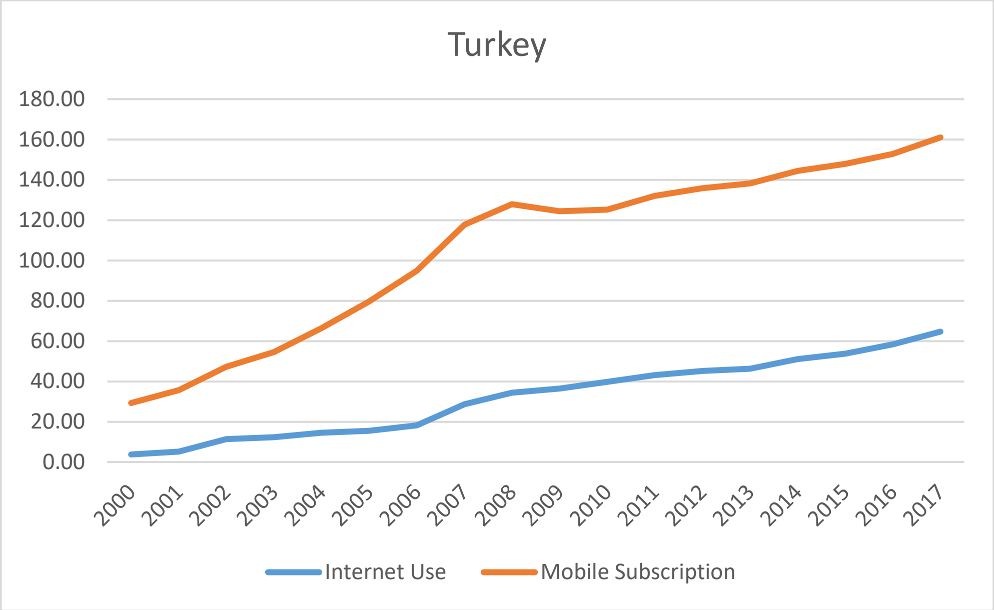


Fig 3. 11: Internet usage and Mobile phones in Turkey (Source: ITU, 2018)

The difference in landline and mobile internet use follows a similar pattern as in Chile. Figure 3.10 has the exact figures for Turkey (International Telecommunication Union, 2020).

3.6 UKRAINE

3.6.1 Demographics

Ukraine's population is estimated to be 43,733,759 in July 2021, and the eighth-most populous country in Europe (Fig 3.12). It is a heavily urbanised country, and its industrial regions in the east and southeast are the most densely populated—about 69.6% of its total population lives in urban areas. Ukraine has a sex ratio of 86.3% as of 2020, per World bank reports. The population pyramid reflects the median age of 35-39, a supposedly youthful population.

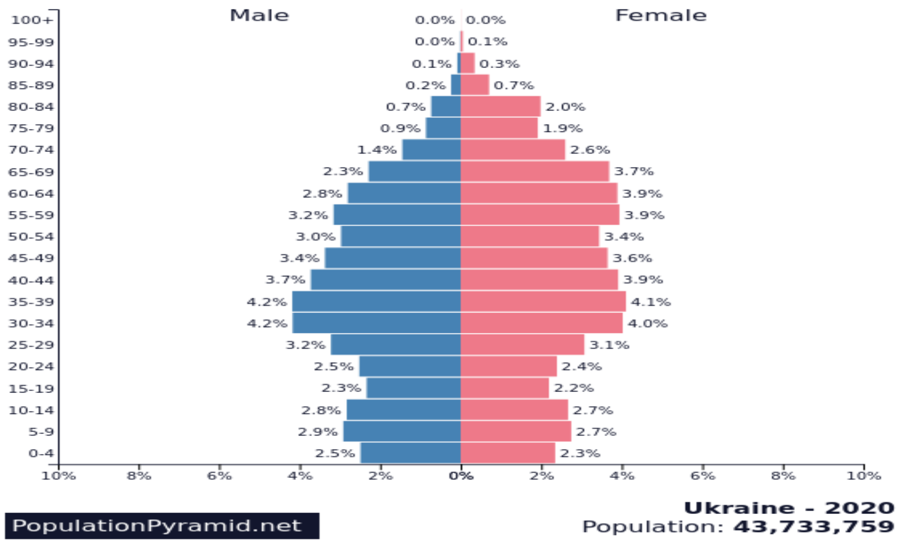


Fig 3. 12: Population Pyramid of Ukraine

3.6.2 Language

The Ukrainian constitution declares sovereignty and Ukrainian as the official language, though Russian is extensively spoken, particularly in eastern and southern Ukraine. Most aboriginal Ukrainian talk to Russian as a second language because Russian was the *de facto* official language of the Soviet Union. In August 2012, a new legislature on regional languages was promulgated, allowing any local language spoken by a minimum 10% minority to be declared official within that region. However, on 23 February 2014, after the 2014 Ukrainian revolution, the Ukrainian Parliament voted to nullify the legislation on regional languages, making Ukrainian the only national language; however, the repeal was not signed by President Turchynov or by President Poroshenko. Later, in February 2019, the law allowing for regional languages was declared unconstitutional, affirming Ukrainian as the official language.

3.6.3 Religion

The world's second-largest eastern Orthodox population are in Ukraine. A survey by the Kyiv International Institute of Sociology in 2021 reported majority (82%) of Ukrainians subscribe to a religious denomination, 7% were atheists, and 11% found it difficult to answer the question.

Religiosity in Ukraine is highest in Western Ukraine (91%) and the lowest in the Donbas (57%) and Eastern Ukraine (56%). In 2021, 82% of Ukrainians were Christians; 72.7% declared themselves Orthodox, 8.8% were Greek Rite Catholics, 2.3% Protestants, 0.9% were Latin Rite Catholics, and 2.3% were other Christians. Judaism, Islam, and Hinduism were 0.2% of the population each.

3.6.4 Education

According to the Ukrainian constitution, free education is compulsory for all citizens. Complete general secondary education is mandatory in the state schools, which constitute the overwhelming majority.

The Soviet Union emphasised total access to education for all citizens, it has continued to date, and the literacy rate is estimated at 99.4%. An eleven-year school programme replaced the twelve-year plan in 2005. Primary education takes four years (starting at age six), middle education (secondary) takes five years, and upper secondary takes three years. In the 12th grade, students take school-leaving exams as a government, and these tests are subsequently used for university admissions.

The Ukrainian higher education system comprises scientific and methodological facilities under national, municipal, and self-governing bodies in charge of education. In July 2014, the Ukrainian Parliament changed the higher education system by establishing an independent collegiate body to supervise Ukrainian education quality. The following types of higher education qualifications were based: Junior Bachelor, Bachelor, Master, Doctor of Philosophy (PhD) and Doctor of Science; the load on lecturers and students was reduced; academic mobility for faculty and students has increased.

3.6.5 Health

Also, the World Health Organization (2021) reports that by 2019, Life expectancy at birth (years) for Ukrainians was 73.0 and 64.3 years for healthy life expectancy. Also, maternal mortality was 19 in every 100,000 live births—the proportion of births attended by skilled health personnel was 100%. The report also revealed that under-five and neonatal mortality rates were 8 and 5 per 1000 live births in 2019. In 2017 the UHC index for Ukraine was 68, and the population with household expenditures on health>10% of total household expenditure or income (%) was 7.8 between 2011 – 2018. Notably, the proportion of health facilities with a core set of relevant essential medicines available and affordable on a sustainable basis was 12.5%. Also, the density of medical, nursing and midwifery personnel (per 10 000 population) was 29.9 and 66.6, respectively, in 2019 (World Health Organization, 2021).

Reports also indicate that the domestic general government health expenditure (GGHE-D) percentage of public government expenditure (GGE) was 8.9% in 2018. Ukraine's healthcare system is partly state-sponsored and accessible to all Ukrainian citizens and registered residents. Also, several privately owned medical facilities are available, so treatment in a state-run hospital is not compulsory like in any European country. The public sector employs most healthcare professionals. In Ukraine, professionals working in private medical centres must retain their state employment as a mandatory social service to public health facilities.

3.6.6 Economy

Ukraine's lower-middle-income economy is the 55th largest by nominal GDP and the 40th largest. It is amongst the world's leading grain exporters and called the "Breadbasket of Europe". However, it is the poorest in Europe and among the most severely corrupt. IMF reports that Ukraine's GDP per capita was $2,818.22 in 2019.

An estimated 1.1% of Ukrainians lived below the national poverty line in 2019, and unemployment in the country was 4.5% in 2019. Ukraine is also a producer and processor of natural gas and petroleum. However, Ukraine imports most of its energy needs, and 80% of Ukraine's natural gas supplies are imported, mainly from Russia.

3.6.7 Internet Usage and Mobile Phones

The difference in landline and mobile internet use follows a similar pattern as in Chile. Figure 3.13 has the exact figures for Ukraine (International Telecommunication Union, 2020).

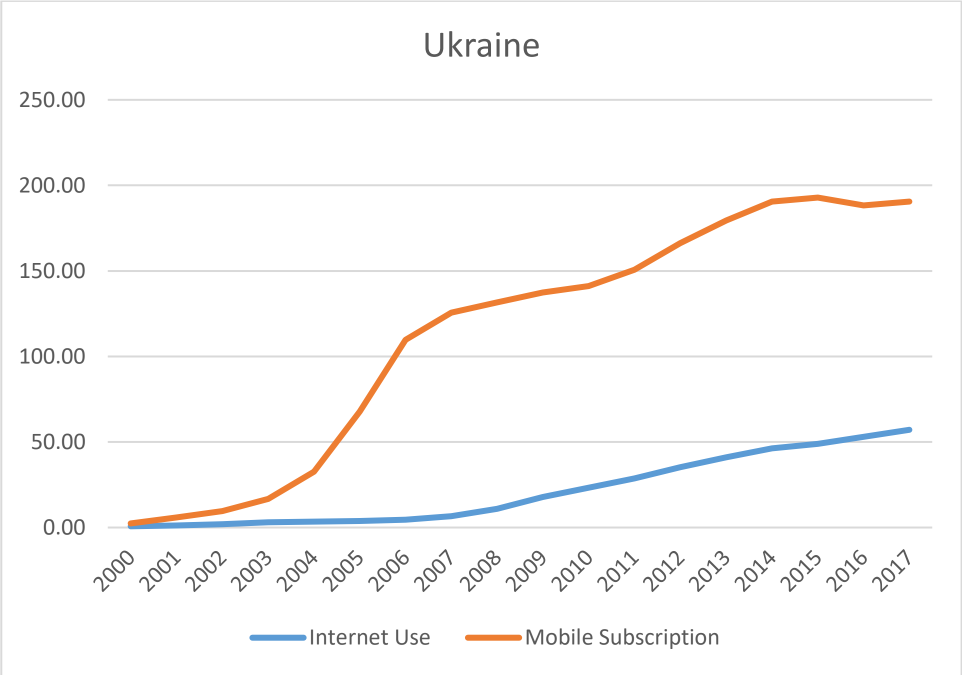


Fig 3. 13: Internet usage and Mobile phones in Ukraine (Source: ITU, 2018)

CHAPTER FOUR: MATERIALS AND METHODS

In this chapter, we outline the research design, data collection, sampling, and techniques for the data analysis. We discuss the research methodology employed, the research processes designed to achieve the main objective, and the method used to collect the data in the first four sections of this chapter. Then, the following two sections discuss the data collection and validation using quantitative techniques. The last section espouses the steps taken to develop the predictive model for the maturity of the citizens of LMICs.

We adopted a survey method to assess the maturity of the citizens of LMICs for ConsHI in large populations. This resulted in quantitative data collection tools, such as structured questionnaires. Specifically, we used a descriptive cross-sectional study (Ye *et al.*, 2019) to elicit the maturity of the citizens of LMICs for ConsHI from January 2018 to December 2019. The first step after our literature search was to create a concept of the instrument and pilot it in the population of interest. We considered items from the family of UTAUT and PAM and made new items for ConsHI levels. We fine-tuned the variables from these three models needed for the study, such as maturity level as objectives and Low and Middle-Income Countries (LMICs) as context.

4.1 DEVELOPMENT OF THE ConsHI QUESTIONNAIRE

It is inappropriate to use electronic or computer-related instruments to collect data on a study that seeks to assess the use of technology. Some studies have suggested that using technology-related data collection tools can influence our respondents and result in them providing erroneous data. Notably, in a study to assess the prevalence of patients with diabetes using self-management tools such as personal computers, smartphones, and mobile phones, Bloomfield *et al.* (2014) examined patients with diabetic conditions. They reported that, in technology-oriented research, respondents should not be exposed to technology platforms since this could bias their response in favour of the technology. Also, Shibuta *et al.* (2017) reported the limitation to their study caused by using technology platforms to test technology usage. Their study concluded that more than 50% of the patient's expressed willingness, although only 16% used those tools. Reporting the limitation, they reiterated that the data collection medium could have influenced the responses. However, studies that do not seek to assess the use or otherwise of technology can employ technology to collect data for ease of data collection. Consequently, for our study, we used hard – copy structured questionnaires for the data collection, which are designed as follows:

4.1.1 Likert Items and Scales

There are several measurement scales in research studies like rating, ranking and catogorizing. Rating scales for instance are used to assess the properties or objects of a study without reference to the objects, an examples is the Likert scale. Dalati (2018) defined Likert scale as a positive or negative attitude statement, towards the object of a study. Researchers over the years have used the Likert scale to assess several behavioural concepts like the technology adoptions and use (Venkatesh, Thong and Xu, 2012).

Likert items propounded in 1932 by Rensis Likert are used to measure psychometric attributes (Brown, 2011). An aggregation of Likert items yields a Likert scale of at least three options (Dolnicar, 2013). The possibilities for an item are either odd (3,5,7, etc.) or even (4,6,8 etc.), numbered and labelled 'strongly disagree' to 'strongly agree' or the reverse (Dolnicar, 2013). Usually, for odd-numbered options, a neutral position is indicated. To administer Likert items, researchers must decide on suitability on the measurement scale.

Measurement is assigning numbers to empirical events, objects or phenomenon, which should be related to specific rules and measurement design (Dalati, 2018). The attributes of measurements are classifications, order, distance and zero origin. A measurement scale can be unidimensional or multi-dimensional, when its unidimensional, only one attribute is used to assess the objective of interest, while multi-dimensional consist of using multiple attributes to assess the object of interest (Dalati, 2018).

Measurement scales are in four distinct levels, each representing a different level of measurement—nominal, ordinal, interval, and ratio (Sarstedt *et al.*, 2017).

First, the nominal scales are the lowest level of measurement scales because they are the most restrictive in terms of application in data analysis. A nominal scale (also called categorical scale) assigns numbers used to identify and classify objects (e.g., residential status, gender, marital status, etc.). For instance, in case a survey wants a respondent to identify their nationality and the categories are Ghanaian, Chileans, Turkish, Ukrainians and so forth, the question has a nominal scale (Hair *et al.*, 2017).

Attributes of nominal scales include two or more sub-categories, but each sub-category is mutually exclusive, and all possible sub-categories are included. Usually, a number is assigned to each sub-category, which is used to ascertain the frequency of responses in each sub-category (Hair *et al.*, 2017).

Second, the ordinal scale is next to the nominal scale. The ordinal is a derivative or order or ranked; when a variable is measured on an ordinal scale, the variable's value can increase or decrease, giving order or ranks in information. In this study, we classified responses for various questions as 1= strongly disagree, 2=disagree, 3=neutral, 4=agree, and 5=strongly agree. The activity or participation level increases when the use variable's value increases. Measures on ordinal scales provide information about the order of respondents. Also, the differences in the order are not equally spaced. The difference between "strongly disagree" and "disagree" is not the same as between "agree" and "strongly agree," even though the differences in the numeric values (i.e., 0 – 1 and 1 – 2) are equal. Thus, calculating arithmetic before, it is not appropriate to calculate arithmetic means or variances for ordinal data. Also, categories are mutually exclusive.

The third is the interval scale; this improves the weaknesses in using ordinal scales since one can assume interval (equidistant) measures, thus supporting parametric and non-parametric statistics (Hartley, 2014; Gosavi, 2015; Graffigna *et al.*, 2015; Youn *et al.*, 2017). The Interval scale offers more precise information on the rank order in which it measures things and makes it easy to interpret the magnitude of the differences in values directly. For example, if the temperature is 90°F, we know that if it drops to 80°F, the difference is precisely 10°F. This difference of 10°F is the same as the increase from 90°F to 100°F. The precision of "spacing" is called equidistance, and equidistant scales are necessary for specific analysis techniques, such as SEM (Hair *et al.*, 2017).

However, the interval scale does not consider the absolute zero point. As earlier, when the temperature is 0°F, it feels cold, and the temperature can even reach negative values. The value of 0 does not connote the absence of temperature (Mooi and Sarstedt, 2014). The value of interval scales is that almost any mathematical computations, including the mean and standard deviation, can be carried out.

Moreover, researchers can convert and extend interval scales to alternative interval scales. For example, instead of degrees Fahrenheit (°F), many countries use degrees Celsius (°C) to measure the temperature. While 0°C marks the freezing point, 100°C depicts the boiling point of water. You can also convert temperature from Fahrenheit into Celsius and the reverse (Hair *et al.*, 2017).

Lastly, the ratio scale seems at the apex of measurement scales. This scale provides enough information since measurements here have a value of absolute zero (0) means that a particular characteristic for a variable is not present. For instance, when a respondent's income is zero (value = 0), the respondent has no income. Therefore, the zero point or origin of the variable is equal to 0. The measurement of length, mass, and volume, as well as the time elapsed, uses ratio scales. With ratio scales, all types of mathematical computations are possible (Hair *et al.*, 2017).

There are two essential caveats in Likert items: the midpoint (neutral) and different languages. First, the middle perceived as 'Neutral' or 'Neither Agree nor Disagree' provides an optional neutral level. Youn *et al.* (2017) argued that respondents do not always use it as an impartial opinion but as a dumping ground when the survey items are ambiguous or socially undesirable. We mind that such ambiguity may be present in our instrument since distinguishing neutral phrases like "I do not care" from "I do not know, or understand, or want to say" are present in the questions adopted for the research. We will be mindful of these spurious or biases in the data during the analysis.

Secondly, language (or cultural) differences may occur in our study since there were six countries (Chile, Ghana, Kosovo, Iraq, Ukraine, and Turkey). Croasmun and Ostrom (2011) investigated how the answers of Chinese, Japanese and Americans differ in five areas (difficulty in responding, out-of-range responding, varied patterns of responding, scale reliability, and construct validity) that influenced the decision of the response to Likert items. They concluded in their multi-cultural study that Likert items showed different response patterns in other languages, which could be a result of culture.

In summary, we used Likert items with 5-options labelled "strongly disagree," disagree," "neutral," "agree," strongly agree". These are ordinal measures and supported our constructs' generation of Likert scales. Mainly, we measured Likert items as ordinal (assuming unequal distance between options) data and used non-parametric statistics for analysis.

4.1.2 Literature Search

The first step in our search was PubMed, using different combinations of the terms for Consumer Health Informatics, maturity, instruments, and participants to find relevant research works and published papers. Subsequently, we searched Google Scholar, PsycINFO and ScienceDirect. We used Mendeley to manage the literature search and citation since it supports the creation of a direct search and reference database.

Notably, Wetter (2016) alluded to the absence of precisely fitting MeSH keywords for ConsHI. He commented that the content does not live up to the ConsHI definition and often gives the client or consumer a passive role. He combined ConsHI services with medical problems that suggest ConsHI and ICT as specific as possible. We used a similar strategy in this study. Flaherty (2014) identifies the most regularly used words in ConsHI definitions (Table 4.1). Mainly these terms helped search for ConsHI information in most search engines like PubMed.

Table 4. 1: Most frequently used words in consHI definition

Health	48	Designed	4
Informatics	28	Defined	4
Information	26	Communication	4
Consumer	25	Tools	3
Consumers	12	Tele-communication	3
Medical	10	Technologies	3
Care	10	Studies	3
Systems	7	Science	3
Computer	7	Models	3
Technology	5	Management	3
Patients	5	Making	3
Healthcare	5	Electronic	3
Support	4	Development	3
Public	4	Delivery	3
Patient	4	Decisions	3
Needs	4	Better	3
Internet	4		

The inclusion criteria were articles written in English, available as full free text and describing an instrument for patients or consumers. The title should include at least one or two terms like 'empowerment', 'questionnaire', 'self-management', 'health literacy, 'active participation' or 'technology'. Also, the abstract should mention at least one or two combinations of the term's 'concept', 'design', 'questionnaire', 'interview', 'survey', 'measurement', 'attitude', 'skills', 'eHealth', 'mHealth', 'healthcare’, ‘healthcare services, ‘low- and middle- income countries, ‘maturity’, and ‘readiness’. Conversely, we excluded articles without abstracts and older than 15 years and articles that did not relate to our definition of ConsHI.

Table 4. 2: Search terms used for various topics in literature reviews

Topics	Search terms
Consumer Health Informatics	eHealth, telehealth, mHealth, health care service, social media
maturity	readiness, ability
instruments	questionnaires, patient-reported outcomes, health care survey
participations	patient, health care provider

4.1.3 Conceptual Design

We chose a structured questionnaire which is a quantitative data collection tool. The idea of the questionnaire includes items appropriate to assess maturity factors and potential modifiers of maturity.

Therefore, the profile of respondents was essential in assessing how their demographics influence the response and modifying our theoretical framework like Venkatesh, Thong and Xu (2012). The questionnaire captured demographic questions about age, gender, marital status, and place of residence. Essentially, most of the demographic variables were nominally scaled.

We selected variables from UTAUT, UTAUT2 (including UTAUTe), PAM, and ConsHI to constitute items for assessing the maturity of the citizens in ConsHI. There are constructs from UTAUT, ConsHI levels and PAM that underlie the items in our instrument's. ConsHI and PAM have four levels of ordered activity, also assessing an increase in skills or participation. Therefore, a conflation of ConsHI levels and PAM categories would inform the maturity of a population in ConsHI.

4.1.4 Modification of Words and Phrases:

Notable changes include replacing 'mobile Internet' and ‘mHealth' from (Venkatesh, Thong and Xu, 2012) and (Hoque and Sorwar, 2017), respectively, with 'mobile phone and the Internet because our target population was LMIC. Also, for some (Hibbard *et al.*, 2005; Roberts *et al.*, 2016), we replaced "health condition" with "health" and "healthy lifestyle" to warrant the inclusion of healthy laypersons who were encouraged to imagine their attitudes and behaviours. Hence, some variables are constructed with "when I am sick” to satisfy the conditions of healthy respondents.

Also, in most LMICs, a few possess personal computers at home (International Telecommunication Union, 2016), and we define mobile access according to Hartzler and Wetter (2014) as owning or could use a family member's phone in case of medical need. We replaced mHealth' with 'mobile phones and the Internet in Hoque and Sorwar (2017), and their items revealed negative associations with technology.

Consequently, in the first phase of the instrument, we created 14 -variables related to demographics and 64 – variables assessing the maturity of ConsHI. The breakdown of the 64 is 26 items from UTAUT2 (Venkatesh, Thong and Xu, 2012), five items from UTAUTe (Hoque and Sorwar, 2017), 21 items from PAM (Hibbard *et al.*, 2004, 2005), and constructed 12 new items to represent ConsHI.[1] (Wetter, 2016). The total number of variables on the first draft were 78, structured in Likert formats, resulting in a 5 - point Likert scale from 'Strongly Disagree' to 'Strongly Agree’. Since the first draft questionnaire was in English, we had to translate it into other languages like Spanish for Chile, Turkish for Turkey etc. (see chapter for profiles).

4.1.5 Translations into various languages

Following the assertion of Croasmun and Ostrom (2011), we cured the weakness of Likert scales by using the double reverse translation method to minimise the effect of variable response due to language

[1] Combination of ConsHI levels and newly refined questions by the research team

differences in non-English speaking countries (see earlier, chapter three country profiles). The scales had to be translated into various national languages because the questionnaires would be distributed among respondents in all six countries (Chile, Kosovo, Ukraine, Turkey, Iraq and Ghana).

Our approach to translating our instrument is similar to earlier studies on cultural differences using Likert scales (Lee *et al.*, 2002). First, as is done with the translation processes, we recruited native language speakers who had some appreciable level of education (at least a bachelor's degree) and were fluent in speaking English and skilled in scientific research translation to translate our scales into the national language. Fortunately, all our researchers met this criterion, reducing the number of translators we engaged. Remarkably, our researchers also understood the research concept, so they were more precise in doing the translations. Furthermore, we had to consider a cross-cultural adaptation, certain expressions needed to be modified to avoid misinterpretation, which was also done (Lee *et al.*, 2002).

Secondly, we also requested the services of second opinions from different people invited to read the translated scales and provide recommendations for our modifying scales, consequently ensuring comprehensibility, appropriateness, and readability in the context of culture. Again, we were interested in their ages, genders, and educational levels. Lastly, the scales underwent a reverse translation process by an English-speaking friend to check for conceptual discrepancies and ensure consistency with the original English version.

It is worthy of note that, for instance, in Kosovo, the questionnaire was translated into Albanian, the official language of Kosovo, by Bleta Emini (University of "Kadri Zeka" in Gjilan, Faculty of Computer Science). In contrast, for Chile, we translated the questionnaire into Spanish. However, the instrument was not translated in Ghana since English is the country's second official language.

4.2 PRE-TESTING AND PILOT STUDY

Despite the availability of guidelines about properly designing questionnaires, it is often difficult for researchers to identify and curb all the potential issues that may arise during data collection (Messer, Edwards and Dillman, 2012). Pre-testing is, therefore, imperative for the survey questionnaire to confirm that there is no ambiguity in the questions and that the respondents can understand the questions the way they are designed and intended (Sekaran, 2003). The pre-testing process "helps to rectify any inadequacies, in time, before administering the instrument orally or through a questionnaire to respondents, and thus reduce biases" (Sekaran, 2003, p. 249).

Most pre-tests aim to address problems that, if not resolved, would increase measurement error (Blair and Conrad, 2011). Kumar (2009) asserted that the purpose of pre-testing a questionnaire is to ensure a) *the correct wording of the questions*, b) *that we* establish *the proper sequence of questions for the* *concept being assessed*, and c) *the respondents have clearly understood all the questions*, d) *additional questions are needed, or some questions should be eliminated*, and e) *the instructions are clear and adequate*. Thus, in survey methods, it is proper that all developed scales, or items, whether adopted or adapted, are pre-tested to ensure the questions work accurately in a new setting with the new respondents (Kumar, 2012).

Hence, the first draft of the instrument was pre-tested in Heidelberg amongst five respondents. Though these respondents resided in a developed country (Germany), the number could help achieve the objectives of pre-testing, particularly regarding the language, clarity, and timelines for completing the instrument. For this purpose, the five respondents have conveniently selected to pre-test the instrument. Later, the results of the five respondents were used to re-word some of the questions, and researchers also reviewed the interview time since our target was to administer the questionnaire within 15 minutes. We validated the questionnaire in similar settings to our intended populations. Thus, the next phase of piloting was done in developing countries since that was the target population of our study.

4.2.1 Pilot Study

We conveniently conducted the pilot study in three countries (Chile, Ghana, and Kosovo) since only researchers from these countries were available to implement the instrument at the time of piloting. Also, because it was a multi-country study, we anticipated variations and sensitivity in answering the questions. Therefore, demographic variables were revised to support the interpretation in a countrywide context. For instance, religious categories in Ghana are different from Chile and Kosovo. Also, residential status was defined differently, and these demographics were revised separately for our data collection pilot phase (see Appendices A). However, the resultant instrument included 14 demographic variables and 64 ConsHI-related items. See Table 4.3 for details.

Table 4. 3: Selected variables for pilot instrument

Model	Total items for data collection at the pilot stage	# of Questions	Literature Source
UTAUT, UTAUT2 and UTAUTe	3,4,5,6,7,8,11,12,13,14,15,16,17,18,19,31,36,37,38,39,40,**41**,42,43,**44**,**45**,54,55,56,58	30	(Venkatesh *et al.*, 2003; Venkatesh, Thong and Xu, 2012) (Hoque and Sorwar, 2017)
PAM (PAM 32 and 13)	1,2,20,22,24,25,28,30,32,33,34,35,46,47,48,50,51,57,61,62,63	21	(Hibbard *et al.*, 2004, 2005; Hibbard and Gilburt, 2014)
ConsHI Maturity	9,10,21,23,26,27,29,49,52,53, 59,60,64	13	(Wetter, 2016)
	Total of ConsHI Maturity Questions	64	
Demographics	1,2,3,4,5,6,7,8,9,10,11,12,13,14	14	
	Total Questions on the instrument	78	

NB: Bold face (41,44, and 45) are variables of technological anxiety that did not pass validation but were included because of their thematic importance.

4.3 SAMPLING AND SAMPLE SIZE ESTIMATION

The sampling was multi-staged, starting with the convenient selection of countries from different continents. The next was selecting hospitals and data collection sites (malls and bus stations) and, lastly, selecting respondents who were 18 and above years. This sampling approach is convenient (also called grab, accidental or opportunity) sampling (Etikan, Musa and Alkassim, 2016). It is a nonprobability sampling that involves samples drawn from that part of the population close at hand. Convenience sampling is a kind of nonrandom sampling in which members of the target population, as Dörnyei and Taguchi (2006) mentioned, are selected for the study if they meet specific practical criteria, such as geographical proximity, availability at a particular time, easy accessibility, and the willingness to volunteer. Dörnyei and Taguchi (2006) further explain that "captive audiences such as students in the researchers" own institution are prime examples of convenience sampling."

However, Etikan, Musa and Alkassim (2016) pointed out that the apparent disadvantage of convenience sampling is that it is likely biased. They advise that researchers should not use convenience sampling to represent the population. This type of sampling is beneficial for pilot testing, as in our case of the first draft instrument. Remarkably, this method does not require a probabilistic selection of first respondents since the sample was given through the willingness and availability of the respondent to participate (Dörnyei and Taguchi, 2006).

4.3.1 Participant Selection

We recruited respondents from people clustered in various locations, such as passengers waiting at bus stations. The rationale was that the majority were healthy and had an active lifestyle. Since they do not own or use a car, we assumed middle-income people.

Also, to select our respondents with medical conditions, we visited facilities (hospitals). Particularly those visiting chronic disease clinics such as HIV/AIDS, Diabetes and Hepatitis. We sought the consent of authorities in the facility to administer our instruments. When a respondent did not finish answering and had to leave, we discarded that instrument to reduce missing and incomplete responses in our dataset. Also, we included some medical and paramedical staff of the facilities in selecting the professional respondents. The diagram below (Fig 4.1) shows the strata of the population we recruited as our respondents. Interviewers personally addressed interviewees, most of whom complied though less than 10% declined.

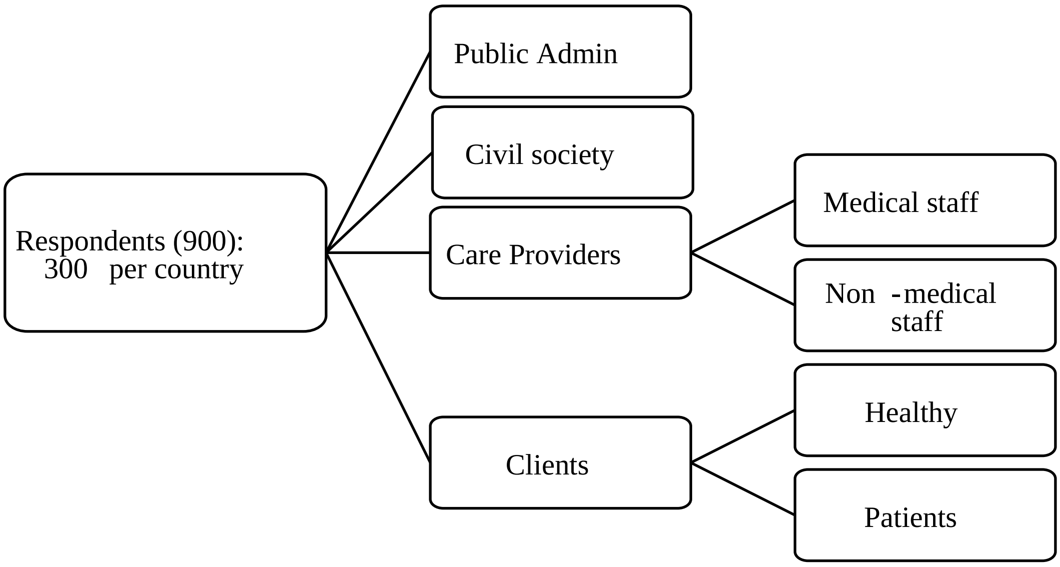


Fig 4. 1: Tree diagram of respondents' selection

4.3.2 Pilot sample Size

Until recently when the power of computing eased the burden of sample size estimation, researchers have mostly used a variety of techniques for estimating needed sample size, ranging from the quick and dirty to the elaborate (Tabachnick and Fiddell, 2007). The crude approaches, however, have negatively affected sample sizes and the final results of their findings. Essentially, the sample size for the pilot study must be sufficient to warrant any meaningful analysis of this stage in the data collection process.

In discussing sample size estimations, Memon *et al.*(2020 p ii) write, "There is no one-size-fits-all solution to address this issue". Also, Chuan and Penyelidikan (2006) argued that, in conducting research, the sample size is best assessed during the designing stage. Exceptionally, noting the following essential elements: (1) how much sampling error can be tolerated; (2) population size; (3) how varied the population is concerning the characteristics of interest; and (4) the smallest subgroup within the sample for which estimates are needed Salant and Dillman (1994) as cited in (Chuan and Penyelidikan, 2006). For our study.

$$S = \frac{X^2NP\ (1-P)}{d^2\ (N-1) + X^2P\ (1-P)}$$

Eqn 4. 1: Sample size estimation formular using power analysis

S = required sample size.

X^2 = the table value of chi-square for one degree of freedom at the desired confidence level

N = the population size

P = the population proportion (assumed to be 0.50 since this would provide the maximum sample size)

d = the degree of accuracy expressed as a proportion (0.05)

According to Cohen (1988), to perform a statistical power analysis, five factors need to be considered: 1. significance level or criterion, 2. effect size, 3. desired power, 4. estimated variance and 5. sample size.

Subsequently, Lenth (2001) shared a similar position as Cohen (1988), asserting that the relationships among the five are such that each is a function of the other four. Consequently, the application of these arguments results in using the formula (Eqn 4.1) proposed earlier researchers with a little modification using online calculators (Messer, Edwards and Dillman, 2012).

To operationalise it, taking Ghana's population of 30 million in 2018, since access to mobile phones for ConsHI is the focus of this study; we assumed our target population is estimated to be 70% (21 million people of age >= 18 years, i.e., P=0.7). We considered a 5% degree of accuracy (i.e. d = 0.05), thus calculated the sample at a d = 0.5 (5% margin of error and 95% confidence level), giving a representative sample size of 68 for Ghana (similarly for 10% and 90% error margin and confidence level we got 323) (*Sample Size Calculator*, no date; Memon *et al.*, 2020). Comparatively, Ghana (30 million) has a larger population than Chile and Kosovo, 18.95 million and 1.87 million, respectively.

Hence, their sample sizes will be smaller (<68). To balance our data for factor analysis and fallouts during the pilot phase of the data collection, we settled on 100 respondents per country.

Alternatively, we compared our sample size using the online estimator with Cohen's formula and sample table (Chuan and Penyelidikan, 2006). We arrived at approximately the same sample size for Ghana and applied it to all the other countries (Chile, Kosovo, Iraq, Turkey and Ukraine).

Also, we noted several rules for determining the sample size for a pilot study (Memon *et al.*, 2017). For example, Cooper and Schindler (2014) suggested a sample between 25 and 100 individuals. Alternatively, a range of 10 to 30 individuals is enough for a pilot test. Moreover, several scholars suggested that the sample size should be 10 percent of the sample project for the main study. Furthermore, we could also choose the sample size based on the type of analysis at the preliminary stage. A sample of 30 individuals is permissible. This number originates from the Central Limit Theorem, which makes a distributional assumption of the sample size of 30 or more to ensure the mean of any samples from the target population approximates the population (Memon *et al.*, 2017). Hence, our sample size of 351 is supported by extant approaches (Memon *et al.*, 2017).

However, when adopting a rule of thumb, several issues deserve consideration since this method can bias the research for a particular subgroup and has insufficient power to identify differences in subgroups in populations. Also, cultural variations of responses may occur since it was conducted in different countries (Chile, Ghana, Kosovo, etc.). After collecting the data on 351 respondents from Chile, Ghana and Kosovo, we analysed the data to validate the instrument before the final data collection.

Table 4. 4: Distribtution of respondents for various countries in the pilot study

Country	Respondents
Chile	101
Ghana	102
Kosovo	148
Total	351

4.4 VALIDATION AND RELIABILITY OF THE INSTRUMENT

The appropriate method for analysing ordinal data is non-parametric (Meek, Ozgur and Dunning, 2007). We collected 351 responses, a large enough sample size for the z – values table (Wilson Von Voorhis and Morgan, 2007). A z-score describes the position of a raw score in terms of its distance from the mean, when measured in standard deviation (σ) units. The z-score (ranges from negative infinity to positive infinity and depends on the measurement of interest) is positive if the value lies above the mean, and negative if it lies below the mean. A positive z-score indicates the raw score is higher than the mean score of the variable of interest. For example, if a z-score is equal to +1, it is 1 standard deviation above the mean. A negative z-score reveals the raw score is below the mean score of the variable of interest. For example, if a z-score is equal to -2, it is 2 standard deviations below the mean. Another way to interpret z-scores is by creating a standard normal distribution (also known as the z-score distribution or probability distribution). The Standard Normal Distribution (SND) (i.e., z-distribution) is always the same shape as the raw score distribution. For example, if the distribution of raw scores is normally distributed, so is the distribution of z-scores. The mean of any SND always = 0. The standard deviation of any SND always = 1. Therefore, one standard deviation of the raw score (whatever raw value this is) converts into 1 z-score unit.

A non-parametric test is the ideal technique for comparing our items in the survey instrument. Notably, we could have used several methods in validating our scaled items; however, we are mindful of using non-parametric techniques, so we adopted the Wilcoxon Signed–Rank Test (WSRT) and the Item Response Theory (IRT).

4.4.1 Wilcoxon Signed-Rank Test (WSRT)

WSRT demonstrates whether pairs of items have a similar meaning because their answering distributions are equal, that is equal median or equal means scores based on the frequency of the response. WSRT is a good measure where we compare variables with different distributions. To ascertain whether any two items were identical, using their distribution as measure of the comprehension of the wording, we hypothesised that:

H_0: Items are similar, and H_1: Items are not similar

We wanted to discard statistically identical items; we independently applied the WSRT for all three countries' datasets. We calculated $Q_{(i,j), R.}$ where Q is the estimated parameter, i, j stands for the pair of questions, and R stands for the initials of Kosovo (K), Ghana (G), Chile (C), and the sum of responses from all countries (T). We retained both items if H_1 was accepted for at least one country (and used T to confirm). WRST was used to assess Paired items and z-value for each country at a 95% confidence level (α=0.05). We fail to accept the null hypothesis (H_0) if $Q_{(i,j), R}$ < 95% quantile of the z distribution and conclude that pairs (i,j) were not similar (i.e., i≠j). Conclusively, we excluded one item when a pair was similar (i=j), and for non-similar (i≠j) items we included both. We should note that we used the shorthand i=j to denote that the text items indexed by i and j do not differ in meaning; resp. for i≠j. Similar items we also call twins.

Example 1:

Item 4: Using a mobile phone or the Internet helps me to do things more quickly

Item 5: Using a mobile phone or the Internet increases my productivity.

The quantiles of the z – values at 95% are: Z ($Q_{4,5,K}$) = 63% (Kosovo), Z($Q_{4,5,G}$) = 77% (Ghana) respectively Z($Q_{4,5,C}$) = 0% (Chile). Since all three countries had Z_{95} <95%, we rejected H_0 and concluded that items 4 and 5 are not similar and hence included both in the final instrument.

Example 2:

Item 59: Assuming, I am willing, I can share my personal experience of my health condition through blogs.

Item 60: Assuming, I am willing, I can interact with people who have the same health condition through Internet forums.

The quantiles of the z – values at 95% are: Z ($Q_{59,60,K}$) = 13.2% (Kosovo), Z($Q_{59,60,G}$) = 78% (Ghana) respectively Z($Q_{59,60,C}$) = 95.2% (Chile). Since Chile had a different outcome from the hypothesis, we pulled all three countries' data together and reran the hypothesis. At this stage we calculated Z ($Q_{59,60,T}$) = 95.84%. Item 59 and 60 are twins Z ($Q_{59,60,T}$)= 95.84%). We failed to reject H_0 and concluded that Items 59 and 60 are similar; hence, we chose 59 and excluded 60 in the final instrument. The decision whether to keep one (here 59) and exclude the other item was based on Item Response Theory.

4.4.2 Item Response Theory (IRT)

In psychological measurement, there is an underlying variable of interest, referred to as an unobservable or latent trait (trait) (Baker, 2001). The primary goal of psychological measurement is the determination of how much of such a latent trait a respondent possesses. The amount of latent trait a respondent possesses is called “ability”; thus, ability is how much of a latent trait respondents possess when studying a concept of interest. In IRT, researchers seek to measure the ability of a respondent to latent traits that is the objective of the study.

IRT was first propounded in the 1970s when it was used to develop standardised tests, such as scholastic aptitude tests (SAT). It has become a widely accepted and utilised psychometric approach in the validation of measurement tools for research (Samejima, 1969; Toland, 2014).

Cole, Turner and Gitchel (2019) mentioned that IRT is a probabilistic model that estimates the underlying latent trait since it considers individual response patterns in calculating latent trait scores. Latent characteristics are "abilities" to solve a particular problem. In our application performance expectancy and Confidence are examples of latent traits. Hence, the goal of measurement is to determine how much of a latent trait an individual possesses (Baker, 1994). In applying IRT, everyone is assigned a numerical value theta represented by the Greek alphabet θ and the likelihood that an individual solves the problem with the ability θ *is* denoted by P(θ). Theoretically, P(θ) is directly proportional to ability score on a scale of θ values, for instance, at the lowest level of ability, the probability of a correct response is near zero, increasing until, at the highest level of ability, the likelihood [P(θ)] of a correct response approaches 1. The S-shaped (see Fig 4.2) curve describes the relationship between the probability of a correct answer to an item and the ability score, called the Item Characteristic Curve (ICC). Each item in a questionnaire has its ICC, and the ICC is the foundation of IRT.

Below in Fig 4.2 is an example of an ICC showing ability (θ) on the horizontal axis and probability of ability P(θ) on the vertical axis. The left one is for dichotomous variables while the right-hand side one is for a polytomous variable with four categories.

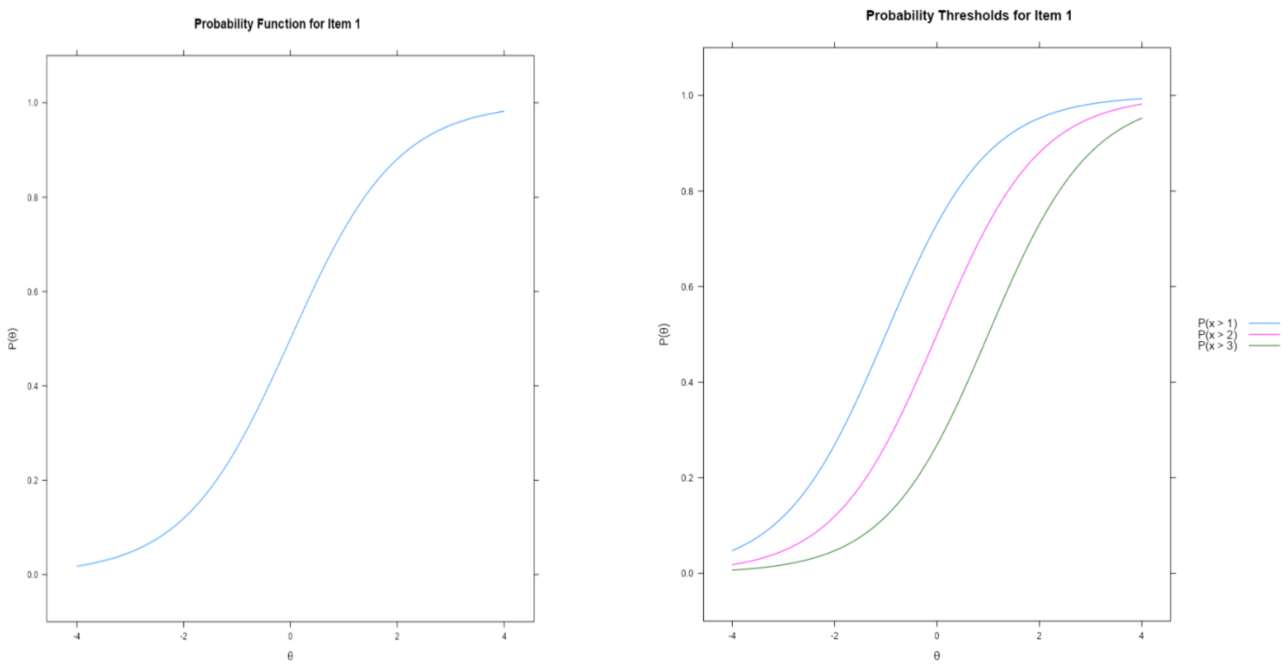


Fig 4. 2: Item characteristics curve (ICC) of a dichotomous (left hand side) and polytomous (right hand side)

IRT is a trait theory that helped us choose amongst twin items suggested by WSRT to ascertain the ability of people answering our questions correctly. The focus of IRT is improving the accuracy and efficiency of the survey instrument at the item level, instead of the test level (summed score result) (Kean *et al.*, 2018). The item level statistics (properties) help to choose the best items that explain the latent trait and are represented by the discrimination (a) and difficulty (b) parameters. Item discrimination (a) refers to the item's ability to distinguish one person from another and the difficulty (b), is how difficulty it is for a person to answer a question correctly using the category response functions (Wyse and Ayala, 2010). The difficulty parameter is sometimes called the location index on the ability (x-axis) axis and there can be more than one location index for a polytomous item.

The item response may be dichotomous (two categories), such as correct or incorrect, high or low, yes or no. Alternatively, it may be polytomous (more than two categories), such as a rating from a judge or scorer or a Likert-type response scale on a survey. The construct measured by the items may be for instance performance expectancy, ConsHI levels, or taking action (Brzezińska, 2016).

There are several models in testing IRT depending on the options of the outcome variable (latent trait) (Brzezińska, 2016). Recently, polytomous items have become omnipresent in educational and psychological testing, because they can be used for any test question where there are more than two response categories like in this research of ConsHI maturity. There are several types of polytomous IRT models like nominal response model, partial credit model, generalized partial credit model, rating scale model and graded response model.

In addressing dichotomous models, Furr and Bacharach (2007), reported that, the one – parameter (1PL), two – parameters (2PL), three parameters (3PL) and even four – parameters (4PL) models represent IRT measurement models that differ with respect to the number of item parameters that are included in the models.

In the one – parameter (1PL or rasch), – has one item parameter, by keeping constant the discrimination coefficient and a varying difficulty parameter. A slightly more complex IRT model is called the two-parameter logistic model (2PL) because it includes two item parameters (Furr and Bacharach, 2007; Massof, 2011). According to the 2PL model, an individual's response to a binary item is determined by the individual's trait level, the item difficulty, and the item discrimination. The difference between the 2PL and the Rasch model is the inclusion of the item discrimination parameter. Also, the three-parameter model (3PL) has varying discrimination parameter, varying difficulty parameter and a guessing parameter. Lastly, the four-parameter (4PL) model, this has multiple difficulty (locations index) parameters (Massof, 2011; Toland, 2014). Furr and Bacharach (2007), further indicated that, in the case of latent traits with dichotomous outcomes, the 1PL, 2PL and 3PL are sufficient. However, for polytomous outcomes (with more than 2 response options like "strongly disagree, disagree, neutral, agree and strongly agree"), the 4PL, the graded response model and the partial credit model are ideal (Furr and Bacharach, 2007).

Generally, these models differ in terms of the response options but use the same principles as the models designed for binary response items. They both exhibit the idea that an individual's response to an item is influenced by the individual's ability and by the item properties (Furr and Bacharach, 2007).

To assess the model fit of an item the probability function curve is applicable (see Fig. 4. 3). When all the options show their independent peaks (like item 5 in Fig 4.3), we conclude the model fits the data well for that item. For instance, in the diagram below (Fig 4.3), we evaluate the 4PL model fit for our ConsHI maturity pilot dataset.We used 4PL because our items were a 5-point Likert scale, so the ideal model is the number of options (five) less one (i.e 5 less 1) is four (Furr and Bacharach, 2007). We randomly selected two items (Items 19 and Item 5) from our pilot dataset for purposes of explaining the application of the principles. The graphs below show that for Item 19, first (strongly disagree) and third (neutral) were below other options, hence a 4PL is not a good fit for Item 19. While, in the case of Item 5, all the options exhibited their peaks and so the 4PL model fits the data well. However, because the instrument is a combination of several questions using the 5-point Likert scale, we would rather transform the non-conforming items like Item 19 and proceed with our analysis.

To evaluate the probabilities of responding to specific categories in a polytomous item's scale, we use the Category Response Curves (CRC). CRCs depict the probabilities of responding to a particular category (option) as shown (Fig 4.3) below. Symmetrical curve represents the probability of confirming a response option (P1 = 'Strongly disagree', P2 = 'Disagree", P3 = "Neutral", P4 = "Agree", and P5 = "Strongly agree). CRCs have a functional relationship with θ; As θ increases, the probability of choosing an option increase and decreases as responses transition to the next category. The CRCs show that the response categories cover a wide range of θ.

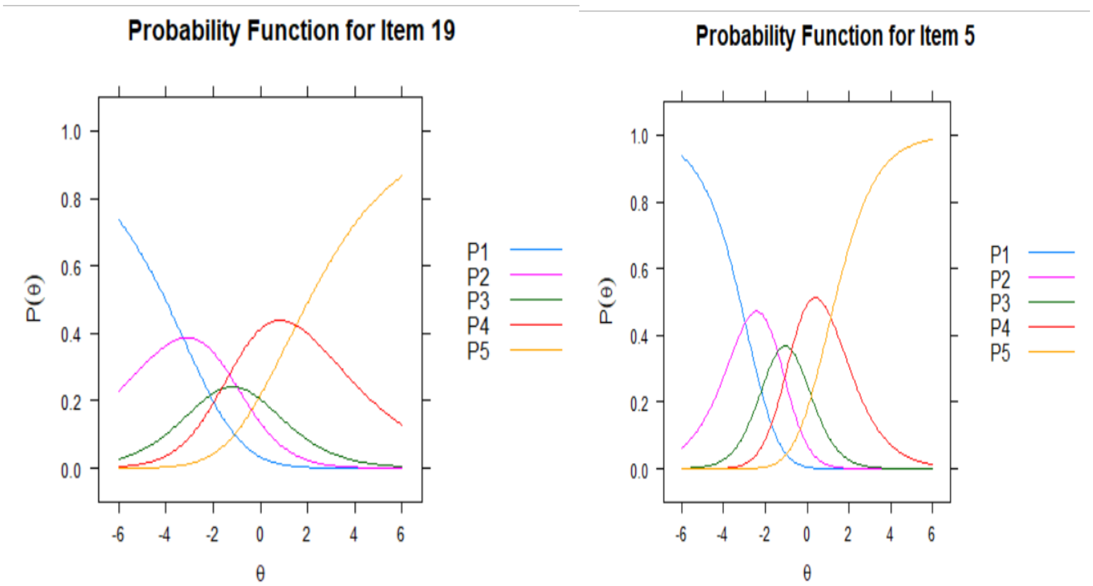


Fig 4. 3: Comparing a 4PL model fit to our data using Items 19 and Items 5.

The two main attributes of IRT are the item level information and the test level information. Item information is the extent to which a particular item contributes to evaluating the constructs or latent trait of interest. Item level information is a function of the discrimination and difficulty parameters of the items. While test level information is how much the test (entire questionnaire or cumulative of all items) can assess the particular trait of interest. For instance, an item will assess the performance expectancy of our instrument, but the entire instrument is set to assess the maturity of the citizens of LMICs for ConsHI in LMICs.

The precision of these estimated parameters indicates information obtained from the respondents. The predicted parameter's variance also, depicts the estimated parameter's accuracy (Cor *et al.*, 2012; Bustamante and Chacón, 2016). The amount of information is closely related to the discrimination parameters, the item discrimination parameter is positively correlated to the information the item provides in a test.

We could specify good working items by assessing the amount of information on each item (Pallant and Tennant, 2007). In the diagram (Fig 4.4) below, items with very high peaks contribute adequately to assessing the latent trait, while items with wider base show that a respondent with a wide range of abilities can answer the item correctly. The desired graph for all items is like that of item 16 and 17 below (Fig 4.4).

Information is a statistical concept that refers to the ability of an item to estimate scores on ability accurately. Item-level information clarifies how well each item contributes to scoring estimation precision, with higher levels of information leading to more accurate score estimates.

The amount of information an item contributes depends on the slope parameter in polytomous models. The higher the parameter, the more information the item provides. Further, the broader the location parameters (b1, b2, b3, b4), the more information the item offers. Typically, an informative polytomous item will have a prominent location and broad category coverage (as shown by location parameters) over θ.

Mounting evidence by Cole, Turner and Gitchel (2019) espouses, some essentials in IRT, like information provided by an item gives a measure of the precision of the estimated trait score for examinees along the trait scale. This differs from traditional reliability in a classical sense because traditional reliability of a scale is constant for all examinees. In IRT, however, the information provided by an item may differ for those with low, moderate, or high estimated θs. Test information is calculated as the sum of item information for the set of items as each θ level. Item and test information are inversely related to the standard error of measurement for θ.

Item Information Curves (IIC) best illustrate the information functions displayed by each item (see Fig 4.4). IICs show that item information is not a static quantity but depends on theta levels. The relationship between slopes and information is illustrated below. Item 19 has the least slope and therefore, the least informative item. Also, Items 12 and 20 has no peak and theoretical not useful to our test. Alternatively, Item 4 had the highest slope and provided the highest amount of statistical information, and items provided the most information between the -6 to + 6 theta range. The "wavy" form of the curves reflects that item information is a composite of category information; each option has an information function which is then combined to form the item information function.

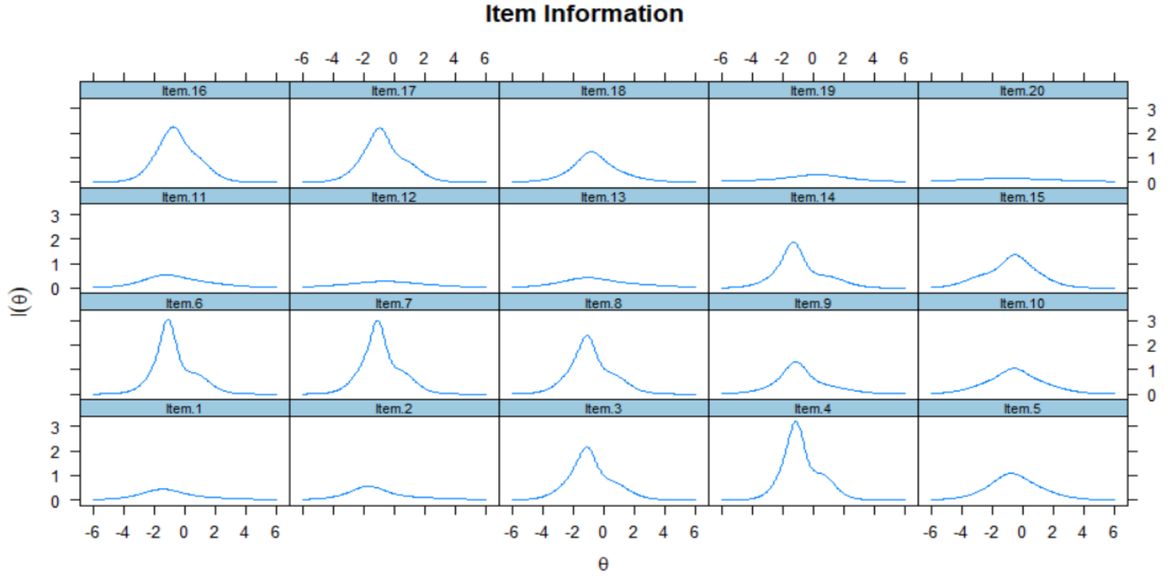


Fig 4. 4: Item information functions of the various items.

Items 4, 6, 7, 8, 16 and 17 give very high information due to their high peaks. Item 16 is also well spread out and that is fairly across all rrespondentss ability. Items 9, 10, 13, 15 and 19 are well spread out across the ability of the respondents. The Ideal choice of best fitting items are Items 4, 6, 7, 16 and 17. Next in Fig 4.5, we compare all the items on one graph and the highest contributor to the concept is shown below in Fig 4.5.

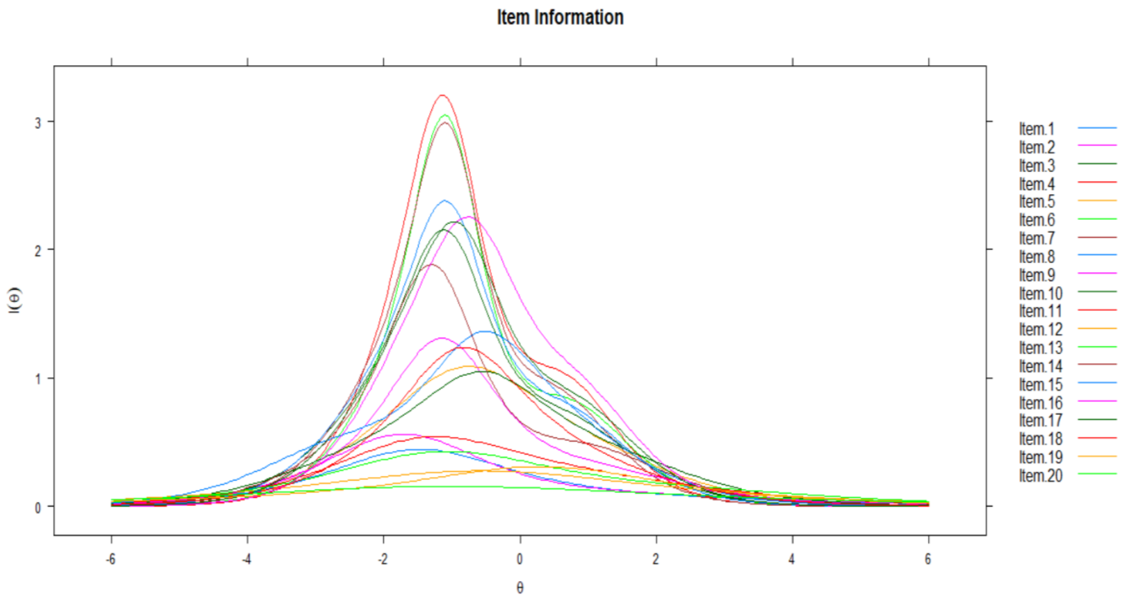


Fig 4. 5: The combined IIC of selected items

The test level information, which is a sum of all the items shows that generally, our items provide sufficient information for assessing the latent trait and spreads evenly from -6 to +6. Notably, most respondents with ability below 0, can answer the items in this study as shown in the peak of the graph below (Fig 4.6). The total score also shows how the response pattern satisfies the ICC.

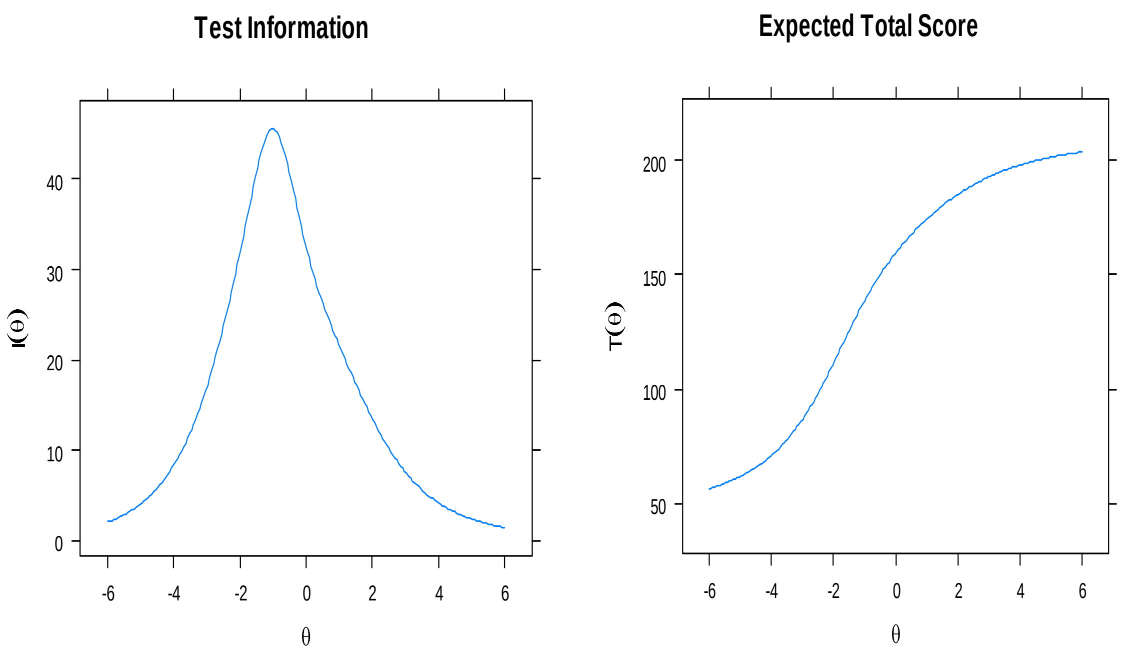


Fig 4. 6: Test level information curve and expected score

In IRT, the difficulty of an item expresses where the item functions on the ability axis. For example, an easy item functions among low-ability respondents and a difficult item function among high-ability respondents; thus, the difficulty is a location index. Also, discrimination describes how well an item can differentiate between respondents with abilities below and above the item location.

Analogous to the information provided by an item in a test, a difficult item requires a relatively high trait level (θ) to be answered correctly, but an easy item needs only a low trait level to be answered correctly. Item discrimination, is the ability of the item to discriminate between higher ability respondents and lower ability respondents (Fan, 1998). An item with a positive (>0) discrimination value (means more information) is related to the underlying trait being measured, and a relatively large discrimination value (e.g., 3.5 vs 0.5) indicates a fairly strong correlation between the item and the underlying quality (Baker, 1994; Toland, 2014). Conversely, items with a lower (0) discrimination value are less related to the underlying construct being measured, and an item with a negative (<0) discrimination value is inversely related to the underlying construct (trait). Graphically this ability reflects the gradient of the ICC (Fig 4.7) in its central section. A gradient is ordered as none, low, moderate, high, and perfect (Baker, 1994). Thus, it is generally desirable for items to have a sizeable positive discrimination value. A sizable positive discrimination value reflects the amount of information the item contributes to the overall test or latent trait of interest.

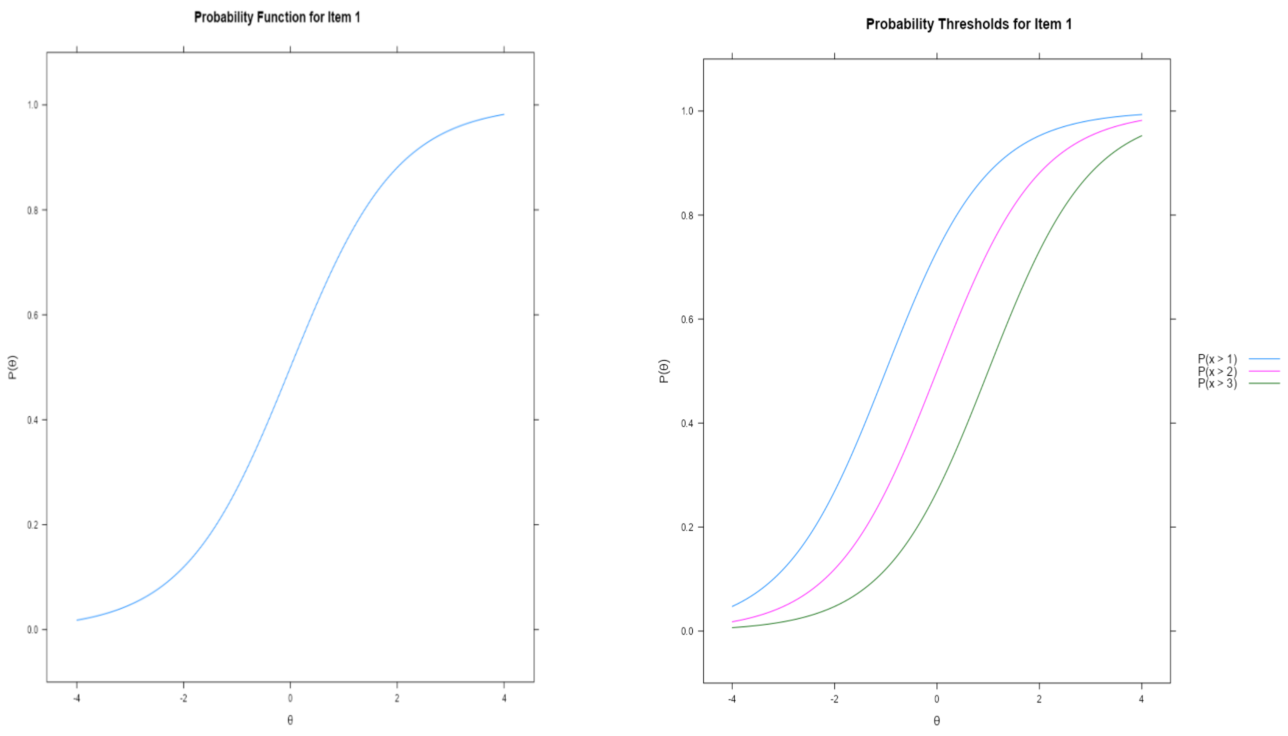


Fig 4. 7: Item threshold and location index curve

Item threshold is the point on the ability (θ) axis where respondents get the right answer to an item. Importantly, IRT places item threshold parameters parameters(-∞ to ∞) and person latent trait scores on the same continuum, which can be conceptualised as a z score type metric (e.g., standard deviation units from the mean) (Toland, 2014).

Rationally, we assume that each respondent has a reasonable level of ability to participate in this study. Thus, at least each respondent will have a difficulty score on the ability scale, and this ability score will be denoted by theta (θ). At each ability level, a respondent's probability of providing the correct answer to the items is denoted by P (θ). Theoretically, this probability positively correlates with ability. Thus, a P (θ) graph against ability (θ) results in a smooth S-shaped curve.

This property reflects the steepness of the ICC at its mid-point. The steeper the curve, the better the item can discriminate. The flatter the curve, the less the item can discriminate since the probability of correct response at low ability levels is hypothetical, and we define difficulty as follows: very easy, easy, medium=0, hard, and very hard. while discrimination is none, low, moderate=0.5, high, and perfect. The following is an algorithm for IRT:

1. When the item discrimination is below 0.5, the item characteristic curve is nearly linear and appears relatively flat.

2. When discrimination is above 0.5, the ICC is S-shaped and rather steep in its mid-point (moderate).

3. When the item difficulty is below 0, most of the ICC has a probability of correct response greater than 0.5.

4. When the item difficulty is above 0, most of the ICC has a probability of correct response less than 0.5.

5. Note that item discrimination is independent of item difficulty.

6. In An item with undefined discriminations, all choices of difficulty results in P (θ) = 0.5.

7. Notably, the point at which P (θ) = 0.5 corresponds to the item difficulty. When an item is accessible, this value occurs at a low ability level. This value corresponds to a high ability level when an item is hard.

The gradient can theoretically range from $-\infty$ to ∞, but a reasonably "good" range is from 0.5 to 3.0 (Hambleton, Swaminathan and Rogers, 1991; Avcu, 2021). However, the slope parameter for ordered polytomous IRT models can have a much broader range.

We assume that discrimination of $a> = 0.95$ is sufficient to discriminate between high ability and low ability respondents. Hence, items with discrimination above 0.95 (i.e., approximately 1) will be preferred to items with discrimination below 0.95 when we must choose from any two items identified to be similarly by our WSRT (Fig 4.8). Below is an example of ICC; the item with $a < 0.95$ are excluded from the questionnaire.

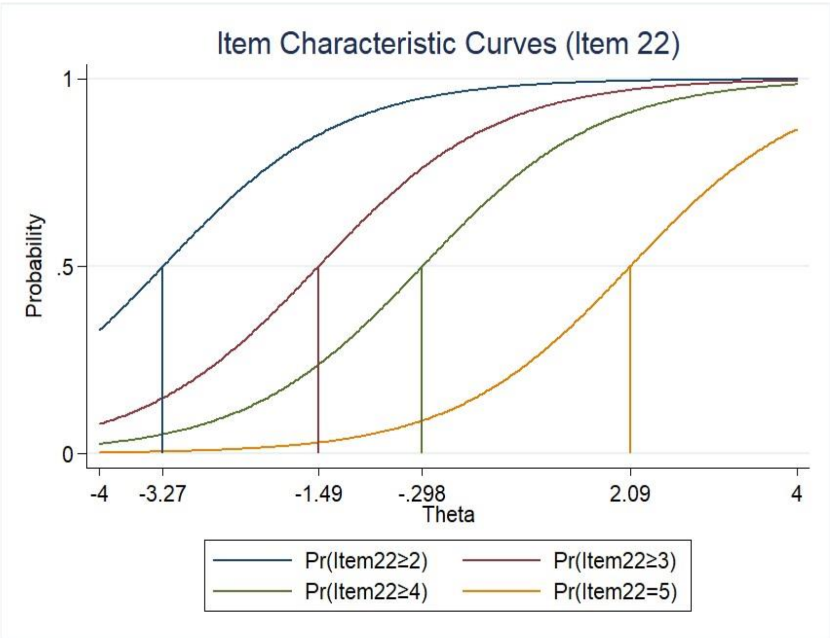


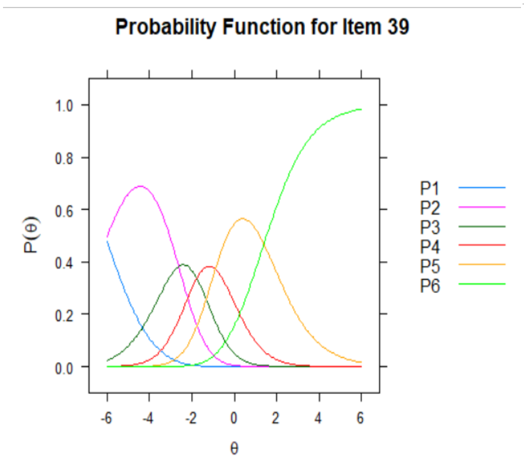
Fig 4. 8: Item characteristics curve of Items 22

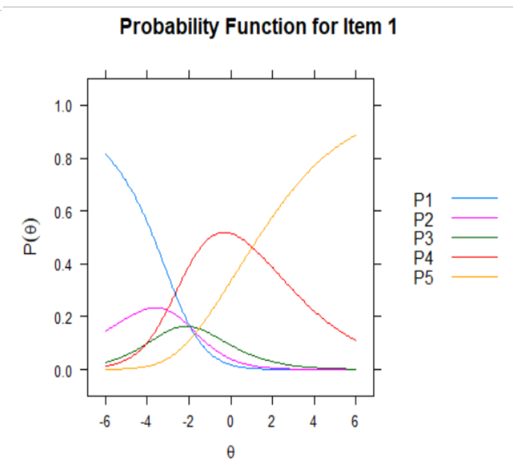
The horizontal axis represents the latent trait level (which has a standard normal distribution by construction), and the vertical axis measures the probability of choosing or endorsing the category exactly proper at a specified latent trait level (from ‘strongly disagree’ to ‘strongly agree’).

Theoretically, the number of dichotomies is proportional to the number of categories minus one. For instance, there are four different dichotomies for a 5-point Likert-type item. These dichotomies are sequentially compared: category 1 is compared with 2, 3, 4 and 5; categories 1 and 2 are compared with 3, 4 and 5; categories 1, 2 and 3 are compared with 4 and 5 and categories 1,2,3 and 4 are compared with category 5 (Avcu, 2021).

In Table 4.5: we use Item 22, the text was, *“I am able to use E-Mail or SMS to contact my health care provider.”* The different curves display the increasing likelihood of answering above thresholds 1, 2, 3, and 4, increasing ability θ (difficulty). The estimated parameters of Item 22 show that a person with θ (maturity for ConsHI); b1 = −2.80 has a 50% chance of choosing (‘strongly disagree’) answering 1 versus greater than or equal to 2. Similarly using locations indices b2, b3 and b4 (see Table 4.5) for item 22, a person with θ: b2 = -0.80 has a 50% chance of answering 1 or 2 versus greater than or equal to 3, and a person with θ; b3 = -1.34 has a 50% chance of answering 1, 2 or 3 versus greater than or equal to 4 and a person with θ; b4 = 2.67 has a 50% chance to answer 1, 2, 3 or 4 versus 5. The relevance of Item 22 to the study is the discrimination parameter which is a = 0.78 < 0.95. Hence Item 22 is excluded from the final instrument since it does not satisfy our discrimination criteria. Thus, it does not measure our trait well.

Conversely, Item 21 has a discrimination parameter of 0.98> 0.95 and is included in the final instrument. However, items 41, 44, and 45 were an exception because these items were the only ones to describe the resistance to change and technology anxiety, according to the WSRT. These items were essential to the constructs of Hoque and Sowar in the UTAUT2 extension (Hoque and Sorwar, 2017). They were, therefore, kept, although their values were below 0.95.





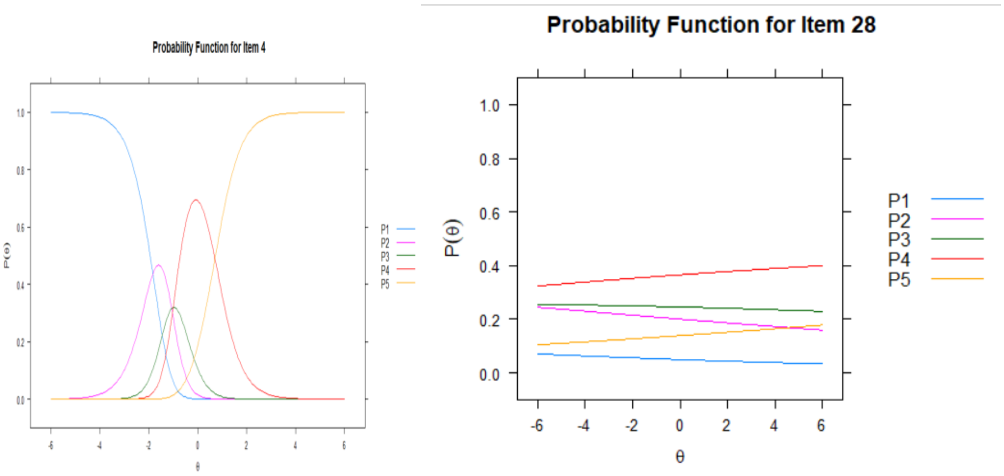


Fig 4. 9: Comparison of individual items information curves for polytomous variables

The instrument is measuring information slightly below the average value of 0. It means respondents did not need so much knowledge of ConsHI to be able to respond to these questions.

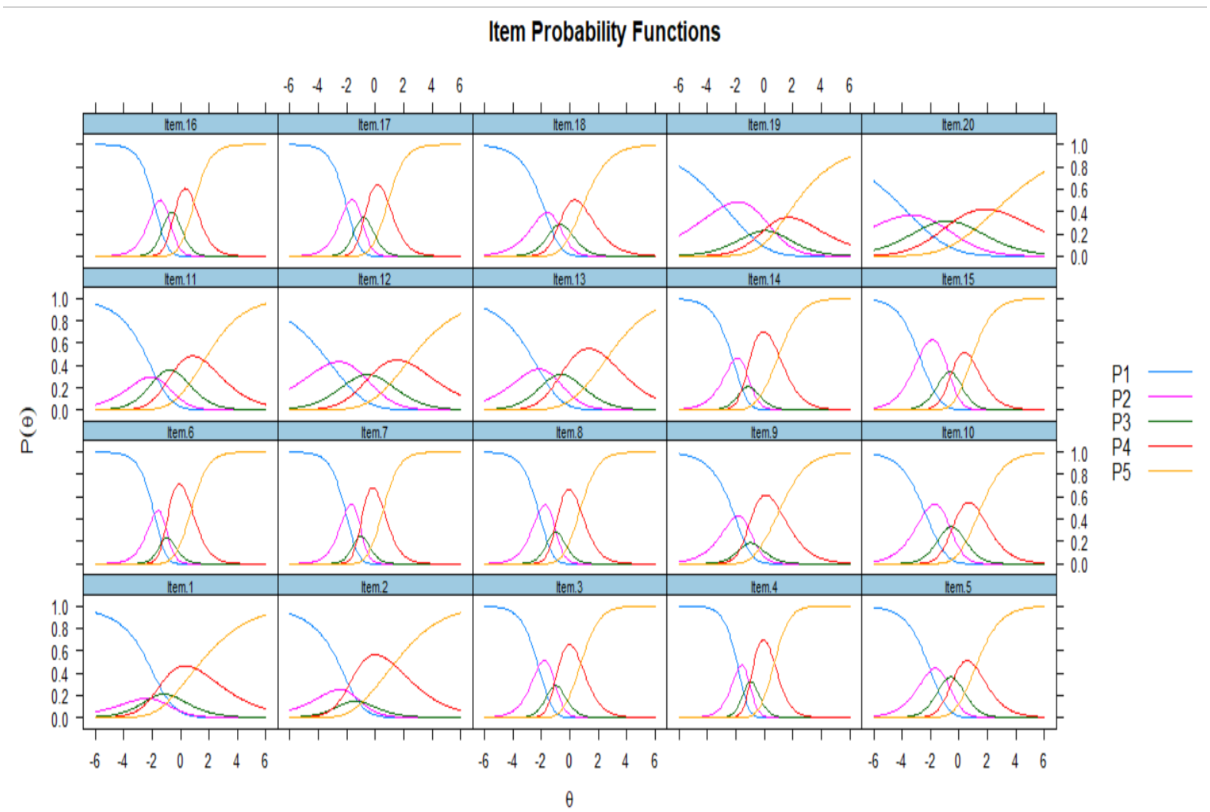


Fig 4. 10: Grid of selected items information curve for polytomous items

Table 4. 5: Item properties (discriminant and difficulty) of the pilot instrument

Variables (Items)	Discrimination	Difficulty			
	a	*b1*	*b2*	*b3*	*b4*
Item 1	0.53	-0.28	-1.97	-1.92	1.01
Item 2	0.60	-1.51	-0.94	-2.95	1.26
Item 3	**1.11**	-2.44	-0.85	-1.33	0.87
Item 4	**1.33**	-1.94	-0.95	-1.18	0.77
Item 5	0.89	-2.14	-0.88	-0.40	1.21
Item 6	**1.35**	-1.92	-0.66	-1.40	0.84
Item 7	**1.55**	-2.23	-0.72	-1.24	0.59
Item 8	**1.15**	-2.43	-0.81	-1.34	0.83
Item 9	**1.02**	-2.11	-0.45	-1.62	1.05
Item 10	**1.04**	-2.48	-0.55	-0.42	1.40
Item 11	0.72	-1.71	-1.58	-0.41	1.58
Item 12	0.45	-3.44	-0.88	-0.30	2.44
Item 13	0.63	-2.21	-1.07	-0.60	2.56
Item 14	**0.99**	-2.42	-0.70	-1.93	1.15
Item 15	**1.05**	-3.11	-0.61	-0.53	0.90
Item 16	**1.36**	-1.88	-0.78	-0.47	0.98
Item 17	**1.41**	-2.14	-0.86	-0.78	0.92
Item 18	**0.98**	-1.71	-0.70	-0.74	0.90
Item 19	0.47	-2.87	0.82	-0.07	1.43
Item 20	0.48	-2.87	-1.28	-0.24	2.07
Item 21	**1.11**	-2.15	-0.74	-0.86	1.27
Item 22**	0.47	-2.80	-0.83	-1.34	2.67
Item 23	0.35	-1.43	0.60	-2.49	3.66
Item 24	0.52	-3.48	-0.65	-2.64	2.45
Item 25	0.87	-2.22	-1.42	-2.00	0.82
Item 26	0.65	-2.38	0.45	0.26	2.21
Item 27	0.46	-2.20	0.35	-0.80	3.44
Item 28	0.71	-2.24	-0.94	-1.43	2.05
Item 29	0.93	-1.61	-0.50	-0.70	1.35
Item 30	**1.03**	-1.77	-1.39	-1.42	1.55
Item 31	**1.91**	-2.35	-0.95	-0.99	0.86
Item 32	**1.06**	-2.82	-0.49	-0.62	1.70
Item 33	**0.97**	-2.20	-1.53	-1.36	1.43
Item 34	0.87	-2.14	-1.69	-1.93	1.89
Item 35	0.53	-2.87	-1.41	-0.72	2.87
Item 36	**1.10**	-3.28	-0.75	-0.67	1.57
Item 37	0.54	-4.19	0.12	-0.65	3.04
Item 38	0.59	-3.75	0.28	-0.52	3.21
Item 39	0.59	-2.65	-0.44	-0.35	3.41
Item 40	0.04	-10.78	17.80	6.38	32.54
Item 41	***-0.04***	***14.07***	***-20.20***	***-4.96***	***-42.37***
Item 42	***-0.01***	***29.93***	***-67.00***	***-14.39***	***-77.25***
Item 43	0.86	-2.16	-1.13	-0.61	1.74
Item 44	0.19	-4.61	-1.32	-0.54	7.30
Item 45	0.24	-5.92	-0.10	-2.60	5.85
Item 46	0.45	-2.65	-1.82	-2.43	3.16
Item 47	0.55	-2.14	-1.63	-1.85	2.96

Item 48	0.48	-3.92	-0.51	-0.14	2.74
Item 49	0.50	-3.92	-0.63	-0.96	3.50
Item 50	0.64	-2.54	-1.00	-1.60	2.53
Item 51	0.58	-2.23	-1.72	-1.04	2.94
Item 52	**1.21**	-1.90	-0.64	-0.16	2.05
Item 53	**1.02**	-2.98	-0.02	0.25	1.98
Item 54	**1.15**	-2.38	-1.31	-1.16	1.10
Item 55	**1.12**	-3.22	-0.94	-0.43	1.20
Item 56	**1.21**	-2.79	-1.11	-0.60	1.66
Item 57	0.57	-2.84	-1.15	-1.51	2.60
Item 58	**1.08**	-2.61	-0.78	-0.92	1.41
Item 59	0.59	-1.45	-0.02	0.24	3.13
Item 60	0.53	-2.14	0.02	-0.25	3.07
Item 61	0.49	-3.64	0.11	-0.62	3.86
Item 62	0.43	-4.80	-1.35	-1.01	4.82
Item 63	0.46	-3.76	-0.16	-0.01	3.71
Item 64	0.67	-2.04	0.20	0.23	1.57

NB: Bold and italic a are negative (technology anxiety) items; Bold are above 1; ** Item 22 used as an example above

In summary to choose items as identified by the WSRT, we first assess the item information which is a function of the discrimination of the items (Baker, 1994). For paired items that are likely to collect the same data as identified by our WSRT, we selected the item with the most information, that is the item with the highest discrimination parameter (a>0.95). heuristically, a discrimination above 0.95 is approximately 1 and that is a near perfect probability, thus contributing near perfect information to the latent trait (Baker, 1994).

4.5 FINAL QUESTIONNAIRE

The final questionnaire consists of 10 questions about demographic facts and 43 items that assess the maturity of ConsHI in LMIC (Appendix B). Table 4.6 shows the questions and items that were removed from the questionnaire.

Table 4. 6: Classifications of items by models considered

Model	Total items for data collection at the pilot stage	# of Questions	Items after WSRT selections	# of Questions	# after IRT selections	# of Questions
UTAUT, UTAUT2 and UTAUTe	3,4,5,6,7,8,11,12,13,14,15,16,17,18,19,31,36,37,38,39,40,**41**,42,43,**44**,**45**,54,55,56,58	30	3,4,5,6,7,8,11,13,14,15,16,17,18,31,36,38,39,43,54,55,56,58	22	3,4,5,6,13,14, 15,18,31,36,39,43,54,55,56,58	16 (*19)
PAM	1,2,20,22,24,25,28,30,32,33,34,35,46,47,48,50,51,57,61,62,63	21	1,2,22,24,25,28,30,32,33,34,35,47,50,51,57	15	1,2,22,24,25, 28,30,32,33,34,35,47,50,51,57	15
ConsHI	9,10,21,23,26,27,29,49,52,53, 59,60,64	13	9,10,21,26,29,52,53, 59,60,64	10	9,10,21,26,29,52,53, 59,64	9
	Total	**64**		**47**		**40 (*43)**
Demographics	1,2,3,4,5,6,7,8,9,10,11,12,13,14	14	1,2,3,4,5,6,7,8,9,14	10	1,2,3,4,5,6,7, 8,9,14	10
	Total Questions on the instrument	**78**		**57**		**50 (*53)**

NB: Bold faced items (item 41, item 44, and item 45) are an exception because these items describe the resistance to change and technology anxiety and should be retained, despite $a < .95$. These constructs could provide more findings in this study. # means 'number'

4.5.1 Final administration of the questionnaire

Following the literature, the Table 4.7 below depicts the various items, broad constructs, and the four factors found in the underlying models.

Table 4. 7: First draft of items and their respective models

Factor	Construct	The final list of items
	PE	3, 4, 5
	EE	6
	SI	9
	FC	10, 21, 26
Attitude	PV	27
	AR	1, 2
	RC	30, 31
	TA	28
	L0	7, 8, 13, 35
Confidence	H	12, 43
	CK	14, 15, 16, 18, 20, 22, 23, 24, 25
	L2	17, 19, 36
Aptitude	BI	29, 37, 38, 41
	TAA	32, 33, 34
Motivation	HM	11, 39
	SCS	40
	L3	42

NB: PE = Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, FC = Facilitating Conditions, AR = believe Active Role is important, L0 = Level 0 Services, HM = Hedonic motivation, H = Habit, PV = Price Value, CK = Confidence and Knowledge to take action, TA = Technology Anxiety, L2 = Level 2 Services, BI = Behavioral Intention, TAA = Taking Action, RC = Resistance of Change, SCS = Staying the Course under Stress, L3 = Level 3 Services.

4.5.2 Final sample size

The final data were collected in six countries: Chile, Ghana, Iraq, Kosovo, Turkey, and Ukraine. We followed a similar sampling approach as the pilot phase and used the statistics of sample size. In each country, the researchers administered the questionnaires themselves.

At the pilot stage of data collection, data analysis methods informed the minimum sample required per country and for the entire study. Also, since the analysis methods would consider factor analysis, extant literature suggests that 300 is a sufficient sample size for a survey using Convenience sampling.

MacCallum *et al.* (1999) summarised some recommendations regarding the sample size for factor analysis. The most interesting result was that there is a rating scale for adequate sample size in factor analysis: 100 = poor, 200 = fair, 300 = good, 500 = very good and 1000 = excellent. Therefore, we decided the number of respondents for the final study to be 300 samples per country, resulting in a total sample of 1,800 respondents. We settled on a final sample size of 1,800 (300 respondents per country) for the six countries as prescribed by Memon *et al.* (2020), and interviewers personally addressed the interviewees. Most of them complied though less than 10% declined.

4.6 DATA ANALYSIS

The data analysis considers demographic variables like age, residence, gender, marital status, highest educational level, employment status, and most recent medical care. Age and highest academic levels were measured as ordinal variables. The remaining demographic variables were nominal since rank was not imperative for these variables in our ConsHI models. This study adopted items from a refined instrument composed of UTAUT, UTAUT2, PAM, and ConsHI. The instrument's details are published by Yakubu *et al.* (2021). A total of 43 theory-related items (variables) are considered for our Structural Equation model (SEM), which is used to establish the relation between the factors and the maturity of the citizens of LMICs.

Civelek (2018) recommended that, before applying SEM, which is a Confirmatory Factor Analysis (CFA), it is essential to conduct an Exploratory Factor Analysis (EFA) to first look at the results of the explanatory factors present in the dataset.

4.7 EXPLORATORY FACTOR ANALYSIS (EFA)

The objectives of EFA are to reduce the number of variables to reflect latent constructs, examine the relationships between variables and their constructs and develop empirical constructs for our models (Siddiqui, 2015). Watkins (2018) suggested a comprehensive approach to interpreting and reporting EFA since EFA identifies the smallest number of hypothetical constructs (factors, dimensions, latent variables, synthetic variables, or internal attributes) and parsimoniously explains the covariation within a dataset. The measured variables (observed, manifest, items, indicators, reflective indicators, or surface attributes) are selected for their utility as indicators of anticipated factors. Measured variables are used to evaluate the factors' content, convergent, and discriminant validity (Izquierdo, Olea and Abad, 2014).

4.7.1 Test of Assumptions

Like any data analysis techniques, there are necessary conditions upon which a dataset is suitable for EFA. Particularly, the distributional properties of the dataset might affect the correlations of variables and factors (Watkins, 2018). Also, there are several properties of data that can affect the result of EFA, and the first is *minimal levels of sample variability from the target population.* In most research samples resulting from some selective samplings are not identical to the population from which they are selected. Suppose a sample is more restrictive than the population, the variance of its variables will also be restricted, leading to an attenuated Pearson product-moment correlations coefficient (r) (Hunter, Schmidt and Le, 2006). Watkins (2018) proposed that it may be appropriate to correct range restriction in such cases by carefully applying a suitable solutions such as meta-analysis, artefact distribution meta-analysis and multipliers as prescribed by Hunter, Schmidt and Le (2006). Remarkably, Yong and Pearce (2013) asserted that heterogeneous samples are preferred to homogeneous samples since homogeneous samples decrease the variance and factor loadings in EFA.

Secondly, verifying sufficient *linear relationship amongst indicators* is an essential requirement for EFA. Watkins (2018) posit that examining scatterplots can subjectively judge adequancy of *indicators linearity*. Theoretically, the *r* coefficient measures the linear relationship between two variables. The *r* coefficient assumes normality, but violations of normality appear to be typical with real datasets (Lloret, Ferreres and Tomás, 2017). Researchers might use a more robust type of correlation coefficient to assess linearity in the dataset instead of *r* for observed nonlinearity in the dataset (Revelle, 2013; de Winter, Gosling and Potter, 2016; Paper, 2016; Lloret, Ferreres and Tomás, 2017). Thirdly, the dataset must have a *normal univariate distribution*. Skewness and kurtosis depict the normality of a dataset, while skewness refers to the symmetry of the score distribution, kurtosis measures the height of the score distribution compared to its width (Watkins, 2018). Remarkably, we reduce the possibility of skewness affecting EFA results by ensuring all indicators are scored in the same direction. So, any negatively valanced variables should be reverse scored so that the scores on all the variables have a similar meaning (Watkins, 2018). The skewness and kurtosis values must be within acceptable range of values and show proof of normal univariate distribution in a dataset. Regardless of statistical significance, simulation studies have found that serious problems may exist when univariate skewness is ≥2.0 and kurtosis is ≥7.0 (Curran, West and Finch, 1996). Fourthly, an *appropriate level of measurement* is required for EFA. The *level of measurement* is determined by the Pearson correlation coefficient *(r).* Pearson correlations assume that normally distributed variables are measured on an interval or ratio scale and continuous data with equal intervals.

Singularity occurs in perfectly correlated variables (bivariate correlations are zero). When variables have identical values, it results in a singular matrix problem. In model estimations, this often means zero variance, implying one or more items have no variance. Also, singularity can occur in bootstrapping under the same conditions of indicators having identical values, leading to the random bootstrapping procedures producing subsamples with duplicate values. Singularity mainly occurs in bootstrapping, when excessive (5% or 15%) missing values are replaced by mean replacement techniques. Statistically, singularity is evinced when the square of multiple correlations is close to zero (Tabachnick and Fiddell, 2007). Researchers must assess their dataset for missing values, particularly to determine the pattern of the missing values, whether random or non-random. The most appropriate approach to missing values is deletion, which prevents overestimation (Tabachnick and Fiddell, 2007).

Yong and Pearce (2013) evinced that the correlation coefficient (r) must be at least 0.30 to show adequate correlation amongst items. Particularly, researchers should ascertain the extent of multicollinearity and singularity in their dataset by assessing the Squared Multiple Correlation (SMC; Tabachnick & Fidell, 2007). The squared multiple correlations are the variance in the bivariate correlations. Yong and Pearce (2013) suggested that researchers should delete items that show singularity (SMC close to 0) and multicollinearity (SMC close to 1.0). According to Tabachnick and Fiddell (2007), extremely highly correlated variables are multicollinear, and perfectly correlated variables cause singularity. The correlation size is evaluated through bivariate or multiple-regression procedures, where all items are cross-correlated. For purposes of EFA, any item with squared multiple correlations (SMC) of more than 0.50 may be considered redundant and deleted from further analysis (Tabachnick and Fiddell, 2007).

Norris and Lecavalier (2010) makes a strong case for estimating correlation matrix, by proposing that, the first step in EFA is to measure the association between the items of interest. Though this assertion differs from other studies, they reasoned that, the inter-item correlations (i.e., the correlation matrix) are used to calculate the communalities (the proportion of observed variance due to common factors, or the total amount of variance for an item explained by the extracted factors) and factor loadings. They further asserted that the nature of the dataset determines the type of correlation between the items. When the dataset is ordered-categorical, polychoric correlations provide better estimates of the inter-item correlation. Notably, tetrachoric correlations are special cases of polychoric correlations, where any two items are dichotomous. They concluded that the relationship between ordered-categorical items may be underestimated when researchers use the Pearson product moment correlations, this in turn would bias eigenvalues and factor loadings. The emphasis of their arguments, however, is not the steps in EFA, but the need to establish accurate correlation matrix to support significance of the factor loadings and interpretation.
Also, variables measured as ordinal (ordered – categorical) and dichotomous scales will not meet the linearity and normality assumptions (Li, Xie and Jiao, 2017). Consequently, they will negatively affect correlation coefficients and the EFA results. To mitigate this, researchers (Gadermann, Guhn and Zumbo, 2007; Holgado–Tello *et al.*, 2010; Monroe and Cai, 2015) have identified more robust correlation estimates (like the Spearman correlation , polychoric correlation and tetrachoric correlation matrices) for nonnormality and situations where their use would be advantageous when

using ordinal level variable. Expressly, the polychoric correlations method assumes unobservable normally distributed continuous variables underlying the observed categorical variable and estimates the Pearson correlation between those underlying hypothetical variables (Holgado–Tello *et al.*, 2010). Polychoric (tetrachoric matrices for dichotomous data) correlation (covariance) matrices are ones in which the correlations within the matrix have been calculated and standardised to represent the relationships between ordinal indicators better. Hence, factor analyses with ordinal data based on polychoric matrices probably yield more accurate results than raw scores (Pendergast *et al.*, 2017). Conclusively, research methodologists have recommended polychoric correlations for EFA when five to seven scales measure the ordinal variables or distributions of the ordinal indicators.

It is sufficient for every study to report the quantity and nature of missing data and the rational methods used to deal with it. Collectively, researchers (DeCarlo, 1997; Aguinis, Gottfredson and Joo, 2013) have agreed that, EFA result should report approaches to detect observations that are influencers, straight line, and outliers. Some (Marshall, 1997; Memon *et al.*, 2017) recommended approaches to dealing with observations include data cleaning.

Accordingly, data cleaning is done using techniques like scatter plots, boxplots, and correlation graphs. Also, the relationship of the indicators in a dataset is essential in applying EFA. It is imperative to ascertain indicators sufficiently intercorrelate to justify factor analysis. A sizable number of indicator correlations should exceed ±0.30, or EFA may be inappropriate (R. MacCallum *et al.*, 1999; Hair *et al.*, 2010). However, high (>0.8) bivariate correlations potentially result in low unique variance for individual indicators (Diamantopoulos *et al.*, 2012). Thus, a of 0.3 – 0.7 is safe for the bivariate correlation of indicators for EFA.

There is sufficient evidence that the suitability of the dataset and adequacy of the sample size for EFA must be verified before conducting EFA. To check the suitability and adequacy of sample size, extant literature has recommended the Bartlett's (1954) sphericity test (BTS) and the Kaiser-Meyer-Olkin (KMO) test. First, we verify the suitability of the dataset for EFA using Bartlett's (1954) sphericity test (BTS). BTS assesses the hypothetical factorability and statistical significance of the correlation matrix by evaluating the hypothesis that the correlation matrix contains the value 1 on the leading diagonal and 0 off the diagonals (Watkins, 2018). Bartlett's test should produce a statistically significant ($p<0.05$) chi-square value to justify the suitability of the dataset for the application of EFA.

Also, the Kaiser-Meyer-Olkin (KMO) is a measure of sampling adequacy that evaluates how strongly an indicator is correlated with other indicators in the EFA correlation matrix. KMO supplements the BTS since KMO is the ratio of correlations that reflects the extent to which correlations are a function of the variance shared across all indicators rather than the variance shared by pairs of indicators (Kaiser, 1974). KMO values range from 0.00 to 1.00 and can be computed for each indicator's total correlation matrix. Generally, KMO values ≥0.70 are desired (Kaiser, 1960, 1974), but values less than 0.50 are generally considered unacceptable (Hair *et al.*, 2010). As precisely described by Hoelzle and Meyer (2013), KMO values are interpreted as shown in Table 4.8 below. Thus, satisfactory BTS (p-value <0.05) and KMO (>0.7) values are required for a dataset to be factorable.

Lastly, there must be an identity matrix of the correlations in the dataset before explorations. To establish identity matrix, the determinant of the correlation matrix must be significant at 5% margin of error.

Table 4. 8: Guidelines for assessing the factorability of data for EFA (Hoelzle and Meyer, 2013, p. 35)

Criterion	Empirical test	Guidelines	Description
Determinant of the correlation matrix	Determinant of identity matrix (|Det|)	<0.05	Acceptable
Measuring sample adequacy	Bartlett test of sphericity (BTS): p-value	<0.05	Acceptable
The measure of Sampling Adequacy (KMO)	Kaiser-Meyer-Olkin (KMO)	>0.9 >0.8 >0.7 >0.6 >0.5 <0.5	marvellous; meritorious; middling; mediocre; miserable; and unacceptable

4.7.1.1 Number of indicators to recognize a factor

To represent these properties (content, convergent and discriminant) in a latent variable, at least three indicators are needed to identify a factor statistically. Relatively, Fabrigar *et al.*(1999); Fabrigar and Wegener (2012) recommend a range of four to six indicators to be required to identify a factor.

4.7.1.2 Adequate sample size for EFA

An appropriate sample size is estimated using different approaches, including rules-of-thumb. For instance, existing literature recommends that EFA is conducted utilising the ratio number of variables to factors such as 5:1 or 10:1, or the number of participants at least 100 or 200 (Schinka and Velicer, 2014; Loehlin and Beaujean, 2017). Knofczynski and Mundfrom (2008) provided handy tables of minimum sample sizes based on these characteristics. Generally, like the central limit theorem, a sample size of 100 and above will suffice for EFA with no complex features.

4.7.2 Models of Factor Analysis

Conceptually, this study seeks to identify latent constructs underlying the dataset for the assessment of the facilitators of ConsHI. After verifying that the dataset is factorable, the researcher must ensure that the appropriate model for EFA is used. EFA is conducted with two models that differ in purpose and computation: Principal Components Analysis (PCA) and Common Factor Analysis (CFA) (Kennedy, Grossman and Ehrenreich-May, 2016). PCA analyses the entire correlation matrix (including the self-correlations of 1.00 found on the diagonal) (Norris and Lecavalier, 2010). In contrast, CFA attempts to separate the total variance of the indicators (used interchangeably with items) underlying the same construct into common variance (communality or h^2, like the standard R^2 in regression) and unique variance (u^2). Also, both PCA and CFA produce communality estimates, but only CFA estimates each indicator's uniqueness (u^2). Essentially, we can identify factors using their communality and their factor loadings.

4.7.2.1 Using communalities to identify factor structure

Norris and Lecavalier (2010) explained that communalities may range from zero (the variable has no correlation with any other variable in the matrix) to one (the variance of the variable is completely accounted for by the underlying factors). Essentially accurate estimation of the communalities psotively impact the model fit. Inaccurate communalities, negatively affects factor solutions interpretation especially for less than 20 variables or when the actual communalities are low (=<0.4) (Norris and Lecavalier, 2010). Also, errorneous estimations of communalities mostly account for the diffirences in solution of PCA and CFA models. Thus, CFA, offers a better solution to this research considering the theoretical and empirical reasons for modelling our dataset (Brown, 2009). Since in PCA, communalities are set to one, as all observed variance is viewed as available to be modeled.

4.7.2.2 Using factor loadings to identify factors in a structure

Factor loadings are numerical values that depict the nature of a measured variable. Factor loadings reflect the degree of influence of a factor on the measured variable. Earlier, Guadagnoli and Velicer, (1988), described factor loadings as the contribution of an item to a factor. They posited that, statistically, a factor should have at least three items and at most six items loading on it. Specifically, item with a factor loadings between 0.40 and 0.60 has a moderately high loadings and should be acceptable (Costello and Osborne, 2005; Yong and Pearce, 2013). Later, Samuels (2017), in his academic advise to researchers suggested that, an item should be removed from a factor structure if the loadings at below 0.3 on all factors. Thus, a less than 30% influence on any factor is enough to delete an item from the factor structure.

4.7.3 Estimation Method

Following our choice of CFA in the previous section, the most common techniques for CFA that differ in assumptions are Maximum Likelihood (ML) and iterated Principal Axis (PA). ML estimations are derived from central limit theory, which is suitable for multivariate normality and large sample sizes. However, PA is a least-squares estimation method with no distributional assumptions (Cudeck, 2000).

The estimated sample size and dataset for this study lend credence to our ability to use either of the techniques, however, opted for the ML since the conversion of raw data to polychoric correlation matrix will resolve the challenge of distributional assumptions.

4.7.4 The Number of Factors to Retain

To avert over-factor (identifying more factors than true) and under-factoring (identifying fewer factors than true) are major issues in the application of EFA (Fabrigar *et al.*, 1999). Researchers share varying opinions on over factoring as preferred to under factoring since the former provides supposedly optimal factor structure and does not leave out any possible solution. Conversely, others think over-factoring negatively affects factor loadings, eventually translating into the variance explained and thus errors in EFA results. Consequently, it is not surprising that extensive methodological literature has developed exploring the issue of determining the optimal number of factors.

There are several procedures for identifying the number of factors in a dataset. The skillful application of EFA astutely balances parsimony and comprehensiveness. Helpfully, the model estimation process assists in estimating the optimal model because the first factor extracts the most common variance, with subsequent factors extracting successively smaller portions of variance.

The eigenvalues produced by a PCA have traditionally been used to estimate the number of factors to investigate in common factor analysis. Other methods include the visual scree plot, parallel analysis, and minimum average partials (MAP), which are accurate empirical estimates of the number of factors to retain (Fabrigar *et al.*, 1999; Cattell, 2010). Consequently, in this study, we selected the scree plot and parallel analysis as a range of plausible factor solutions to evaluate the **smallest and most significant number** of factors suggested by scree plot and parallel analysis criteria. Remarkably, no single method is reliable in all situations (Fabrigar *et al.*, 1999; Cattell, 2010). Hence using various techniques and carefully judging each plausible solution is appropriate (Lloret, Ferreres and Tomás, 2017).

Although, the plethoria of literature (Costello and Osborne, 2005; Norris and Lecavalier, 2010; Yong and Pearce, 2013; Baglin, 2014) on EFA sheds light on several techniques for determining the number of factors to retain, for the purpose of our research we focuse on only three and briefly explain these methods of selecting factors in EFA.

4.7.4.1 Kaiser criterion (K1)

K1 is one of the popular techniques for dealing with the puzzle of the number of factors is the Kaiser criterion (K1 means Kaiser eigenvalue greater than one) (Fabrigar *et al.*, 1999). In this procedure, we compute the eigenvalues for the correlation matrix to determine the number of eigenvalues greater than 1, representing the number of factors in the dataset (Baglin, 2014). One notable weakness of K1 is that it is pretty arbitrary. For instance, it will include an eigenvalue of 1.01 but exclude an eigenvalue of 0.99. This raises concerns about over-factoring and under-factoring by researchers (Fabrigar *et al.*, 1999).

After K1, researchers have proposed, the new Kaiser criterion which supposes a variation of the K1 criterion to lessen the severity of the old Kaiser criterion's weakness. In the new criterion, the researcher calculates confidence intervals for each eigenvalue and retains only factors with an entire confidence interval greater than 1.0. in Rstudio, for instance, some packages estimate both the old and new factors for researchers to compare.

4.7.4.2 Scree Test

Presumably, the items of interest cover a domain and moderately strong correlations (above 0.3). This means, the factors we are interested in should be obvious in a graph than the ones of no interest, including random correlations. Observers have reported that, when we plot eigen values, they are plotted in order of size, the factors of interest will appear first and be larger than the trivial ones. Conventionally, , scree is the rubble at the bottom of a cliff. The cliff itself is identified because it drops sharply. The last part of the cliff that can be seen is where it disappears into the scree, which has a much more gradual slope. Note that the cliff is still seen at the top of the rubble; in the same way the number of factors includes the last factor associated with the drop (Schinka and Velicer, 2014). To identify the number of factors, we observed the point at which the line formed by plotting the eigen values from largest to smallest factor stops dropping and levels out.

Thus, this procedure also employs eigenvalues. However, instead of using a 1.0 cutoff, the user plots successive eigenvalues on a graph and arrives at a decision based on the point at which the curve of decreasing eigenvalues changes from a rapid, decelerating decline to a flat gradual slope (Loehlin and Beaujean, 2017). We observed how the eigenvalues that drop precipitously, and then how a gradual linear decline sets in. This decline is seldom absolutely linear out to the last eigenvalue— often, especially with large matrices, it may shift to a more gradual slope to infinity. This linear or near-linear slope of gradually declining eigenvalues was called the scree by Raymond Cattell, who proposed this test. He arrived at this name from the geological term for the rubble of boulders and debris extending out from the base of a steep mountain slope (Loehlin and Beaujean, 2017).

4.7.4.3 Parallel Analysis

Parallel analysis consists of doing parallel analyses of random data (Schinka and Velicer, 2014). Loehlin and Beaujean (2017), asserted that, this is also eigenvalue-based procedure. Howerver, parallel analysis, does not rely on eigenvalues greater than 1.0, but uses the number of eigenvalues that are greater than those which would result from factoring random data.

The concepts are that they are parallel because, the equal number of observations and items are used in the factor analytic study, but they consist of random data. For instance, fifty to 100 of these are run, and the eigen values are averaged to show what the eigen values would be if the data were only random. The eigen values always start over 1.0 and then drop sharply. Also, in practice, one normally does the random factoring several times, rather than just once, to get a better estimate of the random-data curve (Loehlin and Beaujean, 2017).

4.7.5 Rotation of Factors

Generally, we rotate factors in EFA to aid the interpretation of factor matrixes. Particularly, factor rotation simplify and clarify the data structure for ease of interpretation (Costello and Osborne, 2005). Hence, factor is rotated in multidimensional space to elicit the best factor structure. Factor rotation involves two main procedures: orthogonal and oblique rotations (Tabachnick and Fiddell, 2007; Watkins, 2018).

Orthogonal rotations restrict factors to be perpendicular to each other and hence uncorrelated. Orthogonal rotations are ideal because they violate the data's nature. Three orthogonal rotation methods are varimax, quartimax, equimax, and equinox (Costello and Osborne, 2005; Brown, 2009). First, the varimax rotation is an orthogonal rotation of the factor axes to optimise the variance of the squared loadings of factors on all the variables in the factor matrix. Second, the quartimax rotation is an orthogonal rotation that maximises the squared loadings for each variable rather than each factor. Equimax simplifies the number of factors needed to explain all variables. Forth, the equinox rotation is a compromise between varimax and quartimax criteria (Costello and Osborne, 2005).

Oblique rotation allows correlations of factors. Oblique rotation produces relatively better solutions in a simple structure when factors are expected to correlate and produces estimates of correlations among factors. However, if the factors do not correlate, oblique rotations may create solutions like the orthogonal rotation. There are several oblique rotation procedures, but the common ones include: 1) direct oblimin rotation, the standard oblique rotation method; 2) promax rotation is often seen in older literature because it is easier to calculate than oblimin (Brown, 2009). Alternative oblique rotations include direct quartimin rotation and Harris-Kaiser orthoblique rotation.

4.7.6 Post-factor extraction and interpretation

Post-factor extraction should validate the results of the factor extraction. First, for a successful EFA, a higher average correlation between the items in the derived scales than the moderate correlation between the factors is necessary. Again, the proportion of the total variance explained by the retained factors must exceed 60% (Hair *et al.*, 2012). Researchers must verify the stability of the factor structure using Cronbach's alph, and the average communality for small samples.

The Bayesian information criterion (BIC) is more useful in selecting a correct model. Given a data set, a researcher compute BIC, for all models under consideration. Then, the model with the lowest BIC is selected. BIC penalize by adding parameters to the model, but they do so differently. Models with the minimum Bayesian Information Criteria are selected (Acquah, 2010).

Standardized root mean squared residual (SRMR) is an absolute fit index. SRMR is a function of the differences between the observed and predicted correlation matrix, where lower scores indicate a closer fit. Extant literature (Montoya and Edwards, 2021) have recommend that good fit for SRMR is less than 0.08(Montoya and Edwards, 2021).

Also, the Tucker–Lewis index (TLI) measures the discrepancy between a baseline model and the fitted model. In the case of the number of factors problem, the baseline model is a model with no factors. Researechers (Xia and Yang, 2019), have recommended cutoffs, where values greater than 0.90 are consider indicative of ‘‘good fit’’ and values greater than 0.95 (TLI>0.95) are considered ‘‘excellent’’. Generally, we look for a satisfactory combination of TLI and SRMR.

To label the factors in the model, researchers should examine the factor pattern to see the items with the highest loading on factors and then determine what those items have in common. What these items share in common connotes the meaning of the factor. Alternatively, researchers can use the Gestalt theory of psychology, that is explained below.

4.7.7 "Gestalt" experiment

Admittedly evolution of Gestalt cannot be exhausted in this research. We are delighted to summarise and recommend readers to visit Wikipedia and Smith (1988) for details of this concept. Essentially, Gestalt psychology is a school of taught developed in the early twentieth century in Austria and Germany as a theory of judgement (perception) that was a rejection of primary assumptions of Wilhelm Wundt's and Edward Titchener's Elementalist and structuralist psychology (Smith, 1988).

As used in Gestalt psychology, we interpret the German word *Gestalt* meaning ("form") as "pattern" or "configuration". Gestalt psychologists emphasised that organisms perceive entire patterns or configurations, not individual components. Mostly, they summarise this view using the adage, "the whole is more than the sum of its parts." Gestalt principles, proximity, similarity, figure-ground, continuity, closure, and connection, describe how humans perceive visuals in connection with different objects and environments.

The theory gives rise to the view that the mind constructs all perceptions and even abstract thoughts strictly from lower-level sensations related solely by being associated closely in space and time. The Gestaltists took issue with this general "atomistic" view that the aim of psychology should be to break consciousness down into putative essential elements.

Conversely, Gestalt psychologists believed that breaking psychological phenomena into smaller parts would not lead to understanding psychology. Gestalt psychologists believed that the most fruitful way to view psychological phenomena is as organised, structured wholes. They contend that the psychological "whole" has a preference and that the "parts" are characterised by the structure of the whole, not the reverse. Notably, this approach was anchored on a macroscopic view of psychology rather than a microscopic approach. Gestalt theories of perception depend on human nature and are inclined to understand objects as an entire structure rather than the sum of their parts.

Kutun, Föller-Nord and Wetter (2015) have earlier used a similar concept of Gestalt; subsequently, we apply a similar approach in our EFA to describe facilitators to ConsHI.

For the "Gestalt" experiment, we used the help of ten researchers, answering independently at the Institute of Medical Biometry and Informatics in Heidelberg. Participants were given the wording of the three to five items that had the most significant contribution to the factor variances for each factor. They were instructed to characterise how they comprised the common theme of the given items in their own words. In the next step, we call each common theme a Gestalt and juxtapose it to the statistically best item for the factor. For this purpose, we identified proxy items with the highest loadings as mathematically best representing a factor associated with the models UTAUT2, PAM, and ConsHI levels (Yakubu *et al.*, 2021).

In practice, Costello and Osborne (2005) strongly advised that EFA was designed and is still most appropriate for use in exploring a dataset. Unsuitable for testing hypotheses or theories because it is an error-prone procedure, even with huge samples and optimal data. After validating an instrument with EFA, researchers can proceed to confirmatory modelling techniques like SEM because SEM can test hypotheses using inferential and analytic procedures (Costello and Osborne, 2005).

4.8 STRUCTURAL EQUATION MODEL (SEM)

So far, we have analyzed the measurement model. We have checked and statistically analyzed how to model and evaluate the measurement model using reliability and validity of the LOCs. We now turn to the structural model. Since, this is a higher order model, the estimates of the LOCs are used as the items for the HOCs, and we also analysis the relationship between the factors and the outcome variable (maturity of citizens).

There is sufficient evidence (Goffin, 2007; Venturini and Mehmetoglu, 2019), that, SEMs are best regarded as potentially useful approximations of reality, not perfect reflections of it. Structural Equation Models (SEM) are also called causal models, causal analyses, simultaneous equation models, analyses of covariance structures, path analyses, or confirmatory factor analyses (Gefen, Straub and Boudreau, 2000; Hillman and Neustaedter, 2003; Xiong, Skitmore and Xia, 2015; Cheah *et al.*, 2018). Herman A. O. Wold propounded SEM in the 1970s as an alternative estimator for factor models (Henseler and Chin, 2010). It is precious in inferential data analysis and hypothesis testing, where the pattern of inter-relationships among the study constructs are specified a priori and grounded in established theory (Hooper, Coughlan and Mullen, 2008). SEM is preferred since researchers can assess the interplay between theory and data (Chin, 1998). More importantly, SEM will enable us to (1) model relationships among multiple predictors and criterion variables; (2) assess and produce latent variables or constructs; (3) model errors in measurement for observed variables; and (4) statistically test *a priori* theoretical and measurement assumptions against empirical data (Chin, 1998; Saari, Damberg and Lena Frombling, 2014; Hair, Sarstedt and Ringle, 2020).

To be precise, we are seeking to achieve all four except objective three (model errors in measure for observed variables). Though, we are not particular about objective (3) invariable, is appears in model objective (2) since latent variables are derived from observed variables. The errors of measured variables will therefore affect the latent variables derived from the measured variables.

Wong (2013) posited several distinct structural equation modelling approaches. Subsequently, Hair *et al.* (2017) asserted that there are two main approaches to estimating the relationships in SEM, either the Covariance-Based SEM (CB-SEM) or the Variance-Based SEM (VB-SEM). Remarkably, each is appropriate for a different research context, and researchers need to understand the differences to apply the correct method.

4.8.1 SEM Analysis techniques: Covariance Based (CB)-SEM and Variance Based (VB)-SEM

CB-SEM is preferred when hypothesing models consist of one or more common factors (Jannoo *et al.*, 2014). Conversely, VB-SEM creates proxies as linear combinations of observed variables and uses them to estimate the parameters. It is preferred when hypothesising models that contain composites.

Models are specified based on either formative or reflective relationships between the indicators and the latent variables (constructs). When the indicators are effects of the construct, it is a reflective model, while in formative models, the indicators cause the construct (Sarstedt *et al.*, 2019).

Implicitly, CB-SEM is a better choice where the model relationships are reflective, while VB-SEM is better for formative relationships. The advances in applying VB-SEM reveal its robustness in both reflective and formative context (Hair *et al.*, 2017; Memon *et al.*, 2017).

Literature (Marshall, 1997; Sarstedt, Henseler and Ringle, 2011; Jannoo *et al.*, 2014; Cheah *et al.*, 2018) has reported that, even among the VB-SEM methods available, the Partial Least Squares (PLS) is a well-developed system of analysis. Thus, the best approach to SEM is the PLS-SEM. It is generally capable of handling complex models, requires less demand on data distribution and is better for theory development and predictive context (Robins, 2014; Hair Jr *et al.*, 2017; Cheah *et al.*, 2018).

The choice of CB-SEM or PLS-SEM depends on several factors such as research objective, measurement model specification, structural modelling, data characteristics and model evaluation (Hair *et al.*, 2011). According to Hair *et al.* (2012), there are several rules when selecting between Partial Least Square Structural Equation Models (PLS-SEM) and CB-SEM.

First and foremost, in selecting between these two methods, we identified the objective for conducting research as (1) model relationships among multiple predictors and criterion variables; (2) assess and produce latent variables or constructs; (3) model errors in measurement for observed variables; and (4) statistically test *a priori* theoretical and measurement assumptions against empirical data (Chin, 1998; Saari, Damberg and Lena Frombling, 2014; Hair, Sarstedt and Ringle, 2020).

In the case of theory testing and confirmation, the CB-SEM is appropriate because theory testing requires demonstrating how well a theoretical model fits the observed data (Barclay, Thompson and Higgins, 1995; Memon *et al.*, 2017). In addition, Barclay, Thompson and Higgins (1995) asserted that CB-SEM is more appropriate for modelling where the objective is to minimise the covariance matrix. The rationale for choosing CB-SEM is to minimise the discrepancy (differences) between the observed covariance matrix and the estimated covariance matrix, so that the hypothetical constructs fits well into the dataset, or better still the dataset supports as much as possible the model (at the least 50%) (Wan Afthanorhan, 2013). The VB-SEM (PLS-SEM) is suitable when the research objective is for prediction and theory development, like in the case of this research (Robins, 2014; Sarstedt *et al.*, 2017). In this type of modelling, the focus is on identifying the best prediction relationships between variables, and the focus is on maximising the amount of variance between latent variables to increase the model interpretation (Sosik, Kahai and Piovoso, 2009). Additionally, for VB-SEM, the research objective may be exploratory, in which we know little about the relationships among the variables.

Secondly, the relationship between the indicators and latent variables is critical in the choice of the method used. The CB-SEM is limited only to research models that utilise reflective constructs. Although previous studies have employed formative measures within the structural model, they usually lead to identification problems (Reinartz, Haenlein and Henseler, 2009). For instance, using formative constructs within CB-SEM would create a situation where explaining the covariance of all indicators is impossible (Chin, 1998). Conversely, PLS-SEM can be employed to analyse a research model consisting of reflective and formative constructs (Henseler and Chin, 2010). Thus, PLS-SEM enables researchers to use either reflective, formative or the combination of both constructs simultaneously.

Thirdly, the underlying assumptions of the data are critical in choosing which methods to employ. While CB-SEM has a strict set of assumptions that need to be satisfied, such as 1) data multivariate normality, 2) observation independence, 3) variable metric uniformity, and 4) large sample size before analysis, that is not the case for VB-SEM (Sosik, Kahai and Piovoso, 2009). Hair *et al.* (2012) confirmed that CB- SEM results would be inaccurate if these assumptions were violated. In contrast, PLS-SEM is more robust and can analyse data with non-normal distribution. Notably, data normality is unnecessary since PLS – SEM utilises standardisation mechanisms, which transform any non-normal data into data that adheres to the central limit theorem (Sosik, Kahai and Piovoso, 2009). Notably, PLS-SEM has proven to be more robust and popular lately (Rossiter and Bergkvist, 2009).

PLS-SEM is an excellent alternative to CB-SEM when the following situations are encountered: 1. sample size is small. 2. applications have a little available theory. 3. predictive accuracy is paramount. 4. correct model specification cannot be assured (Astrachan, Patel and Wanzenried, 2014; Jannoo *et al.*, 2014; Memon *et al.*, 2017, 2019; Hult, Sarstedt and Ringle, 2021).

It is important to note that PLS-SEM is not a one-fit-for-all statistical analysis solution. Researchers also need to be aware of some weaknesses of PLS-SEM, including 1) high-valued structural path coefficients are necessary if the sample size is small. 2) multicollinearity problem should be thoroughly assessed and controlled for inaccurate results. 3) since arrows are always single headed, they cannot model undirected correlation. 4) a potential lack of complete consistency in scores on latent variables may result in biased component estimation, loadings, and path coefficients. 5) it may create significant mean square errors in the estimation of path coefficient loading.

Despite these limitations, PLS is the ideal for SEM in applied research and helpful for the achievement of our objectives like model prediction and a prior theory confirmation. It is essential to define the terms used in modelling our dataset, and we pay attention to some terminologies used in PLS-SEM in the next section.

4.8.2 Terminologies in PLS-SEM

The main objective of PLS-SEM is to test and predict the theoretical model that has been suggested based on the literature and not to test which alternate model fits the data better (Sosik, Kahai and Piovoso, 2009). Since the first stage of our analysis employed EFA, the next stage is using SEM to confirm our factors is the best fit for our dataset.

SEMs are typically displayed graphically to allow an easy orientation. In fig. 4.11 below we present a diagrammatic explanation for the SEM model to explain the various terms.

We start with observed (indicator, item, manifest) variables are the measured variables in the data collection process and are included in our dataset, mostly categorical (Item 1 etc) and discrete (gender: male and female) (Civelek, 2018). Rectangles represent them, and Item 1, Item 2, Item 3 … are examples. The Latent variables (LVs) are obtained by connecting the indicators because we cannot directly measure them. LVs are abstract concepts described by ovals (Raykov and Marcoulides, 2006). Examples are BI, TA, Confidence, and ConsHI maturity. Other statistical techniques allow analysis with categorical latent variables, but SEM uses continuous data type to primarily analyse latent variables (Kline, 2011).

A PLS path model comprises two parts; first, the **structural model** (called the inner model) represents the constructs (circles or ovals). The structural model displays the relationships (paths) between the constructs. Second, **the measurement model** (called outer models) shows the relationships between the constructs (BI, TA, TAA, PE etc) and the indicators (Item1, Item 2 etc) (rectangles) (Reinartz, Haenlein and Henseler, 2009).

The structural model, which is the core of SEM – depicts the relationships between LVs and assesses path coefficients for testing the hypotheses. In comparison, the measurement model is used to evaluate the quality of the constructs that commonly includes factor loading, reliability and validity.

In PLS-SEM, relationships between LVs, with their assigned indicators, are shown as arrows. Arrows are always single-headed, thus representing the direction of the relationships. Notably, variables are connected using paths; hence, paths are direct and indirect relationships between variables. Examples in Fig.4.4 are the arrows from BI to Item1, Item 2 and Aptitude. Also, estimated path coefficients are analogous to regression coefficients and are represented by straight arrows (Loehlin and Beaujean, 2017). The direction, strength, and significance of a relationship in SEM are determined by the path, path coefficients and significance level. Mostly, single-headed arrows are considered predictive relationships and, with strong theoretical support, can be interpreted as causal relationships because path models are developed from the left-hand side to right hand side while looking on the screens of a computer.

The endogenous and exogenous distinction is used more accurately when connecting variables since a variable can assume the role of the dependent variable (DV) and independent variable (IV), just like in regression models. Endogenous variables are determined by the system of equations with at least one path pointing to it. Exogenous variables, on the other hand, are independent variables that are not explained by any variables (PE, BI, EE, FC etc.) and factors (Aptitude, Attitude, Confidence and Motivation).

Theoretically, there are both latent exogenous and latent endogenous variables in SEM. Importantly, LVs that have only single-headed arrows going out of them are endogenous latent variables. In contrast, exogenous latent variables can have either single-headed arrows going into and out of them (Aptitude) or only go into them. Note that the exogenous latent variables PE, EE, and SI do not have error terms since these constructs explain the dependent variables in the path model. The constructs (PE, BI, EE etc.) in Fig 2.6 are all Latent Exogenous variables as unobserved variables treated as exogenous since they serve as IV to the Higher (second) order model. Latent Endogenous in our model example is the factors Aptitude and ConsHI maturity (Loehlin and Beaujean, 2017).

Hayduk and Littvay (2012) advised that to model relationships using a single complete SEM is better than separating the measurement model from the structural model for analysis. However, in higher order models, researchers will have to decide which approach to employ in estimating the constructs for the lower orders before evaluating the higher order constructs (Sarstedt *et al.*, 2019; Crocetta *et al.*, 2021). Fig 4.11 below presents the theoretical construction of an SEM with its components and relationships labelled for details of the terminologies used in SEM and PLS-SEM.

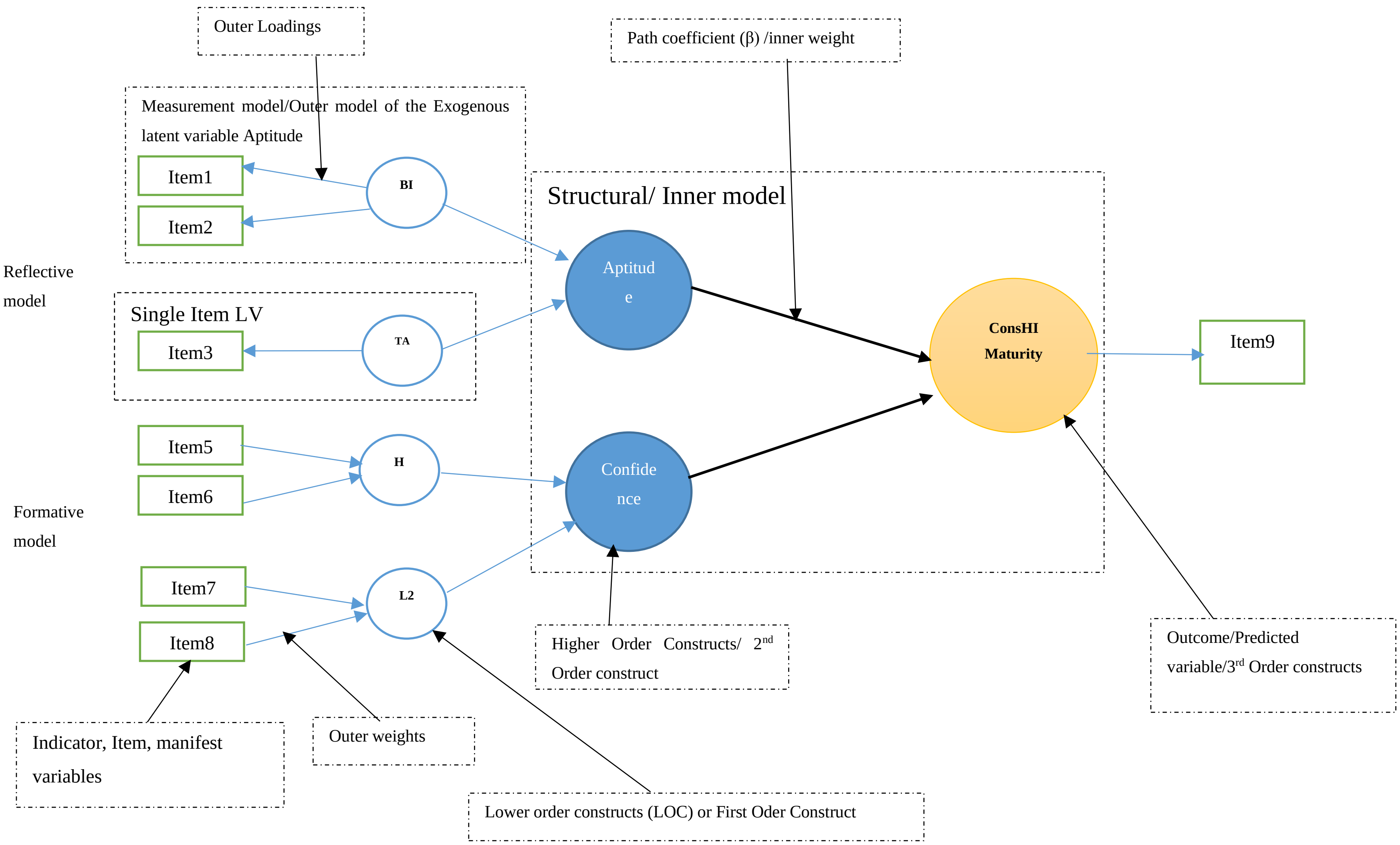


Fig 4. 11 Didactive theoresation of SEM

NB: Reading from the left-hand side to the right hand side just like writing or typing in English, the didactic daigram connotes the following:

i. The structural model is the connection between the second order or latent variables (factors Confidence, Aptittude) and the outcome variable (ConsHI maturity).
ii. The path connecting the factors and outcome variables is the path coefficients that represents the hypothesis of the relationship between exogenous and the endogenous variable
iii. Item 9, is just a hypothetical item measuring the outcome variables as a reflective construct, some studies collect data on the outcome variables, while other estimate them using various methods like our case.
iv. The measurment model includes all Items and their relationship with the first order latent variables (TA, H, BI and L2).
v. The light black arrows are labels of various parts of the model
vi. The thick black arrow is the hypothesis of interest to the study
vii. Blue arrows are first and second order outler weights and outer loadings
viii. Light blue ovals are the first order LVs
ix. The opaque blue ovals are the second order LVs
x. Green rectangles are Items
xi. Dotted black rectangles are text boxes for labelling parts of the diagram
xii. Formative (H, L2) is arrows of the items pointing to the LVs
xiii. Reflective (TA, BI) is arrows of the items pointing away from the LVs
xiv. TA is represented by a single Item reflective model as a special case of LV which is explained in this write-up later.

4.8.3 Data Characteristics

In quantitative studies, data characteristics like minimum sample size, non-normal data, and different measurement scales are among the key reasons for choosing a particular analysis technique. Below we elucidate the guidelines and rules for applying these characteristics in our research.

4.8.4 Estimating a small sample size

Mooi and Sarstedt (2014) argue that the first step in data analysis is establishing an acceptable sample size. The merits of PLS-SEM are the ability to utilise smaller sample sizes and achieve higher levels of statistical power with better convergence (Reinartz, Haenlein and Henseler, 2009; Henseler and Chin, 2010).

A popular heuristic suggests that the sample size for a PLS model should be equal to the larger of the following: *ten times the highest number of indicators used to measure one construct; or ten times the largest number of inner model paths directed at a particular construct in the inner model* (Barclay, Thompson and Higgins, 1995). Another school of thought is the indicators to cases ratio of 1:5, asserted by Osborne and Costello (2004). Researchers are advised against shortcuts to avoid the hassle of sample size estimations, causing scepticism about the applications of PLS-SEM (Hair *et al.*, 2014; Rigdon, 2014).

For example, while the rules of thumb provide a rough estimate of minimum sample size, it fails to take into account the effect size, reliability, or other factors that are known to affect power as per Cohens 1998; for details, see (Barclay, Thompson and Higgins, 1995; Chuan and Penyelidikan, 2006; Henseler, Ringle and Sinkovics, 2009). Also, Jannoo *et al.*(2014) proved in a Monte Carlo simulation study that PLS can produce meaningful results even at 20 units of sample size. They also confirmed the heuristics (Barclay, Thompson and Higgins, 1995) that the sample size should be greater or equal to ten times the number of variables and ten times the largest number of arrows pointing to a particular construct (*ten times rule*).

PLS-SEMs are popular because they can handle small sample size datasets (e.g., Goodhue et al. 2012), so we mostly overlook the method's suitability for analysing large datasets. Empirically, PLS is robust for analysing social media data, mainly focusing on prediction and relying on complex models with little theoretical substantiation (Rigdon, 2014; Saari, Damberg and Lena Frombling, 2014). In case of a lack of comprehensive substantiation on the grounds of measurement theory (Robins, 2014; Hult, Sarstedt and Ringle, 2021). PLS-SEM's non-parametric nature and ability to handle complex models with many (e.g., eight or considerably more) variables, along with its high statistical power, make it a valuable method for analysing large-scale datasets.

Conclusively, Memon *et al.*(2020) offer some remarkable guidance in choosing samples size: 1) the sample to item ratio should not be less than 5:1, but ratios of 15:1 or 20:1 are acceptable; 2) a sample size above 30 and below 500 is suitable for most behavioural studies, while a sample size above 500 may result in a Type II error (Memon *et al.*, 2020).

The rule of particular interest to this research is the multilevel approach. Kreft (1996) recommended the 30/30 rule for multilevel models, which posits that 30 groups (where a group is the same as a cluster; in our research, a country) with 30 individuals per group should be the minimum sample size for a multilevel (hierarchical) study. Later, Hox (2010) modified Kreft's 30/30 rule into a moderate 50/20 rule (50 groups with 20 individuals per group). However, Hox believes that if researchers are interested in random elements (variance, covariance, and their standard errors), they should go with a 100/10 rule (100 groups with a minimum of 10 individuals per group) (Maas and Hox, 2005). Meanwhile, scholars have recommended using power analysis for sample size estimation in multilevel research and a minimum sample size of 50 (Maas and Hox, 2005; Memon *et al.*, 2020). Finally, a sample size of 100 to 200 is usually a good starting point in carrying out path modelling (Wong, 2013).

4.8.5 Distribution of data: Nonnormal data

It is imperative to establish the distributions available in quantitative data. While many distributions exist (e.g., normal, binomial, Poisson), researchers working with SEM generally need to distinguish between normal and non-normal distributions. Generally, PLS-SEM makes no assumptions about the data distributions. However, Hair *et al.* (2017) explained that it is essential to ascertain the distribution when working with PLS-SEM.

To assess the normality of distribution, researchers can apply statistical tests such as the Kolmogorov-Smirnov test, Shapiro-Wilk test and Cramer-van Mises test (Stephens, 1970; Mooi and Sarstedt, 2014; Telforda *et al.*, 2020). Alternatively, researchers can examine the skewness and kurtosis, which allow assessing the extent the data deviate from normality (Hair et al., 2010). The applicable rules are the same as discussed in our section on normality at the EFA test of assumptions (see 4.7.1).
PLS-SEM is less restrictive when working with non-normal data since the PLS algorithm transforms non-normal data following the central limit theorem (Sarstedt *et al.*, 2017). However, the caveat to PLS-SEM providing the ultimate remedy to models using non-normal data is twofold. First, researchers should be aware that highly skewed data can reduce the statistical power of the analysis. Specifically, evaluating the model parameters' significance depends on standard errors from bootstrapping, which might be inflated when data are highly skewed (Saari, Damberg and Lena Frombling, 2014). Otherwise, researchers can reduce the possibility of skewness affecting their results by ensuring all measured variables are scored in the same direction. Hence, any negatively valanced variables should be reverse scored so that high scores on all the variables have a similar meaning (Betancourt *et al.*, 2014). The second caveat is spurious, missing, and outlier observations.

4.8.6 Assessing Missing values, Outliers and Scales of measurement

Missing data occur when a respondent purposely or inadvertently fails to answer one or more question(s) (Jackson, Gillaspy and Purc-Stephenson, 2009). Extant studies profess various guidelines in assessing missing values and dealing with them. For instance, some researchers think we should consider the minimum number of missing values per questionnaire, and others believe it should instead be considered per variable. Specifically, Hair *et al.* (2017) suggest that, the value of missing data on a questionnaire should not exceed 15%. While other researchers (Robins, 2014; Sarstedt, Ringle and Hair, 2014) use the number of missing values per indicator, arguing it should not exceed 5%. Anything beyond this requires a critical review of the dataset and statistical decisions taken by the researcher, including treating missing values. Missing values can be treated with options like mean replacement, expectation-maximisation algorithm, and nearest neighbour (Hair *et al.*, 2011), though with some limitations such as partially different PLS-SEM estimations.

The SmartPLS software (Ringle, Wende, & Becker, 2015) offers three ways of handling missing data. In mean value replacement, the missing values of an indicator variable are replaced with that indicator's mean of valid values. While easy to implement, mean value replacement decreases the variability in the data and likely reduces the possibility of finding meaningful relationships. It should be used only when the data exhibit extremely low levels of missing data. As a rule of thumb, using mean value replacement is appropriate when less than 5% values are missing per indicator. Alternatively, SmartPLS offers an option to remove all cases from the analysis, including missing observations in any variable used in the dataset (referred to as casewise deletion or listwise deletion). Researchers can opt for casewise by deleting all observations with missing values, decreasing variation in the data and biasing certain groups of observations that have been systematically deleted (Ketchen, 2013). However, in applying casewise deletion, two issues warrant further attention. First, casewise deletion would systematically omit this group of respondents and likely yield biased results. Second, casewise deletion can dramatically diminish the number of observations in the dataset. It is, therefore, crucial to carefully check the number of observations used in the final model estimation.

Influential outliers and collinearity influence the Ordinary Least Squares (OLS) regressions in PLS-SEM. Researchers should assess the data and results for these issues (Hair *et al.*, 2010, 2011). An outlier is an unusual response to a particular question or all questions. One must interpret outliers in the context of the study, and this interpretation should be based on the type of information they provide. Outliers can result from data collection or entry errors (e.g., manual coding of "33" instead of "3" on a 1 to 5 Likert scale). However, exceptionally high or low values can also be part of reality (e.g., an unusually high income). Finally, outliers can occur when combinations of variable values are particularly rare (e.g., spending 80% of annual income on holiday trips).

The first step in dealing with outliers is to identify them. Standard statistical software packages offer a multitude of univariate, bivariate, or multivariate graphs and statistics, which allow identifying outliers. For example, when analysing box plots, one may characterise responses as extreme outliers, three times the interquartile range below the first quartile or above the third quartile.

In addition, before analysing their data, researchers ought to examine response patterns. In doing so, they look for a pattern often described as straight-lining (Sarstedt *et al.*, 2017). The straight lining is when a respondent marks the same response for a high proportion of the questions. For example, if a 5-point Likert scale is used to obtain answers and the response pattern is all 4s, then the respondent, in most cases, should be deleted from the data set. Other suspicious response patterns are diagonal lining and alternating extreme pole responses. A visual inspection of the responses or the analysis of descriptive statistics (e.g., mean, variance, and distribution of the responses per respondent) allows for identifying suspicious response patterns (Sarstedt *et al.*, 2017).

Remarkably, researchers should be mindful of the data since the PLS-SEM algorithm generally requires metric data on a ratio or interval scale for the measurement model indicators. However, the PLS-SEM also works well with ordinal scales, interval scales, and binary coded data (Mooi and Sarstedt, 2014).

4.8.7 Properties of Partial Least Square-SEM Algorithm

The PLS-SEM algorithm estimates all unknown elements in the PLS path model. The algorithm calculates the scores of the constructs used as input for (single and multiple) partial regression models within the path model.

After the algorithm has estimated the latent variable scores, the scores are used to calculate all the partial regression coefficients in the path model. Consequently, we obtain the estimates for all relationships in both the measurement (i.e., the loadings and weights) and the structural (i.e., the path coefficients or beta values: β) models. The setup of the partial regression model depends on whether the construct is modelled as reflective or formative. More specifically, when a formative measurement model is assumed for a construct the coefficients, i.e., outer weights are estimated by a partial multiple regression where the latent variables represent the predicted variable, and predictor variables are the independent variables. In contrast, when a reflective measurement model is assumed for a construct, the coefficients (i.e., outer loadings) are estimated through single regressions (one for each indicator variable) of each indicator variable on its corresponding construct. Structural model calculations are handled as follows. The partial regressions for the structural model define a construct as the latent dependent variable.

The dependent latent variable's direct predecessors (i.e., latent variables with a direct relationship leading to the target construct) are the independent constructs in a regression used to calculate the path coefficients. Hence, there is a partial regression model for every endogenous latent variable to evaluate all the path coefficients in the structural model. The PLS-SEM algorithm's iterative procedures estimate all partial regression models, which include two stages. The first stage is to estimate the scores of the constructs. In the second stage, the final estimates of the outer weights and loadings are calculated, as well as the structural model's path coefficients and the resulting R2 values of the endogenous latent variables. Sarstedt, Henseler and Ringle (2011b) describe the stages of the PLS-SEM algorithm.

The stopping criterion of the PLS algorithm is criteria to establish in a modelling algorithm. The PLS-SEM algorithm is designed to iterate until the results are stable. Stabilisation is reached when the sum of changes in the outer weights between two iterations is sufficiently below a predefined limit. A threshold value of 1×10^{-7} (i.e., stop criterion) is recommended to ensure that the PLS-SEM algorithm converges at reasonably low levels of iterative changes in the latent variable scores (Hair Jr *et al.*, 2017). However, researchers must ensure the algorithm terminates at the predefined stop criterion. Thus, we must select a sufficiently high maximum number of iterations. Notably, the algorithm converges after a relatively low number of iterations, even with complex models, with 300 iterations usually sufficient to ensure convergence at $1x10^{-7}$ (i.e., 0.0000001). Previous research indicates that the PLS-SEM algorithm almost always converges (Henseler, Hubona and Ray, 2016).

4.8.8 Evolution of PLS-SEM Software

Notwithstanding the plethora of software (i.e., WarpPLS, SmartPLS, PLS-GUI and XL-STAT) to assess PLS-SEM, this study utilises a relatively new software package, SMART PLS 4.0 (Henseler, Ringle and Sinkovics, 2009; Mourad and Valette-Florence, 2016), to analyse the data.

Memon *et al.* (2021) provided a good briefing of SmartPLS in their recent editorial. They reported that SmartPLS is a graphical user interface software for PLS-SEM. The software builds on a modern Java-based programming environment. After the release of the first online version in 2003, SmartPLS 2 was released in 2005, followed by SmartPLS 3 in 2015. The software was developed and consistently improved by Christian M. Ringle, Sven Wende, and Jan-Michael Becker *(Ringle, C. M., Wende, S., and Becker, J.-M. 2022. "SmartPLS 4." Oststeinbek: SmartPLS GmbH, http://www.smartpls.com).* Regular updates and extensions are provided to improve modelling and analysis capabilities. The application is also compatible with current Apple and Microsoft operating systems. The current version is the SmartPLS 4, which was released in 2022. SmartPLS 4 makes importing data, creating models, managing projects, and analysing results even more direct. In line with its fresh look and feel, rich graphical modelling capabilities are used to implement new methods and algorithms (Memon *et al.*, 2021). Smart PLS 4.0 (Ringle, Da Silva and Bido, 2014) is used to assess the measurement and structural model because it is a statistical software used to evaluate the psychometric properties of the measurement model and estimate the parameters of the structural model.

4.8.9 Settings of Model Parameters

Researchers must select algorithmic options and parameter settings to estimate a PLS path model. Structural model path weighting methods are essential in the algorithm and parameter settings, including initial values to start the PLS-SEM algorithm, the stop criterion, the data metrics and the maximum number of iterations (Hair *et al.*, 2012; Hair, Sarstedt and Ringle, 2020; Hult, Sarstedt and Ringle, 2021). PLS-SEM permits users to apply three structural model weighting schemes: (1) the centroid weighting, (2) the factor weighting and (3) the path weighting scheme. Although their results differ slightly across alternative weighting schemes, path weighting is the recommended approach. This weighting scheme provides the highest R^2 value for endogenous latent variables and applies to all PLS path model specifications and estimations.

According to Henseler, Ringle and Sinkovics (2009), when the path model includes higher-order constructs like in this study, researchers are advised against using the centroid weighting scheme. The details on the three different weighting schemes are available in PLS-SEM software like Smart PLS 4.0 (Henseler, Ringle and Sinkovics, 2009; Reinartz, Haenlein and Henseler, 2009). The PLS-SEM algorithm draws on standardised (normalised) latent variable scores; hence, PLS-SEM applications use standardised indicators like z-values such that each indicator's mean and variance are 0 and 1, respectively, the algorithm. The raw data transformation is recommended when starting the PLS-SEM algorithm (Hult, Sarstedt and Ringle, 2021). SmartPLS is powerful at transforming both observed and latent variables scores for SEM methods (Henseler, Ringle and Sinkovics, 2009; Reinartz, Haenlein and Henseler, 2009).

4.8.9.1 Bootstrap Procedure

PLS-SEM relies on a non-parametric bootstrap procedure to test coefficients for their significance. Streukens and Leroi-Werelds (2016) defined bootstrapping as a non-parametric resampling procedure that assesses a statistic's variability by examining the sample data's variability rather than using parametric assumptions to evaluate the precision of the estimates.

In bootstrapping, many samples (i.e., bootstrap samples) are drawn from the original sample with replacement (Thompson, 1995; Streukens and Leroi-Werelds, 2016). Sampling is done with replacement, which means whenever an observation is drawn randomly from the population, it must be returned to the sampling population before the next case will be drawn. Therefore, an observation for any bootstrap sample can be selected more than once or may not be selected for the sample. The bootstrap samples must be of equal sample sizes (1,800) at all times (often termed bootstrap cases) as the original sample (Hair, Sarstedt and Ringle, 2020).

Sarstedt, Ringle and Hair (2020) reported that a bootstrapping procedure provides standard bootstrap errors which are used to estimate t – values and p – values in our models. Bootstrapping uses to estimate the path model multiple times under slightly changed data constellations. The essential requirement for running the bootstrapping procedure is to draw 5,000 bootstrap samples, including the same number of cases as observations in the original data set. The random nature of the bootstrapping process might cause arbitrary sign changes in the model estimates that researchers can correct by using the construct-level or individual-level sign change options. Sarstedt, Ringle and Hair (2020) recommended the no-sign change option because it is the most conservative option.

4.8.10 Model Characteristics and Evaluation

Notably, the depth of the PLS-SEM analysis depends on the research's scope, the model's complexity, and common presentation in prior literature. In SEM, these characteristics depict the depth and complexity of the model of interest. The characteristic of an SEM is assessed using the structural and measurement models. At this stage, we are interested in obvious attributes like the relationships between the latent variables and the indicators and their various constructs. The characteristics offer first-hand information that will examine the data analysis hypothesis.

4.8.11 Evaluation of Measurement Model – Lower Order Constructs (LOCs)

The evaluation of measurement models is treated as the first step in SEM analysis. In the case of our research where we are seeking to establish a predictive model, this stage will be called the evaluation of the LOCs. The output of the LOCs is used as indicators in modelling the next stage of constructs which are higher order constructs. Mostly, researchers have used Lower Order Constructs (LOCs) and First Order Constructs interchangeably.

Empirically, researchers like Hair *et al.(*2010), have indicated that, the measurement model, also called the outer model in SEM, is the process of assigning numbers to a latent variable (construct) based on a set of rules to represent the latent variable accurately. Explaining that, the measurement model prescribes the relationship between the indicators and the latent construct. They (Hair *et al.*, 2014) collectively deduce this assertion from the measurement theory, which defines the relationship between measured and latent variables (constructs). Evidence shows that there are two different ways to measure latent variables. One approach is called reflective measurement, and the other is a formative measurement. The measurement model's relationship can, however, be reflective, formative or a mix of the two depending on the complexity of the research concept (Hair *et al.*, 2014).

Literature on SEM (Wilson *et al.*, 2007; Rigdon, 2014; Sarstedt *et al.*, 2014; Hult, Sarstedt and Ringle, 2021) is replete with evidence that, the overall quality of a SEM depends on the quality of the measurement model. Thus, the quality of SEM is assessed using the reliability and validity statistics of the measurement model. To evaluate the quality of the measurement model, Cheng (2001) suggests two different approaches; the first is a test of the measure of each construct separately. The second is a test of all measures simultaneously (Cheng, 2001); he further argues that the latter is better than the former. Hence, we adopted the latter for our research work per his recommendation (Cheng, 2001). It is, therefore, essential to start by specifying the relationship between the indicators and the latent variables.

4.8.11.1 Model specification: reflective vs formative

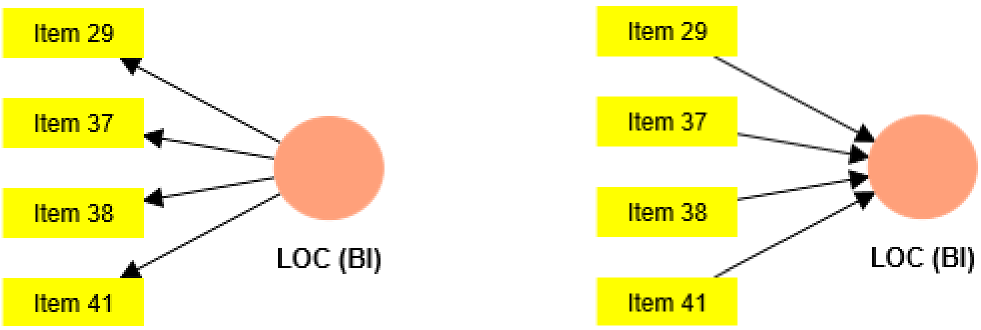
In light of the preceding paragraph, model misspecification negatively impacts the estimates, and fit statistics quality (Diamantopoulos, Riefler and Roth, 2007), thus affecting the conclusions due to bias in these estimates. Researchers have provided support to several forms of misspecifications in SEM modelling. For instance, when one applies a reflective mode to indicators instead of formative mode or the reverse, the resultant factors will mix up since reflective modes produce common factors while formative modes produce components.

Consequently, proper specifications of models should be prime for researchers conducting credible research. According to Hair *et al.* (2014), the model specification stage in SEMs deals with the set-up of the structural (inner) and measurement (outer) models. The first step in using PLS-SEM entails creating a path model that connects variables and constructs based on theory and logic.

Also, in a reflective model, the construct exists (in an absolute sense) independent of the indicators. The indicators used are interchangeable, so when one of the indicators is deleted, the latent variable may still represent the abstract concepts. Conversely, in a formative model, the latent construct changes significantly when one indicator is deleted since it depends on each indicator (Crocetta *et al.*, 2021). Thus, formative measurement theory is modelled based on the assumption that *measured variables cause the construct.* Formative indicators are not interchangeable because each indicator contributes a specific meaning to the latent variable (Coltman *et al.*, 2008). We distinguish the two specifications as follows:

Table 4. 9: Summary table of reflective and formative concepts (Coltman *et al.*, 2008)

Consideration	Reflective	Formative
Nature of constructs	Latent constructs exist independent of our measures	Latent constructs are determined as a combination of the indicators
The direction of causality between items and latent constructs	Causality from constructs to items, variation in the construct causes variations in the item measures, and variation in the item measures does not cause variation in the construct	Causality from items to constructs, variation in the constructs does not cause variation in the items and variation in the items measure causes variation in the constructs
Characteristics of the items used to measure the constructs	The constructs give rise to items, i.e., items share a common theme and are interchangeable. Including or excluding an item does not change the conceptual domain of the construct	Items define the construct, Items need not share a common theme, and Items are not interchangeable. Including or excluding an item may change the conceptual domain of the construct.



Reflective Indicators **Formative Indicators**

Fig 4. 12: A didactic graphical representation of the reflective and formative mode relationship in SEM.

It beholds a researcher to ascertain the relationship between indicators and the LVs (Fig 4.12). Though this should be guided by theory, statistical confirmations are strongly suggested to avoid biases based on the researcher's presumptions. Empirically, Bollen and Ting (2000, p. 4) proposed the Confirmatory Tetrad Analysis (CTA) as "an empirical test of whether a causal or effect indicator specification is appropriate" in specifying indicator relationships.

According to Guderian *et al.* (2008a); Bucic and Gudergan (2004), who applied Ting's (1995) CTA to assess the appropriateness indicator and LVs relationships, they unanimously concluded that CTA is an excellent technique to evaluate cause or effect relationships.

4.8.11.2 Evaluating model specification using Confirmatory Tetrad Analysis (CTA)

As previously mentioned, appropriate model specifications are critical to a credible theorisation of PLS-SEM. However, this can be a daunting task, mainly when there are no established theories supporting the conceptual framework. Also, researchers must frequently specify appropriate models for higher-order levels of abstraction (Wilson, Callaghan and Stainforth, 2007). The choice of a reflective, formative, or combined measurement model in any SEM requires statistical justification, particularly for predictive models (Coltman *et al.*, 2008; Sarstedt *et al.*, 2016, 2019).

The concept of CTA in PLS (CTA-PLS) is that each tetrad (means four items, and denoted by τ) is expected to be zero in a reflective model (Gudergan *et al.*, 2008). Hence, if tetrads significantly differ from zero, it is formative. When a vanishing tetrad equals zero, then all model implied non-significant tetrads vanish in reflective models (Bollen and Ting, 2000). Bollen and Ting (2000) postulated testing the hypothesis:

H_0: $\tau = 0$ (i.e., the tetrad equals zero and vanishes; hence reflective mode)

H_1: $\tau \neq 0$ ((i.e., the tetrad does not equal zero; hence, formative mode)

In view of this, Bollen and Ting (2000) concluded that a non-significant (p-value >0.05) test statistic supports H_0 meaning a reflective model, while, a significant (p-value <0.05) test statistic favours H_1 and casts doubt on the reflective model.

This analysis usually includes several single tetrads per model. However, CTA suffers the multiple testing problem (Falk and Miller, 1992). Subsequently, Smith and Cribbie (2013) suggested that the Bonferroni adjustments of the significance levels could account for this problem. Thus, using the confidence interval (CI) with the Bonferroni adjustment helps solve the problem. If zero falls into the bias-corrected and Bonferroni-adjusted confidence interval, the tetra is not significantly different from zero, meaning it is a "reflective" measurement model. Researchers can use the following Table 4.10 as a guideline to determine the directionality of a relationship.

Table 4. 10: Guideline for using CI to determine measurement model (Adopted from Wong (2013)

Condition	CI Low adj.	CI Up adj.	Measurement Model is
If all values are…	-	-	formative
If all values are…	+	+	formative
If any of the values are	-	+	reflective

It is worth mentioning that, while Ting (1995) asserts that CTA applies to latent variables with less than four indicators; thus, researchers can try CTA and make a sound statistical decision based on the hypothesis of the tetrads' percentage of the entire model. Wong (2013) shares a different perspective, and reechoes the fact that CTA applies to only latent variables with at least four indicators. These diverse opinions, strongly points to the fact that, researchers should use sound theoretical considerations for latent variables with 3 or fewer indicators (Wong, 2013).

4.8.11.3 Single variable (SV) and Multiple variables (MV) constructs.

The multiple and single–indicator relationships with LVs differ considering the objectives and contribution of researchers. Commonly, research models have used MV in assessing latent variables since a combination of indicators is required to measure them. Notably, the recommended number of indicators connected to an LV in SEM should be at least three since LVs represent hypothetical constructs in research models (Raykov and Marcoulides, 2006). Diamantopoulos *et al.* (2012) asserted that, for a sample size larger than 50, the use of MV is preferred to SV in assessing LVs.

Sarstedt, Ringle and Hair (2014) provides perhaps the strongest argument, that SVs have empirical merits like ease of usage, brief, and lower costs associated with their use. Also, SVs enhance the precision and research contribution provided by SEM. When a construct is narrow in scope, unidimensional, and unambiguous to the respondent, SV is the best indicator (Diamantopoulos *et al.*, 2012). Rossiter and Bergkvist (2009) echoed that when a construct is judged to be precise, using a single item to assess it is acceptable. Also, for SVs, the direction of the relationships between the construct and the indicator doesn't matter as construct and item are equivalents (Sarstedt *et al.*, 2017).

Our study draws from these arguments and employs a broad mix of MV and SV constructs for the various LVs. Notably, we use SVs for LVs like EE and PV. Also, there is no reason to require more than one indicator for demographic variables like sex or age. Hence our choice will often favour an SV moderating for some theory-relevant feature rather than MV (Hayduk and Littvay, 2012).

4.8.12 Evaluation of measurement model

The critical objective of researchers is to propound models that are as close to reality as possible. Importantly, model estimation delivers practical measures of the relationships between the indicators and the constructs (measurement models). For this reason, the evaluation of the quality of the PLS-SEM measurement focuses on metrics indicating the model's predictive capabilities (Wong, 2013; Hair *et al.*, 2017; Sarstedt *et al.*, 2019). Notable measurement model metrics for PLS-SEM are reliability, convergence, and discriminant validity.

4.8.12.1 Assessing Reflective Model

The quality of a reflective model is assessed using the reliability (indicator and internal consistency) and the constructs' validity (convergent and discriminant). We proceed to discuss the procedures and recommendations for the application of these measures as follows:

Reliability Analysis of Reflective models

Reliability is the evaluation of the internal consistency of the constructs. A construct (latent variable) is reliable if it produces similar results under the same conditions. SEM has two types of reliability measures: indicator reliability and internal consistency reliability.

Indicator (item) reliability

According to Urbach and Ahlemann (2010), indicator reliability is the extent to which a variable or set of variables is consistent regarding what it intends to measure. That is how well an item measures the underlying construct. The indicator reliability of a model is measured by examining the square of the item (outer) loadings, and the size of the outer loading is also commonly called indicator reliability. High outer loadings on a construct indicate the associated indicators have much in common, which is captured by the construct. An indicator's outer loading should be at least 0.708 since the square (0.7082^2=0.5) equals 0.50; notably, 0.708 is approximately 0.70, hence acceptable (Sarstedt *et al.*, 2017).

The indicator reliability of a measurement model is satisfactory when the square of each item's loading estimates is between 0.5 - 0.7 (at least 50%) (Hair *et al.*, 2010). Also, the outer loadings of all indicators should be statistically significant. Because a significant outer loading could still be weak, a common rule of thumb is that the standardised outer loadings should be 0.708 or higher. Researchers can understand the rationale behind this rule in the context of the square of a standardised indicator's outer loading, referred to as the commonality of an item (Hair *et al.*, 2010).

In addition to indicator reliability, the factor loading indicates that a particular factor (LVs) represents a variable well. Factor Loadings are the correlations between the construct and each item (i.e., correlation weights). A factor loading lower than 0.60 barely explains a third of the variance in the indicator(s), and researchers should consider dropping such an indicator (Huang *et al.*, 2017). However, items with factor loadings from 0.40 to 0.60 shall be considered for removal only if deletion results in a substantial increase of Composite Reliability (CR) or Average Variance Extracted (AVE) over the recommended value (Reinartz, Haenlein and Henseler, 2009; Sarstedt *et al.*, 2016). CR is the correlation between the factors with variance summation from all items of the factor measured, while AVE is a measure of the amount of variance that is captured by a construct in relation to the amount of variance due to measurement error (Fornell and Larcker, 1981; MacCallum, 1986). The recommended minimum values are 0.7 and 0.5 for CR and AVE resepctively (Chin, 2010; Robins, 2014).

Internal Consistency Reliability

A measurement model has satisfactory internal consistency reliability when each construct's composite reliability (CR) exceeds the threshold value of 0.7. Also, internal consistency can be assessed using Cronbach's alpha (CA). Essentially, constructs with high Cronbach's alpha values mean that the constructs' items have the same range and meaning (Risher *et al.*, 2019). Both composite reliability and Cronbach's alpha measure internal consistency, but CR considers that the indicators have different loadings, while CA assumes all indicators are equally weighted (Hair *et al.*, 2012). Recently, researchers of PLS suggested one should consider using the rho Alpha (rho_A) coefficient to check the reliability of PLS construct scores, as defined by Dijkstra and Henseler (2015). Essentially, the minimum requirement to establish reliability for these estimates is 0.7 (Sarstedt *et al.*, 2019).

Validity Analysis of Reflective models

Validity is the assessment of whether a scale measures the concept it is intended to measure. Construct validity is assessed by establishing Convergent and Discriminant validity.

Convergent Validity

According to Urbach and Ahlemann (2010), convergent validity is the degree to which individual items converge. Convergent validity is established when items in a particular measure converge to represent the underlying construct. The average variance extracted (AVE) measures convergent validity by assessing each construct's AVE values. An AVE value of at least 0.5 is required to establish convergent validity in a model (Fornell, Larcker and Fornell, 1981).

Discriminant Validity

Unlike convergent validity, discriminant validity tests whether the items unintentionally measure something else besides the intended construct. Discriminant validity measures the degree of difference between overlapping constructs (Robins, 2014). It is established to ascertain the distinctiveness of the constructs in the study, which shows that each construct in the study have their identity. They are not too highly correlated with other constructs. There are three ways to check discriminant validity: the Fornell-Larcker Criterion (FLC), Cross loadings and Heterotrait-Monotrait (HTMT) ratio**.**

Fornell and Larcker (FLC) (Fornell, Larcker and Fornell, 1981) postulated the classical approach of using the square root of AVE in each latent variable to verify discriminant validity (Fornell and Larcker, 1981). Applying FLC requires a latent variable to share more variance with its assigned indicators than any other latent variable. Thus, the square root of a construct's AVE must be greater than the correlations with other constructs (Robins, 2014)to establish discriminant validity (Robins, 2014).

Cross-Loadings (Henseler, Ringle and Sarstedt, 2015) is the second criteria assessment for discriminant validity assessment. This involves examining indicators and comparing them to all construct correlations. The factor (outer) loadings of indicators on their assigned construct should be higher than their loading on other constructs. If each indicator's loading is higher for its designated construct than any other, it can be inferred that the different constructs' indicators are not interchangeable (Chin, 1998). However, when an item loads well onto another construct compared to its parent construct, there are discriminant validity issues. Specifically, if the difference in the loadings of indicators on two constructs is less than 0.1, this shows a robust cross-loadings level; thus, the constructs should be revised or merged (Brown, 2009). Therefore, Henseler, Ringle and Sarstedt (2015, p. 118) posit that "discriminant validity is shown when each measurement item correlates weakly with all other constructs except for the one to which it is theoretically associated."

Heterotrait-Monotrait (HTMT) Ratio is the third modern approach to checking discriminant validity (Robins, 2014; Sarstedt *et al.*, 2017; Hult, Sarstedt and Ringle, 2021). HTMT (heterotrait correlations: monotrait correlations) is the mean of all the correlations of indicators across all constructs measuring different constructs relative to the mean of average correlations of the indicators measuring the same constructs. Leguina (2015) posited that HTMT less than 0.9 should be used when the path model includes constructs that are conceptually very similar. However, when the constructs in the path model are conceptually more distinct, researchers should consider 0.85 as the threshold (Hult, Sarstedt and

Ringle, 2021). Thus, the preferred HTMT value for establishing discriminant validity is HTMT < 0.85 (Johnston *et al.*, 2014; Henseler, Ringle and Sarstedt, 2015).

Table 4. 11: Summary of measures for assessing the quality of reflective models using reliability and validity

Criterion	Empirical test criterion in PLS-SEM	Guidelines	Description
		Reliability	
Indicator Reliability	Outer/factor loading	>= 0.7 (for exploratory research, 0.4 or higher is acceptable (Hair *et al.*, 2012)	Loadings show the absolute contribution of the indicator to the construct.
Internal consistency reliability	Composite reliability (CR)	>= 0.7	Efforts to estimate the sum of a constructs factor loadings relative to the sum of the factor loadings plus error variance
	Cronbach's Alpha (CA)	>= 0.8 (>= 0.9 is preferred)	Measures the extent to which the MVs load simultaneously when the LV increases
	Rho_A	>= 0.7	
		Validity	
Convergent validity	AVE	>= 0.5	The degree to which individual items reflect a construct converge in comparison to items measuring different constructs
Discriminant Validity	Fomell-Larcker Criterion (FLC),	The square root of the AVE of a construct should be greater than the correlations between the construct and any other constructs in the model (Fornell, Larcker and Fornell, 1981).	
	Items Cross loadings	Item's loading of each indicator is highest for its designated construct.	
	Heterotrait-Monotrait (HTMT) Ratio.	<= 0.85	

4.8.12.2 Assessing Formative Model

The validation of the formative measurement model requires a different approach than the reflective measurement model (Hair *et al.*, 2014). This notion especially holds for PLS-SEM, which assumes that the formative indicators (more precisely, composite indicators) fully capture the content domain of the construct under consideration. Hair *et al.* (2014b) offer a comprehensive procedure for assessing formative models by stating that:

First and foremost, the researcher needs to assess construct validity using content and convergent validity. Content validity is the extent to which the indicators capture the construct's major facets and are evaluated using expert (theoretical) evidence. While convergent validity is the extent to which a measure relates to other measures of the same phenomenon, this is assessed using redundancy analysis (Hair et al., 2014). These are critical steps since omitting a vital indicator can distort the nature of the construct in question (Diamantopoulos, Riefler and Roth, 2007; Diamantopoulos *et al.*, 2012).

Second, the outer model indicators on each construct must be tested for collinearity. As with multiple regression (Mooi and Sarstedt, 2011), high collinearity between two or more formative indicators can seriously bias the results. Finally, researchers should evaluate the significance and relevance of each formative indicator.

Validity Analysis of Formative models

The validity of formative models is evaluated using convergent validity. Convergent validity because researchers seek to establish the extent to which indicator variables converge to cause a latent variable (constructs) in formative relationships. Statistically, redundancy analysis is used to assess the convergent validity of formative models (Chin, 1998).

Sarstedt, Ringle and Hair (2020) mentioned that redundancy analysis is achieved by using a formative construct as an exogenous latent variable predicting the same construct operationalised by reflective indicators (Fig 4.13). Mostly, reflective measurement uses either an established item or a single global item, which summarises the essence of the construct that the formative indicators are intended to measure. To verify convergent validity in a formative model, the magnitude of the path coefficient linking the constructs should be at least 0.70 (i.e. $\beta >= 0.7$) (Hair, Sarstedt and Ringle, 2020).

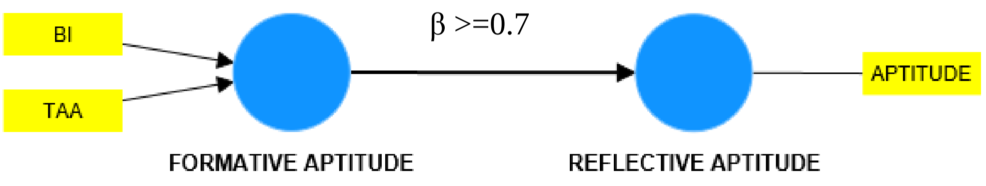


Fig 4. 13: Redundancy Analysis for Convergent Validity Assessment

Reliability Analysis of formative models using collinearity

Unlike reflective models, reliability cannot be easily evaluated in formative models. Rather, formative models are assessed on the issue of collinearity amongst indicators and testing for significance and relevance of these indicators in forming the constructs of interest.

Collinearity of Indicators

The step to assessing formative models (both LOCs and HOCs) includes resolving any possible collinearity issues since the indicators are not essentially interchangeable (i.e adding or removing an indicator in formative models changes the entire construct). High correlation between two formative indicators is called collinearity (Robins, 2014). Collinearity affects the statistical significance of formative indicators because it impacts the estimation of weights. We use the Variance Inflation Factor (VIF) to assess the extent of collinearity in PLS-SEM. The VIF is the ratio of the variance of estimating some parameter in a model that includes multiple other parameters by the variance of a model constructed using only one term. It quantifies the severity of multicollinearity in an model analysis. It provides an index that measures how much the variance of an estimated regression coefficient is increased because of collinearity. There are two widely accepted rules of thumbs:

If VIF >=5; it indicates a potential issue with the collinearity problem (Sarstedt, Henseler and Ringle, 2011),

If VIF >= 3.3, it indicates a potential issue with the collinearity problem (Diamantopoulos and Siguaw, 2006).

Significance and Relevance of Indicators

Also, in assessing a formative (i.e. composite) construct, outer weight is an essential criterion for evaluating the contribution of an indicator. Sarstedt, Ringle and Hair (2020) mentioned that outer weight results from a multiple regression with the construct’s scores as the dependent variable and the indicators as the independent variables. The values of the outer weights can be obtained using bootstrapping technique (t-values are assessed for each indicator weight pointing towards the formative construct) and can therefore be used to determine each indicator's *relative contribution* to the construct or its relative importance in forming the construct. When an indicator's outer weight is non-significant, but its outer loading is high (i.e. above 0.50), the indicator should be interpreted as absolutely important but not as relatively necessary. In this situation, the indicator would generally be retained since that justifies reliability. The distinction between outer loadings and outer weights depends on the measurement model. In reflective model, the outer loadings take precedence over the outer weight in assessing indicators. The reverse occurs when evaluating formative models, where preference is given to outer weight against outer loadings.

However, when an indicator has a non-significant outer weight, and the outer loading is below 0.50, the researchers should decide whether to retain or delete the indicator by examining its theoretical relevance and potential content overlap with other indicators of the same construct.

In the case of formative indicators, formative indicators, like reflective indicators, have accepted ranges for assessing their reliability (Ketchen, 2013; Robins, 2014; Hult, Sarstedt and Ringle, 2021). The steps to establishing indicator reliability in a formative construct after resolving collinearity issues are (Sarstedt *et al.*, 2017):

1. **Outer Weights** are significant (p-value <0.05): retain indicator
2. **Outer Weights** not significant (p-value > 0.05): check outer loadings size
   a. **Outer loadings** high (>0.5) retain indicators
   b. **Outer loadings** low (<0.5) retain indicators
      i. **Outer loadings (p-value <0.05) significant: researcher makes a decision**
      ii. Outer loadings (p-value >0.05) discard indicator

If both, Outer weights and outer loadings are non-significant, remove an indicator from the model. A caveat is that the researcher can retain factors at their discretion supporting with literature reference if there is strong theoretical support.

4.8.13 Evaluation of the Structural model

Structural theory depicts the relationship amongst latent variables (i.e., the path relationships within the structural model). The criteria for assessing the structural model in PLS-SEM are (Step 1): the significance of the path coefficients (Step 2): the level of the R^2 values (Step 3), the f^2 effect size (Step 4): the predictive relevance of Q^2 and (Step 5): the q^2 effect size (Hair *et al.*, 2017). Theoretically, the path coefficients are used to test the hypothesis in the model reflecting various paths (Sarstedt, Henseler and Ringle, 2011).

4.8.13.1 Path Coefficients

One of the criteria for assessing the structural model is to examine the path coefficient value, which predicts the strength of the relationship between two latent variables.

To examine the relationship between two latent variables, the researcher should check the path coefficients, algebraic signs, magnitude, and significance. Path coefficients must exceed 0.100 to account for a specific impact within the model and to be significant at the 0.05 level of significance (Robins, 2014).

Estimated path coefficients close to +1.00 represent strong positive relationships (and vice versa for negative values) that are usually statistically significant (i.e., different from zero in the population). Also, the closer the estimated coefficients are to 0, the weaker the relationships.

In assessing the significance of the path coefficients, the p-value is used. A p-value is equal to the probability of obtaining a t-value at least as extreme as the one observed, conditionally, when the null hypothesis is supported (Sarstedt *et al.*, 2017). The p-value also reflects the significance level of the test, and it can be 10%,5% or 1%, depending on the test's sensitivity. Mainly for the model, we adhere to the 5% significance level (Sarstedt *et al.*, 2017). An empirical guide to path analysis in SEM is shown below.

Table 4. 12: Guidelines for evaluating characteristics of the structural model

Criterion	Empirical test criterion in PLS-SEM	Guidelines	Description
Reliability	Coefficient of determination (R^2)	0.67 0.33 0.19	Substantial Moderate Weak
The magnitude of the path coefficient	Beta (β)	>=0.1 @ ($p<0.05$)	Acceptable

Consequently, the structural model is evaluated and deemed satisfactory if:

1) The coefficient of determination is greater than 0.19.
2) Path coefficients between LVs must be at least 0.1, follow the correct algebraic sign (Positive or negative), and are significant (=< 0.05).

The technique for estimating the significance of path models is the bootstrapping technique discussed earlier **in sub-section 4.11**. Next, we examine the predictive power and relevance of the structural model using the coefficient of determination R-squared (R^2).

4.8.13.2 Coefficient of Determination R-square (R^2)

The structural model variance is explained, is the variance accounted for by the predictive model. It is essential to establish the significance of all path estimates. Variance explained is assessed using the coefficient of determination (R^2); the R^2 value indicates the amount of variance in an endogenous variable explained by the exogenous variables.

This value should be high to explain the endogenous latent variable's variance well; therefore, the predictability of a structural model depends on the R^2 value. Thus, a higher R^2 means better predictability of the structural model. R^2 is the squared correlation of actual and predicted values, including all the data used to estimate the model's predictive power. It represents a measure of in-sample predictive power (Bentler and Huang, 2014; Rigdon, 2014).

The R^2 value ranges from 0 to 1, with higher levels indicating higher levels of predictive accuracy. The rules of thumb for acceptable R^2 values depend on the model complexity and the research discipline. Falk and Miller (1992) recommended that R^2 values of at least 0.10 are required to consider acceptable variance for a particular endogenous construct. In addition, Wilson *et al.* (2007) proposed a scale of R^2 values: 0.26 is substantial, 0.13 is moderate, and 0.02 is weak. Chin (1998) also postulated a hierarchy with different values: 0.67 and above is substantial, 0.33 is moderate, and 0.19 or below is weak.

4.8.13.3 Model's —Effect Size using F-square (f^2)

The model's effect size (f^2) shows how much an exogenous latent variable contributes to an endogenous latent variable's R^2 value. Effect size evaluates the strength of the relationship between the constructs (Marshall, 1997; Hoe, 2008; Kang and Ahn, 2021). Importantly, the effect size is used to ascertain the total contribution of the research. Chin, Marcelin and Newsted (2003) asserted that researchers should report the significance of the relationships between variables and the effect size between these variables. Notably, f^2 is a variable in a structural model that may be affected/influenced by many different variables, such as removing an exogenous variable. The guidelines for interpreting f^2 are: f^2>=0.02 is small; f^2>= 0.15 is medium;f^2>= 0.35 is large (Cohen, 1988).

4.8.13.4 Predictive Relevance using the Stone-Geisser's Q-square (Q^2) values

The Q^2 is a statistic that measures whether a model has predictive relevance or not (Sarstedt *et al.*, 2019). Predictive relevance is established when Q^2 values are above zero (Q^2 >0) (Geisser, 1975). This measure indicates the model's out-of-sample predictive power or predictive relevance. A PLS path model exhibits predictive relevance and predicts data not used in the model estimation. In the structural model, Q^2 values larger than zero for a specific reflective endogenous latent variable indicate the path model's predictive relevance for a particular dependent construct (Geisser, 1975, p. 320).

4.8.13.5 Effect Size q^2

The Q^2 values are estimated by measuring how well the path model can predict the observed initial values. Like the f^2 effect size approach for assessing R^2 values, the relative impact of predictive relevance can be compared using the measure to the q^2 effect size (Hudson, 2009; Shmueli *et al.*, 2016). Under the f^2 effect size for the R^2 values, researchers can estimate the q^2 effect size for the Q^2 values. The q^2 effect size of a selected construct and its relationship to an endogenous construct in the structural model uses the same critical values for the assessment of the f^2 effect size evaluation.

Hair *et al.* (2021) asserted that the effect size (q^2) assesses an exogenous construct's contribution to an endogenous variable's Q^2 value. It is a relative measure of predictive relevance, with q^2 values of 0.02, 0.15, and 0.35, respectively, indicating an exogenous construct has a small, medium, or large predictive relevance for a particular endogenous construct.

4.8.13.6 Assessing the predictive and explanatory power of a model

The model's general goodness-of-fit (GoF) is the starting point of model assessment. When the model does not fit the data, the data contains more information than the model conveys, thus rendering the estimates useless and conclusions likely erroneous (McDonald and Ho, 2002; Barrett, 2007). The global model fit is evaluated in two inclusive approaches: employing inference statistics (tests of model fit) or using fit indices (approximate model fit). Essentially, bootstrap-based tests of the model fit over the unweighted least squares (dULS) and the geodesic discrepancy (dG) between the validated and the assumed model correlation matrix allows examination of the global goodness fit of the model (Dijkstra and Henseler, 2015). When the difference between these two matrices is significant, researchers may have to reject the model.

Furthermore, as a measure of approximate fit, the standardised root mean square residual (SRMR) may help quantify the degree of misfit (Sarstedt *et al.*, 2014). The SRMR of well-fitting models typically does not exceed a value of 0.08 (Sarstedt *et al.*, 2014). In addition, global model fit indices have become customary to determine the model fit for both the estimated and the saturated models. Saturation is a situation where all the constructs in the structural model correlate freely (Henseler, Hubona and Ray, 2016). The estimated model is based on a total effect scheme, which considers the model structure (Henseler, Hubona and Ray, 2016; Cheah *et al.*, 2018).

Conceptually, Q^2 is necessary for assessing the predictive relevance of a structural model, and effect size q^2 represents the predictive relevance of an exogenous construct for a specific endogenous construct (Zeng *et al.*, 2021). Acceptable q^2 values generally include 0.02, 0.15, and 0.35, which indicate weak, moderate, and sound effect levels of predictive relevance, respectively (Chin, 2010).

Once path coefficients are established, it is imperative to ascertain the relationship amongst the latent variables by assessing the multicollinearity.

4.8.13.7 Collinearity using VIF<3.3

After validating the measurement model using the reliability and validity statistics, the next step addresses the assessment of the structural model. We must examine the structural model for collinearity (Step 1) (Hair *et al.*, 2017; Hult, Sarstedt and Ringle, 2021). To assess collinearity, we apply the same measures in evaluating formative measurement models (see sub-section 4.8.12).

A detailed PLS-SEM analysis often includes a multicollinearity assessment using the Variance Inflation Factor (VIF). Notably, each set of latent variables in the inner model is checked for potential collinearity problems to see if any variables should be eliminated, merged into one, or simply have a higher-order latent variable developed. The criteria for assessing structural model collinearity are the same as indicated in assessing multicollinearity in the formative measurement model (see sub-section 4.8.12)

4.8.14 Analysis of Heterogeneity and Moderations Effects

Klesel *et al.* (2019) submitted that researchers mostly assume datasets in scientific studies are collected from a single homogeneous population. However, data sets in most disciplines are fundamentally affected by heterogeneity, which implies that the data were collected from different homogenous populations. For instance, in the case of this multi-country research project, not taking heterogeneity into account will result in questionable conclusions. Heterogeneity can be observed or unobserved, and both occur in our study. There are several statistical options to empirically examine either of them, including moderators using a priori variables or post-data collection techniques (Marshall, 1997). To explain observed heterogeneity, moderator variables are often included in models to investigate whether study characteristics (e.g., between- vs within-participants differences) explain differences in effect sizes.

Statistically, parametric and non-parametric approaches (Chin and Dibbern, 2010) have been proposed to assess differences, thus, heterogeneity across groups. One way of dealing with heterogeneity in a study's variances is group analyses (Klesel *et al.*, 2019). Researchers can conduct Multi-Group Analysis (MGA) to assess heterogeneity.

Hair *et al.* (2012) argued that the theoretical homogeneous population assumption of data for PLS-SEM does not apply to real-world situations. Thus, for different populations, different parameter values are likely to occur (in our case 6 countries). Categories are essential in assessing heterogeneous populations. Therefore, evaluating heterogeneity using categorical variables (country, gender, marital status, etc.) is called moderation; this is necessary for comparing corresponding group-specific path coefficient estimates. Further, evaluating heterogeneity using continuous variables is called interaction effects that possibly affect the strengths (magnitude) and direction of specific path relationships (Henseler and Chin 2010 as cited in Hair *et al.*, 2012). Thus, using categorical variables implies moderation and using continuous variables means interaction.

In moderations, we estimate the difference in path coefficients amongst groups; in interaction, we estimate the relationship strength and direction in a model. Later, Hall and Sammons (2013) refined the discussion and explained that the relationship between the concepts of Statistical Interaction and Moderation could be understood as the difference between a two-tailed hypothesis and a more restrictive one-tailed hypothesis (see (Hall and Sammons, 2013) for detailed discussions).

The moderating relationships are tested based on the researcher's hypotheses as one specific or multiple model relationships and the moderator(s) scores. Ideally, a moderator is either an antecedent tested in past studies, or a contextual factor found relevant across different fields of study. Researchers can also test moderating variables for new theoretical insights. In either case, solid theoretical support is required to justify the inclusion of a moderating variable in an existing or exploratory model.

Rigorous statistical techniques are required to explore differences between groups defined by group variables. Significant differences across at least two groups indicate heterogeneity in the dataset. There are two options in addressing heterogeneity; either the researcher uses separate model estimates per group or categorical moderator variables to control for group differences (Sarstedt, Henseler and Ringle, 2011). Essentially, researchers should consciously address issues of heterogeneity when postulating models.

4.8.14.1 Types of Moderator Variables

Observable characteristics like gender, age, or income are often used as moderators in structural models (Venkatesh *et al.*, 2003; Hibbard *et al.*, 2005). Also, moderators can be latent variables such as resistance to change, experience levels or voluntariness, which are used as moderators (Venkatesh, Thong and Xu, 2012). For reflective and formative models, single or multiple item(s) moderators can be applied to assess heterogeneity. The empirical differentiation, however, relates to the moderator's measurement scale, which involves distinguishing between categorical and metric (continuous) moderators (Henseler and Chin, 2010).

Henseler and Chin (2010) posit that the effect of categorical moderator variables is tested through group comparisons. The categorical moderator(s) are used to split up the data set into two or more groups and estimate the models separately for each data group. In the case of categorical moderators, their influence on the model sometimes changes the focus from evaluating its impact on one specific model to examining its effect on all model relationships. For this purpose, observations are grouped according to the value of the categorical moderator variable. Alternatively, researchers use continuous moderator(s) that influences the strength of the relationship between variables and the product of two variables to represent the interaction effect (Henseler and Chin, 2010).

Furthermore, the moderator's measurement model appears twice when modelling moderating effects—in the moderator variable and the interaction term. The double appearance of the moderators effect amplifies the limitations of single-item measurement in moderation (Sarstedt *et al.*, 2017). This weakness is, however, addressed by using the two-stage approach in moderation analysis (see below).

4.8.14.2 Modelling Moderating Effects

To conceptualise moderating effects and how to model them, we consider a pictorial view of this concept in Fig 4.14 below.

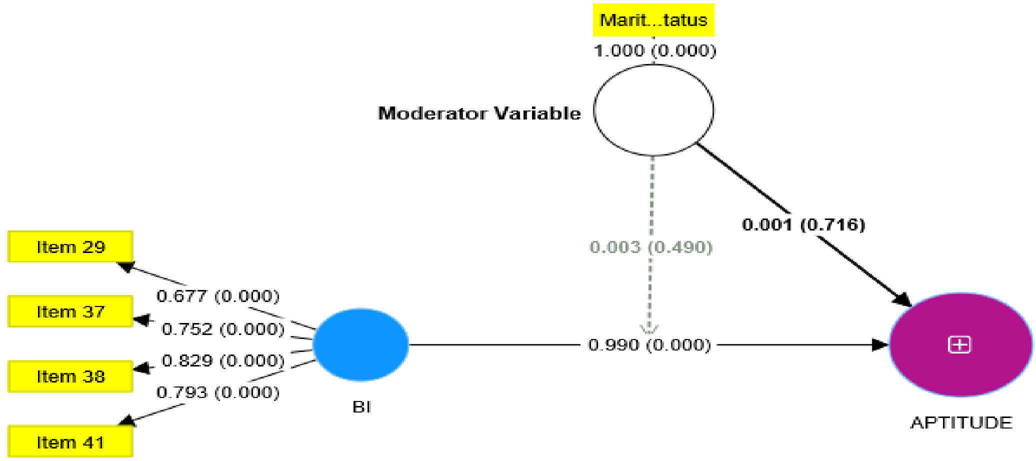


Fig 4. 14: Illustration of moderating effect using marital status as a moderator between BI and Aptitude

This (Fig 4.14) model illustrates marital status as a moderator variable, influencing the relationship between Behavioural Intension (BI) and Aptitude. The **moderating effect** is represented by the dotted lines pointing to the link between BI and Aptitude with the value 0.003 (0.490). Also, when adding the moderating impact on a PLS path model, there is a direct relationship (0.001) from the moderator (marital status) to the endogenous construct (Aptitude). The additional path is crucial (and a frequent source of mistakes) as it controls the direct influence of the moderator on the endogenous construct. When we exclude the direct relationship between marital status and Aptitude, this can inflate the moderating effect (0.003) (Sarstedt *et al.*, 2017).

In operationalising moderation effects, researchers (Henseler and Chin, 2010; Sarstedt, Ringle and Hair, 2014) have proposed several approaches for creating the interaction term. The commonly discussed approaches are: (1) the product indicator approach, (2) the orthogonalising approach, and (3) the two-stage approach. We now summarise all three approaches as follows:

4.8.14.3 Approaches for assessing the moderation effect

The first approach we discuss is the product indicator, which multiplies the independent variable(s) with the indicators of the moderator variable (Chin, Marcelin and Newsted, 2003). Particularly suitable for reflective models, it can be used for multi-group analysis when the moderator is categorical (with a continuous independent variable). However, it is not appropriate when the independent or/and moderator variables are measured formatively (Cheah *et al.*, 2018). One of the weaknesses of this approach is that it produces collinearity in the structural model.

Secondly, the orthogonalising approach is an extension of the product indicator approach (Henseler and Chin, 2010). This approach eliminates the issue of collinearity through residual centring. Additionally, it has superiority in terms of parameter and prediction accuracy. However, it is only applicable when both independent (exogenous) and moderator are reflective. Lower statistical power is considered one of this approach's main weaknesses.

The two-stage approach is recommended when the independent variable or the moderator is a formative variable. Also, the two-stage is preferred because of its universal applicability, regardless of whether the moderator variable and the exogenous construct are measured formatively. Since the two-stage approach also exhibits a higher statistical power level than the orthogonalising method, we recommend using it for modelling the interaction term. Like the product-indicator approach, the two-stage process may, thoiugh, also induce collinearity as it involves an interaction term (Henseler and Chin, 2010).

4.8.14.4 Difference Between Simple Moderation and Multi-Group Analysis

Extant literature (Chin, Marcelin and Newsted, 2003; Rose *et al.*, 2004; Dawson, 2014; Memon *et al.*, 2019) has distinguished between moderating a single path from moderating two or more paths in a PLS-SEM. Further, there are also clear distinctions between moderating with a single variable from multiple items. Multiple items are mostly used to measure moderators, but, in principle, a single item can also be used. When latent variables (LV) are used as moderators, the LV should avoid using a single indicator (Sarstedt *et al.*, 2017). Single indicators lag multi-indicator scales in predictive validity (Marshall, 1997; Sarstedt *et al.*, 2017), which can be particularly problematic in moderation. The reason is that moderation is usually associated with somewhat limited effect sizes, so any lack of predictive power will make it harder to identify significant relationships (Chin, 2010b; Hair *et al.*, 2017).

Finally, we need a clear distinction between using indicator variables as moderators versus using latent variables. The difference is cardinal since it informs the kind of moderation conducted, whether it will be simple or multi-group. Recently, Memon *et al.* (2019) explained that there is a difference between simple moderation and multi-group analysis (MGA). A simple moderation analysis is appropriate when with the support of relevant theory the moderator is expected to exert its effect on the specific structural path(s) (Memon *et al.*, 2019). A simple moderation effect can be assessed by creating a moderated regression model that explains whether a moderator alters the strength or/and direction of the relationship between an independent variable and an outcome (Baron and Kenny, 1986).

They (Memon *et al.*, 2019) also explained that multi-group analysis (MGA) helps researchers to assess whether two or more variables have the same/different relation across groups. MGA is the preferred analytical technique if the moderation effect is on the entire model. In other words, it tests and compares the impact of every structural path across various groups.

Since the moderator is expected to exert its effect on all the structural paths of the model rather than a specific path, in MGA, the measurement invariance test is a necessary (mandatory, requirements) condition; the primary purpose is to ensure that the measurement model assessment conducted under different conditions yields equivalent (reliability and validity) representations of the same constructs (Memon *et al.*, 2019). Furthermore, just like we conduct quality checks of the measurement model in PLS-SEM using reliability and validity indicators, in MGA, we assess the measure invariance (measurement quality) using the configural invariance, compositional invariance, equal means, and equal variances (Henseler, Ringle and Sarstedt, 2016). They recommended that researchers achieve a partial invariance result from the metric invariance (or compositional invariance) test to proceed to MGA.

4.8.14.5 Measurement Model Invariance

As stated earlier, measurement invariance is a necessary condition for MGA. Thus, the primary concern in multi-group analyses is ensuring measurement invariance (quality, equivalence).

Earlier (Marsh *et al.*, 2014) explained, that, measurement invariance examines, the extent to which measurement properties generalize over multiple groups (e.g., male versus female groups, various age groups), situations (urban versus rural, healthy verssus ill-healthy), or occasions. Thus, the tests of whether the underlying construct is the same for different groups or occasions are not ignored in research. They argued that measurement invariance is fundamental to the evaluation of construct validity and generalizability and is an important prerequisite to any valid form of group-based comparison. Subsequently, Pendergast *et al.* (2017) cautioned that the absence of measurement invariance could reduce the power of statistical tests, influence the precision of estimators, and provide misleading results.

Confirming measurement invariance allows researchers to assert that group differences in model estimates are not resulting from the distinct constructs across groups (Hair *et al.*, 2017). Sarstedt, Henseler and Ringle (2011b) developed the Measurement Invariance of Composite Models (MICOM) procedure, which involves three steps: (1) configural invariance (i.e., equal parameterisation and way of estimation), (2) compositional invariance (i.e., equal indicator weights), and (3) equality of composite mean values and variances. These three steps are hierarchically interrelated (Cheah *et al.*, 2020). In practice, configural invariance (Step I) is established when the following is held:

1. the use of equal indicators in all groups for checking reliability and validity.
2. similar data treatment in all groups (e.g., the identical distributions, dealing with missing values using mean value replacement or case-wise deletion); and
3. similar PLS-SEM algorithm settings in all groups (see sub-section on PLS-SEM algorithm settings).

Configural invariance is established when all parameters are freely estimated in all groups (Marsh, Nagengast and Morin, 2013). Mostly, it is a default setting in statistical software like the SmartPLS 4. Thus, the first step of MICOM is established when using SmartPLS. Partial invariance is confirmed when both configural invariance (1) and compositional invariance (2) are established, and researchers can proceed to MGA (Cheah *et al.*, 2020).

Further, full measurement invariance is established when composites exhibit equal means and variances across the groups (Step III). When full measurement invariance is established, pooling the data is a possible option (i.e. it will increase statistical power), rendering MGA unnecessary (Henseler, Ringle and Sarstedt, 2016).

The Measurement Invariance of Composite Models (MICOM) approach is adopted from Cheah *et al*. (2020, p. VII) in summary:

1. If the groups are Configural equivalent; in practice, configural invariance (Step 1) is established when:
   a. The use of equal indicators in all groups when checking reliability and validity.
   b. similar data treatment in all groups (e.g., the identical distributions, dealing with missing values using mean value replacement or case-wise deletion); and
   c. similar PLS-SEM algorithm settings in all groups (e.g., see the sub-section on, e.g., path weighting with a maximum of 300 iterations and a stop criterion of 10^{-7}).
   Automatic by PLS-SEM, we move to the next.
2. Compositional invariance, also called metric equivalence, means that a composite is formed similarly across groups and can be evaluated:
   d. If not significant (p-value >0.05), means the composition of the groups is the same hence the next step (thus, are compositions of the group the same across groups?)
      i. H_0: Group compositions are the same
      ii. If (p-value >0.05) we fail to reject H_0, we have established partial invariances.
   e. Then let's go to MGA.
   f. Else, compositions are different in groups; thus, we cannot do MGA.
3. Equality of composite means and variances
   a. If the p-value <0.05, then are the variances equal? Either case, we go to MGA.
   b. If p-values <0.05, then the means equal? Either case, we go to MGA
   c. Equal variance and means show full invariance

4.8.14.6 Tests for Multigroup Comparisons

Once measurement invariance, either partially or fully, is established using MICOM, the researcher can begin assessing group differences using MGA in PLS-SEM. MGA is suitable for comparing parameters (e.g., path coefficients, outer weights, outer loadings, etc.) between two or more groups based on an existing theory (Klesel *et al.*, 2019; Cheah *et al.*, 2020).

To make group comparisons, SmartPLS offers different assessment approaches based on bootstrapping (Risher *et al.*, 2019). There are four approaches to assessing group differences, namely, the Parametric Test (Keil et al., 2000), the Henseler's bootstrap-based MGA (Henseler et al., 2009), the Welch-Satterthwait Test (Welch, 1947) and the permutation test.

The permutation test is the commonly adopted approach because it uses MICOM to estimate the path coefficient in SmartPLS. For a detailed discussion on the technical details of each approach, we refer to existing literature (Sarstedt *et al.*, 2017; Bido and Da Silva, 2019; Klesel *et al.*, 2019; Cheah *et al.*, 2020).

Henseler's PLS-MGA procedure (Henseler, Ringle and Sinkovics, 2009) is a probability value of a one-tailed test comparing each bootstrap estimate of one group to all the bootstrap estimates of the same parameter in the other groups. Mostly, bootstrap distributions are not normally distributed, thus not suitable for a two-sided hypothesis (Henseler, Ringle and Sinkovics, 2009). Though this approach is suitable, the interpretation of the results may be somewhat challenging due to the nature of the one-tailed test.

Researchers must ensure that there are no large differences in group-specific sample sizes to prevent adverse consequences on the permutation test's performance. Huit *et al.* (2018) recommended that in case one group's sample is at least double the size of the other group, researchers must choose between two options, which are (i) to select Henseler's PLS-MGA or (ii) to randomly draw another sample for the large group that is comparable in size to the smaller group, and subsequently compare the two samples using the permutation test.

Therefore, Cheah *et al.* (2020, p. IX) propose new MGA guidelines that satisfy our proposed tests. Existing MGA procedures consist of four steps:

1. Verifying measurement invariance: before conducting an MGA, a researcher should establish measurement invariance (Henseler, Ringle and Sarstedt, 2016). Otherwise, an MGA is not meaningful. The measurement invariance is necessary for the next step; thus, if verified, the next steps can be applied to assess heterogeneity.
2. Overall evaluation: establishing group differences across all groups is the starting point in conducting MGA. Initially, the researcher must show the significance of group differences in the dataset. Establishing group differences is crucial for models with more than two groups. Because if heterogeneity is not established, the researcher can either choose not to take

heterogeneity into account or respecify the grouping variable (Marsh, Nagengast and Morin, 2013; Marsh *et al.*, 2014).

3. Pair-wise evaluation: when heterogeneity is confirmed in the previous step, the purpose of this step is to examine the heterogeneity in more detail. The above tests can be used for each pair of groups to explore the difference.
4. Effect-wise evaluation: finally, the differences are investigated concerning specific coefficients such as path coefficients. Researchers can draw from parametric approaches (Sarstedt, Henseler and Ringle, 2011) or non-parametric approaches (Hair *et al.*, 2012). Subsequently, we estimate the difference in effects in the model.

4.8.14.7 Evaluation and Interpretation of moderation effects

Studies (Klesel *et al.*, 2019; Cheah *et al.*, 2020) show that the measurement and structural model evaluation criteria apply to moderator models. The moderator variable must be assessed for reliability and validity following the standard evaluation procedures for reflective and formative measures. For the interaction term, however, there is no such requirement. The moderation analysis depends on how the interaction terms are created; hence, the interaction term does not have to be assessed in the measurement model evaluation step. Particularly, measurement model evaluation standards do not apply when using the two-stage approach since the interaction term is measured with a single item. The interaction term relies on an auxiliary measurement model generated by reusing indicators of the exogenous construct and the moderator variable. Subsequently, the moderator analysis is a complementary analysis for the specific moderating relationship.

In the results interpretation and testing of hypotheses, we differentiate between the direct effect (or main effect), on the one hand, and the simple effect, on the other. The direct effect expresses the relationship between two constructs when no moderators are included (Sarstedt *et al.*, 2017). Conversely, the simple effect describes the relationship between two constructs when moderated by a third variable.

When interpreting the results of a moderation analysis, the primary interest is in the significance of the interaction term. Thus, the PLS-SEM analysis should be initially executed without the moderator. When the interaction term's effect on the endogenous construct is significant, we conclude that the moderator significantly moderates the relationship between independent and dependent variables. The next step for a significant moderation effect is determining the moderating effect's strength. Also, during moderation analysis, researchers should pay attention to the f^2 effect size of the interaction effect.

In summary, researchers must: (1) First, focus on the significance of the moderating effect. (2) calculate and report the effect size (f^2) and how much it contributes to R^2 as a function of the moderator, (3) when possible, execute and report a simple slope plot for the visual inspection of the direction and strength of the moderating effect.

As a final note, Memon *et al.* (2019) suggested that researchers should emphasise the substantive meaning in terms of the theoretical understanding of the phenomenon under investigation rather than the statistical significance.

4.8.15 Higher-Order Constructs (HOCs) Analysis

Hierarchical latent variable models, hierarchical component models (HCM), or Higher-Order Constructs (HOC) are used interchangeably (Becker, Klein and Wetzels, 2012; Wan Afthanorhan and Wan mohamad Asyraf Wan Afthanorhan, 2014). They are distinct conceptualisations of multidimensional latent variables at a higher level of abstraction and wholly depict their underlying constructs (Henseler and Chin, 2010). Crocetta *et al.* (2021) reported that establishing such a higher-order model in the context of PLS-SEM often involves testing second-order constructs containing two or more layers.

Subsequently, researchers (Cataldo *et al.*, 2020; Crocetta *et al.*, 2021) offer several reasons for HOCs in PLS-SEM, including (1) reducing the number of indicators in a structural model besides making the model more parsimonious and easy to appreciate; (2) valuable for highly correlated constructs where collinearity is a problem; (3) formative measurement model in PLS-SEM is much easier to handle (MacCallum and Austin, 2000); and (4) modelling HOCs is helpful for researchers to reframe the structural model to be more meaningful besides addressing the prediction and evaluation of SEM.

Theoretically, HOCs have two elements: the higher order elements, which capture the more abstract entity, and the lower order element, which captures sub-dimensions of the abstract entity. The lower elements are called “first-order” factors or lower-order constructs (LOCs), and the higher elements are the “higher order” factors or Higher Order Constructs (HOCs).

Becker, Klein and Wetzels (2012) contend that HOCs are characterised by two issues, the first being the number of layers (dimensions) in the model (often restricted to second-order models). The second is the relationships (formative vs reflective) between the constructs in the model. HOCs are characterised by the relationships between the HOC and LOCs and their indicators. This requires detailed discussion since it determines how the model is estimated (Becker, Klein and Wetzels, 2012).

4.8.15.1 Types of relations in HOCs:

Four major types of HOCs are represented in different relationships with their LOCs and indicators used to operationalise the constructs (Chin, 2010; Wan Afthanorhan and Wan mohamad Asyraf Wan Afthanorhan, 2014; Sarstedt *et al.*, 2019; Crocetta *et al.*, 2021).

Researchers implementing a higher-order construct must decide on (1) the measurement model specification of the lower-order components and (2) the relationship between the higher-order component and its lower-order components (Sarstedt *et al.*, 2019), both of which can be reflective or formative. Earlier studies (Chin, 2010; Wan Afthanorhan and Wan mohamad Asyraf Wan Afthanorhan, 2014; Sarstedt *et al.*, 2019; Crocetta *et al.*, 2021) have proposed four types of higher-order constructs (Fig 4.15): reflective-reflective, reflective-formative, formative-reflective, and formative-formative. It is informative to note that researchers (Chin, 2010; Becker, Klein and Wetzels, 2012; Wan Afthanorhan and Wan mohamad Asyraf Wan Afthanorhan, 2014; Sarstedt *et al.*, 2019; Crocetta *et al.*, 2021) have been consistent in their naming convention of these relationships in the majority of the studies that were reviewed for this study. The conventional naming of HOCs is the mode (reflecitve or formative) of the LOC first followed by the mode of the HOCS. Specifically, we denote as reflective-formative models where the LOC is reflective and the HOC is formative and vice versa for formative-reflective.

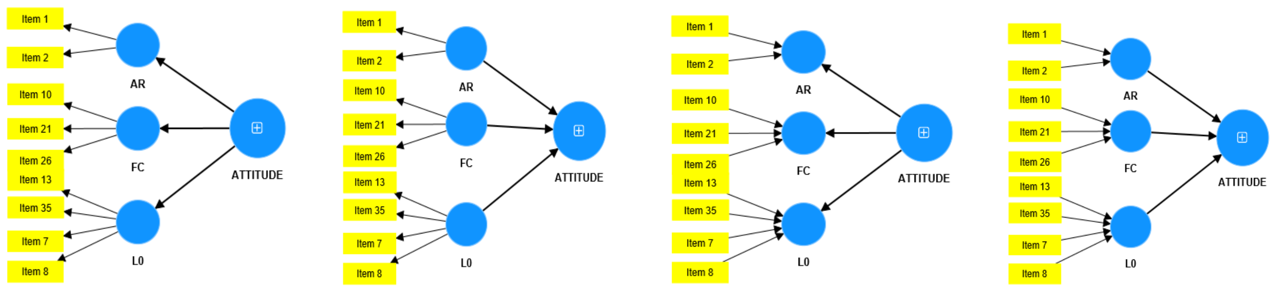
Briefly explaining, Type I is the Reflective-Reflective model; in particular, the causal path of lower-order constructs is imposed on associated indicators. At the same time, the causal pathway of higher-order constructs is exerted on lower-order constructs. Lohmöller (1989) calls this "hierarchical common factor model" type, where the higher order construct represents the common factor of several specific factors. However, Lee & Cadogan (2005), as cited in (Bin Wan Afthanorhan, 2014), contested this theoretical model and classifications, reporting there was nothing like a reflective – reflective hierarchical model, and such a model is "at worst, misleading, and at best meaningless”. Conclusively, later researchers confirmed the position of Lohmöller (1989), nullifying the contention of Lee & Cadogan (2005).

Type II is the Reflective-Formative model; according to Chin's clarification, the LOCs are evaluated as distinct constructs that form a general concept and fully mediate the relationship of the following endogenous variables (Chin, 1998). These models are recently gaining popularity in empirical research due to the increased capabilities and availability of appropriate modelling software like SmartPLS, SemR and STATA. There are several methods of estimating HOCs of any type, particularly type II, as our case may be.

The third type is the formative-reflective model Type III, slightly different from the reflective-formative Type II. In type III, the items relate to the LOCs in a formative mode while the HOC also relates to the LOC in a reflective mode. Strikingly, all variables converge on the LOCs in a type III model. There is a lack of application of type III in the extant literature. However, a practical application of such a model could be from performance as a reflective HOC measured by several different items from performance as formative LOCs.

Lastly, type IV depicts a Formative-Formative model, the least frequently implemented in the SEM family. Its application is appropriate for the HOC and LOCs that are formatively conceptualised.

Remarkably, these studies have also pointed out that more research works applying higher-order constructs in PLS-SEM used the reflective-reflective and reflective-formative higher-order types than the other two (Sarstedt *et al.*, 2019). The type II (reflective – formative shown in Fig 4.16) models have dominated the literature (Becker, Klein and Wetzels, 2012). Following the above discussions, our ConsHI study is designed as a reflective – formative HOC. Specifically, the HOCs (Aptitude, Attitude, Confidence and Motivation) hold a formative relationship with its LOCs (AR, BI, CK, EE, EE, FC, H, HM, L0, L2, L3, PE, PV, RC, SCS, SI, TA, and TAA) that are measured by reflective indicators that hang well together. Note that only for illustration purposes we show below the actually applied model structure reflective-formative together with fictive displays of the other three like they were applied to the same variables.



TYPE I: REFLECTIVE – REFLECTIVE   TYPE II: REFLECTIVE – FORMATIVE   TYPE III: FORMATIVE-REFLECTIVE   TYPE IV: FORMATIVE – FORMATIVE

Fig 4. 15: The four types of HOC relationships with LOCs Adopted from Crocetta *et al.*(2021, p. 729)

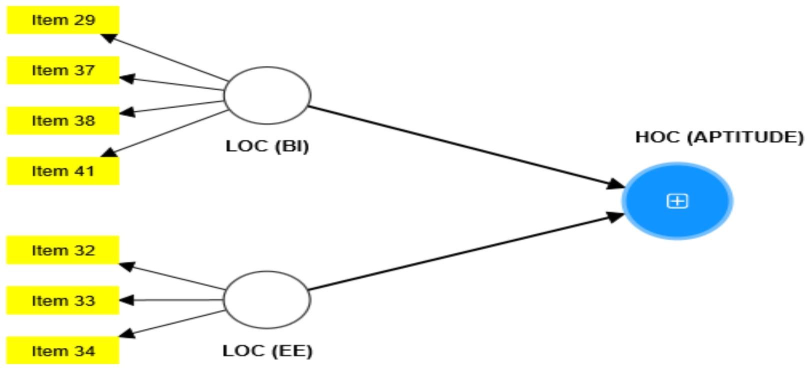


Fig 4. 16: Representation of a reflective – formative (type II) Higher (Second) Order construct.

4.8.15.2 Estimation and Evaluation of HOCs

The estimation and evaluation of HOCs have been an age-old discussion in SEM. To take full advantage of HOCs, the techniques for assessment ought to be rigorous to support the results and interpretation of the model.

According to Crocetta *et al.* (2021), there are four approaches to estimating HOCS within the frame of partial least squares – path modelling (PLS-PM) part namely; the Repeated Indicator, the two Step Approach, the Mixed Two Step Approach and the PLS Components Regression Approach. Notably, other researchers have also considered two dimensions of the two-stage approach naming it as embedded and disjointed. We will briefly describe these approaches next:

First, the Repeated Indicators Approach is the first and the most popular: the indicators of the LOCs are used as the indicators of the HOC. Consequently, the indicators are used twice: (1) for the LOCs variable ("primary" loadings/weights) and (2) for the HOCs variable ("secondary" loadings/weights). Having specified the measurement model in this way, the structural model accounts for the HOCs, as the path coefficients between the LOCs and HOCs represent the loadings/ weights of the second-order latent variable. This approach can be extended to HOCs models (Becker, Klein and Wetzels, 2012). A weakness in the repeated indicator approach is the repeated use of the same indicators that can cause artificially correlated residuals.

Second, the Two-Step Approach, also called the sequential latent variable score method (Becker, Klein and Wetzels, 2012), is described as "consists of two phases: first, the LV scores of the LOCs are computed without the HOC; then, the PLS-SEM analysis is performed using the calculated scores as indicators of the HOCs. It estimates the construct scores of the LOCs in a first-stage model without the second-order construct present. Subsequently, it uses these LOCs scores as indicators for the HOCs in a separate second-stage analysis (Becker, Klein and Wetzels, 2012). However, one can also estimate a repeated indicator model in the first stage and then use the first-order construct scores in a separate second stage.

Again, Sarstedt *et al.*(2019) noted that the two-stage approach could further be subdivided into two; namely, *the embedded two-stage approach* and *the disjoint two-stage approach* slightly differ in the model specifications in both stages. Sarstedt *et al.* (2019) report that both versions yield similar results, and there is no compelling reason for preferring one over the other.

They explained that, in the *Embedded two-stage approach*, the entire HOC is part of the first stage (LOCs models), hence the denominations "embedded", while the *Disjointed Two-Stage Approach* differs from the embedded two-stage approach in the specification of both stages. Rather than using the repeated indicators approach in stage one, the disjoint two-stage approach considers only the LOCs of the HOCs in the path model. These are directly linked to all other constructs theoretically related to the HOC. To execute the disjoint two-stage approach, researchers need to save the construct scores, but only those of the LOCs. In stage two, these scores are then used to measure the HOCs. However, unlike the embedded two-stage approach, all other constructs in the path model are estimated using standard multi-item measures as in stage one.

The third approach is the Hybrid or Mixed Two-Step approach, which begins with implementing the PLS-SEM using the latent variables of the LOCs as the indicators of the HOCs. In this way, the algorithm produces the scores of the LOCs. Then, the scores of the LOCs become indicators of the HOC, and the PLS-SEM algorithm is rerun. Notably, this approach is preferred in our study and will thus be used in analysing our datasets.

The fourth one is the PLS Component Regression Approach, described by Cataldo *et al.* (2020) as consisting of three different steps: "firstly, a HOC is formed of all the indicators of the LOCs; then PLS regression algorithm is applied to obtain the components for each; once the components have been obtained, they represent the indicators of the HOC, and the PLS-PM algorithm is performed".

Cataldo et al. (2017) contrasted all four approaches in a simulation study with only one type of HOCs, particularly the reflective-formative type of HOCs. They concluded that the Mixed Two Step and PLS component regression approaches are always the best options regarding their estimates' bias and Mean Squared Error (MSE). This also holds, when the researcher's goal is to confirm formative relationships in the structural model with reflectively (Crocetta *et al.,* 2021)measured indicators.

In stage one, we evaluate the quality measurement model and assessment of the LOC based on the standard model, which draws direct relationships between the constructs and the indicators for this dissertation.
Then in stage two, the latent variables scores from stage one results are used to estimate the HOCs.

Overall, model validation aims to determine whether the measurement and the structural model meet the quality criteria for empirical research (Urbach and Ahlemann, 2010). The assessment of the HOCs begins with:

> ***First***, HOCs formative measurement model. The result supports the convergent validity of the HOCs when the path coefficient does not below the 0.7 thresholds (Hair *et al.*, 2017).
>
> ***Second,*** find that the HOC measurement model is not negatively affected by collinearity and assess the VIF (<3.3) of the LOCs for the HOC.
>
> ***Third,*** assess the outer loading, outer weights, and their significance (*see assessing formative indicators for details*)
>
> ***Finally,*** confirm all structural model evaluation results (e.g., significance and relevance for path coefficients, Q^2, PLS predict).

In summary, the evaluation of HOC models is the same as the PLS-SEM analysis (Chin, 2010). In assessing HOCs, we consider two additional measurement models (Chin, 2010) for which evaluation criteria apply: Measurement models of the LOC and Measurement models of the HOC represented by the relationship between the HOC and LOCs.

Finally, we chose the disjoint two-stage approach for our study (Fig 4.17). Our reason is that, first, the two-stage approach supports researchers (like us) who are interested in the higher-level estimates (i.e., the path coefficient to and from the HOCs) (Becker, Klein and Wetzels, 2012). Secondly, we are interested in arriving at the coefficients of the factors that predict the maturity of the citizens of LMICs for ConsHI. According to Becker, Klein and Wetzels (2012), such models are more parsimonious as they only incorporate the focal HOCs variables. Further, they asserted that the two-stage approach could be used to assess the nature of the HOCs using a confirmatory tetrad analysis (e.g., CTA-PLS), since this approach needs LOCs values as indicators of the HOCs to assess their covariance structure. Lastly, since we had predominantly unequal numbers of indicators in our LOCs, Becker, Klein and Wetzels (2012) recommend using the two-stage approach.

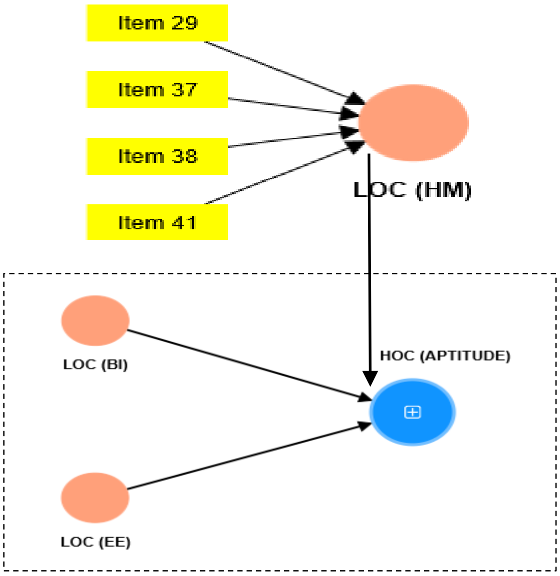


Fig 4. 17: A conceptual model of the two-stage disjointed approach

4.8.15.3 Reporting HOCs

We summarise reporting of HOCs using the standards of earlier studies (Becker, Klein and Wetzels, 2012; Robins, 2014; Hair *et al.*, 2017; Cataldo *et al.*, 2020) for such hierarchical models. Hence, the reporting of HOCs in this study will follow:

1. We will report the type (I, II, III and IV) of the HOC model used, as the model type is critical for subsequent reporting and choosing the appropriate model for the hierarchical latent variable model.
2. We will narrate the approach (repeated indicator, two-stage, hybrid etc.) we used to estimate the HOCs model and the inner weighting scheme (i.e., centroid, factor, or path) used for the PLS-SEM algorithm.

3. We will precisely assess the measurement model of the LOCs following the recommended reporting standards for reflective constructs, indicator loadings, AVE, composite reliability, discriminant validity, etc., and for formative constructs, indicator weights, the significance of weights, multicollinearity of indicators, etc. (Hair Jr *et al.*, 2017).
4. We will assess the appropriateness of the HOCs measurement models since the weights and loadings in the analysis are obtained from the relations between HOCs and LOCs.
5. Finally, we will report the structural model of the HOCs.

4.9 REPORTING FINDINGS.

The final step in interpreting and reporting PLS-SEM results involves running one or more robustness checks to support the results' stability, considering our research objectives. Essentially, the value of these robustness checks anchors on the research context and the available data (Hair *et al.*, 2014).

4.9.1 Ethical Approval

In all six countries (Chile, Ghana, Iraq, Kosovo, Turkey, and Ukraine), we obtained ethics approval from administrative and the appropriate authorities or waivers; in the absence of any visible risk to the subjects' formal approval processes were not initiated. Notably, the impact of our methods is regarded as negligible according to the ethics of human subjects' research. Also, the researchers controlled the risk of a patient's personal information slipping out from the care environment with strict subject anonymity (Yakubu *et al.*, 2021).

4.9.2 Refinement of vocabulary.

Fig 2.3 explains the transition of terminologies, from variables to constructs, from constructs to factors that serve as predictors of the maturity of citizens (ConsHI maturity). We interchangeably use observed, measured, and manifest variables, items, indicators, reflective indicators, or surface attributes in our study. These are selected for their utility as indicators of anticipated constructs, for example, in UTAUT and represented in Fig 2.3 (Venkatesh, Thong and Xu, 2012). We also use constructs, latent traits, latent variables, components, and factors interchangeably. As a reminder, we used measured variables to evaluate the factors' content, convergent, and discriminant validity (Izquierdo, Olea and Abad, 2014). Conceptually, in Fig 2.3, we propose a transition from constructs to factors, presuming that the facilitators of ConsHI maturity are factors. To distinguish between factors as facilitators in Fig 2.3 and the terminology (i.e. factors as a construct, latent trait, latent variables), we deduce three dominant categories of factors in our study.

First, in chapter two, discussing facilitators and barriers of ConsHI, we enumerated several factors that served as facilitators. Hartzler and Wetter (2014) listed the first three (1,2, 3) micro facilitating factors, namely:

1. Instincts and emotions, broken down into trust, privacy, and Confidence directly related to ConsHI concepts (Hartzler and Wetter, 2014).
2. Acquired skills, knowledge, and cultural beliefs pulverised into literacy, and personal motivation, which mandates cultural appropriateness as an essential theme beyond general usability principles. Thus, cultural appropriateness may technically mean availability in multiple languages (Hartzler and Wetter, 2014).
3. Societal influence decomposed into material possessions that connote the ability to acquire and sustain the running cost of mobile services as enablers. We atomise this into religious beliefs and practices; dovetailing with a source of information on moral support from religion will facilitate the adoption of ConsHI.

Huh *et al.* (2018) offered an additional three, namely:

4. Early user engagement through iterative user-centred design.
5. Engaging users throughout the design and development process and identifying their health information needs.
6. They involve proxies, such as caregivers or family members, who are more familiar with technology and use ConsHI on behalf of the users.

Second, in chapter four (see Table 4.7), we derived 17 constructs (factors) from the applicable theories (UTAUT, UTAUT2, UTAUTe, PAM and ConsHI) for our study, named and arranged at random as follows; 1)Performance Expectancy, 2) Effort Expectancy, 3) Social Influence, 4) Facilitating Conditions, 5) believe Active Role is important, 6) Level 0 Services, 7) Hedonic motivation, 8) Habit, 9) Price Value, 10) Confidence and Knowledge to take action, 11) Technology Anxiety, 12) Level 2 Services, 13) Behavioral Intention, 14) Taking action, 15) Resistance of Change, 16) Staying the Course under Stress, and 17) Level 3 Services.

Empirically, the first set of micro (personal) factors, which are the educed facilitators from extant literature ((Hartzler and Wetter, 2014; Huh *et al.*, 2018), is what we sort to corroborate in the exploratory factor analysis of our dataset will be labelled e – factors (meaning exploratory factors). In interpreting the e – factors, we established a relationship between the 17 theoretical constructs (t – factors; meaning theoretical factors) and the e-factors. Consequently, there is enough evidence to conduct our SEM modelling since the sets of e-factors are a subset of the t-factors.

Subsequently, at the confirmatory stage, the t – factors are composed into four major components (factors) as predictors of ConsHI maturity and will be labelled m – factors (meaning maturity factors).

CHAPTER FIVE: PRESENTATION OF RESULTS

The results chapter is the statistical representation of the data collected using the convenience sampling approach. The results are classified into three sub-sections: the hypotheses, the demographic orientation, the exploratory factor analysis, and the Structural Equation Models (SEM) using SmartPLS to model and predict the maturity of the citizens. Also, this chapter follows standard guidelines for reporting EFA and PLS-SEM analysis as suggested by previous studies (Chin, 2010; Taherdoost, Sahibuddin and Jalaliyoon, 2014) that includes the factor structure (factors), measurement and structural models. Initially, we assess the underlying structure using EFA, to identify parsimonious constructs in our dataset. Next, we assess the validity and reliability of the measurement model for SEM and analyse the structural model afterwards. Since this dissertation involves the prediction of citizens' maturity, which are higher-order constructs, a disjoint two-stage approach was used to estimate the second and third-order constructs to predict the citizens' maturity for ConsHI.

Table 5. 1: Descriptions of socio-demographic (moderator) variables

Indicator	Missings	Median	Observed min	Observed max	Std dev	Kurtosis	Skewness	CvM p-value
Country Code	0.00	4.00	1.00	6.00	1.71	-1.27	0.00	0.00
Residence	1.00	2.00	1.00	2.00	0.38	0.95	-1.72	0.00
Gender	1.00	2.00	1.00	2.00	0.50	-2.00	-0.07	0.00
Age	1.00	3.00	1.00	6.00	1.23	-1.01	0.19	0.00
Marital Status	1.00	2.00	1.00	6.00	1.06	5.11	**2.10**	0.00
Educational Level	1.00	4.00	0.00	6.00	1.80	-0.03	-1.11	0.00
Employment status	1.00	1.00	1.00	3.00	0.53	0.74	1.31	0.00
Medical Services	1.00	2.00	0.00	3.00	0.59	-0.57	0.18	0.00

NB: Bold values exceeded threshold (2); estimates are rounded to two decimals places; CvM: Cramer-van Mises; the skewness of marital status is above (>2) normal

5.1 DEMOGRAPHIC ANALYSIS OF RESPONDENTS

The observed response rate was 100% since the researchers administered the interviews ourselve using the survey instrument. We were conscious of the fallouts and intentionally replaced them with other respondents for what ever reason if a case was not ideal for our study. The demographic analysis in Table 5.2 depicts the descriptive statistics of our respondents using a balanced sample of 300 from all six countries. Subsequently, we run our test of assumptions.

The demographic distribution of respondents shows more people, residents in urban (83%) areas, particularly in Chile, all respondents were in urban areas. Also, in Table 5.2, 49.80% are married, and a cumulative of 62.05% have one way or the other experienced some form of relationship or lived with another person before. Also, most of the respondents were in the youthful age group, 20 – 29 was the highest (31%) age group and cumulatively the respondents from 20 – 49 years were 75%, indicating a high chance of technology-savvy respondents. The majority (39%) of our respondents had tertiary education. Specifically, 98.7% have one form of schooling or the other, however we note that Ukraine was not part of this categorization since the classification was slightly different. The majority (70%) of the respondents were employed and may be able to afford essential technology services. The respondents (57%) have mostly not sought medical services in the last four weeks, and perhaps they use other sources to seek support for minor illnesses and disease conditions.

Table 5. 2: Frequency distribution of demographic (moderator) variables per country and aggregate of all country variables

Variables	Chile (N=300)	Ghana (N=300)	Iraq (N=300)	Kosovo (N=300)	Turkey (N=300)	Ukraine[1] (N=300)	All Countries (N=1,800)
Age (n,%) in years							
Less than 20	30 (10%)	37 (12%)	24 (8.0%)	10 (3.3%)	20 (6.7%)	15 (5.0%)	136 (7.6%)
20-29	110 (37%)	137 (46%)	71 (24%)	80 (27%)	87 (29%)	66 (22%)	551 (31%)
30-39	64 (21%)	77 (26%)	70 (23%)	76 (25%)	76 (25%)	95 (32%)	458 (25%)
40-49	83 (28%)	18 (6.0%)	66 (22%)	57 (19%)	69 (23%)	47 (16%)	340 (19%)
50 & Over:	12 (4.0%)	28 (9.3%)	69 (23%)	77 (26%)	47 (16%)	76 (25%)	309 (17%)
Unknown	1 (0.3%)	3 (1.0%)	0 (0%)	0 (0%)	1 (0.3%)	0 (0%)	5 (0.3%)
Gender (n,%)							
Male	132 (44%)	153 (51%)	150 (50%)	136 (45%)	154 (51%)	144 (48%)	869 (48%)
Female:	168 (56%)	147 (49%)	150 (50%)	164 (55%)	146 (49%)	155 (52%)	930 (52%)
Residential status (n,%)							
Rural	0 (0%)	30 (10%)	57 (19%)	117 (39%)	46 (15%)	64 (21%)	314 (17%)
Urban	300 (100%)	270 (90%)	243 (81%)	183 (61%)	254 (85%)	235 (79%)	1485(83%)
Marital status (n, %)							
Never Married:	182 (61%)	164 (55%)	113 (38%)	82 (27%)	99 (33%)	42 (14%)	682 (38%)
Married:	56 (19%)	113 (38%)	167 (56%)	206 (69%)	165 (55%)	190 (64%)	897 (50%)
Informal (Consensual)	62 (21%)	4 (1.3%)	0 (0%)	4 (1.3%)	12 (4.0%)	18 (6.0%)	100 (5.6%)
Separated:	0 (0%)	7 (2.3%)	4 (1.3%)	2 (0.7%)	8 (2.7%)	2 (0.7%)	23 (1.3%)
Divorced:	0 (0%)	5 (1.7%)	9 (3.0%)	3 (1.0%)	9 (3.0%)	27 (9.0%)	53 (2.9%)
Widowed:	0 (0%)	7 (2.3%)	7 (2.3%)	3 (1.0%)	7 (2.3%)	20 (6.7%)	44 (2.4%)
Educational Level (n, %)							
None (Pre- School)	0 (0%)	11 (3.7%)	0 (0%)	4 (1.3%)	8 (2.7%)	1 (0.3%)	24 (1.3%)
Primary:	3 (1.0%)	10 (3.3%)	3 (1.0%)	6 (2.0%)	36 (12%)	2 (0.7%)	60 (3.3%)
Middle/Junior high:	62 (21%)	35 (12%)	10 (3.3%)	10 (3.3%)	55 (18%)	0 (0%)	172 (9.6%)
Secondary:	151 (50%)	60 (20%)	106 (35%)	77 (26%)	100 (33%)	0 (0%)	494 (27%)
Tertiary:	84 (28%)	156 (52%)	159 (53%)	196 (65%)	101 (34%)	0 (0%)	696 (39%)
Other (Technical/Vocational):	0 (0%)	28 (9.3%)	22 (7.3%)	7 (2.3%)	0 (0%)	24 (8.0%)	81 (4.5%)
Different[2]	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	272 (91%)	272 (15%)
Employment status (n, %)							
Yes:	250 (83%)	153 (51%)	146 (49%)	261 (87%)	195 (65%)	254 (85%)	259 (70%)

[1] The demographic variables of the last observation in Ukraine was missing, however we could not delete it because that will reduce the number of observations for Ukraine.
[2] the education variable emanates from the classification in Ukraine, where only two categories were used 1 and 6 (see 3.6.4)

Variables	Chile (N=300)	Ghana (N=300)	Iraq (N=300)	Kosovo (N=300)	Turkey (N=300)	Ukraine[1] (N=300)	All Countries (N=1,800)
No:	50 (17%)	124 (41%)	143 (48%)	30 (10%)	99 (33%)	41 (14%)	487 (27%)
Not Applicable:	0 (0%)	23 (7.7%)	11 (3.7%)	9 (3.0%)	6 (2.0%)	4 (1.3%)	53 (2.9%)
Medical Services (n, %)							
Yes:	100 (33%)	100 (33%)	106 (35%)	92 (31%)	132 (44%)	119 (40%)	649 (36%)
No:	196 (65%)	164 (55%)	118 (39%)	200 (67%)	168 (56%)	172 (58%)	1018 (57%)
Don't Remember:	4 (1.3%)	36 (12%)	76 (25%)	8 (2.7%)	0 (0%)	7 (2.3%)	131 (7.3%)
Erroneous entry	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	1 (0.3%)	1 (<0.1%)

NB: the gold colour shows an erroneous entry in the medical services for Ukraine. Also, the Unknown in the Education variable emanated from the Ukraine classification where only two categories were used 1 and 6 (see 3.6.4). In the final analysis, we exclude education in the aggregate dataset to avoid biases but will later compare it with the rest of the countries.

5.2 EXPLORATORY FACTOR ANALYSIS (EFA)

Our objectives were to reduce the number of variables and to identify factors that will facilitate the maturity of the citizens of LMICs for ConsHI. This will serve as the first step in our data analysis. Also, we examine the relationships between variables and their constructs and develop empirical constructs for our structural equation models, as recommended by Watkins (2018). At this stage, we did not include the demographic variables since these variables are to moderate the relationships of the factors that will determine the maturity of the citizens of LMICs.

Using the statistical SmartPLS 4.0 and Rstudio, we evaluated the serial number, missing observations, median, standard deviation, minimum value, maximum value, Kurtosis and Skewness of each item. The measure of central tendency is median because our items are predominantly categorical, which does not support average values estimates.

5.2.1 Setting up data

Setting the data for EFA entails reporting irregular observations and how they are corrected in the analysis process. Various guidelines are used in determining acceptable levels of these irregularities in the data. It is imperative to note that, in this EFA, we did not include the demographic variables shown in Table 5.1 because those are moderators that will be used to test for their effect in the predictive model. Also, we are particular about underlying factor structures in the ConsHI related items.

Tables 5.1 and 5.4 shows that our missing observations are less than 1% of the dataset, raising no concern in the dataset. specifiHowever, we used mean replacement methods to fill the gaps of these few missing observations in our dataset and proceeded to do our test of assumptions as shown below (Schumacker, 2015). Fundamentally, the indicator correlations were perfect, with a few loadings exceeding 0.3 but none reaching 0.8 to pose any of the challenges out lined in section 4.7.1 in our dataset. Fig 5.1 and Table 5.3 show the correlation graph and matrix of the ConsHI related items for our EFA. Our data adequately exceeded (> ±0.30) the recommendations of R. MacCallum *et al.* (1999) and Hair *et al.* (2010). Conversely, far below (0.8) for all bivariate correlations (Diamantopoulos *et al.*, 2012). Thus, adequately satisfying the range of 0.3 – 0.7 for EFA.

We sufficiently acquired the least amount of data for factor analysis, with a final sample size of 1,800, providing a ratio of over 41 cases per variable, significantly exceeding the required ratio as stated literature (see 4.7.1.2). Remarkably, items (item 28, item 30, and item 31) labelled R and bold were reverse coded since they have negative valence in the questionnaire design process.

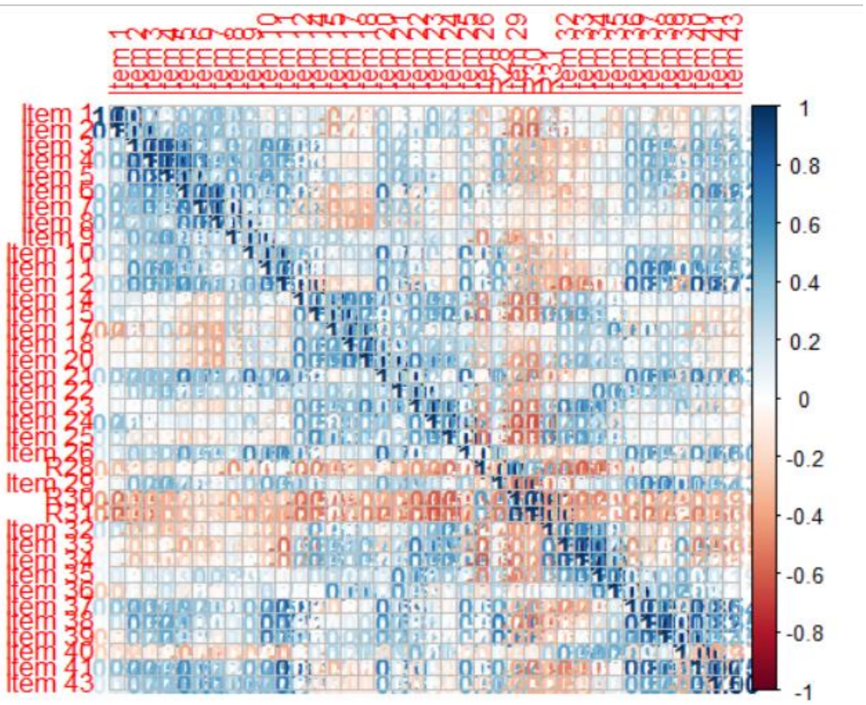


Fig 5. 1: Graphical representation of the indicator correlation matrix

Table 5. 3: Correlations matrix of items for measuring the maturity of the citizens of LMIcs for ConsHI

Indicators	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	R28	29	R30	R31	32	33	34	35	36	37	38	39	40	41	42	43
Item 1	**1.00**																																										
Item 2	0.53	**1.00**																																									
Item 3	0.23	0.28	**1.00**																																								
Item 4	0.29	0.37	0.56	**1.00**																																							
Item 5	0.18	0.24	0.53	0.56	**1.00**																																						
Item 6	0.27	0.30	0.34	0.40	0.37	**1.00**																																					
Item 7	0.22	0.31	0.24	0.37	0.27	0.45	**1.00**																																				
Item 8	0.23	0.24	0.20	0.25	0.20	0.44	0.46	**1.00**																																			
Item 9	0.20	0.15	0.36	0.31	0.37	0.19	0.17	0.23	**1.00**																																		
Item 10	0.26	0.21	0.23	0.25	0.26	0.35	0.20	0.23	0.27	**1.00**																																	
Item 11	0.07	0.16	0.33	0.32	0.32	0.26	0.23	0.06	0.19	0.26	**1.00**																																
Item 12	0.21	0.21	0.31	0.32	0.27	0.34	0.31	0.25	0.17	0.31	0.43	**1.00**																															
Item 13	0.23	0.25	0.23	0.25	0.26	0.32	0.37	0.28	0.23	0.26	0.22	0.37	**1.00**																														
Item 14	0.15	0.16	0.21	0.12	0.20	0.15	0.08	0.05	0.23	0.26	0.16	0.11	0.30	**1.00**																													
Item 15	0.20	0.23	0.17	0.15	0.16	0.13	0.10	0.08	0.22	0.12	0.16	0.10	0.21	0.34	**1.00**																												
Item 16	0.30	0.25	0.18	0.13	0.12	0.25	0.23	0.19	0.10	0.20	0.07	0.19	0.26	0.24	0.37	**1.00**																											
Item 17	0.01	-0.02	0.20	0.13	0.32	0.05	0.01	0.01	0.26	0.20	0.19	0.07	0.16	0.25	0.24	-0.01	**1.00**																										
Item 18	0.14	0.11	0.14	0.08	0.19	0.11	0.10	-0.01	0.15	0.22	0.14	0.11	0.16	0.36	0.27	0.20	0.31	**1.00**																									
Item 19	0.24	0.22	0.14	0.21	0.13	0.22	0.17	0.22	0.22	0.18	0.13	0.25	0.31	0.18	0.18	0.18	0.24	0.20	**1.00**																								
Item 20	0.11	0.20	0.17	0.12	0.22	0.13	0.08	0.00	0.17	0.25	0.23	0.10	0.18	0.31	0.34	0.24	0.29	0.38	0.24	**1.00**																							
Item 21	0.23	0.26	0.28	0.30	0.29	0.51	0.35	0.31	0.17	0.44	0.28	0.38	0.36	0.20	0.17	0.27	0.11	0.22	0.27	0.34	**1.00**																						
Item 22	0.15	0.17	0.31	0.30	0.34	0.24	0.33	0.26	0.27	0.15	0.31	0.24	0.39	0.20	0.27	0.15	0.33	0.16	0.22	0.29	0.36	**1.00**																					
Item 23	0.13	0.18	0.17	0.19	0.27	0.15	0.13	0.07	0.17	0.18	0.18	0.07	0.11	0.29	0.26	0.17	0.21	0.23	0.12	0.38	0.26	0.33	**1.00**																				
Item 24	0.25	0.23	0.15	0.17	0.18	0.22	0.18	0.15	0.17	0.25	0.07	0.15	0.23	0.27	0.26	0.38	0.04	0.25	0.19	0.27	0.29	0.16	0.37	**1.00**																			
Item 25	0.19	0.19	0.11	0.07	0.16	0.07	0.07	0.12	0.17	0.10	0.13	0.08	0.21	0.23	0.31	0.16	0.17	0.17	0.18	0.23	0.13	0.22	0.27	0.30	**1.00**																		
Item 26	0.22	0.18	0.29	0.26	0.28	0.40	0.29	0.29	0.21	0.40	0.28	0.37	0.36	0.22	0.16	0.19	0.22	0.27	0.29	0.23	0.51	0.33	0.20	0.27	0.22	**1.00**																	
Item 27	0.09	0.12	0.17	0.20	0.23	0.18	0.12	0.08	0.17	0.16	0.23	0.23	0.16	0.21	0.15	0.16	0.21	0.18	0.15	0.23	0.28	0.25	0.29	0.17	0.22	0.23	**1.00**																
R28	-0.05	-0.03	0.07	0.04	0.03	0.10	0.06	-0.01	-0.09	0.06	0.08	0.06	-0.04	-0.05	-0.04	-0.01	-0.05	0.03	-0.07	0.03	0.09	0.00	-0.02	-0.03	-0.08	0.08	-0.09	**1.00**															
Item 29	0.10	0.13	0.28	0.29	0.28	0.22	0.14	0.09	0.18	0.22	0.25	0.29	0.15	0.17	0.12	0.09	0.17	0.14	0.10	0.21	0.31	0.21	0.25	0.15	0.11	0.26	0.34	-0.03	**1.00**														
R30	-0.06	-0.12	-0.01	-0.04	-0.04	0.06	0.08	0.02	-0.06	0.06	-0.01	-0.03	-0.07	-0.08	-0.10	-0.04	0.04	0.05	-0.06	-0.02	0.00	-0.02	-0.10	-0.10	-0.14	0.10	-0.17	0.28	-0.09	**1.00**													
R31	-0.04	-0.12	-0.01	-0.02	-0.04	-0.01	0.05	0.02	0.03	-0.01	-0.03	-0.10	-0.07	-0.08	-0.10	-0.09	0.09	-0.02	-0.04	-0.08	-0.07	0.01	-0.10	-0.10	-0.11	0.02	-0.14	0.21	-0.09	0.64	**1.00**												
Item 32	0.21	0.20	0.06	0.07	0.05	0.10	0.12	0.19	0.10	0.12	0.07	0.07	0.11	0.11	0.30	0.18	0.05	0.13	0.13	0.23	0.14	0.20	0.23	0.27	0.32	0.17	0.10	-0.05	0.09	-0.04	-0.05	**1.00**											

Item 33	0.08	0.12	0.06	0.11	0.23	0.02	0.06	0.05	0.15	0.09	0.06	-0.08	0.01	0.22	0.25	0.06	0.27	0.17	0.01	0.26	0.09	0.19	0.39	0.22	0.19	0.06	0.17	-0.11	0.19	-0.10	-0.05	0.33	**1.00**										
Item 34	0.13	0.14	0.05	0.08	0.16	0.17	0.13	0.11	0.15	0.18	0.07	-0.03	0.17	0.27	0.27	0.16	0.25	0.26	0.12	0.30	0.16	0.20	0.29	0.27	0.28	0.15	0.19	-0.13	0.19	-0.08	-0.03	0.38	0.52	**1.00**									
Item 35	0.15	0.22	0.16	0.26	0.24	0.22	0.38	0.32	0.21	0.14	0.19	0.15	0.27	0.17	0.21	0.11	0.21	0.14	0.17	0.21	0.24	0.45	0.27	0.19	0.24	0.26	0.24	-0.07	0.25	-0.07	0.01	0.28	0.36	0.46	**1.00**								
Item 36	0.11	0.08	0.16	0.24	0.27	0.15	0.19	0.15	0.21	0.24	0.26	0.19	0.22	0.12	0.13	-0.05	0.45	0.23	0.15	0.29	0.26	0.37	0.20	0.09	0.17	0.34	0.21	0.05	0.22	0.11	0.15	0.19	0.24	0.28	0.49	**1.00**							
Item 37	0.24	0.31	0.29	0.31	0.25	0.29	0.28	0.16	0.12	0.27	0.31	0.44	0.31	0.14	0.14	0.25	0.06	0.14	0.25	0.24	0.44	0.26	0.14	0.19	0.16	0.37	0.25	0.13	0.29	-0.04	-0.09	0.10	-0.03	0.01	0.23	0.28	**1.00**						
Item 38	0.12	0.22	0.34	0.31	0.34	0.28	0.20	0.12	0.16	0.24	0.40	0.42	0.27	0.16	0.14	0.12	0.14	0.14	0.18	0.24	0.36	0.31	0.23	0.18	0.17	0.32	0.30	0.08	0.40	-0.12	-0.13	0.09	0.05	0.11	0.26	0.29	0.54	**1.00**					
Item 39	0.02	0.11	0.29	0.29	0.33	0.26	0.22	0.09	0.19	0.25	0.39	0.29	0.20	0.20	0.14	0.06	0.27	0.27	0.14	0.29	0.35	0.27	0.26	0.12	0.12	0.29	0.27	0.09	0.36	0.01	-0.01	0.08	0.21	0.24	0.32	0.37	0.35	0.53	**1.00**				
Item 40	0.05	0.10	0.06	0.14	0.13	0.01	0.13	0.07	0.03	0.04	0.15	-0.03	-0.03	0.10	0.13	0.01	0.20	0.17	0.03	0.20	0.11	0.22	0.27	0.09	0.15	0.13	0.15	0.05	0.13	0.01	0.05	0.20	0.32	0.24	0.31	0.37	0.11	0.21	0.25	**1.00**			
Item 41	0.21	0.29	0.30	0.31	0.27	0.39	0.27	0.23	0.15	0.27	0.31	0.51	0.33	0.14	0.08	0.18	-0.03	0.09	0.24	0.14	0.40	0.21	0.10	0.19	0.15	0.37	0.26	0.10	0.35	-0.08	-0.14	0.04	-0.07	0.00	0.21	0.15	0.50	0.59	0.38	0.06	**1.00**		
Item 42	0.20	0.24	0.18	0.21	0.29	0.24	0.26	0.27	0.21	0.19	0.20	0.24	0.27	0.21	0.13	0.08	0.27	0.20	0.31	0.21	0.27	0.26	0.18	0.18	0.18	0.34	0.20	-0.05	0.19	-0.04	0.04	0.15	0.17	0.22	0.36	0.37	0.21	0.27	0.30	0.22	0.31	**1.00**	
Item 43	0.11	0.11	0.24	0.22	0.26	0.35	0.24	0.30	0.20	0.22	0.22	0.43	0.31	0.17	0.05	0.10	0.11	0.08	0.24	0.08	0.27	0.19	0.02	0.09	0.08	0.30	0.15	-0.06	0.22	-0.05	-0.04	0.05	-0.01	0.11	0.23	0.20	0.28	0.30	0.29	-0.06	0.49	0.32	**1.00**

NB: the pink colouration shows values above 0.3 for inter-item correlations. The able shows that all items correlated sufficiently with one or more other items. Also, wit the exception of the leading diagonals, which was item-self correlations (1), none of the bivariate correlations exceeded the recommended threshold of 0.8 by Tabachnick and Fiddell (2007), evidence that, there was no multicollinearity in the dataset, thus our items were sufficiently correlated to support an EFA. Bivariate correlation less than 0.3, connotes a weak amongst items, however this should be close to zero to raise issues of singularity (Tabachnick and Fiddell, 2007; Yong and Pearce, 2013; Samuels, 2017) . **Bold** numbers are worth noting in the database since they could influence the analysis. Notably, variables with R (i.e. R28, R30 and R31) attached were reverse coded since they measured technology anxiety, to reduce the possibility of skewness by ensuring all measured variables are scored in the same direction (Betancourt *et al.*, 2014).

5.2.2 Test of assumptions

We ran four tests of assumptions (see 4.7.1); first, we tested for linearity and homogeneity of our dataset after the correlation matrix. The diagrams below support a linear relationship amongst the items and a good level of homogeneity. We then tested normality using the standard histogram and normal distribution curve. The results of statistical (Table 5.4) values show that univariate skewness (2.10) of marital status was above the threshold of 2.0 but below (5.11) the threshold of 7.0 for kurtosis, thus not extremely as described by Patrick J Curran, West and Finch (1996). Also, marital status is not part of the ConsHI items and that offers a relief for our EFA procedure.

Fig 5.2 (A: left hand side) shows the test of homogeneity and *minimal levels of sample variability from the target population.* Evidently, fitted model is heterogeneous supporting the argument of Yong and Pearce (2013) that heterogeneous samples are preferred to homogeneous samples since homogeneous samples decrease the variance and factor loadings in EFA. Thus, there was no need for correction of the data for homogeneity (Hunter, Schmidt and Le, 2006). Further, verified sufficient *linear relationship amongst indicators* is an essential requirement for EFA (Fig 5.2; B: right hand side). Watkins (2018) posit that examining scatterplots can subjectively judge adequancy of *indicators linearity*. While, we see the items have a good enough linear relationship from the Q-Q plot, we hesitant to conclude and will further, assess the normality to make a good judgement as to a transformation into polychoric will be necessary. Researchers might use a more robust type of correlation coefficient to assess linearity in the dataset instead of *r* for observed nonlinearity in the dataset (Revelle, 2013; de Winter, Gosling and Potter, 2016; Paper, 2016; Lloret, Ferreres and Tomás, 2017).

Furthermore, we evaluated non-normality since CvM (p-value <0.05) is significant (Table 5.4), and the histogram of variables (left side of Fig 5.3A) shows a skewed distribution in our dataset. Principally, the ordinal scale of items amplifies such an uneven distribution. Hence a polychoric correlation matrix was necessary to transform the data, as shown in the right-hand side graph, to make the data appropriate for EFA (Bandalos & Gerstner, 2016; Fabrigar et al., 1999; Lloret et al., 2017). Thus, we had to convert to polychoric correlations to attain normality in our dataset. Notably, the results below showed the raw dataset was skewed to the right.

Also, our results of Bartlett's test of sphericity show that the correlation matrix was not random [χ^2 (703) = 1552.858, p-value = 0.000 **<0.05]**, and the KMO statistic (Kaiser, 1974) was (KMO=0.892>0.7), well above the required minimum thresholds for conducting factor analysis (see Table 4.8) guidelines on adequacy of dataset for EFA.

Also, the determinant of the identity matrix was significant (**det**=0.000<0.05), indicating the significant differences between the correlation and identity matrices. Beavers *et al.* (2013) recommended that, these overall properties of the dataset, presupposed that, our dataset was appropriate (Fig 5.2 and Fig 5.3) for us to conduct factor analysis with all 43 items.

A B

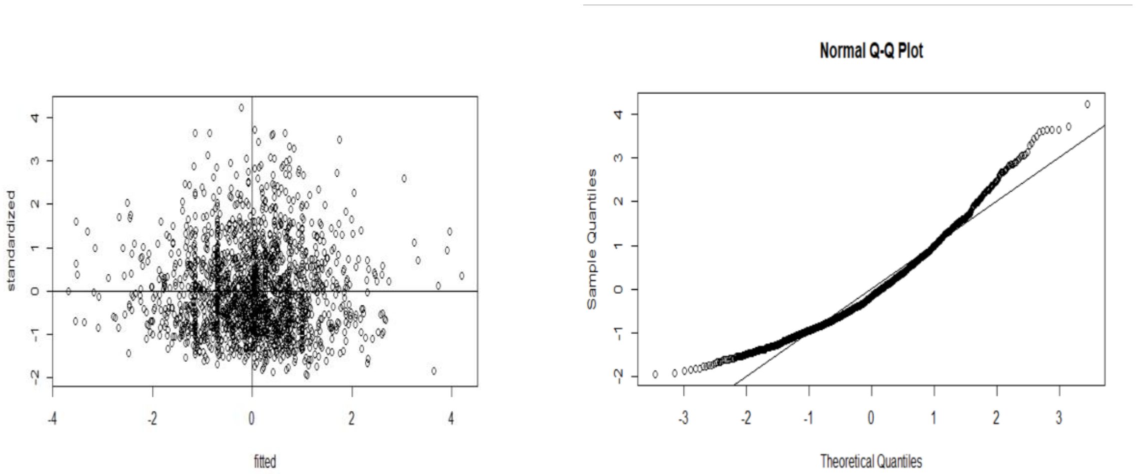


Fig 5. 2: A is the test of homogeneity and B is the test of linearity amongst items in the dataset.

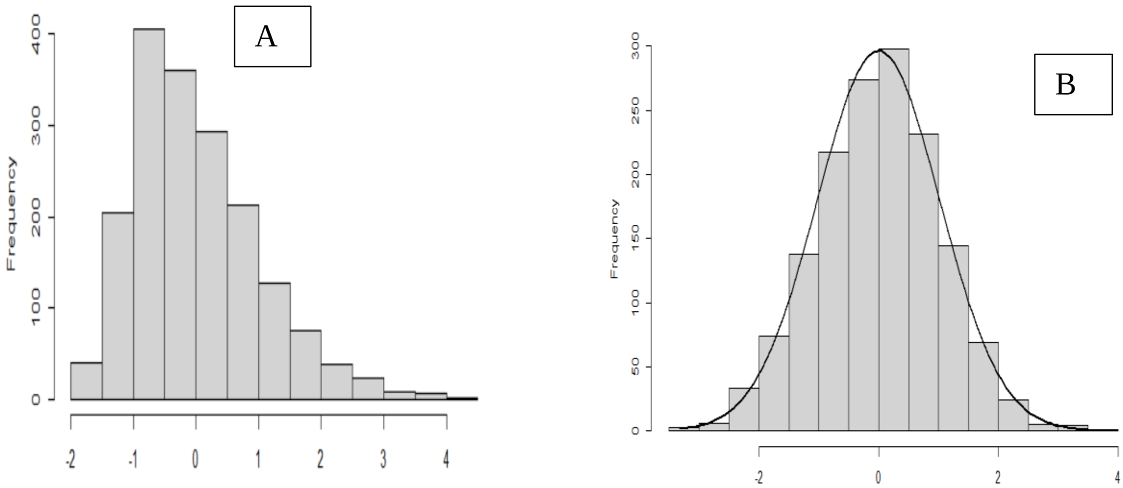


Fig 5. 3: Graph **A** is the histogram of the raw data that is skewed, showing non-normal distribution and **B** is normal distribution after converting the data to polychoric matrix also see (Baglin, 2014).

In Table 5.4, item content of the ConsHI maturity and demographic scales are presented with psychometric information pertaining to item medians, variability, and distributions (Thurber and Bonynge, 2011). Only marital status, evinced skewness of 2.1 which is marginally beyond 2.0 threshold for normality of dataset. Several indices suggested that the instrument did not consist of homogeneous items (e.g., mean correlation among the a priori scales or average item-total correlation).

Table 5. 4: Descriptive statistics item content, median, standard deviations, skew, and kurtosis

Name	Missing	Median	Min	Max	Stdev	Kurtosis	Skewness	CvM
Residence	1.00	2.00	1.00	2.00	0.38	0.95	-1.72	0.00
Gender	1.00	2.00	1.00	2.00	0.50	-2.00	-0.07	0.00
Age	1.00	3.00	1.00	6.00	1.23	-1.01	0.19	0.00
Marital Status	1.00	2.00	1.00	6.00	1.06	**5.11**	**2.10**	0.00
Educational Level	1.00	4.00	0.00	6.00	1.80	-0.03	-1.11	0.00
Employment status	1.00	1.00	1.00	3.00	0.53	0.74	1.31	0.00
Medical services	1.00	2.00	0.00	3.00	0.59	-0.57	0.18	0.00
Item 1	0.00	4.00	1.00	5.00	0.97	1.75	-1.31	0.00
Item 2	0.00	4.00	1.00	5.00	0.89	1.49	-1.08	0.00
Item 3	0.00	4.00	1.00	5.00	0.88	1.41	-1.07	0.00
Item 4	0.00	4.00	1.00	5.00	0.89	1.71	-1.17	0.00
Item 5	0.00	4.00	1.00	5.00	1.01	-0.28	-0.54	0.00
Item 6	0.00	4.00	0.00	5.00	0.96	1.84	-1.34	0.00
Item 7	0.00	4.00	1.00	5.00	0.96	0.66	-0.97	0.00
Item 8	0.00	4.00	1.00	5.00	1.10	-0.64	-0.47	0.00
Item 9	0.00	4.00	1.00	5.00	0.95	0.03	-0.61	0.00
Item 10	0.00	4.00	1.00	5.00	0.88	1.94	-1.23	0.00
Item 11	0.00	4.00	1.00	5.00	0.98	-0.06	-0.62	0.00
Item 12	0.00	4.00	1.00	5.00	1.10	-0.10	-0.81	0.00
Item 13	0.00	4.00	1.00	5.00	1.00	0.89	-1.07	0.00
Item 14	0.00	4.00	0.00	5.00	0.97	0.46	-0.78	0.00
Item 15	0.00	4.00	1.00	5.00	0.86	1.07	-0.90	0.00
Item 16	0.00	4.00	1.00	5.00	0.84	2.40	-1.31	0.00
Item 17	0.00	3.00	1.00	5.00	1.24	-1.07	0.02	0.00
Item 18	0.00	4.00	1.00	5.00	0.98	0.51	-0.90	0.00
Item 19	0.00	4.00	1.00	5.00	1.14	-0.53	-0.57	0.00
Item 20	0.00	4.00	1.00	5.00	0.86	0.95	-0.82	0.00
Item 21	0.00	4.00	1.00	5.00	0.90	1.70	-1.19	0.00
Item 22	0.00	4.00	1.00	5.00	1.00	-0.05	-0.65	0.00
Item 23	0.00	4.00	1.00	5.00	0.85	1.21	-0.87	0.00
Item 24	0.00	4.00	1.00	5.00	0.80	2.06	-1.09	0.00
Item 25	0.00	4.00	1.00	5.00	0.91	0.10	-0.65	0.00
Item 26	0.00	4.00	1.00	5.00	0.89	0.93	-0.88	0.00
Item 27	0.00	4.00	1.00	5.00	1.02	-0.21	-0.47	0.00
R28	0.00	4.00	1.00	5.00	1.10	-0.74	-0.30	0.00
Item 29	0.00	4.00	1.00	5.00	0.92	0.35	-0.67	0.00
R30	0.00	3.00	1.00	5.00	1.15	-0.82	0.25	0.00
R31	0.00	2.00	1.00	5.00	1.14	-0.61	0.51	0.00
Item 32	0.00	4.00	1.00	5.00	0.83	0.87	-0.79	0.00
Item 33	0.00	4.00	1.00	5.00	0.98	-0.41	-0.52	0.00
Item 34	0.00	4.00	1.00	5.00	0.94	-0.11	-0.49	0.00
Item 35	0.00	4.00	1.00	5.00	1.00	-0.57	-0.37	0.00
Item 36	0.00	3.00	1.00	5.00	1.05	-0.91	-0.18	0.00
Item 37	0.00	4.00	1.00	5.00	0.93	1.45	-1.13	0.00
Item 38	0.00	4.00	1.00	5.00	1.02	-0.06	-0.64	0.00
Item 39	0.00	4.00	0.00	5.00	0.96	0.27	-0.69	0.00
Item 40	0.00	4.00	1.00	5.00	1.03	-0.56	-0.38	0.00
Item 41	0.00	4.00	1.00	5.00	1.06	0.48	-0.98	0.00
Item 42	0.00	3.00	1.00	5.00	1.10	-0.81	-0.28	0.00
Item 43	0.00	4.00	1.00	5.00	1.18	-0.80	-0.39	0.00

NB: The skewness of marital status exceeded the maximum of 2.0 to be within a normal range. Implying marital status is not normally distributed. CvM: Cramer-van Mises.

5.2.3 Number of factors to retain

The factor analysis commenced by first verifying the number of factors to retain for our structural model. Initially, we retained six factors following the scree plot (see 4.7.4.2) and parallel analysis (4.7.4.3 graphical results (Fig 5.4). In addition, the old (K1 see 4.7.4.1) confirmed identified 4 considering eigenvalues greater than or equal one, from Fig 5.4 using the solid black line. Interestingly, the new Kaiser criteria, which uses confidence intervals, supported 6 factors, per estimates in R. The variations in the number of factors required further investigation. We further considered the scree plot graph in Fig 5.4, using the red – dotted lines, and this shows a rather higher (11) number of factors.

We are more inclined to join Fabrigar *et al.* (1999) assertions that, over-factoring is safer than under factoring since the scree plot shows more than 6 factors in the dataset. Particularly, noting the theoretical assumptions of our conceptual model which proposed 17 constructs. We are more convinced to retain the highest (11) number of factors emerging in the dataset than the least. Concurrently, there are post-factor procedures (see 4.7.6) to verify the number of factors and compare which factor model satisfies the true structure of the dataset. Noting that we have four, six and 11 factors, relative to 17 constructs of our theoretical model, we proceed to analyse dataset with six and 11 factors. Cautiously, we will use the 11 factors model (over-factoring school), in order not to miss any possible factor for the rest of our analysis.

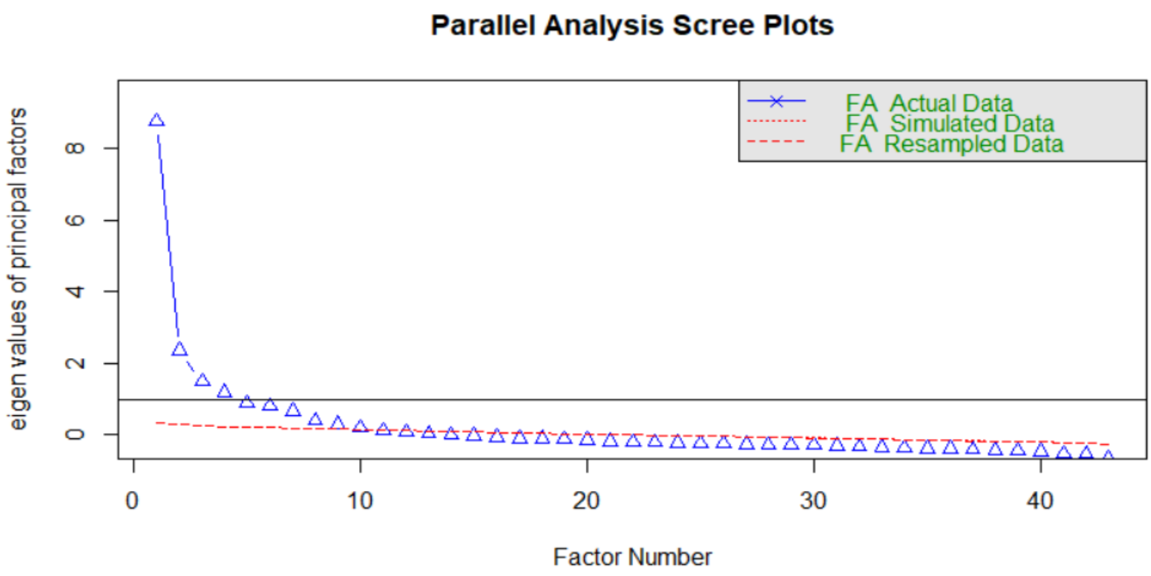


Fig 5. 4: Testing for number of factors to retain using parallel analysis and scree plots

NB: solid black line is K1(eigen values = 1); dotted red lines are scree plots using cliff)

5.2.4 Factor extraction and rotation

Our aim is to identify factors that will facilitate the maturity of the citizens of LMICs for ConsHI. We anticipated some latent construct that define the interrelationship among items. FA is preferred to PCA in the early stages of factor analysis since researchers can evaluate the ratio of a variable's unique variance to its shared variance, known as its commonality.

Accordingly, we chose the common factor analysis method using the iterated principal axis approach. Afterwards. we rotated the factor structure of the 43 variables of the 1,800 observattions using the oblimin (oblique) rotation technique in Rstudio.

EFA is a dimension reduction procedure that identifies items with a shared variance, it is advisable to remove any item with a communality score less than 0.2 (Child, 2006). Items with low communality scores may indicate additional factors which could be explored in further studies by developing and measuring additional items (Costello and Osborne, 2005).

5.2.4.1 Using Communalities to describe factors

Norris and Lecavalier (2010) makes a strong case for estimating correlation matrix, by proposing that, the first step in EFA is to measure the association between the items of interest. Though this assertion differs from other studies, they reason that, the inter-item correlations (i.e., the correlation matrix) are used to calculate the communalities (the proportion of observed variance due to common factors, or the total amount of variance for an item explained by the extracted factors) and factor loadings.

We iterated the EFA processes several times, first, we assessed the communalities of all the variables after our first factor solution (see 4.7.2). Like Norris and Lecavalier (2010) describe earlier, communities is the total amount of variance for an item explained by the extracted factors. They explained that, for datasets with 20 or less items, a minimum of 0.4 communality is required to consider an item as adequately loading on a factor. Notably, our items were more (43) than 20 so we could use a minimum threshold of 0.2 as acceptable (Osborne *et al.*, 2011). Thus, , so we assessed the factor structure to ascertain the communalities of items in our 11 factor structure. A consistent iteration of our factor matrix resulted in removing four items (16,19,27, and 42) with communalities less than 0.2 (Costello and Osborne, 2005). Following the recommendations of Watkins's, we first remove the item with the lowest communiality (i.e., Item 16 = 0.17), then in that order of magnitude, until such a time that we attain a stable solution (all communalities above 0.2) for our factor matrix.

5.2.4.2 Using factor loadings to describe describe factors

The next step is to evaluate the factor laodings of the remaining items to determine their adequacy for our factor structure. According to Guadagnoli and Velicer, (1988), factor loadings shows the contribution of an item to a factor. They posited that, statistically, a factor should have at least three items and at most six items loading on it.

We examined our factor matrix to identify inadequate loadings (factor loadings less than 0.3) as prescribe by Samuels (2017). Notably, we removed four items (13,15,17 and 35), starting with item 13 which had the lowest loadings on all factors in the first round of our analysis. Subsequently, we iterated until items 15, 17 and 35 were also removed.

Lastly, we evaluate items in the remaing factor structure to identify complex loadings, these are items that cross-load on more than one factor with a minimum of 0.4. Emperically, in the rotated factor matrix, items cross-loading on more than one factor at less than 75% or had the highest loading < 0.4, should be excluded (Samuels, 2017).

Finally, we assessed the eleven-factor solution for its adequacy to our dataset. A minimum of three items should adequately loaded on each factor as required (see Table 5.5). The 11-factor solution was adequate since pattern structure coefficients were mostly above 0.5. Also, there are several complexly loaded items on factors with a minimum internal consistency (alpha) reliability of 0.54 (95% CI = 0.54-0.87).

Conclusively, seven (ML1, ML2, ML3, ML5, ML6, ML7 and ML10) out of the 11 – factors satisfied the criteria (at least three items loading at a minimum of 0.3) for inclusion as factors in our dataset (Guadagnoli and Velicer, 1991; Costello and Osborne, 2005; Baglin, 2014). This may be closer to the earlier (see 5.2.3) number (6) of factors suggested by the new Kaiser criteria and the scree plot. A cursory look at Table 5.5 also shows the factor loadings of items on factor four (ML4) were high (>0.75).

We also take a cue from Fig 5.5 which shows that all the 11- factors have no correlation. This suggest that the 11 factors were the exhaustive and minimum number of factors in the dataset since none can be merged again.

Finally, a common factor (com) analysis of the remaining 35 items, using oblimin (Oblique) rotations, was conducted for the final stage, with six factors explaining 87% of the variance (Table 5.6). An oblimin rotation provided the best-defined factor structure. All items in this analysis had primary loadings over 0.5.

Table 5. 5: Standardised loadings (pattern matrix) based upon correlation matrix

Indicators	ML1	ML2	ML6	ML5	ML7	ML3	ML4	ML10	ML8	ML11	ML9	h^2	u^2	com	KMO
Item 38	0.81											0.74	0.26	1.30	0.90
Item 41	0.78											0.78	0.22	1.60	0.88
Item 37	0.70											0.65	0.35	1.70	0.93
Item 39	0.60											0.61	0.39	2.60	0.94
Item 12	0.58											0.55	0.45	2.50	0.91
Item 11	0.46											0.40	0.60	2.80	0.91
Item 29	0.44											0.36	0.64	2.80	0.94
Item 34		0.72										0.68	0.32	1.70	0.85
Item 33		0.68										0.55	0.45	1.40	0.87
Item 35***		0.57										0.70	0.30	3.20	0.87
Item 40		0.46										0.35	0.65	2.40	0.87
Item 32**		0.46										0.40	0.60	2.80	0.86
Item 23**		0.45										0.48	0.52	3.80	0.90
Item 20			0.60									0.54	0.46	2.20	0.90
Item 18			0.57									0.42	0.58	1.70	0.90
Item 14			0.55									0.44	0.56	2.00	0.91
Item 15			0.52									0.45	0.55	2.40	0.90
Item 4				0.73								0.75	0.25	1.90	0.89
Item 5				0.71								0.66	0.34	1.70	0.91
Item 3**				0.69								0.64	0.36	1.80	0.92
Item 9				0.43								0.36	0.64	3.30	0.91
Item 7					0.65							0.59	0.41	1.80	0.89
Item 8					0.60							0.52	0.48	2.00	0.86
Item 6**					0.48							0.66	0.34	4.00	0.88
Item 22**					0.42							0.56	0.44	5.50	0.91
R30						0.88						0.80	0.20	1.10	0.61
R31						0.77						0.66	0.34	1.20	0.60
R28						0.37						0.22	0.78	2.40	0.78
Item 2							0.75					0.71	0.29	1.60	0.86
Item 1							0.73					0.64	0.36	1.50	0.84
Item 21***								0.57				0.72	0.28	3.30	0.91
Item 10								0.55				0.53	0.47	2.70	0.92
Item 26**								0.46				0.60	0.40	4.70	0.94
Item 36**									0.70			0.76	0.24	2.20	0.87
Item 17**									0.47			0.63	0.37	3.40	0.84
Item 25										0.49		0.43	0.57	2.80	0.88
Item 24**										0.34		0.48	0.52	5.80	0.92
Item 43**											0.53	0.59	0.41	2.90	0.86
Average values												0.57	0.43		0.89
Cronbach's Alpha (R^2)	0.87	0.79	0.72	0.80	0.71	0.85	0.76	0.68	0.72	0.54	0.64				

NB: h^2: communalities; u^2: uniqueness; com: common variance; KMO: Kaiser-Meyer-Olkin

5.2.5. Validation of the EFA using post-factor analysis

Post factor correlations test showed no correlation between factors and indicators in the diagram Fig 5.5 below. Cronbach's alpha as a reliability analysis was also run on each factor using the R^2 values to double check.

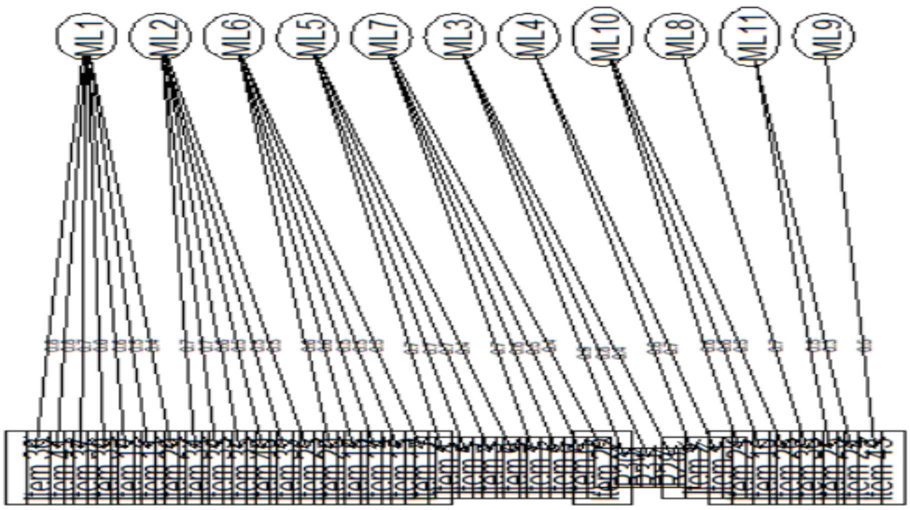


Fig 5. 5: Graphical representation of 11 factors identified in EFA

The proportion of variance explained indicates the amount of variance the factor accounted for by an item, or the variance in the dataset accounted for by the factors. Table 5.6 shows that the first three factors explained 11.0%, 7%, and 7% of the common variance respectively. Also, we preferred the factor solution, which explained more than 60% of the total variance in the dataset (Hair *et al.*, 2012). Table 5.6 shows that by the eighth factor (ML10) the factors accounted for 87% of the variance in the dataset. Factor (ML10) seems to fall short of post-factor stability. For instance, the CA of ML10 is lower than ML4 and ML8, even though it had higher items loading high on it in Table 5.5. Looking at proportion of variance explained, ML4 (8%) and ML10 (7%). The trend is same for regression coefficient where ML4 is higher than ML10, however, the trend reverses on the minimum correlations of factors. The foregoing analysis points to eight factors instead of the seven that were derived by the item's loadings. However, we still run additional analysis to confirm what the smallest number of factors should be in our dataset.

We used the Cronbach's alpha (CA) in Table 5.6 to examine the internal consistency for each factor. The alphas were moderately adequate, the highest being 0.87, and the least being 0.54.

Table 5. 6: Measures of factor scores adequacy using CA, Variance explained and correlations scores

Measures of factor score adequacy	ML1	ML2	ML6	ML5	ML7	ML3	ML4	ML10	ML8	ML11	ML9
Cronbach's Alpha (R^2) of factors	0.87	0.79	0.72	0.80	0.71	0.85	0.76	0.68	0.72	0.54	0.64
SS loadings	4.19	2.75	2.52	2.46	1.95	1.70	1.63	1.56	1.24	0.79	0.79
Proportion Variance	0.11	0.07	0.07	0.06	0.05	0.04	0.04	0.04	0.03	0.02	0.02
Cumulative Variance	0.11	0.18	0.25	0.31	0.37	0.41	0.45	0.49	0.53	0.55	0.57
Proportion Explained	0.19	0.13	0.12	0.11	0.09	0.08	0.08	0.07	0.06	0.04	0.04
Cumulative Proportion	0.19	0.32	0.44	0.55	0.64	0.72	0.80	0.87	0.93	0.96	1.00
Correlation (regression) scores with factors	0.93	0.89	0.85	0.90	0.84	0.92	0.87	0.83	0.85	0.73	0.80
Minimum correlation of factor scores	0.75	0.59	0.44	0.60	0.42	0.70	0.52	0.37	0.45	0.08	0.28

The post – factor analysis of EFA pattern structures uses several measures to assess the stability of the identified factors in representing the underying constructs in the dataset. In this study, we must ascertain whether the decision to use 11 factors was better than the 6 factors identified by the earlier tests.

First, we use the BIC as a relative measure which combines the goodness of fit with model complexity. Models with the minimum Bayesian Information Criteria are selected (Acquah, 2010). Here, BIC for 6-factor is 2.1, and for 11-factor, is 2.5. The BIC is reluctant to add more parameters, thus 6-factors is better than 11. We do additional analysis of the two models and interpret them as follows:

H_0: 6 factors are sufficient for the dataset: χ^2 (522) = 741, we failed to reject the null hypothesis and consider the 6 – factor model adequate for our dataset.

Statistically, we recall that we are looking for a combination of Tucker–Lewis's index (TLI) and Standardized root mean squared residual (SRMR). A TLI 0.98 > 0.96 (Xia and Yang, 2019) is excellent and SRMR of 0.04 (adjusted SRMR = 0.05) < 0.08 is preferred (Montoya and Edwards, 2021). Evidently, the 6-factor model is an ''excellent'' fit for our dataset.

H_0: 11 factors are sufficient for the dataset: χ^2 (340) = 703, we failed to reject the null hypothesis and consider the 11 – factor model adequate for our dataset.

Similarly, A TLI 0.99 > 0.96 (Xia and Yang, 2019) is excellent and Standardized root mean squared residual (SRMR) 0.02 (adjusted SRMR = 0.03) < 0.08 (Montoya and Edwards, 2021) equally adequate. Conclusively, our 11 - factor model is equally an ''excellent'' fit for our dataset.

In summary, looking at the factor that our BIC, TLI and SRMR test supported the 11 – factor models suggests that the decision to model with that was not misplaced. Further, using BIC (2.1 lower than 2.5), the criteria favours a 6- factor model, also, using TLI (0.98 <0.99) though both exceed the threshold of 0.96, TLI favoured 11- factor model. Lastly, the SRMR (0.02 <0.03) also favoured the 11- factor model. Thus, two out of three criteria favoured 11 factors while only one supported the 6 – factor model. We will consider six factors as the best factor structure in our dataset.

The differences in number of factors as revealed by the various indices supports the assertion of earlier researchers that, EFA seeks to identify, the smalled and most significant number of factors (Fabrigar *et al.*, 1999; Cattell, 2010; Lloret, Ferreres and Tomás, 2017). We remind ourselves that, no single technique is reliable in all situations (Fabrigar *et al.*, 1999; Cattell, 2010). Hence using various techniques and carefully judging each plausible solution is appropriate (Lloret, Ferreres and Tomás, 2017).

5.2.6 Factor interpretation

To label the factors in the model, researchers should examine the factor pattern to see the items with the highest loading on factors and then determine what those items have in common. What these items share connotes the meaning of the factor. Alternatively, researchers can use the Gestalt theory of psychology, that is explained below.

Most of our factors have Cronbach's alpha ($\alpha = 0.54 – 0.87$), showing acceptable internal consistency among all items. Also, the average inter-item covariance index shows a good relationship amongst the items loading on factors. Overall, these analyses indicated that six factors which explain 72% of the variance in the dataset (Table 5.6) were underlying the maturity of the LMICs for ConsHI.

In Table 5.5, the Items (4,7,20, 30, 34, and 38) have the highest loadings on the factors ML1, ML2, ML6, ML5 and ML3 respectively (see 4.7.6 and 4.7.7). We therefore supplement our choice of labels with Gestalt results (see 4.7.7). Table 5.7 shows the comparative assessment of both the theoretical and psychological (Gestalt) labelling of our factors in the dataset.

Table 5. 7: Labelling and interpretation of facilitating factors for ConsHI using Gestalt and theoretical models

Item number	Item descriptions	Factor label (t – factors)	Theoretical model (t-factors)	Gestalt theme (e – factors)
4	Using a mobile phone or the Internet helps me do things more quickly.	Performance Expectancy	UTAUT and UTAUT2	Benefits of mobile phones
7	I believe that I can search the Internet for health information.	Level Zero Services	ConsHI 0	Confidence in Level 0 or 1
20	I am confident that I could take actions that will help prevent or minimise some symptoms or problems associated with my health condition.	Confidence and knowledge to take action	PAM	
30	I don't want a mobile phone or the Internet to change the way I deal with health relevant problems.	Resistance to Change	UTAUTe	Self-awareness of health consciousness
34	I am confident I can figure out solutions when new situations or problems arise with my health condition.	Taking Action	PAM	
38	I plan to use a mobile phone or the Internet frequently.	Behavioural Intention	UTAUT and UTAUT2	Habit of using mobile phones/internet

We labelled the dominant factors as e – factors (meaning exploratory factors), that could influence the maturity of the citizens for ConsHI using the highest factor loadings and validated it through a “Gestalt” experiment (Table 5.7).

Notably, the Gestalt experiment (Table 5.6) supported four of the six e – factors (Table 5.7). On the other hand, the Gestalt experiment did not identify one of the dominant factors labelled by the high factor loadings and theoretical models. Six prevalent factors are stable across the whole data set as facilitators of the maturity of Citizens for ConsHI.

5.3 STRUCTURAL EQUATION MODELS (SEM)

Conventional proponents of EFA (Costello and Osborne, 2005; Henson and Roberts, 2006; Memon *et al.*, 2017) agree that results from EFA are a starting point for theory development since EFA results are mostly thought – provoking. Researchers should report notable limitations of EFA in accurately identifying constructs for model predction, particularly in our case where model prediction is a key objective. Resumably, researchers should meticulously follow best practices that require admission of such limitations and supporting the need for confirmatory techniques.

Considering the stability of our factors in explaining a more than 50% of the variance in the dataset, it will be acceptable to proceed with the SEM using these factors as the first step manifest variables in our predictive modelling. However, the factors of the EFA results are not accurate for model prediction and theory development. For instance, EFA techniques do not support the testing of measurement invariance (in relation to groups and covariates), which is inherent in our study of ConsHI maturity.

In addition, Marsh *et al.* (2014) have opinioned that, researchers use optimal techniques (e.g., t-tests, analyses of variance [ANOVAs], or multiple regressions) to statistically model the relationships between items and critical constructs. They explained that constructs identified by EFA must be converted to suboptimal scale or factor scores, which inevitably affects the precision of the scores. When these scores are used in model prediction, the resultant effect is error models that mislead the scientific community and negatively direct knowledge growth. Hence, we proceeded with our SEM using the initial items (original dataset) in the dataset instead of constructs that were produced from our EFA.

Hypothesis of the study:

1. HA: There is a positive relationship between APTITUDE and the maturity of citizens for ConsHI
2. HB: There is a positive relationship between ATTITUDE and the maturity of citizens for ConsHI
3. HC: There is a positive relationship between CONFIDENCE and the maturity of citizens for ConsHI
4. HD: There is a positive relationship between MOTIVATION and the maturity of citizens for ConsHI

Generally, we hypothesis that:

There is a significant categorical moderating effect of demographic variables (Residence, Gender, Age, Marital Status, Education, Employment status, recent medical care) on the relationship between constructs (lower (first) order components (LOCs) and factors (higher (second) order components; HOCs).

5.3.1 Data Characteristics

The characteristics of the data is described using the sample size, the distribution, hold out sample and measurement of the various items in the dataset. Researchers share different views on the acceptable minimum sample size. First Jannoo *et al.*(2014), argued that PLS can produce meaningful results even when the sample size is 20. We are also recall that others (Kreft and Aschbacher, 1994; Barclay, Thompson and Higgins, 1995; Cohen, 2013; Wong, 2013; Memon *et al.*, 2020) have made varying suggestions on the minimum sample size required for PLS-SEM. Remarkably, our sample size of 1,800 seems to satisfy more than 80% of the recommendation and other criteria used in choosing sample size. Table 5.8 shows the various recommendations and their literature source for choosing sample size.

Table 5. 8: Establishing the adequacy of sample size using various criterion.

Guiding Rules	*Expected sample size*	Observed sample size	Decision	Literature Source
10 - times indicator rule	*510*	**1800**	Very high	(Barclay, Thompson and Higgins, 1995)
10 times the largest number of inner model paths directed at a particular construct	*160*	**1800**	Very high	(Barclay, Thompson and Higgins, 1995)
sample to item ratio (5:1)	*255*	**1800**	Very high	(Memon *et al.*, 2020)
The power analysis model	*200*	**1800**	Very high	(Cohen, 2013)
100/10 rule (100 groups with a minimum of 10 individuals per group)	*1000*	**1800***	very high	(Kreft and Aschbacher, 1994; Wong, 2013)

NB: *Six countries with 300 respondents per group at 3 levels of abstraction; *italics* are guiding rules for each criterion. **Bold,** is the results of our dataset

After establishing the adequacy of the sample size, we ascertain the distribution of the dataset. Table 5.4 above shows distributional characteristic of our dataset for both the moderating (demographic) items and the ConsHI related items (Item 1 – Item 43). Our dataset satified the requirement for a normal distribution and shows a good normal distribution (see 5.2.2).

Furthermore, the SmartPLS 4.0 offers the benefit of the Cramer von- Mises (CvM) p-value analysis (Stephens, 1970). In the CvM, we test the hypothesis:

H_0: the dataset is not normally distributed and H_1: the dataset is normally distributed

At 95% confidence level, if the CvM (p – value) is less than 0.05 we fail to accept the null hypothesis. In Table 5.4, all the CvM values (0.00) are all less than 0.05. Thus, we fail to accept the null hypothsis that the dataset is not normally distributed and concluded that our dataset met the assumptions of normality and proceed to test our model.

We further examined influential outliers and collinearity in the data and results for these issues (Hair *et al.*, 2010, 2011). We did not see any pattern like a straight lining and suspicious response patterns using the standard deviations of the indicators (Sarstedt *et al.*, 2017). Our assessment of the standard deviations also supported that our data did not show any spurious, missing, or influential indicators. In *Table C.1* of the appendices, we observed some erroneous zero entry in three variables (Item6, Item 14, and Item39). We assessed the missing and spurious observations in the dataset, and there was no problem in our data to raise any concerns. The threshold for missing values differs depending on the study type. However, according to best practices, 5% is the maximum acceptable missing per variable for a study to proceed with analysis (Robins, 2014; Sarstedt, Ringle and Hair, 2014). Notably, in Table 5.4, it was 1 missing value to one item of the demographic variables, resulting in about 8 out of 1,800 observations, that is 0.4% which is far less than the threshold of 5%. Thus, our dataset is sufficient for PLS-SEM. Also, using number of missing values (*Table C.1*) per observations, the acceptable threshold is 15%, again, our data is below the 15% observation ratio per Hair *et al.* (2017) prescription. Furthermore, we adopted mean replacement in our SmarptPLS software for these instances (Hair *et al.*, 2011). Our variables supported our research's parametric and non-parametric statistics (Gosavi, 2015; Graffigna *et al.*, 2015; Youn *et al.*, 2017).

The foregoing establishes that the characteristic of our dataset is appropriate to proceed with our PLS – SEM model. We proceed to analyse the characteristics of the model we intend to use considering our conceptual model (Fig 2.6).

5.3.2 Model Characteristics

Model characteristics consisting of graphically representing all the relationships in the proposed model. This also includes establishing the relationship between items and the first order consttructs, the first order and higher order constructs including teh moderating variables and how these are related either reflective or formative (Diamantopoulos and Siguaw, 2006; Crocetta *et al.*, 2021).

First our nomological model is design using the recommendation of Hayduk and Littvay (2012) that modelling relationships using a single complete SEM is better than separating the measurement model from the structural model for analysis. In Fig 5.6, we present the complete nomological model that will be used to establish the magnitude of the items for the LOCs, the relationship of all items with the respective LOCs and validate this model using the reliability and validity of this model.

Consequently, we assessed the quality of our measurement model for the LOCs with a composite nomological framework of the entire model using the repeated indicator approach to estimate our second-order parameters since we are building a model from indicators to latent variables (Crocetta *et al.*, 2021).

Once, our nomological model is complete (Fig 5.6), next we need to confirm the specification of the measurement model (see 4.8.11.1) whether all relationships are reflective, or formative and maybe a combination using the CTA (4.8.11.2).

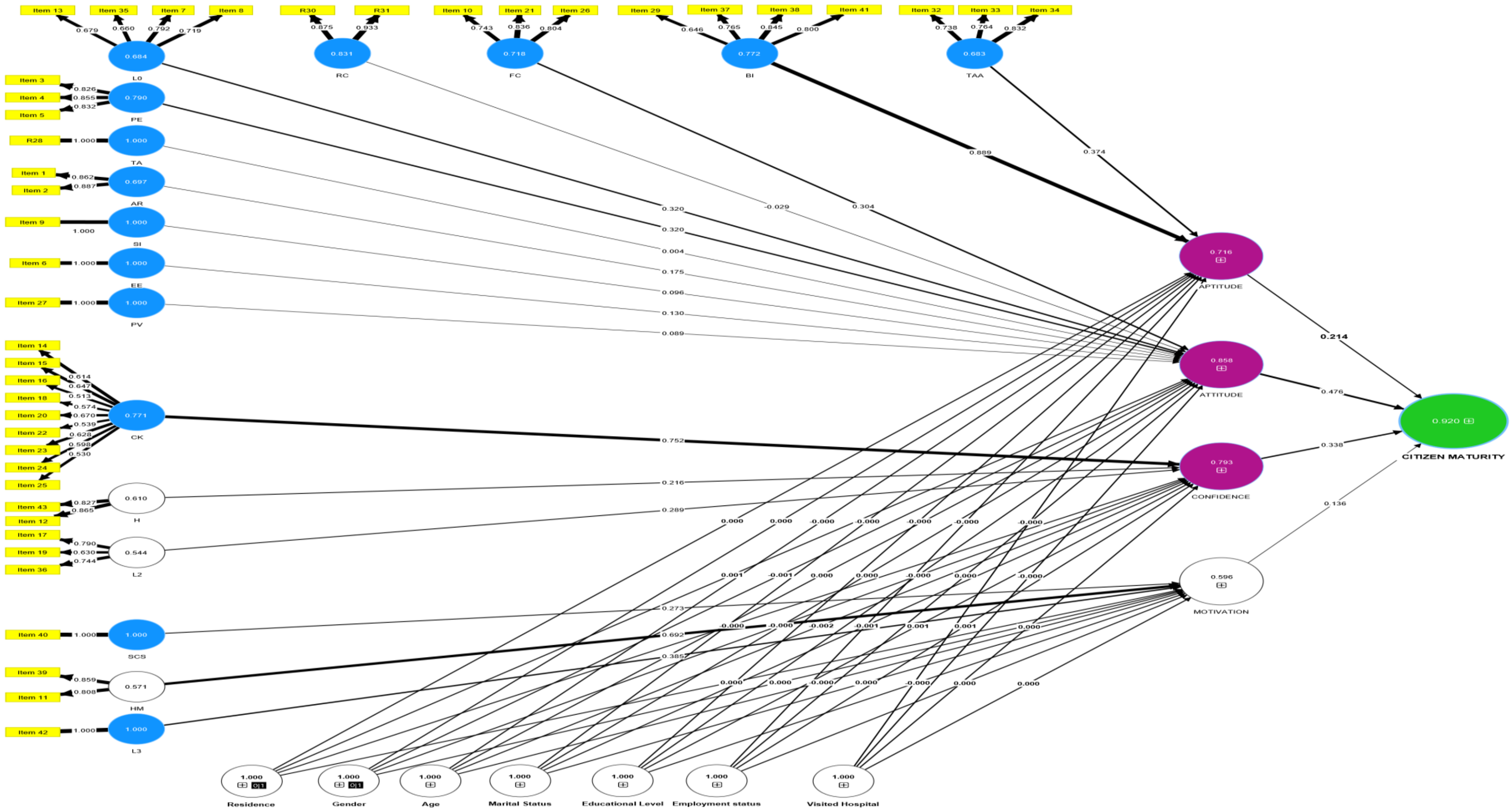


Fig 5. 6: Illustration of nomological mode for assessing the measurement model of LOCs and estimating their values

5.3.2 Assessing model specification using Confirmatory Tetrad Analysis (CTA)

Model specification is establishing whether the relationship between the items and the LOCs are reflective or formative mode (see 4.8.11.1 for definitions of reflective and formative). In a complex nomological model, researchers sometimes encounter a mix of the two in one nomological model (Coltman *et al.*, 2008; Sarstedt *et al.*, 2016, 2019). The relationship is hypothesed first based on theory and confirmed using the CTA.

In our case we hypothesed all items and LOCs have a reflective relationship. For such a hypothesis, according to Guderian *et al.* (2008b), each tetrad (means four items, and denoted by τ) is expected to be zero to confirm our theoretical position. When one or more of the tetrads in the model is significantly different from zero, it is formative.

Using a vanishing tetrad equals zero, then all LOCs implied non-significant tetrads must vanish (Bollen and Ting, 2000). Bollen and Ting (2000) postulated testing the hypothesis:

H_0: $\tau= 0$ (i.e., the tetrad equals zero and vanishes; hence reflective mode)

H_1: $\tau\neq 0$ ((i.e., the tetrad does not equal zero; hence, formative mode)

In view of this, Bollen and Ting (2000) concluded that a non-significant (p-value >0.05) test statistic supports H_0 meaning a reflective model, while, a significant (p-value <0.05) test statistic favours H_1 and casts doubt on the reflective mode.

Referring to tables in appendice (Table C.1), and considering the guidelines of Wong (2013), we observed that, contrary to the assertion of Ting (1995), the SmartPLS 4.0 algorithm for CTA- SEM did not support constructs with less than four indicators, compelling us to adhere to the suggestion of Wong (2013) that we consider only LOCs with a mimum of four items. In addition, we also used the supporting theories (Hibbard *et al.*, 2005; Venkatesh, Thong and Xu, 2012) to formulate the mode of the constructs with less than four indicators as suggested by literature (Wong, 2013).

Using Table C. 2 (appendice) to assess the mode of the LOCs with more than four items using CTA-SEM, the results show that all but CK was different (see Fig C.1 in appendices). Notably, we failed to reject the alternative hypothesis for CK and conclude that CK is a formative mode construct (Fig C.1) in our model. We validated the results with the suggestions of Smith and Cribbie (2013) using the Bonferroni adjustments of the significance and CK was still significantly different from zero.

However, subsequent iterations of the measurement model using CK in formative and reflective mode, showed insignificant difference in the factor loadings and other parameters of the measurement model. Further, considering the majority (19) of the tetrads being reflective compared to only 8 that were formative, and the fact that all the theoretical constructs used in this study are reflective, we switch the mode CK to reflective. Thus, keeping our initial model (Fig 5.6) and proceeding with all LOCs in reflective mode for the assessment of the measurement model.

5.3.3 Evaluation of the measurement model of LOC

The quality of the constructs in the study is assessed based on the evaluation of the measurement model. We evaluate the quality of the measurement model using the reliability and validity of the indicators and constructs in the measurement model.

5.3.3.1 Assessment of the Reliability of LOCs

Indicator reliability using indicator loadings on a factor

Reliability is evaluated using indicator loadings or factor loadings in the model. According to Urbach and Ahlemann (2010), indicator reliability is how well an item measures the underlying construct. The indicator reliability of a model is measured by examining the square of the item (outer) loadings, because the size of the outer loading is indicator reliability. An indicator's outer loading should be at least 0.708 before it is acceptable (Sarstedt *et al.*, 2017). Also, the outer loadings of all indicators should be statistically significant (Hair *et al.*, 2010).

To establish indicator reliability, we used the outer loadings of 0.7 or higher (Sarstedt *et al.*, 2017). In Table 5.9, we see that some indicators, particularly all the CK items have loadings (0.53-0.67) less than 0.7, meaning, these items do not sufficiently explain CK. However, extant studies (Reinartz, Haenlein and Henseler, 2009; Sarstedt *et al.*, 2016) suggested that items with factor loadings from 0.40 to 0.60 shall be considered for removal only if deletion results in a substantial increase of the factor loadings of the remaining items and consequently, increasing either the composite reliability (CR) or average variance extracted (AVE). The deletion of items in done in increasing order of magnitude, with the smallest (Item 16) first and assessing the effect of such on the CR and AVE. eventually, we removed five items (Item 16, Item 22, Item 23, Item 24 and Item 25) before establishing sufficient indicator reliability (see Table 5. 10).

Table 5. 9: First stage validation of factor loadings of LOC Measurement model

Indicators	AR	BI	CK	EE	FC	H	HM	L0	L2	L3	PE	PV	RC	SCS	SI	TA	TAA
Item 1	0.86																
Item 2	0.89																
Item 29		0.65															
Item 37		0.76															
Item 38		0.84															
Item 41		0.80															
Item 14			0.61														
Item 15			0.65														
Item 16			0.51														
Item 18			0.58														
Item 20			0.67														
Item 22			0.54														
Item 23			0.63														
Item 24			0.59														
Item 25			0.53														
Item 6				1.00													
Item 10					0.74												
Item 21					0.84												
Item 26					0.80												
Item 12						0.86											
Item 43						0.83											
Item 11							0.80										
Item 39							0.86										
Item 13								0.68									
Item 35								0.66									
Item 7								0.79									
Item 8								0.72									
Item 17									0.79								
Item 19									0.63								
Item 36									0.75								
Item 42										1.00							
Item 3											0.83						
Item 4											0.86						
Item 5											0.83						
Item 27												1.00					
R30													0.87				
R31													0.94				
Item 40														1.00			
Item 9															1.00		
R28																1.00	
Item 32																	0.74
Item 33																	0.77
Item 34																	0.83

NB: CK (Formative) was converted to reflective constructs following the results of the CTA-SEM in the model characteristics analysis.

Bold are outer loadings less than 0.708

Table 5. 10: Revised factor loadings of LOC Measurement model

Indicator	AR	BI	CK	EE	FC	H	HM	L0	L2	L3	PE	PV	RC	SCS	SI	TA	TAA
Item 1	0.86																
Item 2	0.89																
Item 29		0.65															
Item 37		0.76															
Item 38		0.84															
Item 41		0.80															
Item 14			0.70														
Item 15			0.68														
Item 18			0.70														
Item 20			0.74														
Item 6				1.00													
Item 10					0.74												
Item 21					0.84												
Item 26					0.80												
Item 12						0.86											
Item 43						0.83											
Item 11							0.80										
Item 39							0.86										
Item 13								0.68									
Item 35								0.66									
Item 7								0.79									
Item 8								0.72									
Item 17									0.79								
Item 19									0.62								
Item 36									0.75								
Item 42										1.00							
Item 3											0.83						
Item 4											0.86						
Item 5											0.83						
Item 27												1.00					
R30													0.87				
R31													0.94				
Item 40														1.00			
Item 9															1.00		
R28																1.00	
Item 32																	0.74
Item 33																	0.77
Item 34																	0.83

NB: After removing five items of CK. Total items remaing are 38 (43 less 5)

Table 5. 11: Revised and validated indicators of the LOCs first draft for the model

Factor	Construct	The final list of items
	PE	3, 4, 5
	EE	6
	SI	9
	FC	10, 21, 26
Attitude	PV	27
	AR	1, 2
	RC	30, 31
	TA	28
	L0	7, 8, 13, 35
Confidence	H	12, 43
	***CK**	14, 15, 18, 20,
	L2	17, 19, 36
Aptitude	BI	29, 37, 38, 41
	TAA	32, 33, 34
Motivation	HM	11, 39
	SCS	40
	L3	42

NB: *PE = Performance Expectancy, EE = Effort Expectancy, SI = Social Influence, FC = Facilitating Conditions, AR = believe Active Role is important, L0 = Level 0 Services, *HM = Hedonic motivation, H = Habit, PV = Price Value, CK = Confidence and Knowledge to take action, TA = Technology Anxiety, L2 = Level 2 Services, *BI = Behavioral Intention, TAA = Taking Action, RC = Resistance of Change, *SCS = Staying the Course under Stress, L3 = Level 3 Services. **Bold and asterisk** CK indicates the validated number of indicators (Unvalidated Item 16, Item 22, Item 23, Item 24 and Item 25).

5.3.3.2 Assessing internal consistency using Cronbach's Alpha (CA), Composite reliability (CR) and rho_A

Internal consistency reliability is the extent to which a measuring instrument is stable and consistent. A measurement model is said to have satisfactory internal consistency reliability when the CR of each construct exceeds the threshold value of 0.7 (Risher *et al.*, 2019). According to Sarstedt *et al.* (2019), The minimum requirement to establish reliability for these estimates is 0.7. Specifically, CA ranges between 0.56 – 1.00 while CR is from 0.78 to 1.00. Essentially, the minimum requirement to establish reliability for these estimates is 0.7 (Sarstedt *et al.*, 2019).

Table 5.12 shows that some CA values were below the threshold of 0.7; however, all our CR values exceeded the minimum of 0.7. Further, the rho_A values appeared to be the same as the CA value. We think our instruments are stable and consistent in measuring the constructs since our CR values were very high though some CA and rho_A values fell below the minimum thresholds(Hair *et al.*, 2010). Thus, internal consistency is established, and we proceed to assess the validity of the constructs.

Table 5. 12: Assessing internal Consistency Analysis using CA, rho_A and CRA

Constructs	CA	rho_A	CR
AR	**0.69**	0.70	0.87
BI	0.76	0.77	0.85
CK	**0.67**	**0.67**	0.80
EE	1.00	1.00	1.00
FC	0.71	0.72	0.84
H	**0.61**	**0.61**	0.84
HM	**0.56**	**0.57**	0.82
L0	**0.68**	**0.68**	0.81
L2	**0.54**	**0.55**	0.77
L3	1.00	1.00	1.00
PE	0.79	0.79	0.88
PV	1.00	1.00	1.00
RC	0.78	0.85	0.90
SCS	1.00	1.00	1.00
SI	1.00	1.00	1.00
TA	1.00	1.00	1.00
TAA	**0.68**	**0.68**	0.82

NB: Bold are CA and rho_A values lower than the 0.7 threshold values

5.3.3.3 Assessing the validity of LOCs

Validity in PLS-SEM is assessed using the convergent and discriminant validities of the various constructs.

Assessing convergent validity using AVE

According to Urbach and Ahlemann (2010), convergent validity is the degree to which individual items converge. Convergent validity is established when the AVE value is greater than or equal to the recommended 0.5 (Hair *et al.*, 2010). In table 5.13, we see that the AVE values of all the constructs exceeded 0.5; thus, our items converge to measure their respective underlying construct (Fornell and Larcker, 1981).

Table 5. 13: Assessing construct validity using AVE

Constructs	CR	AVE
AR	0.87	0.77
BI	0.85	0.59
CK	0.80	0.50
EE	1.00	1.00
FC	0.84	0.63
H	0.84	0.72
HM	0.82	0.70
L0	0.81	0.51
L2	0.77	0.53
L3	1.00	1.00
PE	0.88	0.70
PV	1.00	1.00
RC	0.90	0.82
SCS	1.00	1.00
SI	1.00	1.00
TA	1.00	1.00
TAA	0.82	0.61

Discriminant validity:

Discriminant validity is used to differentiate a construct's measures from one another (Urbach and Ahlemann, 2010).

In table 5.14, we used the Fornell-Larcker Criterion (FLC), (Fornell, Larcker and Fornell, 1981); discriminant validity is established when the leading (major) diagonals of the matrix have the highest value. First, using Robins (2014) proposal, the square root of each construct's AVE exceeds the correlations with other latent constructs, as shown in Table 5.14. Also, in the same Table 5.14 we see that the values in the major diagonals are the maximum values in all the constructs. Hence, the latent variables share more variance with their assigned indicators than any other latent variable. We thus assert that our model has passed the first test of discriminant validity.

Table 5. 14: Assessing discriminant validity using FLC

FLC	AR	BI	CK	EE	FC	H	HM	L0	L2	L3	PE	PV	RC	SCS	SI	TA	TAA
AR	**0.87**																
BI	0.30	**0.77**															
CK	0.26	0.28	**0.71**														
EE	0.32	0.38	0.18	**1.00**													
FC	0.33	0.53	0.40	0.53	**0.80**												
H	0.22	0.57	0.16	0.41	0.46	**0.85**											
HM	0.13	0.57	0.34	0.31	0.43	0.43	**0.83**										
L0	0.37	0.40	0.25	0.51	0.49	0.45	0.32	**0.71**									
L2	0.16	0.31	0.44	0.19	0.40	0.28	0.38	0.36	**0.72**								
L3	0.25	0.32	0.26	0.24	0.34	0.33	0.31	0.40	0.43	**1.00**							
PE	0.37	0.46	0.27	0.44	0.41	0.38	0.45	0.41	0.33	0.27	**0.84**						
PV	0.12	0.37	0.27	0.18	0.29	0.23	0.30	0.20	0.26	0.20	0.24	**1.00**					
RC	-0.11	-0.14	-0.09	0.02	0.01	-0.08	-0.01	0.00	0.08	0.01	-0.03	-0.17	**0.90**				
SCS	0.09	0.17	0.21	0.01	0.12	-0.05	0.24	0.16	0.28	0.22	0.13	0.15	0.03	**1.00**			
SI	0.20	0.20	0.27	0.19	0.27	0.22	0.23	0.29	0.31	0.21	0.41	0.17	0.00	0.03	**1.00**		
TA	-0.05	0.09	-0.01	0.10	0.09	0.00	0.11	-0.01	-0.03	-0.05	0.06	-0.09	0.26	0.05	-0.08	**1.00**	
TAA	0.22	0.11	0.42	0.13	0.21	0.03	0.20	0.30	0.31	0.23	0.14	0.20	-0.08	0.32	0.17	-0.12	**0.78**
Maximum value	0.87	0.77	0.71	1.00	0.80	0.85	0.83	0.71	0.72	1.00	0.84	1.00	0.90	1.00	1.00	1.00	0.78
Cronbach's Alpha	0.69	0.76	0.67	1.00	0.71	0.61	0.56	0.68	0.54	1.00	0.79	1.00	0.78	1.00	1.00	1.00	0.68
rho_A	0.70	0.77	0.67	1.00	0.72	0.61	0.57	0.68	0.55	1.00	0.79	1.00	0.85	1.00	1.00	1.00	0.68
Composite Reliability	0.87	0.85	0.80	1.00	0.84	0.84	0.82	0.81	0.77	1.00	0.88	1.00	0.90	1.00	1.00	1.00	0.82
AVE	0.77	0.59	0.50	1.00	0.63	0.72	0.70	0.51	0.53	1.00	0.70	1.00	0.82	1.00	1.00	1.00	0.61
The square root of AVE	0.87	0.77	0.71	1.00	0.80	0.85	0.83	0.71	0.72	1.00	0.84	1.00	0.90	1.00	1.00	1.00	0.78

Cross-Loadings (Henseler, Ringle and Sarstedt, 2015) is the second criterion assessment for discriminant validity assessment. In Table 5.15, the Max column shows the highest loadings of all indicators; observably, these highest scores loaded very well on their respective constructs. We are again affirming that our constructs distinct and we could proceed to the next level of our model analysis using the HTMT.

Table 5. 15: Assessing discriminant validity using indicator cross-loadings

Cross loadings	AR	BI	CK	EE	FC	H	HM	L0	L2	L3	PE	PV	RC	SCS	SI	TA	TAA
Item 1	**0.86**	0.22	0.21	0.27	0.30	0.19	0.05	0.29	0.16	0.20	0.28	0.09	-0.06	0.05	0.20	-0.05	0.18
Item 2	**0.89**	0.31	0.25	0.30	0.28	0.19	0.16	0.36	0.12	0.24	0.36	0.12	-0.13	0.10	0.15	-0.03	0.20
Item 37	0.32	**0.76**	0.24	0.29	0.45	0.43	0.39	0.35	0.27	0.21	0.34	0.25	-0.08	0.11	0.12	0.12	0.04
Item 38	0.19	**0.84**	0.24	0.28	0.39	0.43	0.56	0.29	0.28	0.27	0.40	0.30	-0.14	0.21	0.16	0.08	0.11
Item 41	0.29	**0.80**	0.16	0.39	0.44	0.59	0.41	0.37	0.16	0.31	0.35	0.26	-0.13	0.06	0.15	0.10	-0.01
Item 29	0.13	**0.65**	0.23	0.22	0.33	0.30	0.37	0.21	0.23	0.19	0.34	0.34	-0.10	0.13	0.18	-0.03	0.20
Item 14	0.18	0.20	**0.70**	0.15	0.28	0.16	0.22	0.20	0.25	0.21	0.21	0.21	-0.09	0.10	0.23	-0.05	0.26
Item 15	0.25	0.16	**0.68**	0.13	0.19	0.09	0.18	0.21	0.26	0.13	0.19	0.15	-0.11	0.13	0.22	-0.04	0.35
Item 18	0.14	0.17	**0.70**	0.11	0.30	0.11	0.25	0.14	0.34	0.20	0.16	0.18	0.01	0.17	0.15	0.03	0.24
Item 20	0.18	0.27	**0.74**	0.13	0.35	0.11	0.32	0.16	0.38	0.21	0.20	0.23	-0.06	0.20	0.17	0.03	0.34
Item 6	0.32	0.38	0.18	**1.00**	0.53	0.41	0.31	0.51	0.19	0.24	0.44	0.18	0.02	0.01	0.19	0.10	0.13
Item 10	0.27	0.32	0.30	0.35	**0.74**	0.32	0.31	0.29	0.28	0.19	0.29	0.16	0.02	0.04	0.27	0.06	0.17
Item 21	0.28	0.49	0.33	0.51	**0.84**	0.39	0.38	0.44	0.29	0.27	0.35	0.28	-0.05	0.11	0.17	0.09	0.17
Item 26	0.23	0.43	0.31	0.40	**0.80**	0.40	0.34	0.42	0.39	0.34	0.33	0.23	0.06	0.13	0.21	0.08	0.17
Item 12	0.24	0.54	0.15	0.34	0.45	**0.86**	0.42	0.39	0.23	0.23	0.36	0.23	-0.08	-0.03	0.17	0.06	-0.01
Item 43	0.13	0.42	0.13	0.34	0.33	**0.83**	0.31	0.38	0.25	0.32	0.29	0.15	-0.05	-0.06	0.20	-0.06	0.07
Item 11	0.14	0.42	0.24	0.26	0.34	0.39	**0.80**	0.24	0.27	0.20	0.38	0.23	-0.03	0.14	0.19	0.08	0.09
Item 39	0.08	0.53	0.32	0.26	0.38	0.34	**0.86**	0.29	0.36	0.30	0.36	0.27	0.00	0.25	0.19	0.09	0.23
Item 13	0.27	0.35	0.30	0.32	0.41	0.40	0.24	**0.68**	0.31	0.27	0.29	0.16	-0.07	-0.03	0.23	-0.04	0.13
Item 7	0.30	0.29	0.13	0.45	0.36	0.33	0.27	**0.79**	0.16	0.26	0.35	0.12	0.07	0.13	0.17	0.06	0.13
Item 8	0.27	0.19	0.05	0.44	0.35	0.32	0.09	**0.72**	0.17	0.27	0.26	0.08	0.02	0.07	0.23	-0.01	0.15
Item 35	0.21	0.31	0.26	0.22	0.27	0.22	0.31	**0.66**	0.40	0.36	0.27	0.24	-0.03	0.31	0.21	-0.07	0.47
Item 19	0.26	0.25	0.28	0.22	0.31	0.29	0.16	0.30	**0.62**	0.31	0.19	0.15	-0.06	0.03	0.22	-0.07	0.12
Item 17	-0.01	0.11	0.39	0.05	0.22	0.10	0.27	0.13	**0.79**	0.26	0.25	0.21	0.07	0.20	0.26	-0.05	0.24
Item 36	0.11	0.31	0.28	0.15	0.35	0.23	0.38	0.35	**0.75**	0.37	0.27	0.21	0.14	0.36	0.21	0.05	0.31
Item 42	0.25	0.32	0.26	0.24	0.34	0.33	0.31	0.40	0.43	**1.00**	0.27	0.20	0.01	0.22	0.21	-0.05	0.23
Item 3	0.29	0.39	0.24	0.34	0.34	0.33	0.37	0.29	0.23	0.18	**0.83**	0.17	-0.01	0.06	0.35	0.07	0.07
Item 4	0.38	0.40	0.16	0.40	0.34	0.32	0.36	0.39	0.26	0.20	**0.86**	0.20	-0.03	0.14	0.31	0.04	0.11
Item 5	0.24	0.37	0.27	0.37	0.35	0.32	0.39	0.34	0.33	0.29	**0.83**	0.23	-0.04	0.13	0.37	0.03	0.18
Item 27	0.12	0.37	0.27	0.18	0.29	0.23	0.30	0.20	0.26	0.20	0.24	**1.00**	-0.17	0.15	0.17	-0.09	0.20
R30	-0.11	-0.11	-0.05	0.06	0.06	-0.05	0.00	-0.01	0.04	-0.04	-0.03	-0.17	**0.87**	0.01	-0.06	0.28	-0.09

R31	-0.10	-0.15	-0.10	-0.01	-0.03	-0.08	-0.02	0.00	0.09	0.04	-0.02	-0.14	**0.94**	0.05	0.03	0.21	-0.05
Item 40	0.09	0.17	0.21	0.01	0.12	-0.05	0.24	0.16	0.28	0.22	0.13	0.15	0.03	**1.00**	0.03	0.05	0.32
Item 9	0.20	0.20	0.27	0.19	0.27	0.22	0.23	0.29	0.31	0.21	0.41	0.17	0.00	0.03	**1.00**	-0.08	0.17
R28	-0.05	0.09	-0.01	0.10	0.09	0.00	0.11	-0.01	-0.03	-0.05	0.06	-0.09	0.26	0.05	-0.08	**1.00**	-0.12
Item 32	0.23	0.11	0.27	0.10	0.18	0.07	0.09	0.23	0.17	0.15	0.07	0.10	-0.05	0.20	0.10	-0.05	**0.74**
Item 33	0.12	0.04	0.32	0.02	0.10	-0.06	0.17	0.15	0.24	0.17	0.16	0.17	-0.08	0.32	0.15	-0.11	**0.77**
Item 34	0.16	0.10	0.39	0.17	0.21	0.04	0.20	0.29	0.30	0.22	0.12	0.19	-0.06	0.24	0.15	-0.13	**0.83**
Item 22	0.18	0.32	0.33	0.24	0.36	0.26	0.34	*0.49*	0.43	0.26	0.38	0.25	-0.01	0.21	0.26	0.00	0.25
Item 23	0.18	0.24	*0.42*	0.15	0.27	0.05	0.26	0.20	0.25	0.18	0.25	0.29	-0.11	0.27	0.16	-0.02	0.38
Item 24	0.27	0.23	*0.37*	0.22	0.34	0.14	0.12	0.26	0.14	0.18	0.20	0.17	-0.11	0.09	0.17	-0.03	0.33
Item 25	0.21	0.19	0.33	0.07	0.19	0.09	0.15	0.22	0.23	0.18	0.13	0.22	-0.14	0.15	0.17	-0.08	*0.34*
Item 16	0.31	0.21	0.36	0.25	0.28	0.17	0.08	0.28	0.05	0.08	0.17	0.16	-0.08	0.00	0.10	-0.01	0.18

NB: Bold text are factor loadings of items on their constructs

Heterotrait-Monotrait (HTMT) Ratio is the third and most modern approach to checking discriminant validity proposed by researchers (Robins, 2014; Sarstedt *et al.*, 2017; Hult, Sarstedt and Ringle, 2021). When using HTMT, less is better, researchers can use 0.85 which is the highest level or 0.9 which is equally acceptable (Johnston *et al.*, 2014; Henseler, Ringle and Sarstedt, 2015). Accordingly, we preferred 0.9 as the HTMT value for establishing discriminant (Johnston *et al.*, 2014; Henseler, Ringle and Sarstedt, 2015). Table 5.16 shows that HM and BI had a value of 0.86, which exceeds the 0.85 threshold but is less than 0.9 (Hult, Sarstedt and Ringle, 2021). Hence, discriminant validity is again confirmed using HTMT.

Table 5. 16: Assessing discriminant validity using HTMT

HTMT	AR	BI	CK	EE	FC	H	HM	L0	L2	L3	PE	PV	RC	SCS	SI	TA	TAA
AR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BI	0.41	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CK	0.38	0.39	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
EE	0.39	0.44	0.22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
FC	0.47	0.71	0.57	0.63	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
H	0.34	0.84	0.26	0.52	0.70	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
HM	0.20	**0.86**	0.55	0.41	0.68	0.74	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
L0	0.54	0.56	0.38	0.61	0.70	0.70	0.52	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
L2	0.29	0.49	0.72	0.26	0.66	0.50	0.68	0.61	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
L3	0.30	0.36	0.32	0.24	0.40	0.42	0.40	0.49	0.59	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PE	0.49	0.60	0.37	0.50	0.55	0.55	0.67	0.56	0.50	0.30	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PV	0.15	0.43	0.33	0.18	0.33	0.29	0.40	0.25	0.36	0.20	0.27	0.00	0.00	0.00	0.00	0.00	0.00
RC	0.15	0.18	0.14	0.04	0.08	0.11	0.03	0.10	0.19	0.05	0.04	0.19	0.00	0.00	0.00	0.00	0.00
SCS	0.10	0.19	0.26	0.01	0.14	0.07	0.31	0.23	0.37	0.22	0.15	0.15	0.03	0.00	0.00	0.00	0.00
SI	0.24	0.23	0.33	0.19	0.32	0.28	0.30	0.35	0.43	0.21	0.46	0.17	0.06	0.03	0.00	0.00	0.00
TA	0.06	0.13	0.07	0.10	0.11	0.09	0.14	0.07	0.10	0.05	0.06	0.09	0.30	0.05	0.08	0.00	0.00
TAA	0.32	0.19	0.62	0.15	0.30	0.13	0.30	0.45	0.50	0.28	0.20	0.24	0.11	0.39	0.21	0.15	0.00

NB: HTMT = Heterotrait-Monotrait Ratio; Bold

In summarising using the above nomological framework and applying our data, the preceding discussions show that our model is reliable and valid. Particularly, both indicator reliability and internal reliability of constructs were adequate. Also, both the convergent and discriminant validity were well established in our LOC model. SWe proceed to assess the HOCs using the LOCS of our nomological framework.

5.3.4 Specification and evaluation of HOCs

Our first stage, Reflective-Formative HOCS, is shown in Fig 5.7 below. We follow the steps as proposed in the specification and estimations of HOCS in chapter four (section 4.8.15)

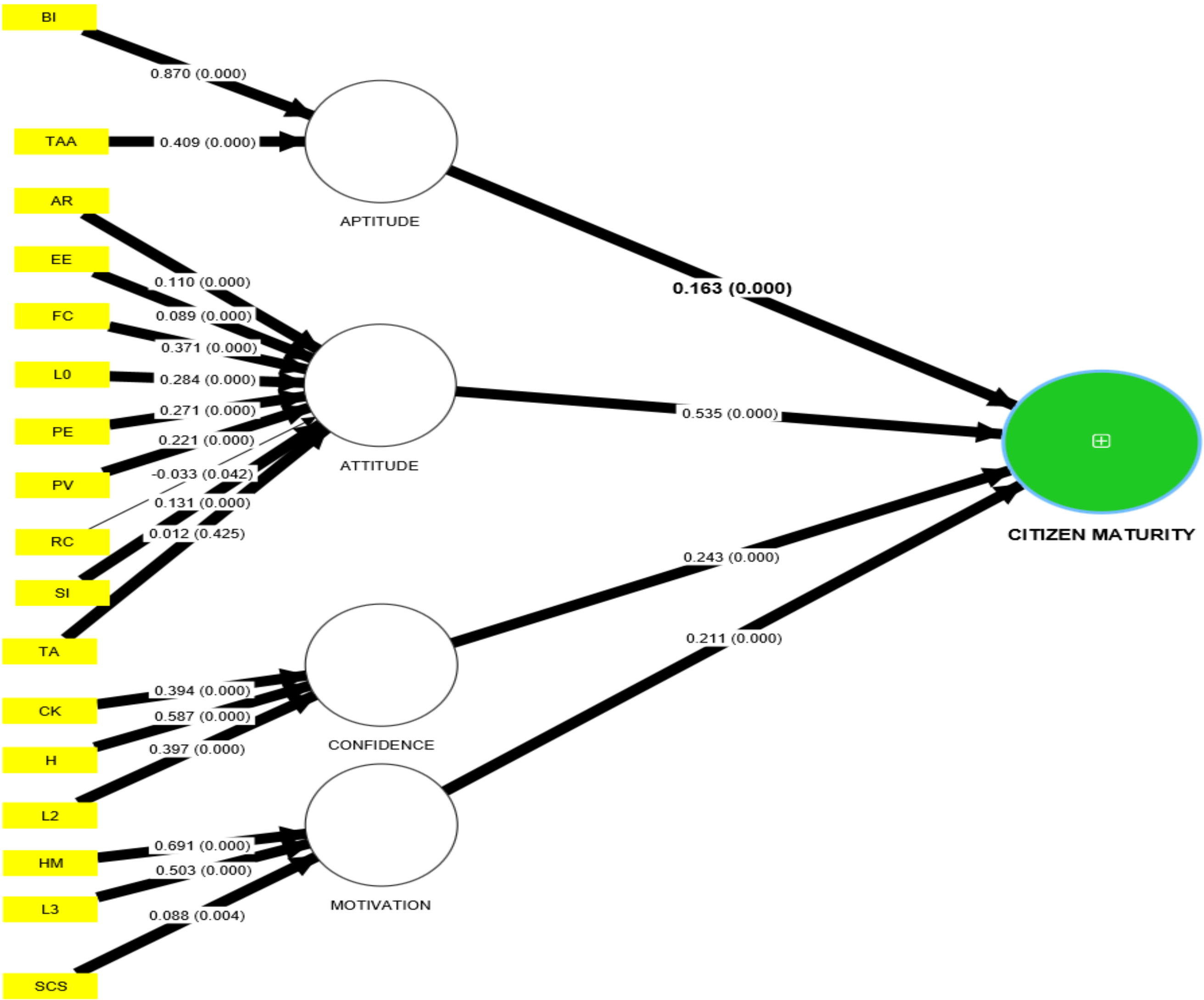


Fig 5. 7: The HOCs nomological model is shown above:

5.3.4.1 Assessing the measurement model of the hocs

The tests conducted on our data have provided enough evidence to support the quality of LOCs. Precisely, we have measured the indicators for our LOCs and, as such, can use their latent values to estimate our HOCs as required by the disjoint two-stage approach. Subsequently, we include the latent values of the LOCs into our dataset and proceed similarly to assess our HOCs measurement model.

Assessing the validity of reflective – formative HOCS models

The validity of formative models is evaluated using convergent validity. Convergent validity is the degree to which indicators converge to cause a latent variable (constructs). Statistically, redundancy analysis is used to assess the convergent validity of formative models (Chin, 1998). To establish convergent validity in a formative mode, the path coefficient (Beta = β) linking the constructs should be at least 0.70 (i.e. $\beta >= 0.7$) (Hair, Sarstedt and Ringle, 2020).

Sarstedt, Ringle and Hair (2020) mentioned that redundancy analysis is achieved using a formative construct as an exogenous latent variable predicting the same construct operationalised by reflective indicators. Alternatively, a single global item summarises the essence of the construct that the formative indicators are intended to measure. To identify indicators that have a global level representation of our constructs, we used the outer loadings table of the LOCs, which included these constructs in the nomological framework. The Table 5.17 below, shows that Item 38, Item 6, Item 20 and Item 39 loaded highly on Aptitude, Attitude, Confidence and Motivation, respectively. Specifically, Hair *et al.* (2017) advocated that, all the outer loadings should be equivalent to 0.7, meaning they each explained more than 50% of the variances on these constructs and thus made them highly representative of their respective constructs (Hair Jr *et al.*, 2017). We, therefore, used these items as global indicators for their individual constructs in our redundancy analysis.

Table 5. 17: Identifying globally indicators as global proxies for second-order constructs

Indicators	APTITUDE	ATTITUDE	CONFIDENCE	MOTIVATION
Item 29	0.64			
Item 32	0.39			
Item 33	0.35			
Item 34	0.43			
Item 37	0.68			
Item 38	**0.78**			
Item 41	0.69			
Item 1		0.49		
Item 2		0.54		
Item 3		0.61		
Item 10		0.54		
Item 13		0.56		
Item 21		0.66		
Item 26		0.62		
Item 27		0.38		
Item 35		0.49		
Item 4		0.67		
Item 5		0.63		
Item 6		**0.69**		
Item 7		0.61		
Item 8		0.55		
Item 9		0.48		
R28		0.03		
R30		-0.04		
R31		-0.06		
Item 12			0.43	
Item 14			0.56	
Item 15			0.56	
Item 16			0.42	
Item 17			0.53	
Item 18			0.55	
Item 19			0.50	
Item 20			**0.63**	
Item 22			0.60	
Item 23			0.54	
Item 24			0.50	
Item 25			0.47	
Item 36			0.52	
Item 43			0.39	
Item 39				**0.76**
Item 40				0.56
Item 42				0.68
Item 11				0.65
Max	**0.779**	**0.695**	**0.625**	**0.761**

NB: Bold text and numbers are indicators used as proxies for our global models.

Looking at the diagrams (Fig 5.8) below, the beta (β >=0.7) values of Aptitude (0.845), Attitude (1.000), Confidence (0.744) and Motivation (0.865) are all above the required minimum of 0.7. Hence, we have established convergent validity for all our second-order latent constructs and can proceed to conduct our reliability analysis.

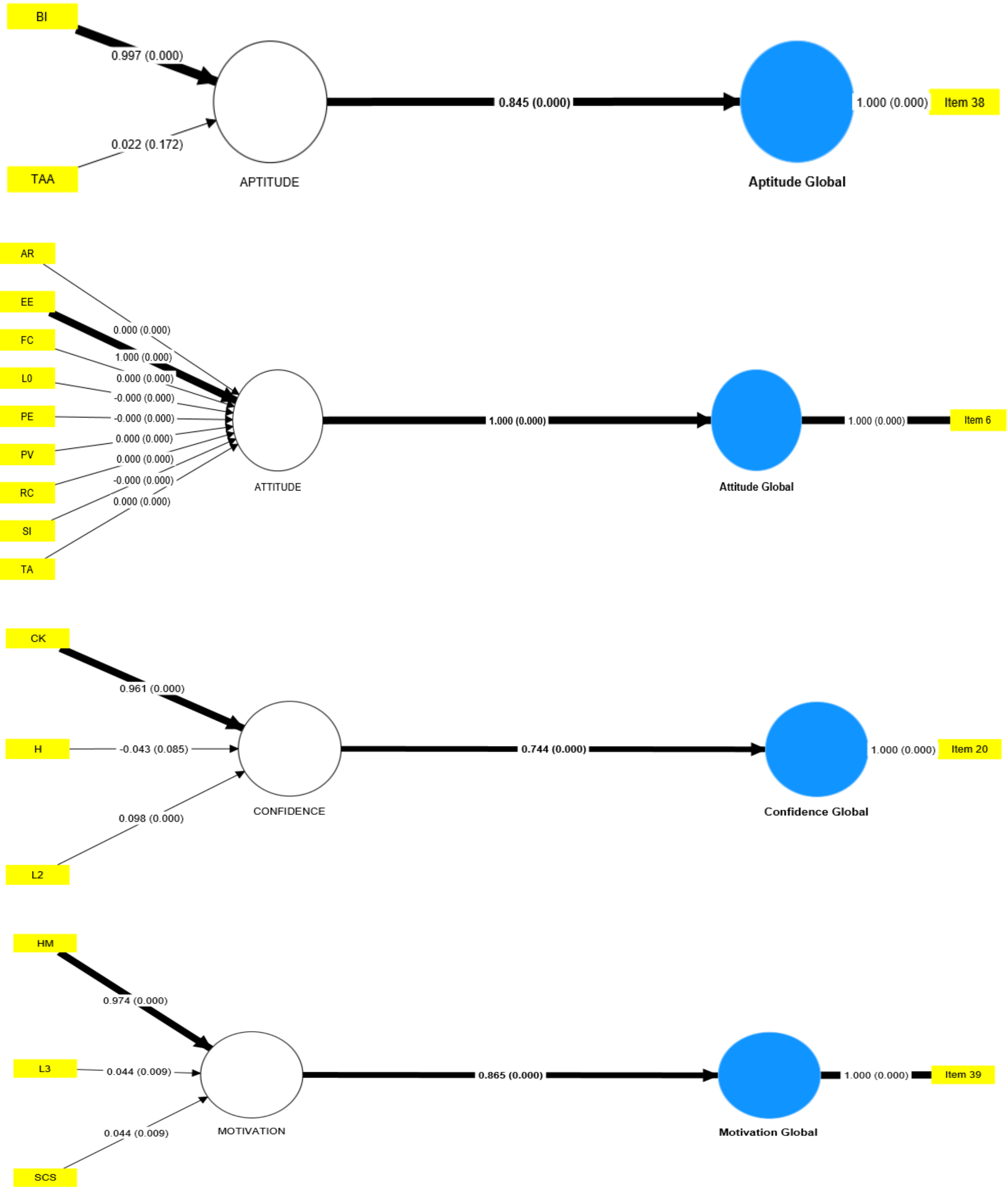


Fig 5. 8: Analysis of convergent validity using redundancy (Hair, Sarstedt and Ringle, 2020).

Reliability Analysis of formative models using Collinearity

We ascertain the quality of an indicator in formative models by how they relate to each other. Collinearity is when there is a high correlation between two formative indicators (Robins, 2014). Similarly, to assess Collinearity in our reflective LOCS, we used the guidelines of Diamantopoulos and Siguaw (2006) suggested that VIF should not exceed 3.3 (VIF<3.3) and Sarstedt, Henseler and Ringle (2011b) increased VIF threshold for Collinearity to 5. In table 5.18, the maximum VIF value was 2.28, which is far less than the 3.3 and 5 thresholds. Hence, we do not see collinearity issues amongst the indicators (LOCs) and can proceed to run our analysis at the next stage for the significance and relevance of these indicators.

Table 5. 18: Assessing indicator collinearity amongst formative indicators using VIF.

Construct	VIF<3.3
AR	1.38
BI	2.28
CK	1.58
EE	1.75
EE	1.68
FC	2.03
H	1.88
HM	1.84
L0	1.85
L2	1.69
L3	1.42
PE	1.78
PV	1.28
RC	1.19
SCS	1.30
SI	1.32
TA	1.17
TAA	1.45
Max	2.28

NB: Max means maximum value in the Table 5.18

Hence, our HOCs have no Collinearity issues, and we proceed to assess the model for the significance and relevance of these constructs to predict our outcome variable.

Significance and Relevance of Indicators

Statistically, we need to assess the relevance and significance of indicators. In PLS-SEM formative models, outer weights and outer loadings are used to evaluate formative indicators' statistical relevance and significance (Sarstedt *et al.*, 2017). Notably, all our formative indicators were relevant and significant except for TA. Table 5.19 revealed that TA was not significant (p-value = 0.43>0.05); thus, we considered the outer loadings of TA; again, the outer loadings (0.02) are also low and insignificant (0.55). Consequently, Hair et al. (2017a) offer an empirical ground to delete TA from the model and re-run the algorithm.

Table 5. 19: The statistics of the HOC nomological model

Outer Weights					Outer Loadings				
HOC	LOC	Path Coeff	t-value	P values	HOC	LOC	Path Coeff	t-value	P values
APTITUDE	BI	0.87	45.83	0.00	APTITUDE	BI	0.91	77.32	0.00
	TAA	0.41	15.32	0.00		TAA	0.50	13.96	0.00
ATTITUDE	AR	0.11	7.25	0.00	ATTITUDE	AR	0.52	18.28	0.00
	EE	0.09	5.25	0.00		EE	0.65	29.58	0.00
	FC	0.37	19.72	0.00		FC	0.80	60.22	0.00
	LO	0.28	16.12	0.00		LO	0.74	45.30	0.00
	PE	0.27	16.83	0.00		PE	0.73	41.58	0.00
	PV	0.22	14.53	0.00		PV	0.50	19.81	0.00
	RC	-0.03	2.03	0.04		RC	-0.08	2.29	0.02
	SI	0.13	8.98	0.00		SI	0.50	17.81	0.00
	TA	0.01	0.80	**0.43**		TA	**0.02**	0.59	**0.55**
CONFIDENCE	CK	0.39	13.48	0.00	CONFIDENCE	CK	0.66	22.11	0.00
	H	0.59	25.04	0.00		H	0.76	40.96	0.00
	L2	0.40	16.85	0.00		L2	0.73	40.42	0.00
MOTIVATION	HM	0.69	27.24	0.00	MOTIVATION	HM	0.87	55.53	0.00
	L3	0.50	17.61	0.00		L3	0.73	31.18	0.00
	SCS	0.09	2.84	0.00		SCS	0.36	9.26	0.00

NB: Bold values are insignificant values at 0.05

Conclusively, our first model has no reliability and validity issues; however, TA is not relevant and significant to the model since the path coefficient was not significant at a 5% confidence level (Sarstedt *et al.*, 2017). Further, we used the loadings, and both confirmed loadings were less than 0.7 and insignificant at 5%. Thus, in Fig 5.9, we remove TA and re-run our model until we meet all the sufficient requirements and move to the next step (Sarstedt *et al.*, 2017).

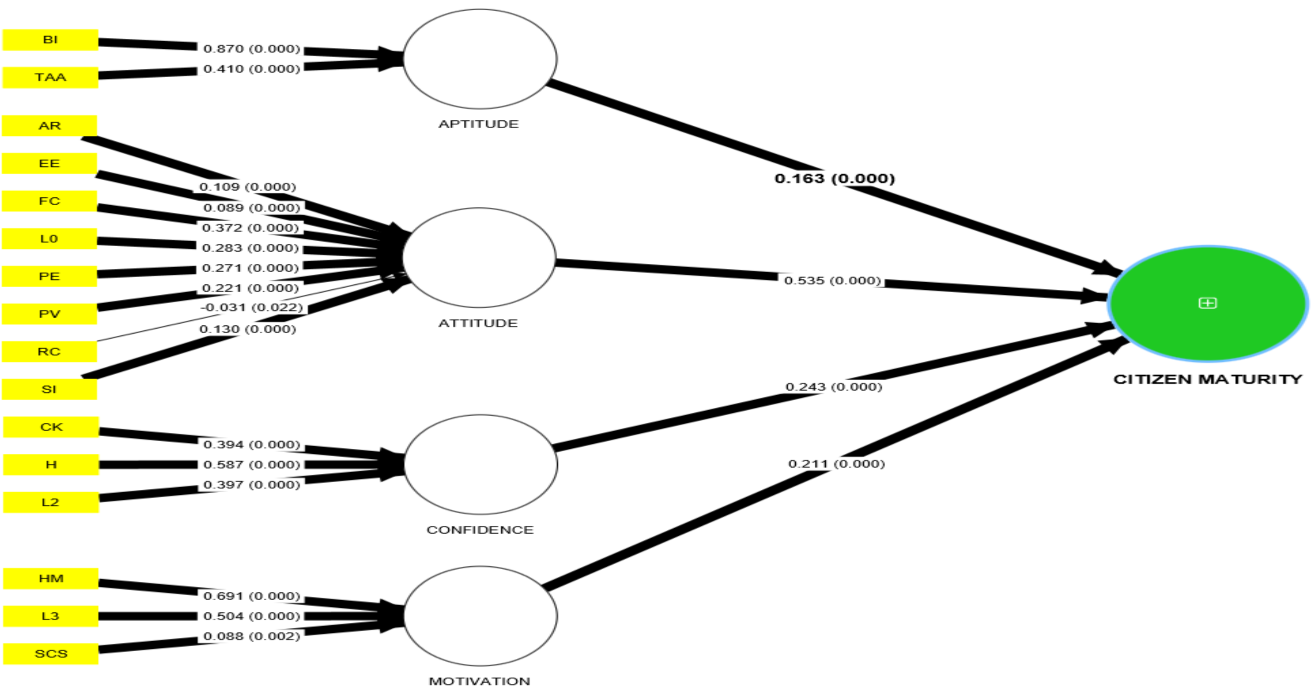


Fig 5. 9: The revised nomological framework

Following the earlier guidelines (Sarstedt *et al.*, 2019), our revised model satisfies the collinearity criteria since the highest VIF value is 2.26, which is less than 3.3 and 5 (Table 5.20). Also, our indicators are all significant and relevant using their outer weights per research standards. We are, however, hesitant to delete RC and SCS because their outer loadings are below 0.5 but significant at the 5% confidence level. In the case of SI, we posit that 0.497 is equivalent to 0.5 and so does not pose any problem for our prediction. In summary, our nomological construct of the HOCs is sufficient for our predictions of the maturity of the citizens of LMICs.

Table 5. 20: The statistics of the revised nomological model of the HOCs

		Outer weights			Outer loadings			Collinearity	
HOC	LOC	Path Coeff	t-value	P values	Path Coeff	t-value	P values	LOC	VIF
APTITUD	BI	0.870	46.321	0.000	0.913	78.056	0.000	BI	2.26
	TAA	0.410	15.576	0.000	0.502	14.177	0.000	TAA	1.43
ATTITUDE	AR	0.109	7.253	0.000	0.521	18.332	0.000	AR	1.38
	EE	0.089	5.297	0.000	0.650	29.599	0.000	EE	1.74
	FC	0.372	19.679	0.000	0.802	60.498	0.000	FC	2.02
	L0	0.283	16.042	0.000	0.745	45.476	0.000	L0	1.85
	PE	0.271	16.809	0.000	0.726	41.645	0.000	PE	1.78
	PV	0.221	14.416	0.000	0.504	19.959	0.000	PV	1.26
	RC	-0.031	2.016	0.022	**-0.085**	2.381	0.009	RC	1.11
	SI	0.130	9.002	0.000	0.497	17.931	0.000	SI	1.31
CONFIDENCE	CK	0.394	13.489	0.000	0.664	22.130	0.000	CK	1.58
	H	0.587	25.059	0.000	0.763	40.980	0.000	H	1.88
	L2	0.397	16.852	0.000	0.733	40.443	0.000	L2	1.69
MOTIVATION	HM	0.691	27.282	0.000	0.866	55.487	0.000	HM	1.83
	L3	0.504	17.663	0.000	0.734	31.318	0.000	L3	1.42
	SCS	0.088	2.832	0.002	0.365	9.245	0.000	SCS	1.29

NB: Bold values are negative and relatively smaller.

Since we have now ascertained all the significant and relevant constructs (indicators) for our structural model, which established the quality of our measurement model for HOCs, we also proceed to estimate the structural model.

5.3.5 Estimation of Structural model of HOCs

The estimation of HOCs has been an age-old discussion in SEM and PLS-SEM. To take full advange of HOCs, the techniques for assessment ought to be rigorous to support the results and interpretation of the model. Theoretically, there are seven steps in reporting a structural model. They are (see also sub – section 4.8.13 in chapter four): 1) the significance of the path coefficients; 2) the level of the R^2 values; 3) the f^2 effect size; 4) the predictive relevance Q^2; 5) and 6) the q^2 effect size (Hair *et al.*, 2017).

1)Path coefficients:

The path coefficients have standardised values between –1 and +1 (Sarstedt *et al.*, 2017). Also, a path coefficient should be at least 0.1 and significant at 0.05.

Table 5.21 presents our hypothesised relationships' path coefficients, *t*-statistics, and significance level. Using the results from the path assessment (Fig 5.10), our data failed to reject the null hypothesis, thus supporting the claim that there was a significant positive relationship between the factors (Aptitude, Attitude, Confidence and Motivation). This is evident in Table 5.21 where Aptitude, Attitude, Confidence and Motivation explain 16%, 53%, 24% and 21% of the variation in ConsHI maturity, respectively. These factors have significant statistics at 5% and thus support our null hypothesis.

Table 5. 21: Parameters of the Predictive HOC model

CITIZEN MATURITY	Path coefficients (>=0.1)	t-value	P values	Outer loadings (>=0.7)	Hypothesis (H_0)
APTITUDE ->	0.16	28.34	0.00	0.85	Accepted
ATTITUDE ->	0.53	54.06	0.00	0.86	Accepted
CONFIDENCE ->	0.24	35.12	0.00	0.86	Accepted
MOTIVATION ->	0.21	27.22	0.00	0.83	Accepted

2) Coefficient of Determination (R^2)

The coefficient of determination (R^2) value indicates the amount of variance in a dependent (ConsHI maturity) variable explained by the independent variables (Aptitude, Attitude, Confidence and Motivations). In table 5.22, the R^2 value is 99% (0.99) which is very close to 100% and thus deemed to be substantial per literature (Falk and Miller, 1992; Marshall, 1997; Wilson *et al.*, 2007; Hair, Ringle and Sarstedt, 2011).

3) Effect Size using F-square (f^2)

Similarly, the model's effect size (f^2) shows how much an exogenous latent variable (Aptitude, Attitude, Confidence and Motivations) contributes to an endogenous latent variable's (ConsHI maturity) R^2 value. Again, in Table 5.22, we observed that the f^2 far exceeded all the required minimum values and is classified as large (see sub – section 4.8.13) (Marshall, 1997; Hoe, 2008; Kang and Ahn, 2021).

Table 5. 22: Evaluating predictive ability using R^2 and f^2

	Indicator	R^2	CA	CR	rho_A	AVE	f^2
	APTITUDE	0.999	0.871	0.912	0.872	0.722	2.093
ConsHI Maturity	ATTITUDE						20.933
	CONFIDENCE						4.408
	MOTIVATION						3.845

NB: the R^2, CA, CR, rho_A and AVE are applicable to all the exogenous variables (Aptitude, Attitude, Confidence and Motivation) and their relationship with the endogenous variable (ConsHI maturity)

4) Predictive relevance using the Stone-Geisser's Q-square (Q^2) values and Effect size (q^2).

The Q^2 is a statistic that measures whether a model has predictive relevance or not (Sarstedt *et al.*, 2019). Predictive relevance is established when Q^2 values are above zero ($Q^2 > 0$) (Geisser, 1975). Table 5.23 conspicuously tells the relevance of our model per the dataset, and so we proceed to assess the effect size of the various constructs. Conceptually, Q^2 is necessary for evaluating the predictive relevance of a structural model, and effect size q^2 represents the predictive power of an exogenous construct for a specific endogenous construct (Zeng *et al.*, 2021). Notably, q^2 measures predictive power; acceptable q^2 values generally include 0.02, 0.15, and 0.35, which indicate weak, moderate, and sound effect levels of predictive relevance, respectively (Chin, 2010). All four factors recorded q^2 S values greater than 0.35 and hence sound effective size on the predictive power of our model. Hair *et al.* (2021) asserted that the effect size q^2 is used to assess an exogenous construct's contribution to an endogenous latent variable's Q^2 value.

Table 5. 23: Evaluating predictive power and relevance of the model using Q^2 and q^2

	Indicator	Q^2	q^2
ConsHI maturity	APTITUDE	0.994	0.724
	ATTITUDE		0.737
	CONFIDENCE		0.740
	MOTIVATION		0.681

NB: the Q^2, is applicable to all the exogenous variables (Aptitude, Attitude, Confidence and Motivation) and their relationship with the endogenous variable (ConsHI maturity)

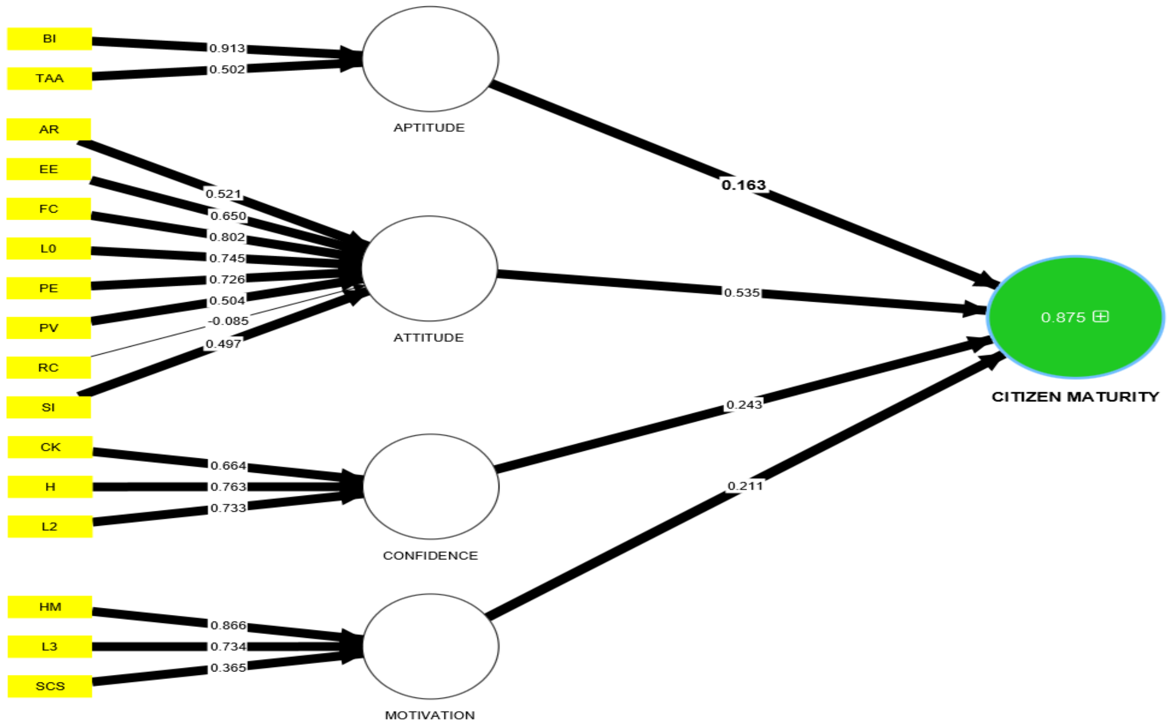


Fig 5. 10: The revised framework for predicting maturity of ConsHI with path coefficients

It is imperative to establish at this point that our dataset has validated our model's direct effect (or main effect), and we need to assess the simple effect (Sarstedt *et al.*, 2017). According to Sarstedt *et al.* (2017), the direct effect expresses the relationship between constructs when no moderators are included. Further, the simple effect describes the relationship between two constructs when moderated by a third variable. We conduct our moderation analysis to ascertain the simple effect in our model.

5.3.6 Assessment of Heterogeniety and Moderation Effects

Some model specifications are made automatically in the SmartPLS software and cannot be manually changed. We apply the algorithm of Cheah *et al.* (2020, p. VII) in the Measurement Invariance of Composite Models (MICOM), by reporting that configural invariance which is the first step is automatically established for all our moderators because:

1. The use of equal items in all groups when checking reliability and validity.
2. similar data treatment in all groups (e.g., the identical distributions, dealing with missing values using mean value replacement or case-wise deletion); and
3. similar PLS-SEM algorithm settings in all groups (e.g., see 4.8.9).

Also, we have achieved the second step which is compositional invariance (metric equivalence) means all the factors are composed in the same way across the various categories in an items. For instance, the formation of Aptitude is the same for both males and females in gender.

The principal issues we are assessing the third step which the equality of mean and variances in the various items. Prior to assessing moderations effects using MICOM, we quickly examine the moderators in the next sub-sections.

5.3.6.1 Assessing moderators and their significance

A moderating variable influences the nature (magnitude and direction) of the relationship between an exogenous (factors: Aptitude, Atttitude, Confidence and Motivation) and endogenous (ConsHI maturity) variables (Memon *et al.*, 2019). We commence with assessing the descriptive statistics of our moderators as shown in Table 5.24 below. We also model the moderators first by assessing their values in the various demographic indicators.

Table 5. 24: Assessment of moderator variables and their sample size

Item	Name of Group	Frequency (n)
Country	Turkey	300
	Iraq	300
	Kosovo	300
	Ghana	300
	Ukraine	300
	Chile	300
Residential status	Rural	314
	Urban	1485
Gender	Females	930
	Males	869
Age(years)	30-39	458
	20-29	551
	40-49	340
	>=50	309
	<20	136
Marital status	Married	897
	Never married	682
	Divorced	53
	Informal/Union	100**
	Widowed	44
	Separated	23**
Educational level	Secondary	494
	Middle/Junior high	172
	Primary	60
	Tertiary	696
	None or Pre-school	24
	Others or Vocational	81
	Ukraine Error (0)*	272*
Employment status	Yes Empl	1259
	NA Empl	53
	No Empl	487
Medical service	Yes Med serv	649
	No Med serv	1018
	Don’t Remember Med serv	131

NB:* is the outlier of educational classification from Ukraine and ** shows items with similar values resulting in singularity problems (Tabachnick and Fiddell, 2007; Yong and Pearce, 2013) as reported by SmartPLS 4.0 (see 4.7.1).

We used the 2-tailed test of t – value and p-value since they are more than two categories for some of our moderator variables. Also, we confirmed our position with a one-tail test for gender and residential status, and the results were the same for both one-tailed and two-tailed tests. Notably, the examination of group differences in MGA uses the bootstrap approach (see 4.8.9.1); since this is based on random samples to estimate model parameters. We report only the significance or non-significance of the comparison because the size (beta coefficients) could change with another bootstrap approach. However, the significance remains the same for the same data.

Since the moderator is expected to exert its effect on all the structural paths of the model rather than a specific path in MGA, a measurement invariance test is mandatory (see 4.8.14.5). The primary purpose is to ensure that the measurement model assessment conducted under different conditions yields equivalent representations of the same constructs (Hair *et al.*, 2010).

There were significant differences between the countries how strongly the four factors influenced ConsHI maturit

Countries

Our model satisfied the necessary conditions for the MGA, that is configural invariance and compositional invariances (see 4.8.14.5). This means the composition of the six countries is the same (thus, compositions of group formation are the same across groups). In the MGA, the data revealed the following:

In Table 5.25, we noticed significant differences between the pairs (country 1 vs country 2) of countries how strongly the four (Aptitude, Attitude, Confidence and Motivation) factors influenced ConsHI maturity, though with slight variation within the pairs per factor. However, there were no significant pairwise differences between Iraq and Kosovo, between Iraq and Ukraine and between Kosovo and Ukraine.

1. There was a significant difference between the pairing of Chile and the rest of the countries, except for Ghana vs Chile regarding the Confidence factor. Thus, the Confidence was not a significant factor on the ConsHI maturity between Ghana and Chile.
2. There were no significant differences mutually in all the factors for Iraq, Kosovo, and Ukraine.
3. There was no significant difference in the Confidence variable between Turkey vs Iraq, Turkey vs Kosovo and Turkey vs Ghana
4. Considering Motivation as a predictor of ConsHI maturity, there was no significant difference between Turkey vs Kosovo, Turkey vs Ukraine, Iraq vs Kosovo, Iraq vs Ghana, Iraq vs Ukraine, Kosovo vs Ghana, Kosovo vs Ukraine, and Ghana vs Ukraine.

Table 5. 25: Comparison of the predictor variables amongst countries

Citizen Maturity	Aptitude	Attitude	Confidence	Motivation
Turkey vs Iraq	**0.001**	**0.002**	0.275	**0.021**
Turkey vs Kosovo	***0.000***	***0.000***	0.378	0.063
Turkey vs Ghana	**0.009**	***0.000***	0.249	**0.005**
Turkey vs Ukraine	**0.011**	***0.000***	**0.010**	0.132
Turkey vs Chile **	***0.000***	***0.000***	**0.031**	***0.000***
Iraq vs Kosovo	0.394	0.419	0.744	0.853
Iraq vs Ghana	0.583	0.473	**0.041**	0.741
Iraq vs Ukraine	0.402	0.424	0.282	0.297
Iraq vs Chile **	***0.000***	**0.000**	**0.014**	***0.000***
Kosovo vs Ghana	0.152	0.845	**0.048**	0.618
Kosovo vs Ukraine	0.087	0.931	0.101	0.455
Kosovo vs Chile **	***0.000***	***0.000***	**0.017**	**0.000**
Ghana vs Ukraine	0.778	0.904	***0.000***	0.137
Ghana vs Chile **	***0.000***	***0.000***	0.063	***0.000***
Ukraine vs Chile **	***0.000***	***0.000***	**0.005**	***0.000***

NB: bold numbers are significant at 0.05, and bold italic is at 0.001. ** are a significant difference in all factors between Chile and the remaining countries.

Age (years):

Our model satisfied the necessary conditions for the MGA (see 4.8.14.5). Notably, the dataset supported the necessary conditions (configural and compositional invariances) for MICOM when Age was moderator, so we proceed to run our MGA. In the MGA, the data revealed the following:

1. There was a significant difference in Aptitude for ConsHI maturity between the 40 – 49 vs 30 – 39 and 40 – 49 and >=50; the rest were not significantly different.
2. There was a significant difference in Attitude to ConsHI maturity for all the Age groups except the 20-29 vs >=50-year group.
3. There was a significant difference in Confidence for ConsHI maturity between the 40 – 49 vs >=50 and 20 – 29 vs >=50; the rest were not significantly different.
4. There was a significant difference in Motivation for ConsHI maturity between the 30-39 vs 40 – 49 and 30 – 39 vs >=50, and the rest were not significantly different.

Table 5. 26: Assessing the moderating effect of Age

Citizen Maturity	Aptitude	Attitude	Confidence	Motivation
20-29 vs 30-39	0.093	**0.031***	0.129	0.719
20-29 vs 40-49	0.379	0.769	0.977	0.129
20-29 vs <20	0.282	**0.000***	0.070	0.133
20-29 vs >=50	0.212	0.220	**0.022**	0.063
30-39 vs 40-49	**0.014**	0.086	0.159	**0.045**
30-39 vs <20	0.924	**0.017***	0.466	0.074
30-39 vs >=50	0.584	0.200	0.606	**0.011**
40-49 vs <20	0.110	**0.000***	0.081	0.655
40-49 vs >=50	**0.036**	0.428	**0.042**	0.993
<20 vs >=50	0.688	**0.000***	0.667	0.623

NB: * indicates significant differences that were negatively related per the bootstrap results.

The 20-29 vs 40 – 49 age group did not meet the conditions for partial invariance. Thus, the various relationships were formed differently across these groups.

The multi-group analysis revealed that all the factors are predictably moderated by Age except Motivation (see Table 5.26 above). Also, many of the relationships moderated by Age had specific Age groups moderating different relationships between constructs and their factors. We did not get balanced data on education because the classification of Ukraine was different from the rest of the countries, so education was treated as an unstable moderator.

Marital status

Notably, the relationship between informal/consensual union and separated suffered a singularity problem. There are many explanations for this challenge in model estimations, this often means zero variance, implying one or more items have no variance (Tabachnick and Fiddell, 2007; Yong and Pearce, 2013). Also, singularity can occur in bootstrapping under the same conditions of indicators having identical values, leading to the random bootstrapping procedures producing subsamples with duplicate values. Thus, we could not achieve compositional invariance; hence our MGA truncated at this level.

In the quality assessment of our moderator for its effect on our models, there was no compositional invariance between the Married vs Informal, Married vs Never married. However, the other paired comparisons satisfied the necessary conditions for MGA, and we thus presented it as follows (Table 5.27):

Table 5. 27: Assessment of moderation effect of Marital status

Citizen Maturity	Aptitude	Attitude	Confidence	Motivation
Divorced vs Informal/Union	0.782	0.156	0.344	0.399
Divorced vs Married	**0.025**	0.218	0.598	0.299
Divorced vs Never married	0.303	0.210	0.826	0.192
Divorced vs Separated	**0.013**	0.060	0.568	0.707
Divorced vs Widowed	0.054	0.319	0.870	0.615
Informal/Union vs Married **	0.117	0.375	0.150	0.077
Informal/Union vs Never married	0.662	0.440	0.324	0.051
Informal/Union vs Separated **	**0.026**	0.351	0.967	0.972
Informal/Union vs Widowed	0.173	0.477	0.421	0.652
Married vs Never married **	**0.000**	0.801	0.055	0.455
Married vs Separated	0.069	0.102	0.386	0.456
Married vs Widowed	0.958	0.984	0.456	**0.047**
Never married vs Separated	**0.021**	0.120	0.622	0.378
Never married vs Widowed	0.085	0.893	0.982	**0.026**
Separated vs Widowed	0.105	0.144	0.639	0.870

NB: the ** though met the configural invariance, these pairs did not meet the compositional invarainces for MICOM

All the factors revealed significant differences within the model for some countries and Age (years) groups. Also, Marital status (Table 5.27) was significant for all the factors except Confidence, which did not show any significance amongst our respondents' marital status.

Though we did not delete the moderators that did not meet our reliability and validity test, we are emphasising these moderators are not valid. Our data did not support using them to moderate the relationships in our structural model for ConsHI maturity.

Significant differences in the Aptitude of Divorced vs Married, Divorced vs Separated and Never married vs Separated as a predictor of the ConsHI maturity. Also, the factor Motivation was significantly different between married vs widowed and never married vs widowed in predicting the ConsHI maturity of LMICs.

Conversely, there was no significant difference in the marital status of our respondents Attitude and Confidence to predict the ConsHI maturity of citizens.

We save space by combining the Gender, Residential status, Employment status and medical services in the last four weeks. Remarkably, all these moderators provided enough evidence for our compositional invariances (see 4.8.14.5), thus sufficient for MGA.

In Table 5.28 below, we modelled four of demographic variables (Gender, Residential status, Employment status and Medical services in the last four weeks) together, the reason was optimizing the space and the Table 5.28 as well. When we used Aptitude, Attitude, Confidence and Motivation as predictors of ConsHI maturity amongst LMICs, we observed the following:

1. The difference between females and males was significant in Aptitude to predict ConsHI maturity.
2. There was a significant difference between employed and unemployed in using Aptitude and Confidence to predict ConsHI maturity.
3. There was no significant difference between all categories of the predictor variables.

Table 5. 28: Assessment of Gender, Residential status, Employment status and recent medical care

	Citizen Maturity	Aptitude	Attitude	Confidence	Motivation
Gender					
	Females vs Males	**0.000**	0.948	0.390	0.366
Residential status					
	Rural vs Urban	0.069	0.876	0.315	0.671
Employment status					
	No vs Yes	**0.041**	0.247	**0.022**	0.508
	NA vs Yes	0.700	0.305	0.173	0.569
	NA vs No	0.698	0.611	0.659	0.393
Medical services in the last 4 weeks	No vs Yes	0.898	0.305	0.352	0.199
	DR vs Yes	0.666	0.195	0.681	0.999
	DR vs No	0.595	0.053	0.425	0.401

In addition, there were significant differences in the employment status of our respondents for Aptitude and Confidence, while only Aptitude for Gender.

Education level

We are not particular about including education (Table 5.29) in our moderation analysis though we find some striking observations. Our decision is because the educational classification of Ukraine was radically different from the rest of the five countries (see 3.6.4 for details), and we are hesitant to conclude on these variables. Specifically, we think including Ukraine will create a different category that will affect our compositional invariance and thus the interpretation of the results. Also, excluding Ukraine will reduce our sample size to 1,500 and thus makes an unbalanced sample size for our study since all others were 1,800 observations. Below we see the result on education.

Table 5. 29: Assessment of the moderation effect of educational level

CITIZEN MATURITY (P-Value)	Aptitude	Attitude	Confidence	Motivation
Middle/Junior high vs None or Pre-school	0.511	0.924	0.318	0.532
Middle/Junior high vs Others or Vocational	0.585	0.056	0.514	**0.003**
Middle/Junior high vs Primary	0.678	0.973	0.691	0.244
Middle/Junior high vs Secondary	0.077	**0.000**	0.162	**0.000**
Middle/Junior high vs Tertiary	0.423	**0.008**	0.251	**0.000**
Middle/Junior high vs Ukrain Error (0))	0.390	**0.010**	0.112	**0.014**
None of Pre-school vs Others or Vocational	0.333	0.388	0.602	0.357
None of Pre-school vs Primary	0.735	0.917	0.489	0.996
None of Pre-school vs Secondary	0.118	0.097	0.100	0.187
None of Pre-school vs Tertiary	0.273	0.291	0.125	0.121
None of Pre-school vs Ukrain Error (0)	0.257	0.296	0.086	0.671
Others or Vocational vs Primary	0.397	0.113	0.810	0.085
Others or Vocational vs Secondary	0.332	0.168	0.114	0.452
Others or Vocational vs Tertiary	0.953	0.765	0.151	0.230
Others or Vocational vs Ukrain Error (0)	0.876	0.776	0.093	0.206
Primary vs Secondary	0.076	**0.003**	0.125	**0.007**
Primary vs Tertiary	0.284	**0.041**	0.183	**0.001**
Primary vs Ukrain Error (0)	0.265	**0.046**	0.092	0.339
Secondary vs Tertiary	0.137	0.144	0.681	0.537
Secondary vs Ukrain Error (0)	0.252	0.153	0.819	**0.004**
Tertiary vs Ukrain Error (0)	0.882	0.995	0.501	**0.000**

5.3.6.2 Assessing moderation effects

The paragraphs above deliver a comprehensive analysis of data quality and all types of individual effects. We now draw the complete picture of the model (Fig 5.11) to predict ConsHI maturity from items aggregated from UTAUT, PAM, and ConsHI levels and from various demographic variables.

The rest, residential status, and medical services in the last four weeks showed no significant differences. We are also mindful of the classification challenge in Ukraine, for which we are conservative about the statistical significance of the educational moderation of our model.

Table 5. 30: SmartPLS setup of data and model characteristics of our moderating indicators

Data setup	Setting
Algorithm to handle missing data	Mean replacement
Weighting vector	-
PLS-SEM algorithm	Setting
Initial weights	1.0
Max. number of iterations	3000
Stop criterion	10^{-7}
Type of results	Standardised
Use Lohmoeller settings?	No
Weighting scheme	Path
Permutation algorithm	Setting
Groups A	Females
Groups B	Males
Parallel processing	Yes
Samples	1000
Seed	Fixed seed
Significance level	0.05
Test type	Two-tailed

5.3.7 Assessing the interaction effect of our moderators in the predictive model

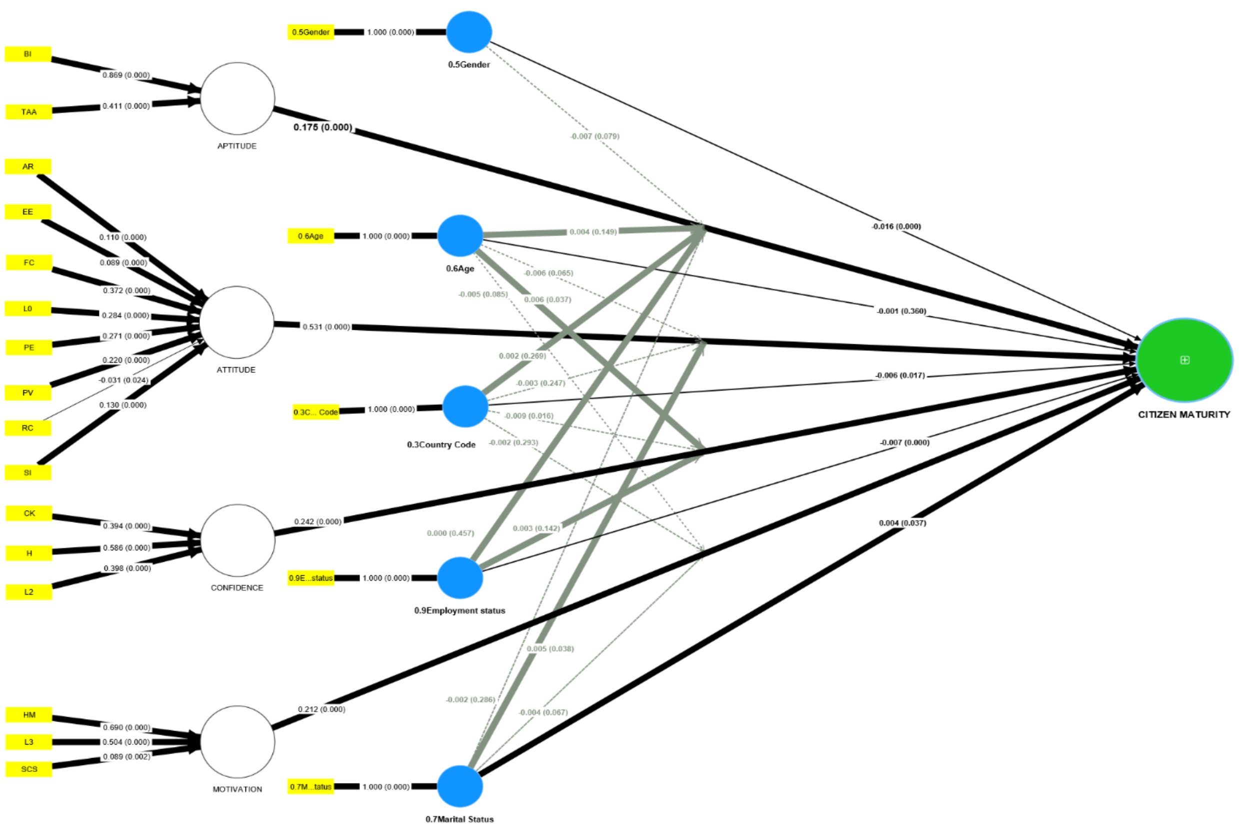


Fig 5. 11: The final model includes the moderation effect by significant moderators

Like the rules guiding (see 4.8.13) our predictive relevance (Table 5.23) before the interaction effects, here in Table 5.31, we again assess the predictive relevance of the model including the interaction effects. All the values are equally high and supports the predictive relevance of our model.

Table 5. 31, establishes predictive relevance and explanatory power (see 4.8.13) after interaction effects of significant moderators

CITIZEN MATURITY	Q^2predict	q^2predict	f^2
APTITUDE	0.994	0.727	6.102
ATTITUDE		0.737	27.324
CONFIDENCE		0.739	30.033
MOTIVATION		0.680	31.08

NB: the Q^2,is applicable to all the exogenous variables (Aptitude, Attitude, Confidence and Motivation) and their relationship with the endogenous variable (ConsHI maturity)

In Table 5.32 we assess the reliability and validity of our predictive model before formulating the regression equation (Eqn 5.1). We are convinced that the quality of the model determines the usefulness of the model to the scientific community.

Table 5. 32: Reliability of the final predictive model using the CR, CA, rho_A and AVE (see 4.8.12)

Parameter	Estimate
Cronbach's alpha	0.871
rho_A	0.872
Composite reliability	0.912
Average variance extracted (AVE)	0.722
Q^2predict	0.994
RMSE	0.078

In Table 5.33, we present the coefficient of the model including the coefficient of the interaction effects. Table 5.33 shows only the values that were significant at 0.05 level, excluding all the insignificant ones (see Fig 5.11).

Table 5. 33: Interaction analysis of the predictive model

Constructs	Path coefficient	T statistics	P values
APTITUDE -> CITIZEN MATURITY	0.175	18.978	0.000
ATTITUDE -> CITIZEN MATURITY	0.531	52.956	0.000
CONFIDENCE -> CITIZEN MATURITY	0.242	34.530	0.000
MOTIVATION -> CITIZEN MATURITY	0.212	26.905	0.000
Country x CONFIDENCE -> CITIZEN MATURITY	-0.009	2.146	0.016
Age x CONFIDENCE -> CITIZEN MATURITY	0.006	1.785	0.037
Marital Status x ATTITUDE -> CITIZEN MATURITY	0.005	1.775	0.038

In Table 5.34, we compare the path coefficients of our exogeneous variables before and after the moderation effect. Remarkably, there was a marginal increase in the coefficient of Aptitude after the moderation effect although the rest of the factors remained the same. Like our earlier explanations in this chapter, the interaction effect has improved on some of the factors that determine the maturity of ConsHI in LMICs.

Table 5. 34: Comparison of the path coefficients of the explanatory factors before and after moderations

CITIZEN MATURITY	Path coefficients without moderations	Path coefficient with moderations
APTITUDE ->	0.16	**0.18**
ATTITUDE ->	0.53	0.53
CONFIDENCE ->	0.24	0.24
MOTIVATION ->	0.21	0.21

NB: Bold is the Aptitude coefficient that increased when we introduced the interaction effects.

We conclude chapter five with two regression models, Eqn 5.1, we formulate our model without the interaction effects, that could predict the outcome variable (ConsHI maturity). In Eqn 5.2 we reformulate the model with the interaction effects.

$$\textbf{ConsHI} = 0.16{*}\text{Aptitude} + 0.53{*}\text{Attitude} + 0.24{*}\text{Confidence} + 0.212{*}\text{Motivation}$$

Eqn 5. 1: A linear predictive model, excluding interaction terms for ConsHI in LMICs

$$\begin{aligned}\textbf{ConsHI} = {} & 0.175{*}\text{Aptitude} + 0.531{*}\text{Attitude} + 0.242{*}\text{Confidence} + 0.212{*}\text{Motivation} \\ & - 0.009{*}\text{Country}{*}\text{Confidence} + 0.006{*}\text{Age}{*}\text{Confidence} + 0.005{*}\text{MaritalStatus}{*}\text{Attitude}\end{aligned}$$

Eqn 5. 2: A linear predictive model, including interaction terms for ConsHI in LMICs

Distribution of the outcome (ConsHI maturity) shows an excellent normal distribution of the variance as shown in Fig 5.12 below.

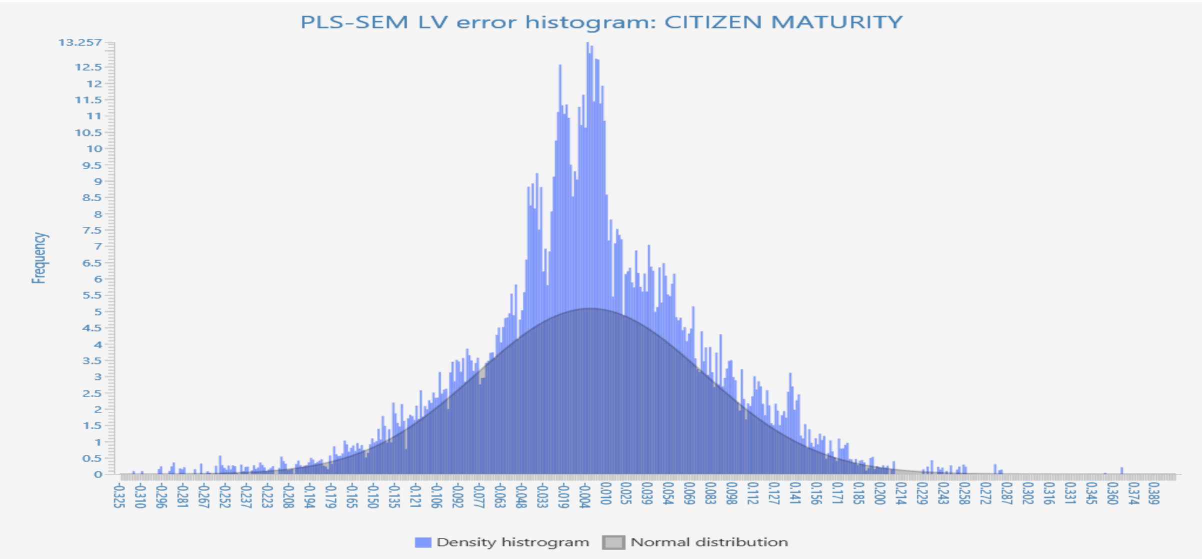


Fig 5. 12: Distribution of the endogenous latent variable (ConsHI maturity) using the final predictive model

CHAPTER SIX: DISCUSSIONS

This chapter compares the results of our research with extant literature. We start the discussions with the demographics, which may be moderators of the relationships we developed based on our theoretical framework. Subsequently, we discuss the factors that support the maturity of the citizens for ConsHI. We also discuss our SEM model for our study concerning earlier findings. Finally, we contribute to the research by proposing a comprehensive model for assessing the maturity for ConsHI.

For consistent estimation of the parameters, we used the Smart PLS 4.0 software, which is the latest version on the market (see *Please cite the use of SmartPLS: Ringle, C. M., Wende, S., and Becker, J.-M. 2022. "SmartPLS 4." Oststeinbek: SmartPLS GmbH, http://www.smartpls.com.)*. To obtain the reference distribution of the test statistics, we used default settings of the necessary statistical tools except for instances like sampling, where we increased it to our size and beyond. Also, we made the necessary changes where we needed path estimates or factor loadings (latent variables). We made a conscious effort to report all settings in our dataset and the software we used in this analysis (see Table 5.30). We can make the dataset available to reviewers upon their request, however, upon publications of some papers, the dataset will be available online.

6.1 EXPLORATORY FACTORS

Hartzler and Wetter (2014) enumerated three personal t – factors that can facilitate the maturity of citizens for the health-related use of the Internet and Mobile phones in LMICs. The results of this study affirmed most of the t – factors (trust; item7, item20, confidence; item1, item15, item20) identified in their studies (Hartzler and Wetter, 2014; Huh *et al.*, 2018). Further, our findings corroborated t-factors such as skills (item20, item38 and items41), knowledge (item22), and cultural beliefs as facilitators (Hartzler and Wetter, 2014). We also found similar factors, including personal motivation (item3, item4, item5), which mandates cultural appropriateness as an essential theme beyond general usability principles. The six e – factors that facilitate the individual adoption of ConsHI align with earlier studies of facilitators (Hartzler and Wetter, 2014; Huh *et al.*, 2018).

The facilitators of ConsHI maturity in LMICs are diverse amongst the theoretical constructs. Our convention in this discussion is to label our factors using Gestalt themes and to juxtapose the theoretical constructs (factors) called t-factors with them. In places where our Gestalt did not provide a theme, we use only the theoretical constructs (t-factors) as empirically provided.

Following the results of the factor analysis and Gestalt experience, the first t-factor is *the Benefits of mobile phones* (UTAUT: Performance expectancy; defined as the amount to which technology will benefit consumers in performing certain activities). Practically, our model points out that when users can appreciate the benefits of using technology in their healthcare, they will gladly adopt and use it, as earlier asserted by Venkatesh, Thong and Xu (2012).

Our second t-factor was Confidence in levels 0 or 1 (*ConsHI levels 0) and 1*, as confirmed by the Gestalt experiment. Citizens will willingly initiate and search the Internet and may even make diagnostic decisions from their search (Wetter, 2016). Further, the patient and physician will improve their face-to-face encounters using social media, Whatsapps, to share medical information.

Our third t-factor is *Confidence and knowledge to act;* However, our Gestalt did not capture this factor, and it is reasonable to report that patients' self–confidence and the knowledge to take action are crucial in the maturity of the citizens of LMICs for ConsHI. They mainly considered the core concept of ConsHI as patient empowerment rather than provider empowerment. This corroborates the assertion of Hibbard et al.(Hibbard *et al.*, 2005) that patients should be confident and participate in their healthcare. Also, as reported by Hartzler and Wetter (2014), acquired skills, knowledge and Confidence in the use of technology will facilitate the success of micro-level ConsHI adoption in LMICs.

Our fourth t-factor is *Self-awareness of health consciousness* (resistance to change), which is Self-awareness of health consciousness. Adoption is not rapid due to the resistance human beings have always posed to changing behaviours. Hoque and Sorwar (2017) asserted that resistance to change is a challenge in adopting technology. Our findings corroborate this position that to facilitate ConsHI in LMICs, actors must be aware that there will be resistance, and we must manage the change process well. In addition, this confirms the assertion of Hartzler and Wetter (2014) that trust and privacy are serious issues to address driving success factors ConsHI in LMICs.

The fifth t-factor is *taking action*, which is citizens' self-initiative. As Hartzler and Wetter (2014) rightly captured it, personal motivation is a significant facilitator for the success of ConsHI in LMICs. Interestingly, when citizens see the need to take action, as confirmed by Hibbard *et al.* (2005), it suggests that, as asserted in our second i-factor, ConsHI level 0 or 1, by searching and finding possible explanations for their situation.

Last t-factor is the *Habit of using mobile phones/internet* (behavioural intention). The Habit of using a phone is what Venkatesh, Thong and Xu (2012) call intentionality. Behaviours reflect our beliefs, with culture and religion latently driving human behaviours. Our t-factor is congruent with Venkatesh, Thong and Xu (2012), who see behavioural intention as a composition of many factors, all facilitating technology adoption. Similarly, Hartzler and Wetter (2014) pointed to culture, belief and religion as catalysts for adopting ConsHI in LMICs.

To summarize, these six i-factors that will facilitate the maturity of the citizens of LMICs to adopt ConsHI are theoretically grounded.

6.2 DATA CHARACTERISTICS OF THE STRUCTURAL EQUATION MODELS

The results from our dataset showed well-organised and cleaned data; for instance, Table 5.1 indicates only 0.4% missing values in the entire dataset at an average of one case per indicator for all the 1,800 observations. Our data offer a higher level of acceptance as stated in the literature; for instance, Robins (2014); Sarstedt, Ringle and Hair (2014) argued that up to 5% missing value per indicator in a dataset was acceptable. Further, using the observation rule, our data showed that the total missing value for cases was far below the 15% missing values to observation ratio prescribed by Hair *et al.* (2017). Lastly, we did not ignore even the 0.4% missing value but used the mean replacement, in our SmarptPLS software for these instances, connoting a 100% dataset for our analysis (Hair *et al.*, 2011).

Evidently, our data did not show any trend of influencers, outliers, spurious trends, or straight lining as anticipated in a large sample sized dataset like ours. Our data reflects a high standard dataset devoid of possible variations due to such case (Ringle, Wende, & Becker, 2015). Hence, a good-to-go dataset. We observed a well balanced set for ranges of all variables. Also, the sample size, distributional and indicator correlations were beyond doubt, thus supporting earlier researchers (Kreft and Aschbacher, 1994; Barclay, Thompson and Higgins, 1995; Cohen, 2013; Wong, 2013; Memon *et al.*, 2020) who recommended a range (0.3 – 0.8) of acceptable correlations values for PLS analysis. Specifically, some indicator correlations exceeded 0.5 implying they were indicators of a component (construct). The majority that did not represent a common factor was less than 0.3, meaning these were not strongly correlated, hence our data supported the theoretical foundations of our model. Conclusively, our data exhibited all the required characteristics to ensure accurate analysis.

6.2.1 Demographic Analysis

Our data revealed striking trends in the demographics of our respondents. A colossal majority (82.5%) were urban dwellers. These people by international housing standards have access to basic social amenities and live with more than 5,000 people. Also, 75% were within the age brackets of 20 – 49. Those in the active and youthful group indicate a possible high inclination for ICT. There was equal distribution in the gender of our respondents in the study, and we found this notable since, in most developing countries, there are more females than males. A good percentage (49.8%) were married with others having different forms of relationships; this implies that access to a phone per our definition was highly probable with the respondents. The majority (83.5%) of respondents had some level of education and were mostly (69.94%) employed. However, few (36.06%) respondents had consumed medical services within the last four weeks of the study.

6.3 MODEL CHARACTERISTICS

All our first-order models were reflective, and all our higher-order models were formative. Resulting in a reflective – formative type II higher order construct as prescribed by researchers like Bollen and Ting (2000) and Gudergan *et al.*(2008a). Finally, though our CTA analysis of the nomological model indicates that CK was a formative construct, we changed it to a reflective construct. Our decision is fully supported by the theoretical assertion of Wong (2013) and confirmed by the emperical evidence of the PAM and UTAUT models adopted in this study.

6.4 MODEL EVALUATIONS

6.4.1 Assessing the LOCs measurement model quality

First, we had to establish indicator reliability by assessing that all the outer loadings of the indicators were above 0.7. For exploratory study, we could use researcher discretion for outer loadings of 0.4-0.6. However, we adopted improving the reliability of our research by assessing the impact of low outer loadings of indicators on the AVE of their respective constructs. Subsequently, our algorithm for determining indicator and internal consistency reliability resulted in deleting five ConsHI-related items belonging to the CK construct (Item 16, Item 22, Item 23, Item 24 and Item 25). Our findings corroborated that of Reinartz, Haenlein and Henseler (2009) and Sarstedt *et al.* (2016). They postulated that researchers should remove indicators from a dataset if the AVE of the model (CK) will improve due to the deletion. Subsequently, we assessed the CR, CA, and rho_A to check the internal consistency; all of these were within the recommended literature thresholds. Also, our collinearity assessment proved positivesince all VIFs were less than 3.3 and 5, sufficiently showing no concern for multicollinearity (Diamantopoulos, Riefler and Roth, 2007; Hair, Sarstedt and Ringle, 2020). The next check was the model's validity since we had deleted five indicators.

To check the validity of a reflective model, we used convergent and discriminant validity. Notably, all our AVEs of the constructs in the model met the minimum requirement of 0.5 to establish convergent validity per the recommendations of the literature (Sarstedt *et al.*, 2014, 2019; Risher *et al.*, 2019). Also, we assessed the discriminant validity using the three (FLC, Cross-loadings, and HTMT) popular statistics. All these test requirements were satisfied, connoting the establishment of discriminant validity. We thus validated our model and proceeded to run our higher-order model, SEM.

6.4.2 Assessing the quality of the HOCs measurement models

Heuristically, we confirmed our HOCs as a formative model before conducting our quality analysis of the measurement model. HOCs were formative; hence the assessment of their measurement model was quite different from that of the LOCs, which were reflective (Evermann and Tate, 2016; Sarstedt *et al.*, 2019; Crocetta *et al.*, 2021). For formative, we had to validate the models using the redundancy analysis of the same constructs in a formative and reflective mode. Notably, if the coefficient of the relative models was above 0.7, we have ascertained convergent validity. We selected specific indicators that measured at least 62.5% of the variances in the constructs as proxies for these second-order constructs. Our data supported all four formatively formed models with coefficients of 0.8 and above; thus, we have confirmed the convergent validity of our model, and we could check for collinearity. In formative models, highly correlated factors connote multicollinearity, a major concern. However, since formative models result in components, researchers can merge such constructs to create parsimonious constructs of interest.

However, our dataset did not show such a problem for our model. The VIFs of all the constructs were less than 3.3; the maximum was 2.28 for the BI construct. That implies we have sufficient grounds to proceed to the relevance and significance analysis of the various constructs in our model. The check of relevance and significance is to ascertain which LOCs to retain in the final model for the structural evaluation.

Our analysis pointed out a need to remove one indicator (TA) since it did not meet the minimum requirement for all three tests. Therefore, we reduced the number of LOCs to 16 instead of the earlier 17. Also, we hesitantly included SI, RC and SCS in our model for a theoretical reason. Though their outer loadings were low (less than 0.4), they were significant at 5% for both outer weight and outer loadings. We included these constructs in the final model based on researcher discretion, supported by Hair *et al.* (2017), because we did not want to reduce the LOCs to a very small number.

6.4.3 Assessment of the structural model of the HOCS

To assess the structural model of conceptual frameworks, several authors (Marshall, 1997; Hayduk *et al.*, 2007; Hair *et al.*, 2011; Memon *et al.*, 2017) have provided guidelines indicating that researchers should report the path coefficient, the coefficient of determination (R^2), the effective size (f^2), the predictive relevance and explanatory power. Notably of interest to our researcher is the predictive relevance of our model since that is the end goal of the study.

Notably, all four (Aptitude, Attitude, Confidence and Motivation) m – factors and hence predictors of ConsHI maturity were significant at the 5% confidence interval. Their signs were all positive, and their sizes were also significant at two decimals places. Table 5.20 shows the details of the coefficients of our model predictors.

Notably, the results in the table reveal that our data support the hypothesis that there is a positive relationship between the m-factors Aptitude, Attitude, Confidence and Motivation and the maturity of the citizens of LMICs for ConsHI.

Specifically, Attitude was the factor with the highest (0.53) path coefficient. Attitude explained 53% of the variance in the maturity of the citizens of LMICs for ConsHI. Thus, to determine the maturity of the citizens of the six countries, policies can be initiated that change their Attitude toward ConsHI; more than 50% of the expected change will occur. The next three factors were Confidence, Motivation and Aptitude at 24%, 21% and 16%, respectively.

Subsequently, we assessed the strength of our model. The coefficient of determination (R^2) shows the variance in ConsHI maturity explained by the m-factors Aptitude, Attitude, Confidence and Motivations. While Falk and Miller (1992) and Wilson *et al.* (2007) respectively recommended that R^2 values maximum of 0.26 (26%) and 0.67(67%) were substantial, our R^2 was 0.99, meaning 99% of the four m – factors explain almost 100% of the variations in our ConsHI maturity. Also, in that same Table 5.21, all the reliability indicators, including AVE, were above 70%, supporting a well-explained model.

Our R^2 value (99%) confirms the positions of Bentler and Huang (2014) and Rigdon (2014), who opinioned that R^2 should be high enough to explain the variance of endogenous latent variables sufficiently. Therefore, a more significant R^2 value increases the predictive ability of the structural model also intimated that a high R^2 is required to explain the endogenous latent variable's variance well; thus, a more considerable R^2 value increases the predictive ability of the structural model. Our findings are higher than Jewer (2018), who reported a 66% variance explained by the outcome variable behavioural intention in their UTAUT model. A close match to our R^2 is Cimperman, Makovec Brenčič and Trkman (2016), who recorded a 77% variance in their outcome variable earlier.

We also assess the predictive relevance (Table 5.22) of our model per the data collected. Sarstedt *et al.* (2019) maintained that establishing whether a model has predictive relevance or not is vital in predictions. Our study adopted the guiding criteria for predictive relevance from, Geisser (1975) who earlier asserted that, when Q^2 values are above zero ($Q^2 > 0$), it confirms the predictive relevance of the hypothesised model.

6.5 ASSESSMENT OF HETEROGENEITY USING MULTIGROUP ANALYSIS (MGA)

We adopted eight (8) moderating variables (Country of origin, Age, Gender, Residential status, Educational level, Employment status, Marital status, and Medical services in the preceding four weeks), based on literature (Venkatesh *et al.*, 2003; Hoque and Sorwar, 2015) recommendations. Since our study was in multiple countries, assessing the various countries' effects on our model was imperative. However, our sample was balanced (see Table 5.2: 300 for all countries). There are significant differences in the structural model between the countries. There was also a difference between the four (Aptitude, Attitude, Confidence and Motivation) factors that influenced the maturity of the citizens of LMICs for ConsHI. A notable observation is the difference between Chile and the other countries in all four factors. We take particular interest in this because in chapter three (see Table 3.1), we reported that Chile was in economic transition at the time of the study compared to the rest of our selected countries. While all were categorically LMICs, Chile was ranked as a high-income country by the IMF. Therefore, we suspect that our model has supported the assertion of IMF and pointed out that the behaviour of a high-income country will be different from LMICs.

The heterogeneity of the model using age was insignificant in all factors for any age group. These findings contradict the assertions of Bawack and Kamdjoug (2018) that age was the only significant moderating factor, improving the model to 46% in UTAUT. Notably, our findings confirmed the position of Palau-saumell, Forgas-coll and Javier (2019), who claimed that the moderating effect of gender and age were insignificant. Further, the results, revealed significant differences between some age groups for some m – factors. Since Attitude explained more than 50% of the variance of ConsHI maturity, we focused on it. We observed that all the significant age differences were negative for any group compared to <20 years. Our findings align very well with the literature that the younger generations are ICT savvy and more likely to embrace ConsHI concepts with a positive Attitude.

Marital status did not show many differences in most of the m – factors, except for Aptitude, which revealed significant differences in the marital status of respondents, particularly in the divorced category. The rest of the classes and m-factors were not significant. For instance, there was no significant difference in the Attitude and Confidence of any respondents concerning their marital status.

Our data did not offer a balanced classification of the educational status of respondents, so it was not easy to assess the heterogeneity of our data based on educational level. Our test revealed that none of the m-factors was significantly different for all the educational categories. However, we are conservative in reporting on this because of the peculiar nature of the educational systems in Ukraine.

Essentially, we observed a significant difference in the Aptitude of males and females for ConsHI and employment status (employed and unemployed). Further, Confidence was significantly different amongst the employed and unemployed. There was no significant difference in the other m-factors when using gender as the moderator, residential status, employment status and those who had received medical services in the last four weeks.

Our findings are not different from Or and Karsh (2009), who claimed that age did not show a consistent effect in their plethora of studies examined. Specifically, they reported that, among 39 studies, 26 (67%) found significant relationships, and 13 did not. Further, gender, the second most studied variable, demonstrated no effect in 84% of the studies that tested differences. However, while they could discuss education, our results did not include education in our model. also, they did not mention other socio-demographic variables that were significant to report, like our country-wide heterogeneity. Remarkably, the interaction effect of the significant moderating variables did not influence the nature (directions and strength) nature of the relationship between the m – factor.

6.6 EMPIRICAL ANALYSIS

To wrap up our discussion of the findings of this research, we compare it to earlier studies that layed the foundations for this work.

Variables include "I am the person responsible for managing my health condition" and "I am confident that I can tell when I need to go get medical care and when I can handle a health problem myself." which were significant in our SEM and reflect earlier e – factors like privacy and confidence in oneself to take action and actively get involved with personal healthcare. These factors corroborate earlier findings of Hartzler and Wetter (2014).

Our results identified other e – factors like "I use a mobile phone or the internet frequently.", "I know how to prevent problems with my health.", "I believe that I can search the internet for health information." which were named using Gestalt.

Our study also elicited some individual factors like Age, Gender, Marital status, and Employment status (Fig 6.1). These are the same as Magsamen-Conrad *et al.* (2015) and Zhao, Ni and Zhou (2018) find in their studies. Also, Or and Karsh (2009) reported that Age and Gender were significant in earlier studies that tested similar models like ours.

6.6.1 Unified Theory of Acceptance and Use of Technology (UTAUT, UTAUT2, UTAUTe)

1. Contrasting our results to the UTAUT models of technology adoption (UTAUT, UTAUT2, UTAUTe), our data supported most of the constructs. However, the first variation was that BI (Beharioral Intention) was treated as an input construct in our model versus as a mediating variable in UTAUT models.

2. Also, all the constructs adopted from UTAUT2 and UTAUTe, are significant, judging from our results, except technology anxiety (TA). Our results confirm previous studies' assertions (Venkatesh *et al.*, 2003, 2016; Hoque and Sorwar, 2017).

3. On the moderation of the m – factors, we did not include the moderating variables experience and voluntariness from UTUAT2. Although we moderated all the paths in our model, statistically not all paths were significant. For instance, in UTAUT2, there was no significant moderation of performance expectancy, effort expectancy and social influence; meanwhile, in UTAUT, they were moderated by

age, gender, voluntariness, and experience. We contribute to research by composing the several t – factors into four theming components (m – factors).

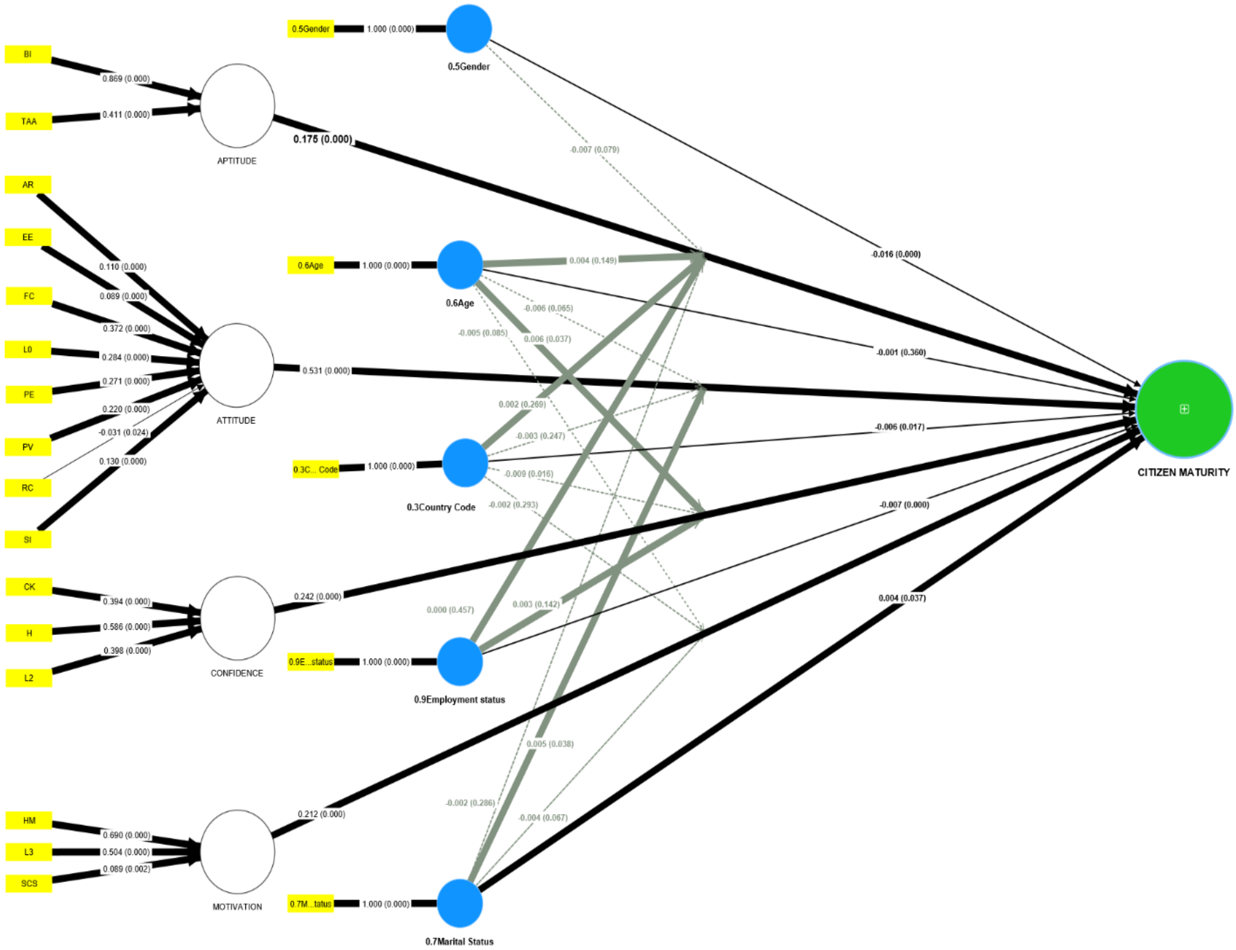


Fig 6. 1: Final nomological model of ConsHI maturity in LMICs

6.2.2 Patient Activation Measure (PAM)

1. Our results similarly confirmed models of PAM as earlier suggested (Hibbard *et al.*, 2004, 2005; Roberts *et al.*, 2016). Notably, we significantly validated all the constructs of PAM for assessing patient activation to contribute to ConsHI.

2. We have added that certain socio-demographic variables like Age, Gender, marital status, and employment status can influence these constructs.

3. Our results show that we can aggregate these demographic factors with similar constructs that seek to facilitate consumer adoption of technology and activity in their healthcare. Importantly, we have used a 5-point Likert scale, which has facilitated the options for incorporating PAM (Hibbard *et al.*, 2004, 2005; Roberts *et al.*, 2016) into UTAUT, UTAUT2 and ConsHI. To the best of our knowledge, this is a novel composition.

6.6.3 Consumer Health Informatics (ConsHI): Levels of service

1. Our results similarly supported the prescription of Wetter (2016), who described ConsHI from the perspective of services and defined four Levels in which individuals safely play an active part in their health care using technology. We also evaluated all four m-factors; however, our data did not support Level 1 of ConsHI, which is characterised through clients and service providers enhancing their face-to-face interactions by exchanging information.

2. In the ConsHI levels, we have again introduced moderating variables as proposed by earlier studies (Or and Karsh, 2009).

6.7 HYPOTHESIS OF CONSHI

The hypothesis of the Dependent Variable (maturity of citizens):

We proposed several hypothetical relationships after our literature reviews. Practically, our results tested these hypotheses, and our findings are:

1. HA: There is a positive relationship between APTITUDE and the maturity of citizens for ConsHI.

It is evident from our data that there was a significant and positive relationship between Aptitude and ConsHI maturity at a 5% confidence level. Empirically, the variance in ConsHI explained by Aptitude was above 10%. Also, the R^2 (0.92) and f^2 (6.102) values show that the variance explained by Aptitude to predict the maturity of the citizens of LMICs for ConsHI is significant. Further, there is a significant moderating effect of Age, Gender, Marital status, and employment status.

2. HB: There is a positive relationship between ATTITUDE and the maturity of citizens for ConsHI

It is evident from our data that there was a significant and positive relationship between Attitude and ConsHI maturity at a 5% confidence level. Empirically, Attitude explained more than 50% of the variance in ConsHI with the R^2 (0.92) and f^2 (27.32) values, showing the variance explained by Attitude to predict the maturity of the citizens of LMICs for ConsHI was significant. Further, there is a significant moderating effect of Age, Gender, Marital status and employment status.

3. HC: There is a positive relationship between CONFIDENCE and the maturity of citizens for ConsHI

The results again supported our hypothesis that Motivation has a positive and significant relationship with ConsHI maturity. At a 5% confidence level, confidence explained more than 10% of the variance with the R^2 (0.92) and f^2 (30.03) values, showing the variance explained by Confidence to predict the maturity of the citizens of LMICs for ConsHI was sufficient. Further, there is a significant moderating effect of Age, Gender, Marital status and employment status.

4. HD: There is a positive relationship between MOTIVATION and the maturity of citizens for ConsHI

The results again supported our hypothesis that the factor Confidence has a positive and significant relationship with ConsHI maturity. At a 5% confidence level, motivation explained more than 10% of the variance with the R^2 (0.92) and f^2 (31.80) values, showing the variance explained by Confidence to predict the maturity of the citizens of LMICs for ConsHI was sufficient. Further, there is a significant moderating effect of Age, Gender, Marital status and employment status.

6.7.1 Commending our ConsHI model

The profusion of studies discussing ConsHI called for a different look at this concept and offered empirical facilitators to its adoption in LMICs. As a far-reaching consequence of this endeavour, we answered the question, "How can we conceptualise the maturity of the citizens of LMICs for this momentous concept?" The answer to this is in Table 5.34 and Eqn 5.1, where we concretely offer the four m – factors, namely, Aptitude, Attitude, Confidence and Motivation, as the bandwagon drivers to the promised land of ConsHI maturity for LMICs. Our regression model (Eqn 5.2) describes the significance, size and sign of all the m – factors on ConsHI maturity in LMICs.

Consequentially, the four m – factors will perform the magic at different magnitudes with the Attitude of citizens spearheading the change, Confidence will fuel the bandwagon, Motivation bonds the movement and Aptitude will provide unwavering support for all to the promised land.

6.8 LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

6.8.1 Limitation of our study

1. In using this instrument, several issues deserve consideration. The sampling was a convenient approach which has inherent limitations of such non-probabilistic methods.
2. Cultural variations of responses may occur in our study since it was conducted in different countries (Chile, Ghana, Iraq, Kosovo, Turkey and Ukraine) (Croasmun and Ostrom, 2011).
3. We used a descriptive-cross-sectional survey to collect data from respondents. Thus, changes in consumer behaviours associated with citizens' Attitudes toward ConsHI may not have been captured.
4. Further, we used a convenient sampling technique; at all stages, literature has pointed to the weakness in generalising such findings in populations. Since there are likely biases in selecting the respondents, particularly for a multi-country study like this case.

5. We conducted our study from a snapshot (static) perspective and, therefore, failed to consider dynamic changes in respondents.
6. We found that the constructs Knowledge to take action, had the highest (9) number of items (indicators) assigned to it, while others were singular variable items. We find this a potential for biases towards a particular construct and m – factor.
7. Although our sample met the characteristics of typical LMICs, we did not consider the feature of census data from the various countries, which could have enriched our study.
8. Lastly, we used equal sample sizes for all the selected countries regardless of the different population sizes, we think this could biase our study. Proportions are cardinal in multiple site studies to justify inference.

6.8.2 We think future studies should consider the following issues

1. Use a proportionate sample size based on country population size
2. Employ probabilistic sampling approaches to enhance generalization, particularly at the multi-stage levels
3. Consider behavioural changes in respondents and adopt dynamic data collections approaches.
4. Als, the number of respondents recruited from the different study sites was proportional to the different country populations size, this could biase the response in representing the more populous countries.
5. Rigorous formulations of the constructs with evenly distributed items and constructs on the progression from items, to constructs to factors will help assess the effect of potential biases due to uneven distribution of items on some constructs while others were singular constucts.
6. We strongly recommend detailed testing of our regression model with various datasets, moderations effects and possibly non – linear regression models.

CHAPTER SEVEN: CONCLUSIONS

In this chapter, we assess the implications of our findings on theory, policy, and Sustainable Development Goals (SDGs). We profess key issues worth noting in rolling out ICT-based interventions as a medium for Consumer Health Informatics (ConsHI) development amongst Low and Middle-Income Countries (LMICs).

7.1 CONCLUSION AND CONTRIBUTION OF RESEARCH

Despite the several studies on ConsHI, a model to predict the maturity of the concept in a population (group) has not been available thus far. We first articulate that our study contributes to the existing literature by proposing a predictive model of four factors moderated by categorical variables such as Age, Gender, Marital status, and Employment status to predict the maturity of a population in LMICs for ConsHI. Specifically, we have determined:

1. The study constructively aggregated three models from technology adoption (UTAUT family), patient activations (PAM) and consumer health informatics (ConsHI). The result is a composite structured Likert scale questionnaire to test and explore these models in one instance. Before this, these models had been applied and used separately for research and policy. In this study, we have composed one whole model to assess consumers, particularly in LMICs.
2. We have set the stage for future exploration of this aggregate model with a structured survey instrument that could be refined and utilised in other places for developing and developed countries, notably on a common measurement scale. Our validation used several statistical models, and we recommend other researchers test the instrument in other places.
3. Our Exploratory Factor analysis (EFA) elicited six e – factors that reflect six of our earlier t – factors (performance expectancy, level zero ConsHI services, knowledge to take action, resistance to change, taking action and behavioural intention) from the three theoretical models.
4. We have established four significant m – factors (Aptitude, Attitude, Confidence, and Motivations) as the major determinants of ConsHI maturity in LMICs. These constructs are composites of all three theories and are the first of their kind.
5. We asserted that this model has categorical influences, including age, gender, marital status, and employment status. These influences can direct the relationship between the dependent and independent variables. We recommend that future studies modify our list of moderators and test these variables' moderating effects in our model.
6. Finally, we have formulated a regression model, that shows the size, strength and significance of the four m – factors that predict maturity of the citizens of LMICs.

7.2 IMPLICATIONS OF THE STUDY RESULTS

7.2.1 Implication for theory and policy

We conducted our research in six countries, namely, Chile, Ghana, Iraq, Kosovo, Turkey, and Ukraine, to reveal consistency in data collection and cultural traits. Since ConsHI is an evolving concept, it isn't easy to conduct any study in more than one country under the same practice. However, we were fortunate to get the opportunity to work on this study among citizens of LMICS following the same procedure in these six countries.

Our findings shed light on several theoretical and practical implications issues of global concern (Janowski & Janssen, 2015) for ICT, policymakers, and medical professionals. In the first phase, we shed light on the theoretical implications of consumer (patient as a consumer) behaviour modelling and accentuating consumer technology adoption behaviours. The UTAUT is a general model to conceptualise adoption behaviour for ICT-related artefacts (Venkatesh *et al.*, 2003). Nevertheless, in the consumer (micro) context, this model's refinement is essential to ascertain the patient aspects of technology adoption. Thus the authors proposed the UTAUT2 model (Venkatesh, Thong and Xu, 2012) and UTAUT extensions (Hoque and Sorwar, 2017). Conversely, this study of ConsHI provides an additional service delivery channel, exploring citizens' preference for technology use in such media as mobile phones.

Importantly, ConsHI is a revolutionary system to continuously offer a flexible healthcare service in any hard-to-reach and isolated place with the help of wireless technology to maintain healthcare services.

It is a comprehensive model integrating technological, patient activation, and consumer levels of behaviour to adopt ConsHI with four determinants established. The author contends that the aggregations of constructs from these models, moderated by age, gender, and marital status, are the first of their kind to the best of our knowledge.

We conclude that all four determinants differed significantly in the six countries of interest. Chile was an exceptional case in assessing the moderating effects in countries of our study. We attributed the differences in the model in Chile to the economic classification that had changed before the study period, now rendering Chile and emerging economy. Also, we think that culture could have been another factor in determining the behaviour of citizens toward the concept of ConsHI.

It is insightful to state that of the 17 constructs deduced from the 43 variables, 16 were validated by our SEM. We also identified 5 of the 43 variables that were insignificant in our dataset.

Finally, the findings point to an administrative direction for policymakers of ConsHI using mhealth. Our healthcare systems face challenges due to constraints like shortage of healthcare professionals, cut downs in healthcare budgetary allocations from government, and accelerating population increase in the wake of increasing demands to curb epidemics and pandemics. Hence, healthcare providers must meet patients' different service requirements from this ConsHI perspective. These requirements are captured by revealing the antecedents of consumers with other moderating variables. Considering all the issues mentioned, it’s imperative for policy makers to enhance the predictors of ConsHI maturity to help consumers maximise the little available resources.

7.2.2 Implications for ICT

Venkatesh *et al.* (2003) asserted that ICT researchers so far have been using fragmented models and behavioural theories to capture the adoption of ICT. The UTAUT model provided an integrated insight into the overall intention of final usage behaviour. mHealth, as a revolutionary and modern alternative health service providing system, is a detailed illustration of ICT adoption behaviour. Undoubtedly, researchers in ICT appreciate that most of the determinants of the UTAUT model can capture ConsHI adoption behaviour quite appropriately, which applies to consumers of LMICs. More so, the aggregation with PAM and ConsHI levels makes it noteworthy that ICT has a colossal impact in supporting alternative traditional healthcare delivery systems. Primarily, the maturity of the citizens of LMICs is pivotal to the success of ICT in health. We note vital issues such as Age, Marital status and Gender as influencers in ICT adoptions and maturity of the citizens of LMICs for ConsHI.

7.2.3 A powerful tool for disease prevention and control

ConsHI, like mHealth, is evolving faster than expected because of the pressure on the healthcare system. The lifeline to resuscitation of most healthcare systems post the Covid-19 pandemic is ConsHI.

In **Ghana**, mobile technology, available even in remote communities, has proven to be a valuable tool to help bridge the gap between access to health information and service provision. The Mobile Technology for Community Health (MOTECH) initiative focused on improving maternal and child health. The project uses mobile phones to enhance access to and demand for health information and services among rural women while providing data on health service delivery and outcomes to the Ghana Health Service.

In Africa, Kenya is one of the champions of mobile phone activities like mobile money and has the potential to transfer this knowledge to other sectors like health. Currently, a system enables residents with a mobile phone to download a locally developed application to assess a doctor's or clinic's credibility before seeking their services. By sending an SMS, the user is shown up-to-date lists of licensed medical professionals and approved hospitals, starting with those nearest them.

In **Nigeria**, the SMART programme strengthens early infant HIV diagnosis services by reducing the turnaround time for test results by more than 50%. Nearly every district in Nigeria has network coverage for mobile telecommunication, even in remote areas lacking roads and electricity. Health facilities can receive and print test results using mobile SMS technology and small battery-operated printers without computers and Internet access.

In **South Africa**, the MAMA SMS service supports pregnant women and new mothers through an evidence-based free messaging service that extends the support provided at health facilities. The service offers pregnancy, postnatal and baby care information to women in their preferred local language.

The projects list above are a few of the document initiatives that are changing the healthcare delivery systems in developing countries. The resultant effect of ConsHI is the bandwagon to achieving SDG 3 and the universal health coverage target of the United Nations.

CHAPTER EIGHT: SUMMARIES

8.1 ENGLISH (ABSTRACT)

Introduction: Consumer Health Informatics (ConsHI) is a discipline based on methods, services, and Information and Communication Technology equipment to enable lay citizens to play an active role in their healthcare safely (ConsHI) promises to be the panacea to the myriads of health challenges plaguing the world, mainly post the Covid – 19 pandemics. While ConsHI promises a lot, there is a lack of models to assess the adoption of these concepts in various countries, particularly developing countries. Also, the numerous models of technology and healthcare adoptions are disparate, and the critical need for a composite model is more pronounced now than ever. This study aimed to assess factors that facilitate the adoption of ConsHI in low-middle income countries (LMICs) and to model the dominant factors that will predict the maturity of their citizens for the adoption of ConsHI.

Methods: We conducted a comprehensive search of how lay citizens adopted ICT for their health in both developed and developing countries and identified three essential models amongst the many options. The models were the Unified Theory of Acceptance and Utilisation of Technology (UTAUT), Patient Activation Measure (PAM) and Consumer Health Informatics (ConsHI) models that examined individual adoption and participation in technology and healthcare concurrently. We developed a composite instrument using these three empirical models. Subsequently, we validated the instrument using the Wilcoxon Signed Rank Test and Item Response Theory. We used a multi-stage convenient sampling to administer the questionnaire to 1,800 respondents from six LMICS in a cross-sectional survey. The respondents included healthy and ill-healthy people aged 18 years and above — the response rate was almost 100% except for a few fallouts since the researchers personally administered the survey. The dataset was analysed using both exploratory and confirmatory factor analysis techniques such as partial least square structural equation models in Rstudio and SmartPLS 4.0, respectively. Our dataset passed all the fundamental assumptions of both exploratory and confirmatory factor analysis with no significant problems.

We extracted factors from the exploratory factor analysis (e – factors) and juxtaposed them to the empirical model factors (t – factors). Also, we composed maturity factors (m-factors) from the t-factors using structural equation models.

Results: We achieved two distinct outcomes. First, in the preliminary investigation, we composed and validated a 43 items questionnaire designed as 5-point Likert items and added eight demographic items used as moderators of the m – factors to predict ConsHI maturity. Secondly, we extracted six exploratory factors (e-factors) as facilitators of ConsHI from the dataset. The e – factors were mainly labelled with a Gestalt experiment and reflected our three models' theoretical factors (t-factors). Also, we applied higher order confirmatory modelling to compose four m – factors (Aptitude, Attitude, Confidence and Motivation) as predictors of the maturity of the citizens of LMICs for ConsHI.

Attitude contributed the most to the prediction of the maturity of the citizens of LMICs for ConsHI, while Aptitude contributed the least. The predictive relevance and power of the model were validated and significant at a 95% confidence level. Notably, a multi-group analysis confirmed the statistical significance of observed heterogeneity and the moderation effect of several demographic variables, like age, influencing the predictability of ConsHI maturity in LMICs.

Conclusions: As far as we researched, our study is pioneering in establishing a composite model of UTAUT, PAM and ConsHI; this research brings to the fore the need for policy formulations to maximise technology in healthcare and optimise the expanded access to mobile telephony. The study formulated a predictive linear model for determining the maturity of the citizens of LMICs for ConsHI. The use of convenient sampling was a significant limitation of our study; as a cross-sectional study, many factors change over time, so the dynamic environmental factors could elude the researchers. We recommend that future studies employ random sampling approaches, and efforts to use active techniques in the behavioural study will help.

Keywords: Consumer Health Informatics, facilitators, Maturity of the citizens, low-middle income countries and predictive models

8.2 GERMAN ("Zusammenfassung")

Einführung: Consumer Health Informatics (ConsHI) ist eine Fachdisziplin, die basierend auf Methoden, Diensten und Informations- und Kommunikationstechnologie-Ausstattung Laien in die Lage versetzt, eine aktive Rolle hinsichtich ihrer Gesundheit sicher zu spielen. ConsHI verspricht, ein Heilmittel für die Myriaden an Gesundheitsherausforderungen zu sein, welche die Welt bedrängen, hauptsächlich nach der Covid – 19 Pandemie. Während Consumer Health Informatics (ConsHI) eine Menge verspricht, besteht ein Mangel an Modellen zur Bewertung der Annahme dieser Konzepte in verschiedenen Ländern, insbesondere Entwicklungsländern. Auch sind die zahlreichen Modelle der Annahme von Technologie und von Gesundheitsfürsorge uneinheitlich und der kritische Bedarf an einem zusammengesetzten Modell ist mehr ausgeprägt denn je. Diese Studie zielt darauf ab, Faktoren zu bewerten, die die Annahme von ConsHI in low-middle income countries (LMICs) zu erleichtern und die vorherrschenden Faktoren zu modellieren, welche Vorhersagen über die Reife ihrer Bürger für die Annahme von ConsHI treffen.

Methoden: Wir haben eine umfassende Suche danach durchgeführt, wie Laien in Entwicklungs- wie in entwickelten Ländern IKT für ihre Gesundheit einsetzten und haben aus vielen Optionen drei wesentliche Modelle identifiziert. Die Modelle waren Unified Theory of Acceptance and Utilisation of Technology (UTAUT), Patient Activation Measure (PAM) und Consumer Health Informatics (ConsHI) Modelle, welche die individuelle Annahme und Teilnahme an Technologie und Gesundheitsfürsorge parallel überprüften. Wir haben unter Nutzung dieser drei Modelle ein zusammengesetztes Modell entwickelt. Wir haben es anschließend mittels Wilcoxon Signed Rank Test und Item Response Theory validiert. Wir haben eine mehrstufige ad-hoc-Datensammlung (convenience sampling) durchgeführt, um den Fragebogen 1800 Befragten aus sechs LMICs in einer Querschnittserhebung vorzulegen. Die Befragten waren z.T. gesund, z.T. bei eingeschränkter Gesundheit, 18 Jahre oder älter – der Rücklauf war fast 100%, von einigen fehlenden Daten abgesehen, da die Untersucher die Erhebungsblätter persönlich vorlegten. Die Daten wurden sowohl mit explorativen wie auch konformativen Faktoranalyse-Techniken analysiert, so zum Beispiel partial least square structural equation models in Rstudio und SmartPLS 4.0, je nach Gegebenheit. Unser Datensatz erfüllte alle Grundannahmen der explorativen und konfirmativen Faktorenanalyse ohne signifikante Probleme. Aus der explorativen Faktorenanalyse haben wir Faktoren (e – factors) extrahiert und Fakten aus empirischen Modellen (t – factors) gegenübergestellt. Auch haben wir mittels Strukturgleichungsmodellen Reifefaktoren (m – factors) aus den t – factors zusammengestellt.

Ergebnisse: Wir haben zwei hauptsächliche Ergebnisse erzielt. Zunächst, in einer Voruntersuchung, haben wir einen Fragebogen mit 43 Items, gestaltet als 5-Punkt-Likert-Items zusammengestellt und validiert und acht demographische Items hnzugefügt, als Moderatoren der m – factors zur Vorhersage der ConsHI-Reife. Zum zweiten haben wir aus dem Datensatz sechs explorative Faktoren als erleichternde Elemente für ConsHI extrahiert. Die e – factors waren wesentlich durch ein Gestaltexperiment gekennzeichnet und spiegelten die drei theoretischen Faktoren (t – factors) unseres Modells wider. Wir haben auch konfirmative Modellierung höherer Ordnung angewandt, um vier m – factors (Aptitute, Attitude, Confidence und Motivation) als Prädiktoren der Reife von Bürgern in LMICs zusammenzusetzen. Attitude (Haltung) trug am meisten zur Vorhersage der Reife von Bürgern in LMICs bei, aptitude (Eignung) am wenigsten. Die prädiktive Relevanz und Stärke des Modells wurden validiert und waren auf dem 95%-Konfidenzniveau signifikant. Zu beachten ist, dass eine Mehrgruppenanalyse die statistische Signifikanz der beobachteten Heterogenität und den moderierenden Effekt mehrerer demogrpahischer Variablen, wie z.B. Alter, die Vorhersehbarkeit für ConsHI in LMICs bestätigten.

Schlüsse: Soweit es uns bekannt ist, ist unsere Studie ein Vorreiter, indem sie ein zusammengesetztes Modell aus UTAUT, PAM und ConsHI erstellt; diese Forschung macht die Notwendigkeit von Politikformulierung zur Maximierung der Technologie in der Gesundheitsversorgung und zur Optimierung eines ausgeweiteten Zugangs zu mobiler Telefonie zum zentralen Thema. Die Studie hat ein prädiktives lineares Modell zur Bestimmung der Reife von Bürgern in LMICs für ConsHI formuliert. Die Ad-Hoc-Datenerhebung war eine wichtige Einschränkung der Studie; als Querschnittstudie, da sich Faktoren mit der Zeit ändern, könnten ihr auch dynamische Umgebungsfaktoren entgangen sein. Wir empfehlen, dass künftige Studien Zufallsstichprobenvefahren anwenden, und Anstrengungen, aktive Techniken in einer Verhaltensstudie zu verwenden, würden auch helfen.

Schlüsselwörter: Verbrauchergesundheitsinformatik, Moderatoren, Reife der Bürger von LMICs, Ländern mit niedrigem mittlerem Einkommen und Vorhersagemodelle

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PERSONAL CONTRIBUTION TO DATA ACQUISITION / ASSESSMENT AND PERSONAL PUBLICATIONS

This project was conducted as part of the ConsHI Project. Survey data was collected and compiled by me and my colleague students at the masters and bachelor's level. Doctoral candidate Abubakari Yakubu, I alone conducted the analysis and evaluation of the data to model and predict the maturity of the citizens of ConsHI in LMICs which serves as the main results for this dissertation. Subsequently, four of us published the methods paper in 2021.

Part of this dissertation has already been published in the following articles:

> Yakubu, A., Paloji, F., Bonnet, J. G. P., Wetter, T., (2021). **Development of an Instrument for Assessing the Maturity of Citizens for Consumer Health Informatics in Developing Countries: The Case of Chile, Ghana, and Kosovo.** Methods Inf Med 2021; 60:62–70.

This Publication is based on the composite survey instrument from extant theories of UTAUT, UTAUT2, PAM and ConsHI, that was designed from the literature reviews in chapter two. In this publication we established the validity of the instrument that can be used in different Low- and middle-income countries to collect survey data for the analysis of Consumer Health Informatics (ConsHI). Subsequently, the instrument was used in 3 different countries.

My personal contribution to this publication consisted in the collection of data for the pilot and final data analysis in Ghana. The analysis of the final phase instrument using data from Chile, Ghana and Kosovo and the manuscript's composition, specifically the results and conclusion sections of the paper.

APPENDICES

A: Pilot phase instrument

Questionnaire of Consumer Health Informatics

The purpose of this research is to assess the maturity of healthcare consumers in utilization of mobile phones for healthcare management. We hereby assure that any information provided shall be treated with the utmost confidentiality and will be used solely for the purpose for which it was obtained.

1. Location: Area/ Village / Town / City:

2. Do you presently live in a rural or urban region?

Rural ❑	Urban ❑

3. Gender:

Male ❑	Female ❑

4. Age: How old are you?

1. Less than 20 years	❑	4. 40-49 years	❑
2. 20-29 years	❑	5. 50 & over	❑
3. 30-39 years	❑	6. No response	❑

5. Marital Status: Which of the following best describes your marital status?

1. Never married	❑	4. Separated	❑
2. Married	❑	5. Divorced	❑
3. Informal/Consensual Union	❑	6. Widowed	❑

6. Religion: What is your religious affiliation?

1. Catholic	❑	5. Islam	❑
2. Protestant	❑	6. Traditional Religion	❑
3. Pentecostal/Charismatic	❑	7. Other Religion	❑
4. Other Christians	❑	8. No religion	❑

7. Ethnicity/Tribe: Please identify your tribe or ethnicity:

1. Akan ❑	4. Guan ❑	7. Gruma ❑
2. Ga/Dangme ❑	5. Mole-Dagbani ❑	8. Hausa ❑
3. Ewe ❑	6. Grussi ❑	9. Other ❑

8. Education: What is your educational attainment?

1. None or Pre-school	❑	4. Secondary ❑
2. Primary	❑	5. Tertiary ❑
3. Middle/Junior High	❑	6. Other ❑
		(Name, if other)____________________________

9. Employment: Are you currently employed?

1. Yes ❑	2. No ❑	3. Not Applicable ❑

10. If yes, what is the term of your employment?

1. Full-time ❑	3. Part-time ❑
2. Temporary/Contract ❑	4. No response/NA ❑

11. Occupation: If you're working, what is your occupation?

1. Administration and Managerial ❑	5. Services ❑
2. Professionals & Technical professionals ❑	6. Agriculture, Animal, Forestry ❑
2. Officers ❑	7. Craftsmen and similar worker ❑
3. Clerical work and Related ❑	9. Other (not listed) ❑
4. Sales ❑	10. Not applicable ❑

12. Sector: If you're employed, what is the sector of your employment?

1. Public ❑	5. non-governmental organization ❑
2. Private formal ❑	6. Intergovernmental Organisation ❑
3. Private informal ❑	7. Other ❑
4. Semi-public or parastatal ❑	8. Not application ❑

13. Can you tell me, in strict confidence, your gross (before tax) monthly household income?

1.	Less than the existence minimum (< GhC 240)	❑
2.	The existence minimum (GhC 240)	❑
3.	2 times the existence minimum (GhC 480)	❑
4.	4 times the existence minimum (GhC 720)	❑
5.	8 times the existence minimum (GhC 960)	❑
6.	16 times the existence minimum (GhC 1,200)	❑
7.	More than 16 times the existence minimum (>GhC 1,200)	❑
8.	No response	❑

14. Have you sought professional medical services within the past four weeks?

1. Yes ❑	2. No ❑	3. Don't remember ❑

Interviewers' Name: ______________________________

Please complete the following questionnaire by placing a CROSS in the appropriate box ☒

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1. I am the person who is responsible for managing my health condition.	☐	☐	☐	☐	☐
2. Taking an active role in my own health care is the most important factor in determining my health and ability to function.	☐	☐	☐	☐	☐
3. I find a mobile phone or the internet useful in my daily life.	☐	☐	☐	☐	☐
4. Using a mobile phone or the internet helps me do things more quickly.	☐	☐	☐	☐	☐
5. Using a mobile phone or the internet increases my productivity.	☐	☐	☐	☐	☐
6. Learning how to use a mobile phone or the internet is easy for me.	☐	☐	☐	☐	☐
7. I understand clearly what I do with a mobile phone or the internet.	☐	☐	☐	☐	☐
8. I find a mobile phone or the internet easy to use.	☐	☐	☐	☐	☐
9. I believe that I can search the internet for health information.	☐	☐	☐	☐	☐
10. I believe I can distinguish a trustworthy website from an untrustworthy website.	☐	☐	☐	☐	☐
11. People who are important to me think that I should use mobile phone or internet.	☐	☐	☐	☐	☐
12. People who influence my behaviour think that I should use mobile phone or internet.	☐	☐	☐	☐	☐
13. People whose opinions that I value prefer that I use mobile phone or internet.	☐	☐	☐	☐	☐
14. I have the resources necessary to use mobile phone or internet. (electricity, Wi-Fi, mobile internet etc.)	☐	☐	☐	☐	☐

15. Using a mobile phone or the internet is fun.	☐	☐	☐	☐	☐
16. Using a mobile phone or the internet is enjoyable.	☐	☐	☐	☐	☐
17. Using a mobile phone or the internet is very entertaining.	☐	☐	☐	☐	☐
18. The use of a mobile phone or the internet has become a habit for me.	☐	☐	☐	☐	☐
19. I am addicted to using a mobile phone or the internet.	☐	☐	☐	☐	☐
20. I know what each of my prescribed medications do.	☐	☐	☐	☐	☐
21. I know that I can find information about my medication, when I search for them in the internet.	☐	☐	☐	☐	☐
22. I am confident that I can tell my health care provider concerns I have, even if he or she does not ask.	☐	☐	☐	☐	☐
23. I am able to use E-Mail or SMS to contact my health care provider.	☐	☐	☐	☐	☐
24. I am confident that I can tell when I need to go get medical care and when I can handle a health problem myself.	☐	☐	☐	☐	☐
25. I know how my lifestyle can influence my health.	☐	☐	☐	☐	☐
26. To control my lifestyle, I would use an app.	☐	☐	☐	☐	☐
27. I would use a device such as a heart rate monitor to measure my activities.	☐	☐	☐	☐	☐
28. I am confident that I can follow through on medical treatments I need to do at home.	☐	☐	☐	☐	☐
29. I would use an app that reminds me to take my medication in the right dosage and frequency.	☐	☐	☐	☐	☐
30. I am confident that I could take actions that will help prevent or minimize some symptoms or problems associated with my health condition.	☐	☐	☐	☐	☐
31. I have the knowledge necessary to use a mobile phone or the internet.	☐	☐	☐	☐	☐
32. I am confident that I can find trustworthy sources of information about my health condition and my health	☐	☐	☐	☐	☐

choices. To find this information I would also use the internet.					
33. I am confident that I can follow through on medical recommendations my health care provider makes, such as changing my diet or doing regular exercise.	☐	☐	☐	☐	☐
34. I understand the nature of my health condition(s).	☐	☐	☐	☐	☐
35. When I am sick, I know the different medical treatment options available for my health condition.	☐	☐	☐	☐	☐
36. A mobile phone or the internet is compatible with other technologies I use.	☐	☐	☐	☐	☐
37. A mobile phone or the internet is reasonably priced.	☐	☐	☐	☐	☐
38. A mobile phone or the internet is a good value for the money.	☐	☐	☐	☐	☐
39. At the current price, a mobile phone or the internet provides a good value.	☐	☐	☐	☐	☐
40. Using a mobile phone or the internet would make me very nervous.	☐	☐	☐	☐	☐
41. Using a mobile phone or the internet make me worried.	☐	☐	☐	☐	☐
42. Using a mobile phone or the internet make me feel uncomfortable.	☐	☐	☐	☐	☐
43. I will always try to use a mobile phone or the internet in my daily life.	☐	☐	☐	☐	☐
44. I don't want a mobile phone or the internet to change the way I deal with health relevant problems.	☐	☐	☐	☐	☐
45. I don't want a mobile phone or the internet to change the way I interact with other people.	☐	☐	☐	☐	☐
46. I have been able to maintain a lifestyle that is good for my health.	☐	☐	☐	☐	☐
47. I know how to prevent problems with my health.	☐	☐	☐	☐	☐
48. When I am sick, I know about the self-treatments for my health condition.	☐	☐	☐	☐	☐

49. I know that I can look on the internet to find out more about self-treatments.	☐	☐	☐	☐	☐
50. I have made the changes in my lifestyle like diet and exercise that are recommended for my health condition.	☐	☐	☐	☐	☐
51. I am confident I can figure out solutions when new situations or problems arise with my health condition.	☐	☐	☐	☐	☐
52. I am confident that I will find information through my mobile phone or on the internet when new situations or problems arise with my health condition.	☐	☐	☐	☐	☐
53. I am able to use a mobile phone or the internet to help me control medical conditions throughout time on my own.	☐	☐	☐	☐	☐
54. I intend to use a mobile phone or the internet in the future.	☐	☐	☐	☐	☐
55. I plan to use a mobile phone or the internet frequently.	☐	☐	☐	☐	☐
56. A mobile phone or the internet is a pleasant experience.	☐	☐	☐	☐	☐
57. I am confident that I can maintain healthy lifestyle like diet and exercise even during times of stress.	☐	☐	☐	☐	☐
58. I use a mobile phone or the internet frequently.	☐	☐	☐	☐	☐
59. Assuming, I am willing, I can share my personal experience of my health condition through blogs.	☐	☐	☐	☐	☐
60. Assuming, I am willing, I can interact with people who have the same health condition through internet forums.	☐	☐	☐	☐	☐
61. I am able to handle problems of my health condition on my own with the help of devices like blood pressure monitor, blood glucose monitor, etc.	☐	☐	☐	☐	☐
62. I am confident I can keep my health problems from interfering with the things I want to do.	☐	☐	☐	☐	☐
63. Maintaining the lifestyle that is recommended for my health condition is too hard to do on a daily basis.	☐	☐	☐	☐	☐
64. I spend a lot of time on a mobile phone or the internet.	☐	☐	☐	☐	☐

Thank you for your time!!!!

B: Final phase instrument

Questionnaire of Consumer Health Informatics

The research seeks to assess the maturity of the citizens of LMICs for consumer health informatics using mobile phones. The information provided here will be used only for the purpose of this research and shall no way be exploited for other gains.

Interviewers' Name: ___________________________________

1. Where do you live? (Village / Town / City):

2. Do you presently live in a rural or urban region?

Rural ❑	Urban ❑

3. Gender:

Male ❑ Female ❑

4. Age: How old are you?

1. Less than 20 years ❑	4. 40-49 years ❑
2. 20-29 years ❑	5. 50 & over ❑
3. 30-39 years ❑	6. No response ❑

5. Marital Status: Which of the following best describes your marital status?

1. Never married ❑	4. Separated ❑
2. Married ❑	5. Divorced ❑
3. Informal/Consensual Union ❑	6. Widowed ❑

6. Religion: What is your religious affiliation?

1. Catholic ❑	5. Islam ❑
2. Protestant ❑	6. Traditional Religion ❑

3. Pentecostal/Charismatic	❑	7. Other Religion	❑
4. Other Christians	❑	8. No religion	❑

7. Ethnicity/Tribe: Please identify your tribe or ethnicity:

1. Akan	❑	4. Guan	❑	7. Gruma	❑
2. Ga/Dangme	❑	5. Mole-Dagbani	❑	8. Hausa	❑
3. Ewe	❑	6. Grussi	❑	9. Other	❑

8. Education: What is your educational attainment?

1. None or Pre-school	❑	4. Secondary	❑
2. Primary	❑	5. Tertiary	❑
3. Middle/Junior High	❑	6. Other	❑

9. Employment: Are you currently employed?

1. Yes ❑	2. No ❑	3. Not Applicable ❑

10. Have you sought professional medical services within the past four weeks?

1. Yes ❑	2. No ❑	3. Don't remember ❑

Interviewers' Name: ________________________________

Please complete the following questionnaire by placing a CROSS in the appropriate box ☒

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1. I am the person who is responsible for managing my health condition.	☐	☐	☐	☐	☐
2. Taking an active role in my own health care is the most important factor in determining my health and ability to function.	☐	☐	☐	☐	☐
3. I find a mobile phone or the internet useful in my daily life.	☐	☐	☐	☐	☐
4. Using a mobile phone or the internet helps me do things more quickly.	☐	☐	☐	☐	☐
5. Using a mobile phone or the internet increases my productivity.	☐	☐	☐	☐	☐
6. Learning how to use a mobile phone or the internet is easy for me.	☐	☐	☐	☐	☐
7. I believe that I can search the internet for health information.	☐	☐	☐	☐	☐
8. I believe I can distinguish a trustworthy website from an untrustworthy website.	☐	☐	☐	☐	☐
9. People whose opinions that I value prefer that I use mobile phone or internet.	☐	☐	☐	☐	☐
10. I have the resources necessary to use mobile phone or internet. (electricity, Wi-Fi, mobile internet etc.)	☐	☐	☐	☐	☐
11. Using a mobile phone or the internet is fun.	☐	☐	☐	☐	☐
12. The use of a mobile phone or the internet has become a habit for me.	☐	☐	☐	☐	☐
13. I know that I can find information about my medication, when I search for them in the internet.	☐	☐	☐	☐	☐
14. I am confident that I can tell my health care provider concerns I have, even if he or she does not ask.	☐	☐	☐	☐	☐
15. I am confident that I can tell when I need to go get medical care and when I can handle a health problem myself.	☐	☐	☐	☐	☐

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
16. I know how my lifestyle can influence my health.	☐	☐	☐	☐	☐
17. To control my lifestyle, I would use an app.	☐	☐	☐	☐	☐
18. I am confident that I can follow through on medical treatments I need to do at home.	☐	☐	☐	☐	☐
19. I would use an app that reminds me to take my medication in the right dosage and frequency.	☐	☐	☐	☐	☐
20. I am confident that I could take actions that will help prevent or minimize some symptoms or problems associated with my health condition.	☐	☐	☐	☐	☐
21. I have the knowledge necessary to use a mobile phone or the internet.	☐	☐	☐	☐	☐
22. I am confident that I can find trustworthy sources of information about my health condition and my health choices. To find this information I would also use the internet.	☐	☐	☐	☐	☐
23. I am confident that I can follow through on medical recommendations my health care provider makes, such as changing my diet or doing regular exercise.	☐	☐	☐	☐	☐
24. I understand the nature of my health condition(s).	☐	☐	☐	☐	☐
25. When I am sick, I know the different medical treatment options available for my health condition.	☐	☐	☐	☐	☐
26. A mobile phone or the internet is compatible with other technologies I use.	☐	☐	☐	☐	☐
27. At the current price, a mobile phone or the internet provides a good value.	☐	☐	☐	☐	☐
28. Using a mobile phone or the internet make me worried.	☐	☐	☐	☐	☐
29. I will always try to use a mobile phone or the internet in my daily life.	☐	☐	☐	☐	☐
30. I don’t want a mobile phone or the internet to change the way I deal with health relevant problems.	☐	☐	☐	☐	☐
31. I don’t want a mobile phone or the internet to change the way I interact with other people.	☐	☐	☐	☐	☐
32. I know how to prevent problems with my health.	☐	☐	☐	☐	☐

33. I have made the changes in my lifestyle like diet and exercise that are recommended for my health condition.	☐	☐	☐	☐	☐
34. I am confident I can figure out solutions when new situations or problems arise with my health condition.	☐	☐	☐	☐	☐
35. I am confident that I will find information through my mobile phone or on the internet when new situations or problems arise with my health condition.	☐	☐	☐	☐	☐
36. I am able to use a mobile phone or the internet to help me control medical conditions throughout time on my own.	☐	☐	☐	☐	☐
37. I intend to use a mobile phone or the internet in the future.	☐	☐	☐	☐	☐
38. I plan to use a mobile phone or the internet frequently.	☐	☐	☐	☐	☐
39. A mobile phone or the internet is a pleasant experience.	☐	☐	☐	☐	☐
40. I am confident that I can maintain healthy lifestyle like diet and exercise even during times of stress.	☐	☐	☐	☐	☐
41. I use a mobile phone or the internet frequently.	☐	☐	☐	☐	☐
42. Assuming, I am willing, I can share my personal experience of my health condition through blogs.	☐	☐	☐	☐	☐
43. I spend a lot of time on a mobile phone or the internet.	☐	☐	☐	☐	☐

THANK YOU FOR PARTICIPATING!!!!!!!

C: List of Tables and Figures

Appendic C. 1: Descriptive statistics of indicators

Indicator	Missing	Median	Observed min	Observed max	Std dev	Kurtosis	Skewness	CvM p-value	SD	D	N	A	SA	TOTAL
Item 1	0.00	4.00	1.00	5.00	0.97	1.75	-1.31	0.00	60	92	170	874	604	1800
Item 2	0.00	4.00	1.00	5.00	0.89	1.49	-1.08	0.00	39	72	264	893	532	1800
Item 3	0.00	4.00	1.00	5.00	0.88	1.41	-1.07	0.00	33	89	239	923	516	1800
Item 4	0.00	4.00	1.00	5.00	0.89	1.71	-1.17	0.00	37	93	198	952	520	1800
Item 5	0.00	4.00	1.00	5.00	1.01	-0.28	-0.54	0.00	42	207	424	735	392	1800
Item 6	0.00	4.00	**0.00**	5.00	0.96	1.84	-1.34	0.00	51	105	142	877	624	**1799**
Item 7	0.00	4.00	1.00	5.00	0.96	0.66	-0.97	0.00	39	146	242	866	507	1800
Item 8	0.00	4.00	1.00	5.00	1.10	-0.64	-0.47	0.00	82	335	349	755	279	1800
Item 9	0.00	4.00	1.00	5.00	0.95	0.03	-0.61	0.00	49	212	455	854	230	1800
Item 10	0.00	4.00	1.00	5.00	0.88	1.94	-1.23	0.00	35	67	196	867	635	1800
Item 11	0.00	4.00	1.00	5.00	0.98	-0.06	-0.62	0.00	40	177	412	776	395	1800
Item 12	0.00	4.00	1.00	5.00	1.10	-0.10	-0.81	0.00	71	216	259	758	496	1800
Item 13	0.00	4.00	1.00	5.00	1.00	0.89	-1.07	0.00	61	128	232	851	528	1800
Item 14	0.00	4.00	**0.00**	5.00	0.97	0.46	-0.78	0.00	50	139	388	841	381	**1799**
Item 15	0.00	4.00	1.00	5.00	0.86	1.07	-0.90	0.00	35	119	344	1007	295	1800
Item 16	0.00	4.00	1.00	5.00	0.84	2.40	-1.31	0.00	29	69	147	926	629	1800
Item 17	0.00	3.00	1.00	5.00	1.24	-1.07	0.02	0.00	221	494	387	474	224	1800
Item 18	0.00	4.00	1.00	5.00	0.98	0.51	-0.90	0.00	67	177	311	954	291	1800
Item 19	0.00	4.00	1.00	5.00	1.14	-0.53	-0.57	0.00	89	267	347	687	410	1800
Item 20	0.00	4.00	1.00	5.00	0.86	0.95	-0.82	0.00	34	108	393	971	294	1800
Item 21	0.00	4.00	1.00	5.00	0.90	1.70	-1.19	0.00	39	88	197	911	565	1800
Item 22	0.00	4.00	1.00	5.00	1.00	-0.05	-0.65	0.00	64	224	408	844	260	1800
Item 23	0.00	4.00	1.00	5.00	0.85	1.21	-0.87	0.00	41	92	413	981	273	1800
Item 24	0.00	4.00	1.00	5.00	0.80	2.06	-1.09	0.00	27	81	244	1094	354	1800
Item 25	0.00	4.00	1.00	5.00	0.91	0.10	-0.65	0.00	42	220	448	908	182	1800
Item 26	0.00	4.00	1.00	5.00	0.89	0.93	-0.88	0.00	36	110	333	942	379	1800
Item 27	0.00	4.00	1.00	5.00	1.02	-0.21	-0.47	0.00	94	239	563	707	197	1800
R28	0.00	4.00	1.00	5.00	1.10	-0.74	-0.30	0.00	89	361	442	658	250	1800

Item 29	0.00	4.00	1.00	5.00	0.92	0.35	-0.67	0.00	54	163	497	862	224	1800
R30	0.00	3.00	1.00	5.00	1.15	-0.82	0.25	0.00	191	592	475	368	174	1800
R31	0.00	2.00	1.00	5.00	1.14	-0.61	0.51	0.00	233	746	380	298	143	1800
Item 32	0.00	4.00	1.00	5.00	0.83	0.87	-0.79	0.00	35	128	477	980	180	1800
Item 33	0.00	4.00	1.00	5.00	0.98	-0.41	-0.52	0.00	39	299	382	859	221	1800
Item 34	0.00	4.00	1.00	5.00	0.94	-0.11	-0.49	0.00	34	200	491	807	268	1800
Item 35	0.00	4.00	1.00	5.00	1.00	-0.57	-0.37	0.00	54	336	464	753	193	1800
Item 36	0.00	3.00	1.00	5.00	1.05	-0.91	-0.18	0.00	73	475	419	675	158	1800
Item 37	0.00	4.00	1.00	5.00	0.93	1.45	-1.13	0.00	50	93	242	925	490	1800
Item 38	0.00	4.00	1.00	5.00	1.02	-0.06	-0.64	0.00	64	205	413	800	318	1800
Item 39	0.00	4.00	**0.00**	5.00	0.96	0.27	-0.69	0.00	44	155	423	827	350	**1799**
Item 40	0.00	4.00	1.00	5.00	1.03	-0.56	-0.38	0.00	69	332	466	731	202	1800
Item 41	0.00	4.00	1.00	5.00	1.06	0.48	-0.98	0.00	75	147	258	797	523	1800
Item 42	0.00	3.00	1.00	5.00	1.10	-0.81	-0.28	0.00	147	409	450	656	138	1800
Item 43	0.00	4.00	1.00	5.00	1.18	-0.80	-0.39	0.00	119	337	373	640	331	1800

NB: CvM: Cramer-van Mises; SD: Strongly Disagree; D: Disagree; N: Neutral; A: Agree; SA: Strongly Agree; Std dev: Standard deviation.

Appendic C. 2: CTA Analysis

Constructs	Beta	P values	CI low adj.	CI up adj.	Mode
BI					Reflective
1: Item 29,Item 37,Item 38,Item 41	-0.03	0.06	-0.06	0.00	Reflective
2: Item 29,Item 37,Item 41,Item 38	-0.02	0.30	-0.05	0.02	Reflective
CK					Formative
1: Item 14,Item 15,Item 16,Item 18	0.00	0.73	-0.02	0.02	Reflective
2: Item 14,Item 15,Item 18,Item 16	-0.04	0.00	-0.08	-0.01	Formative
4: Item 14,Item 15,Item 16,Item 20	0.00	0.86	-0.02	0.02	Reflective
6: Item 14,Item 16,Item 20,Item 15	-0.02	0.01	-0.04	0.01	Reflective
9: Item 14,Item 16,Item 22,Item 15	-0.01	0.49	-0.03	0.02	Reflective
10: Item 14,Item 15,Item 16,Item 23	0.00	0.67	-0.02	0.02	Reflective
13: Item 14,Item 15,Item 16,Item 24	0.04	0.00	0.02	0.06	Formative
17: Item 14,Item 15,Item 25,Item 16	-0.02	0.01	-0.04	0.01	Reflective
20: Item 14,Item 15,Item 20,Item 18	0.03	0.00	0.01	0.06	Formative
26: Item 14,Item 15,Item 23,Item 18	0.00	1.00	-0.02	0.02	Reflective
29: Item 14,Item 15,Item 24,Item 18	0.01	0.19	-0.01	0.03	Reflective
33: Item 14,Item 18,Item 25,Item 15	0.04	0.00	0.01	0.07	Formative
41: Item 14,Item 15,Item 24,Item 20	0.00	0.88	-0.02	0.02	Reflective
47: Item 14,Item 15,Item 23,Item 22	0.02	0.03	-0.01	0.05	Reflective
49: Item 14,Item 15,Item 22,Item 24	0.00	0.79	-0.02	0.02	Reflective
51: Item 14,Item 22,Item 24,Item 15	-0.01	0.05	-0.04	0.01	Reflective
57: Item 14,Item 23,Item 24,Item 15	0.00	0.43	-0.01	0.02	Reflective
109: Item 14,Item 18,Item 20,Item 22	0.04	0.00	0.01	0.07	Formative
113: Item 14,Item 18,Item 23,Item 20	0.02	0.10	-0.02	0.05	Reflective
133: Item 14,Item 18,Item 23,Item 25	0.03	0.00	0.00	0.07	Formative
137: Item 14,Item 18,Item 25,Item 24	0.04	0.00	0.01	0.06	Formative
149: Item 14,Item 20,Item 24,Item 23	0.01	0.37	-0.02	0.03	Reflective
151: Item 14,Item 20,Item 23,Item 25	0.01	0.14	-0.01	0.04	Reflective
161: Item 14,Item 22,Item 25,Item 23	-0.02	0.09	-0.04	0.01	Reflective
165: Item 14,Item 24,Item 25,Item 22	0.02	0.02	-0.01	0.04	Reflective
174: Item 15,Item 18,Item 22,Item 16	-0.01	0.09	-0.03	0.01	Reflective
231: Item 15,Item 22,Item 24,Item 18	0.02	0.01	0.00	0.04	Formative
LO					Reflective
1: Item 13,Item 35,Item 7,Item 8	0.01	0.62	-0.02	0.04	Reflective
2: Item 13,Item 35,Item 8,Item 7	0.02	0.10	-0.01	0.05	Reflective
APTITUDE					Formative
1: Item 29,Item 32,Item 33,Item 34	-0.02	0.08	-0.05	0.01	Reflective
2: Item 29,Item 32,Item 34,Item 33	-0.01	0.26	-0.04	0.02	Reflective
4: Item 29,Item 32,Item 33,Item 37	-0.02	0.00	-0.03	0.00	Reflective
6: Item 29,Item 33,Item 37,Item 32	-0.05	0.00	-0.08	-0.02	Formative
10: Item 29,Item 32,Item 33,Item 41	-0.01	0.03	-0.02	0.00	Reflective
13: Item 29,Item 32,Item 34,Item 37	-0.01	0.00	-0.02	0.00	Reflective
19: Item 29,Item 32,Item 34,Item 41	-0.01	0.14	-0.02	0.01	Reflective
25: Item 29,Item 32,Item 37,Item 41	0.03	0.01	0.00	0.06	Formative
30: Item 29,Item 38,Item 41,Item 32	-0.01	0.07	-0.04	0.01	Reflective
34: Item 29,Item 33,Item 34,Item 38	0.01	0.02	0.00	0.02	Formative
38: Item 29,Item 33,Item 41,Item 34	-0.16	0.00	-0.21	-0.11	Formative
40: Item 29,Item 33,Item 37,Item 38	0.07	0.00	0.04	0.11	Formative
50: Item 29,Item 34,Item 38,Item 37	0.08	0.00	0.04	0.12	Formative

55: Item 29,Item 34,Item 38,Item 41	0.10	0.00	0.06	0.15	Formative
ATTITUDE					**Formative**
1: Item 1,Item 10,Item 13,Item 2	0.01	0.02	**-0.01**	**0.03**	Reflective
2: Item 1,Item 10,Item 2,Item 13	-0.06	0.00	-0.10	-0.01	Formative
4: Item 1,Item 10,Item 13,Item 21	-0.01	0.54	**-0.05**	**0.03**	Reflective
6: Item 1,Item 13,Item 21,Item 10	0.03	0.00	0.00	0.06	Formative
10: Item 1,Item 10,Item 13,Item 27	0.00	0.69	**-0.02**	**0.03**	Reflective
13: Item 1,Item 10,Item 13,Item 3	0.01	0.45	**-0.02**	**0.03**	Reflective
17: Item 1,Item 10,Item 35,Item 13	0.03	0.01	**-0.01**	**0.06**	Reflective
20: Item 1,Item 10,Item 4,Item 13	-0.01	0.28	**-0.04**	**0.02**	Reflective
24: Item 1,Item 13,Item 5,Item 10	0.01	0.17	**-0.02**	**0.04**	Reflective
27: Item 1,Item 13,Item 6,Item 10	0.01	0.47	**-0.03**	**0.04**	Reflective
28: Item 1,Item 10,Item 13,Item 7	0.04	0.00	0.01	0.08	Formative
31: Item 1,Item 10,Item 13,Item 8	0.02	0.05	**-0.02**	**0.05**	Reflective
36: Item 1,Item 13,Item 9,Item 10	0.01	0.43	**-0.02**	**0.04**	Reflective
41: Item 1,Item 10,R30,Item 13	0.00	0.88	**-0.03**	**0.03**	Reflective
46: Item 1,Item 10,Item 2,Item 21	-0.11	0.00	-0.16	-0.06	Formative
52: Item 1,Item 10,Item 2,Item 27	-0.04	0.00	**-0.08**	**0.00**	Reflective
58: Item 1,Item 10,Item 2,Item 35	-0.02	0.18	**-0.06**	**0.03**	Reflective
62: Item 1,Item 10,Item 4,Item 2	0.02	0.00	0.00	0.05	Formative
75: Item 1,Item 2,Item 8,Item 10	0.06	0.00	0.01	0.10	Formative
87: Item 1,Item 2,R31,Item 10	0.00	0.87	**-0.04**	**0.04**	Reflective
89: Item 1,Item 10,Item 26,Item 21	0.02	0.04	**-0.02**	**0.06**	Reflective
94: Item 1,Item 10,Item 21,Item 3	0.01	0.04	**-0.01**	**0.04**	Reflective
100: Item 1,Item 10,Item 21,Item 4	0.01	0.03	**-0.01**	**0.04**	Reflective
104: Item 1,Item 10,Item 5,Item 21	0.00	0.84	**-0.04**	**0.03**	Reflective
112: Item 1,Item 10,Item 21,Item 8	0.02	0.01	**-0.01**	**0.05**	Reflective
131: Item 1,Item 10,Item 3,Item 26	-0.01	0.20	**-0.04**	**0.02**	Reflective
132: Item 1,Item 26,Item 3,Item 10	-0.03	0.00	**-0.06**	**0.00**	Reflective
138: Item 1,Item 26,Item 4,Item 10	-0.04	0.00	-0.07	-0.01	Formative
141: Item 1,Item 26,Item 5,Item 10	-0.01	0.24	**-0.04**	**0.02**	Reflective
178: Item 1,Item 10,Item 27,Item 7	0.01	0.14	**-0.01**	**0.03**	Reflective
214: Item 1,Item 10,Item 3,Item 9	0.02	0.03	**-0.01**	**0.05**	Reflective
222: Item 1,Item 3,R30,Item 10	0.02	0.00	0.00	0.05	Formative
241: Item 1,Item 10,Item 35,Item 9	0.01	0.17	**-0.02**	**0.04**	Reflective
246: Item 1,Item 35,R28,Item 10	0.01	0.00	0.00	0.03	Formative
247: Item 1,Item 10,Item 35,R30	-0.03	0.00	**-0.05**	**0.00**	Reflective
253: Item 1,Item 10,Item 4,Item 5	0.05	0.00	0.01	0.10	Formative
265: Item 1,Item 10,Item 4,Item 9	0.00	0.82	**-0.03**	**0.03**	Reflective
281: Item 1,Item 10,Item 7,Item 5	0.01	0.17	**-0.02**	**0.05**	Reflective
284: Item 1,Item 10,Item 8,Item 5	-0.01	0.50	**-0.04**	**0.03**	Reflective
290: Item 1,Item 10,R28,Item 5	0.02	0.02	**-0.01**	**0.05**	Reflective
298: Item 1,Item 10,Item 6,Item 7	0.05	0.00	0.01	0.09	Formative
301: Item 1,Item 10,Item 6,Item 8	0.05	0.00	0.00	0.09	Formative
311: Item 1,Item 10,R30,Item 6	0.03	0.00	0.00	0.07	Formative
321: Item 1,Item 7,Item 9,Item 10	0.01	0.07	**-0.01**	**0.04**	Reflective
329: Item 1,Item 10,R31,Item 7	0.02	0.01	**-0.01**	**0.05**	Reflective
335: Item 1,Item 10,R28,Item 8	0.01	0.25	**-0.02**	**0.04**	Reflective
356: Item 1,Item 10,R31,R28	0.06	0.00	0.02	0.10	Formative
357: Item 1,R28,R31,Item 10	0.00	0.17	**-0.01**	**0.01**	Reflective

418: Item 1,Item 13,Item 21,Item 5	0.01	0.53	-0.03	0.04	Reflective
452: Item 1,Item 13,Item 4,Item 26	-0.04	0.00	-0.07	0.00	Reflective
457: Item 1,Item 13,Item 26,Item 6	0.02	0.09	-0.02	0.05	Reflective
461: Item 1,Item 13,Item 7,Item 26	-0.01	0.24	-0.04	0.02	Reflective
468: Item 1,Item 26,Item 9,Item 13	-0.02	0.06	-0.05	0.02	Reflective
471: Item 1,Item 26,R28,Item 13	0.01	0.31	-0.02	0.04	Reflective
475: Item 1,Item 13,Item 26,R31	0.02	0.00	0.00	0.04	Formative
480: Item 1,Item 27,Item 3,Item 13	-0.01	0.07	-0.04	0.01	Reflective
520: Item 1,Item 13,Item 3,Item 6	0.00	0.81	-0.03	0.04	Reflective
521: Item 1,Item 13,Item 6,Item 3	0.01	0.17	-0.02	0.04	Reflective
539: Item 1,Item 13,R31,Item 3	0.01	0.22	-0.02	0.03	Reflective
541: Item 1,Item 13,Item 35,Item 4	0.02	0.00	0.00	0.04	Reflective
580: Item 1,Item 13,Item 4,Item 9	0.00	0.59	-0.03	0.04	Reflective
623: Item 1,Item 13,R28,Item 6	0.04	0.00	0.01	0.07	Formative
723: Item 1,Item 26,Item 35,Item 2	0.02	0.00	0.00	0.03	Formative
760: Item 1,Item 2,Item 27,Item 5	0.09	0.00	0.04	0.13	Formative
763: Item 1,Item 2,Item 27,Item 6	0.06	0.00	0.01	0.11	Formative
807: Item 1,Item 3,R28,Item 2	0.01	0.35	-0.01	0.03	Reflective
841: Item 1,Item 2,Item 4,Item 5	0.18	0.00	0.12	0.24	Formative
847: Item 1,Item 2,Item 4,Item 7	0.08	0.00	0.03	0.12	Formative
908: Item 1,Item 2,Item 9,Item 7	0.02	0.10	-0.02	0.07	Reflective
913: Item 1,Item 2,Item 7,R30	0.06	0.00	0.02	0.11	Formative
919: Item 1,Item 2,Item 8,Item 9	0.08	0.00	0.03	0.12	Formative
924: Item 1,Item 8,R28,Item 2	0.00	0.49	-0.02	0.03	Reflective
927: Item 1,Item 8,R30,Item 2	-0.01	0.04	-0.04	0.01	Reflective
934: Item 1,Item 2,Item 9,R30	-0.01	0.69	-0.06	0.04	Reflective
943: Item 1,Item 2,R28,R31	0.11	0.00	0.05	0.18	Formative
962: Item 1,Item 21,Item 5,Item 26	-0.02	0.11	-0.06	0.02	Reflective
1017: Item 1,Item 27,R31,Item 21	0.01	0.42	-0.02	0.03	Reflective
1020: Item 1,Item 3,Item 35,Item 21	0.01	0.21	-0.02	0.04	Reflective
1087: Item 1,Item 21,Item 4,Item 9	0.02	0.02	-0.01	0.04	Reflective
1127: Item 1,Item 21,Item 9,Item 6	-0.05	0.00	-0.09	0.00	Reflective
1132: Item 1,Item 21,Item 6,R30	0.01	0.05	-0.01	0.03	Reflective
1175: Item 1,Item 21,R30,R28	0.08	0.00	0.03	0.12	Formative
1179: Item 1,R28,R31,Item 21	0.01	0.04	-0.01	0.02	Reflective
1184: Item 1,Item 26,Item 3,Item 27	-0.01	0.13	-0.04	0.02	Reflective
1189: Item 1,Item 26,Item 27,Item 4	0.02	0.02	-0.01	0.04	Reflective
1211: Item 1,Item 26,R30,Item 27	-0.02	0.02	-0.06	0.01	Reflective
1232: Item 1,Item 26,Item 8,Item 3	-0.02	0.01	-0.05	0.01	Reflective
1267: Item 1,Item 26,Item 35,R30	-0.03	0.00	-0.06	-0.01	Formative
1290: Item 1,Item 4,R28,Item 26	0.03	0.00	0.00	0.06	Formative
1307: Item 1,Item 26,Item 9,Item 5	0.02	0.06	-0.02	0.06	Reflective
1313: Item 1,Item 26,R30,Item 5	0.01	0.23	-0.02	0.04	Reflective
1369: Item 1,Item 26,Item 9,R31	0.00	0.59	-0.02	0.03	Reflective
1381: Item 1,Item 27,Item 3,Item 35	-0.04	0.00	-0.07	0.00	Reflective
1384: Item 1,Item 27,Item 3,Item 4	0.00	0.66	-0.03	0.04	Reflective
1441: Item 1,Item 27,Item 4,Item 6	-0.01	0.17	-0.05	0.02	Reflective
1454: Item 1,Item 27,R28,Item 4	0.01	0.01	-0.01	0.03	Reflective
1494: Item 1,Item 6,R28,Item 27	-0.02	0.08	-0.05	0.02	Reflective
1498: Item 1,Item 27,Item 6,R31	0.04	0.00	0.01	0.07	Formative

1502: Item 1,Item 27,Item 8,Item 7	0.02	0.21	**-0.03**	**0.06**	Reflective
1533: Item 1,Item 9,R30,Item 27	-0.03	0.00	**-0.06**	**0.01**	Reflective
1545: Item 1,R30,R31,Item 27	0.00	0.64	**-0.01**	**0.02**	Reflective
1547: Item 1,Item 3,Item 4,Item 35	0.01	0.07	**-0.01**	**0.03**	Reflective
1645: Item 1,Item 3,Item 7,R30	0.02	0.01	**-0.01**	**0.04**	Reflective
1664: Item 1,Item 3,R28,Item 9	0.00	0.85	**-0.03**	**0.03**	Reflective
1696: Item 1,Item 35,Item 4,R28	0.02	0.00	0.00	0.05	Formative
1747: Item 1,Item 35,Item 7,Item 9	-0.02	0.00	**-0.04**	**0.00**	Reflective
1828: Item 1,Item 4,Item 7,Item 8	0.07	0.00	**0.02**	**0.12**	Reflective
1852: Item 1,Item 4,Item 8,R31	0.01	0.29	**-0.02**	**0.04**	Reflective
1858: Item 1,Item 4,Item 9,R30	-0.01	0.30	**-0.03**	**0.02**	Reflective
1889: Item 1,Item 5,R31,Item 6	0.02	0.10	**-0.02**	**0.05**	Reflective
1957: Item 1,Item 6,Item 8,R30	-0.01	0.31	**-0.03**	**0.02**	Reflective
1995: Item 1,Item 9,R28,Item 7	0.02	0.00	0.00	0.04	Formative
2013: Item 1,Item 9,R28,Item 8	0.01	0.16	**-0.02**	**0.04**	Reflective
2037: Item 1,R30,R31,Item 9	-0.01	0.04	**-0.02**	**0.00**	Reflective
2157: Item 10,Item 26,R31,Item 13	-0.02	0.08	**-0.06**	**0.02**	Reflective
2579: Item 10,Item 2,R30,Item 6	0.00	0.47	**-0.03**	**0.02**	Reflective
2914: Item 10,Item 26,Item 3,Item 9	0.06	0.00	0.03	0.09	Formative
2978: Item 10,Item 26,Item 6,Item 5	0.04	0.00	0.00	0.07	Formative
3236: Item 10,Item 3,Item 7,Item 35	0.04	0.00	0.01	0.08	Formative
3255: Item 10,Item 4,Item 5,Item 3	-0.01	0.37	**-0.04**	**0.02**	Reflective
3298: Item 10,Item 3,Item 6,Item 7	0.01	0.17	**-0.02**	**0.05**	Reflective
3883: Item 13,Item 2,Item 35,R31	0.03	0.00	0.00	0.07	Formative
4096: Item 13,Item 21,Item 35,Item 5	0.01	0.46	**-0.03**	**0.04**	Reflective
4226: Item 13,Item 21,R31,R30	0.27	0.00	0.17	0.37	Formative
4854: Item 13,Item 5,R31,Item 4	0.03	0.03	**-0.02**	**0.09**	Reflective
5241: Item 2,Item 5,Item 7,Item 21	0.00	0.73	**-0.04**	**0.03**	Reflective
5394: Item 2,Item 35,Item 7,Item 26	-0.01	0.17	**-0.04**	**0.02**	Reflective
5861: Item 2,Item 35,R31,Item 5	0.02	0.01	**-0.01**	**0.05**	Reflective
6209: Item 21,Item 26,R31,Item 27	-0.05	0.00	**-0.10**	**0.00**	Reflective
6786: Item 21,Item 5,Item 6,Item 4	-0.14	0.00	**-0.20**	**-0.08**	Reflective
7051: Item 26,Item 27,Item 3,Item 8	0.02	0.01	**-0.01**	**0.05**	Reflective
7328: Item 26,Item 3,R30,R28	0.07	0.00	0.03	0.12	Formative
7673: Item 26,Item 8,R31,Item 9	0.01	0.50	**-0.03**	**0.04**	Reflective
8716: Item 35,Item 6,Item 8,R28	-0.04	0.00	-0.07	-0.01	Formative
8731: Item 35,Item 6,Item 9,R31	0.01	0.19	**-0.02**	**0.03**	Reflective
CONFIDENCE					**Formative**
1: Item 12,Item 14,Item 15,Item 16	0.01	0.08	**-0.01**	**0.04**	Reflective
2: Item 12,Item 14,Item 16,Item 15	-0.02	0.04	**-0.05**	**0.01**	Reflective
4: Item 12,Item 14,Item 15,Item 17	0.00	0.81	**-0.03**	**0.03**	Reflective
6: Item 12,Item 15,Item 17,Item 14	0.00	0.78	**-0.04**	**0.04**	Reflective
7: Item 12,Item 14,Item 15,Item 18	-0.01	0.57	**-0.04**	**0.03**	Reflective
10: Item 12,Item 14,Item 15,Item 19	0.00	0.68	**-0.02**	**0.02**	Reflective
13: Item 12,Item 14,Item 15,Item 20	0.01	0.50	**-0.02**	**0.03**	Reflective
17: Item 12,Item 14,Item 22,Item 15	-0.05	0.00	-0.09	-0.01	Formative
20: Item 12,Item 14,Item 23,Item 15	0.00	0.59	**-0.02**	**0.03**	Reflective
24: Item 12,Item 15,Item 24,Item 14	-0.02	0.01	**-0.04**	**0.01**	Reflective
27: Item 12,Item 15,Item 25,Item 14	0.00	0.71	**-0.03**	**0.02**	Reflective
31: Item 12,Item 14,Item 15,Item 43	-0.01	0.01	**-0.03**	**0.00**	Reflective

42: Item 12,Item 16,Item 19,Item 14	-0.03	0.01	**-0.06**	**0.01**	Reflective
52: Item 12,Item 14,Item 16,Item 24	-0.01	0.41	**-0.03**	**0.02**	Reflective
56: Item 12,Item 14,Item 25,Item 16	0.00	0.88	**-0.02**	**0.02**	Reflective
58: Item 12,Item 14,Item 16,Item 36	-0.03	0.00	-0.05	-0.01	Formative
59: Item 12,Item 14,Item 36,Item 16	-0.05	0.00	-0.08	-0.02	Formative
62: Item 12,Item 14,Item 43,Item 16	-0.10	0.00	-0.15	-0.05	Formative
66: Item 12,Item 17,Item 18,Item 14	-0.01	0.67	**-0.05**	**0.04**	Reflective
78: Item 12,Item 17,Item 23,Item 14	0.00	0.86	**-0.03**	**0.04**	Reflective
92: Item 12,Item 14,Item 19,Item 18	-0.08	0.00	-0.13	-0.03	Formative
98: Item 12,Item 14,Item 22,Item 18	-0.07	0.00	-0.12	-0.03	Formative
100: Item 12,Item 14,Item 18,Item 23	-0.01	0.49	**-0.03**	**0.02**	Reflective
104: Item 12,Item 14,Item 24,Item 18	-0.02	0.01	**-0.05**	**0.01**	Reflective
114: Item 12,Item 18,Item 43,Item 14	-0.17	0.00	-0.23	-0.10	Reflective
121: Item 12,Item 14,Item 19,Item 23	-0.06	0.00	-0.10	-0.02	Formative
134: Item 12,Item 14,Item 43,Item 19	-0.07	0.00	-0.13	-0.01	Formative
144: Item 12,Item 20,Item 24,Item 14	-0.02	0.03	**-0.04**	**0.01**	Reflective
146: Item 12,Item 14,Item 25,Item 20	0.00	0.89	**-0.03**	**0.03**	Reflective
161: Item 12,Item 14,Item 25,Item 22	0.01	0.19	**-0.01**	**0.03**	Reflective
163: Item 12,Item 14,Item 22,Item 36	0.01	0.27	**-0.03**	**0.05**	Reflective
166: Item 12,Item 14,Item 22,Item 43	-0.02	0.00	**-0.05**	**0.00**	Reflective
176: Item 12,Item 14,Item 36,Item 23	-0.03	0.00	**-0.07**	**0.00**	Reflective
179: Item 12,Item 14,Item 43,Item 23	-0.13	0.00	-0.19	-0.08	Formative
181: Item 12,Item 14,Item 24,Item 25	0.00	0.95	**-0.03**	**0.03**	Reflective
194: Item 12,Item 14,Item 43,Item 25	-0.10	0.00	-0.16	-0.05	Formative
245: Item 12,Item 15,Item 24,Item 17	-0.03	0.00	-0.05	-0.01	Formative
249: Item 12,Item 17,Item 25,Item 15	0.00	0.88	**-0.03**	**0.04**	Reflective
278: Item 12,Item 15,Item 43,Item 18	-0.12	0.00	-0.17	-0.07	Formative
284: Item 12,Item 15,Item 22,Item 19	-0.02	0.01	**-0.05**	**0.01**	Reflective
291: Item 12,Item 19,Item 24,Item 15	0.03	0.00	0.00	0.07	Formative
301: Item 12,Item 15,Item 20,Item 22	0.00	0.82	**-0.02**	**0.03**	Reflective
307: Item 12,Item 15,Item 20,Item 24	0.00	0.81	**-0.02**	**0.02**	Reflective
330: Item 12,Item 22,Item 36,Item 15	-0.02	0.02	**-0.05**	**0.01**	Reflective
337: Item 12,Item 15,Item 23,Item 25	0.00	0.58	**-0.02**	**0.03**	Reflective
365: Item 12,Item 16,Item 18,Item 17	0.07	0.00	0.03	0.11	Formative
391: Item 12,Item 16,Item 18,Item 19	0.02	0.01	**-0.01**	**0.04**	Reflective
424: Item 12,Item 16,Item 19,Item 24	-0.05	0.00	-0.09	-0.01	Formative
452: Item 12,Item 16,Item 43,Item 20	-0.08	0.00	-0.13	-0.03	Formative
457: Item 12,Item 16,Item 22,Item 24	-0.04	0.00	-0.08	-0.01	Formative
467: Item 12,Item 16,Item 43,Item 22	-0.03	0.03	**-0.08**	**0.02**	Reflective
537: Item 12,Item 19,Item 25,Item 17	0.03	0.01	**-0.01**	**0.07**	Reflective
544: Item 12,Item 17,Item 20,Item 22	-0.02	0.18	**-0.05**	**0.02**	Reflective
547: Item 12,Item 17,Item 20,Item 23	0.00	0.68	**-0.03**	**0.04**	Reflective
551: Item 12,Item 17,Item 24,Item 20	-0.02	0.01	**-0.06**	**0.01**	Reflective
553: Item 12,Item 17,Item 20,Item 25	0.00	0.90	**-0.03**	**0.02**	Reflective
557: Item 12,Item 17,Item 36,Item 20	-0.04	0.00	-0.08	-0.01	Formative
600: Item 12,Item 25,Item 36,Item 17	0.00	0.79	**-0.05**	**0.06**	Reflective
644: Item 12,Item 18,Item 43,Item 20	-0.17	0.00	-0.23	-0.11	Formative
678: Item 12,Item 24,Item 36,Item 18	-0.01	0.19	**-0.04**	**0.02**	Reflective
715: Item 12,Item 19,Item 22,Item 25	0.01	0.24	**-0.03**	**0.06**	Reflective
755: Item 12,Item 20,Item 23,Item 22	0.01	0.21	**-0.02**	**0.04**	Reflective

766: Item 12,Item 20,Item 22,Item 43	0.00	0.78	**-0.03**	**0.02**	Reflective
800: Item 12,Item 22,Item 24,Item 23	0.03	0.01	**-0.01**	**0.07**	Reflective
848: Item 12,Item 24,Item 36,Item 25	-0.03	0.00	**-0.06**	**0.00**	Reflective
1021: Item 14,Item 15,Item 36,Item 43	0.06	0.00	0.02	0.10	Formative
1361: Item 14,Item 19,Item 25,Item 20	-0.01	0.15	**-0.04**	**0.02**	Reflective
1377: Item 14,Item 22,Item 25,Item 19	-0.02	0.11	**-0.05**	**0.02**	Reflective
1378: Item 14,Item 19,Item 22,Item 36	0.04	0.00	**-0.01**	**0.08**	Reflective
1464: Item 14,Item 23,Item 25,Item 22	-0.01	0.42	**-0.04**	**0.02**	Reflective
1478: Item 14,Item 22,Item 43,Item 24	-0.01	0.23	**-0.03**	**0.01**	Reflective
1656: Item 15,Item 18,Item 19,Item 17	0.01	0.47	**-0.04**	**0.06**	Reflective
1819: Item 15,Item 18,Item 23,Item 25	0.02	0.01	**-0.01**	**0.04**	Reflective
1969: Item 15,Item 22,Item 24,Item 36	-0.05	0.00	-0.09	-0.02	Formative
2077: Item 16,Item 17,Item 22,Item 23	-0.03	0.00	**-0.06**	**0.00**	Reflective
2153: Item 16,Item 18,Item 25,Item 20	-0.01	0.22	**-0.03**	**0.02**	Reflective
2353: Item 16,Item 23,Item 25,Item 36	0.00	0.73	**-0.02**	**0.02**	Reflective
2562: Item 17,Item 25,Item 43,Item 20	-0.01	0.11	**-0.04**	**0.01**	Reflective
MOTIVATION					**Formative**
1: Item 11,Item 39,Item 40,Item 42	0.04	0.00	0.02	0.07	Formative
2: Item 11,Item 39,Item 42,Item 40	0.04	0.00	0.01	0.07	Formative

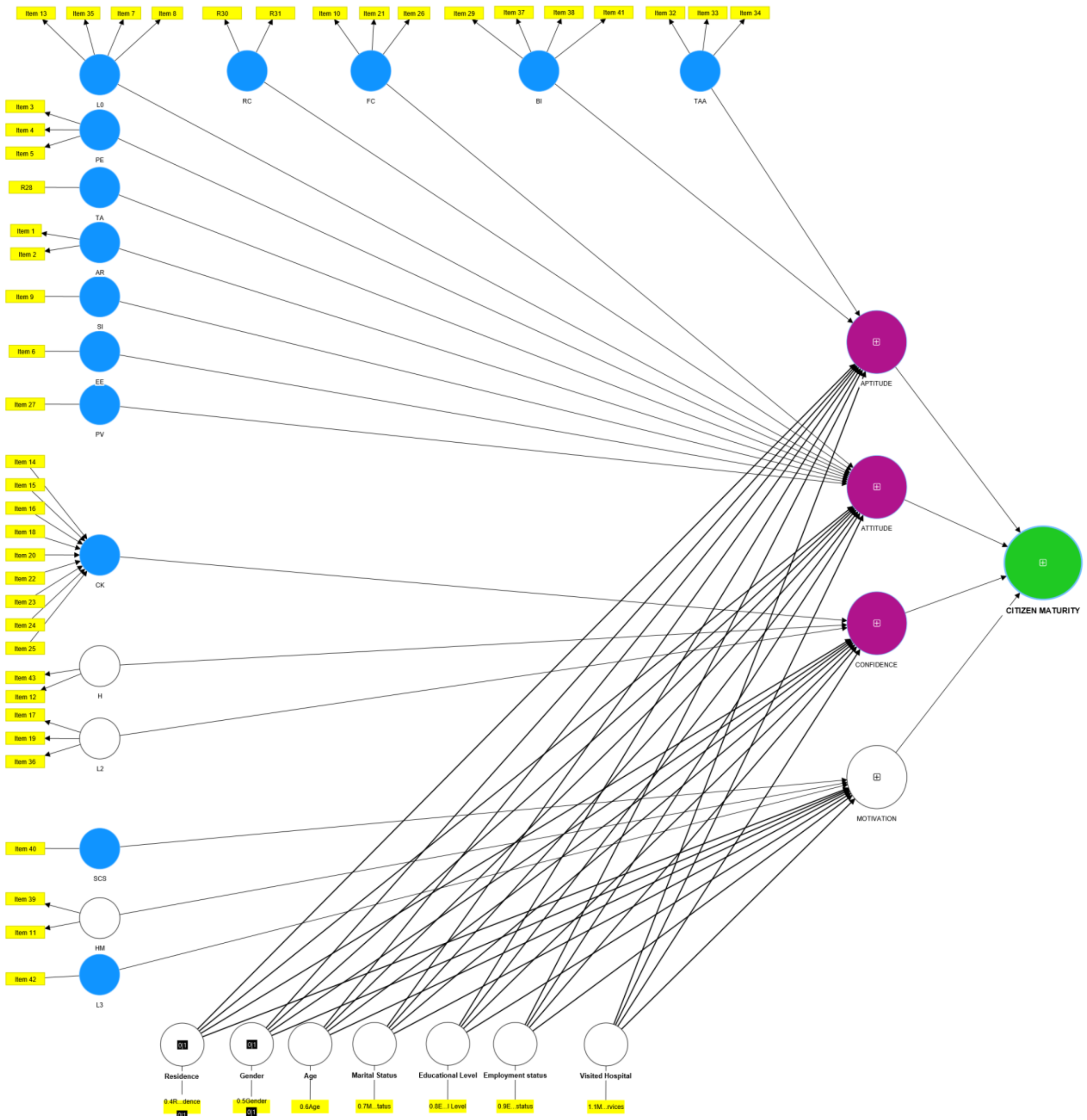

Fig C. 1: Proposed nomological framework of the predictive model at CK is formative

Appendic C. 3: Assessment of the interaction effects of moderating variables

Constructs	Path coefficient	T statistics	P values
Country Code -> CITIZEN MATURITY	-0.006	2.114	0.017
Gender -> CITIZEN MATURITY	-0.016	3.961	0.000
Age -> CITIZEN MATURITY	-0.001	0.359	0.360
Marital Status -> CITIZEN MATURITY	0.004	1.787	0.037
Employment status -> CITIZEN MATURITY	-0.007	3.663	0.000
APTITUDE -> CITIZEN MATURITY	0.175	18.978	0.000
ATTITUDE -> CITIZEN MATURITY	0.531	52.956	0.000
CONFIDENCE -> CITIZEN MATURITY	0.242	34.530	0.000
MOTIVATION -> CITIZEN MATURITY	0.212	26.905	0.000
Country Code x APTITUDE -> CITIZEN MATURITY	0.002	0.615	0.269
Country Code x ATTITUDE -> CITIZEN MATURITY	-0.003	0.684	0.247
Country Code x CONFIDENCE -> CITIZEN MATURITY	-0.009	2.146	**0.016**
Country Code x MOTIVATION -> CITIZEN MATURITY	-0.002	0.545	0.293
Employment status x APTITUDE -> CITIZEN MATURITY	0.000	0.107	0.457
Employment status x CONFIDENCE -> CITIZEN MATURITY	0.003	1.071	0.142
Gender x APTITUDE -> CITIZEN MATURITY	-0.007	1.412	0.079
Age x APTITUDE -> CITIZEN MATURITY	0.004	1.042	0.149
Age x ATTITUDE -> CITIZEN MATURITY	-0.006	1.514	0.065
Age x CONFIDENCE -> CITIZEN MATURITY	0.006	1.785	**0.037**
Age x MOTIVATION -> CITIZEN MATURITY	-0.005	1.371	0.085
Marital Status x MOTIVATION -> CITIZEN MATURITY	-0.004	1.502	0.067
Marital Status x ATTITUDE -> CITIZEN MATURITY	0.005	1.775	**0.038**
Marital Status x APTITUDE -> CITIZEN MATURITY	-0.002	0.565	0.286

CURRICULUM VITAE

PERSONAL INFORMATION

Name:	ABUBAKARI YAKUBU
Date of Birth:	15.06.1980
Place of Birth:	TAMALE
Nationality:	GHANAIAN
Marital Status:	MARRIED
Course of study	MEDICAL INFORMATICS

COMPETITIVE ADVANTAGE

Abubakari has worked on several baseline surveys, impact evaluations and data modelling for different sectors in Ghana and Globally. Insightful researcher using Data Science techniques such as predictive modelling using R-SEM and SmartPLS. Also, he has high-level experience in diverse project Initiation, Planning and Execution with variant stakeholders. Highly successful with technical and academic reviews and astute facilitator on many fronts.

SOFT SKILLS EXCELLENCE

-Team management

-Multi-tasking

-Effective time management

-Networking and Communication

-Conflict management

-Presentation and Facilitation

RELEVANT SKILLS

-Proficiency in Data Science

-Project Manager Specialist

-Ms Office and Ms Project Specialist

-Predictive and Prescriptive models

-Programming analytics using Rstudio, STATA and Smart PLS

EDUCATION

PRIMARY AND SECONDARY SCHOOLS

1986-1991	St. JOSEPH'S PRIMARY
1992-1995	St. JOSEPH'S JUNIOR SECONDARY SCHOOL
1996-1998	TAMALE SENIOR SECONDARY SCHOOL (SSSCE)

UNIVERSITY

2000 - 2004 **BSc:** Mathematics

Kwame Nkrumah University of Science and Technology

Research topic: "**COMPUTERIZATION OF BIRTH AND DEATH REGISTRY**"

2007 - 2009 **MSc:** Public Health Informatics | **University of Ghana – Legon**:

Research title “**Systems Analysis for Health Information Systems”,**

2008 - 2011 **MBA:** Management Information Systems | **University of Ghana-Legon:**

Research title: “**Telemedicine Readiness Assessment Model for Ghana**”

2017 – 2022 **PhD (on-going): Medical Informatics | University of Heidelberg, Germany:**

Research title: “**Conceptualing the maturity of Citizens for Consumer Health Informatics in LMIC**”

WORK EXPERIENCE

LEAD CONSULTANT |Yendi Business Resource Centre – 2020 – Present

Responsible for:

Assessment of viable start-ups, development of scale-up companies and SME growth in the operational zone.

Develop and grow the management team’s efficient delivery.

Delivered Results/Completed Projects

- Prepared and implemented a Strategic Plan using the Balanced Scorecard
- Team building exercises
- Business model and business plan development
- Market survey analysis for various products

RESEARCH MANAGER |Postal and Courier Services Regulatory Commission, Ghana:2018 – 2020

Responsible for:

Periodic reports such as Quarterly, Situational and Status reports.

Anchor for the action plan of the Commission.

Lead in the planning and Design of Surveys.

Identifying, and engaging stakeholders in the sector and supporting in the inspection and monitoring of activities of Operators

Delivered Results/Completed Projects

- Impact Evaluation of COVID-19 on the Postal and Courier sectors in Ghana
- Quarter, bi-annual and annual reports for 2019 and 2020
- Handled the acquisition and redevelopment of the Commissions website

- Submitted Status report to Board members
- Finished clamp down exercise on illegal operators
- Redesigned and updated operator's database for the Commission

RESEARCHER | Universität Heidelberg – Klinikum, July 2019 – October 2019

Assigned to conduct a detailed review of existing literature and related reports from WHO, and ITU for a project, and write summary reports of all reviews and models adopted in relevant documents. Conducted a review of methods and data analysis techniques—presented a draft report on data collected from five countries.

Delivered Results/Completed Projects

- Published a research paper in a Q1 journal
- The draft research report on the Consumer Health Informatics model
- Delivered a comprehensive report on all related literature and concept

RESEARCHER | Universität Heidelberg – Klinikum,: 2017 – 2018

Assigned to conduct a detailed review of existing literature and related reports from WHO, and ITU for a project, and write summary reports of all reviews and models adopted in relevant documents. Conduct a review of methods and data analysis techniques

Delivered Results/Completed Projects

- Delivered a comprehensive report on all related literature and concept
- Formulated and estimated sample size for the project
    - Prepared preliminary report of the project

LECTURER | *Catholic University College of Ghana*, Fiapre: 2010 – 2019

He lectured undergraduate courses like Fundamentals of Health Informatics, Biostatistics, Survey and Population Data analysis in STATA, Health Information Systems, Demographic Analysis and Database management. During my postgraduate taught Health Information Management Systems, Researching and other administrative tasks assigned by the Dean.

Delivered Results/Completed Projects

- Assessment of student performance
- Supervised student's long essays and research work
- Conducted relevant research in Informatics

FACILITATOR (Part-time) |*Kwame Nkrumah University of Science and Technology*: 2010 –

Present:

Facilitated postgraduate and undergraduate courses like Operations Management, Management Information Systems, Project Management and Total Quality Management

Delivered Results/Completed Projects

- Assessment of student performance
- Supervision of Research work and long essays
- Co-publication with Masters's students

CONSULTANCY ENGAGEMENT

CONSULTANT | Eastern Corridor of Northern Region: 2020 - Present

Project Title: Business Resource centres for Local Economic Development

Results Delivered:

- Facilitation of Business processes
- Training of MSMEs in business models
- Evaluation of Local Economy

CONSULTANT | Ghana Statistical Services: March 2014

Project Title| 2010 Population and Housing Census, Ghana Statistical

Results Delivered:

- Reviewed Census reports of Districts in Ashanti, Upper West and Brong Ahafo regions

CONSULTANT | Ghana Statistical Services: December 2013

Project Title: 2010 Population and Housing Census, Ghana Statistical

Results Delivered:

- Reviewed Census reports of Districts in Northern and Upper East regions

CONSULTANT | Council for Technical and Vocational Education: June 2013

Project title: Skills Development Fund.

Results Delivered:

- Successfully submitted Two (2) Business Plans for Financing

DATA ANALYST | Catholic University College of Ghana, Fiapre: **2005 – 2008**

Project Title | CATHOLIC RESEARCH COMMUNITY AND CONSULTANCY

Projects Delivered:

- Data Analysis report on Knowledge and Awareness of HIV/AIDs Amongst Residents of Sunyani Municipality in the Brong Ahafo region of Ghana
- Data Analysis report of Impact of the Media on HIV/AIDS Education in Sunyani Municipality

- Data Analysis Report of the Management of Waterbodies in the Brong Ahafo Region
  - Dataset Coding, Digitization, and Integration of DATA For ROUBAU UNIVERSITY, Netherlands

COMMITTEES AND COMMUNITY SERVICES

CONFERENCE REVIEWER | American Medical Informatics Association (Annual Conference): 2020 and 2022

COORDINATOR | WEBSITE REDESIGN AND OPTIMIZATION: 2019

Postal and Courier Services Regulatory Commission**,** Ghana

CHAIRMAN | BOARD OF SURVEY**:** 2018

The University of Energy and Natural Resource

MEMBER | WEB MANAGEMENT COMMITTEE: 2016

Catholic University College of Ghana, Fiapre

JOURNAL REVIEWER | International Journal of Medical Informatics: 2016 – 2018

DATA ANALYST | Baseline survey for Ghana and Zimbabwe: 2015 – 2016

Opportunity International

INDEPENDENT OBSERVER |Hang Your Net Campaign (HYN), Wa, Ghana: 2012

INDEPENDENT OBSERVER | Child Health promotion week, Wa, Ghana: 2012

PRO-BONO M & E | Team member District Health Directorate Atebubu - Amanting NID, Atebubu, Ghana: 2012

TEAM MEMBER | REGIONAL MONITORING TEAM FOR NATIONAL IMMUNIZATION DAY**:** April 2011

Ghana Health Services, BAR, Ghana

CHAIRMAN | EPIDEMIC MANAGEMENT COMMITTEE: 2013 – 2015

Catholic University, Fiapre

CERTIFICATIONS AND TRAINING

Certificate of Completion: Impact Evaluation and Matchmaking **| Centre for Effective Global Action - GIMPA** – 2020

Certificate of Completion: Fundamentals of Data Science: Data Mining**| LinkedIn Learning** – 2019

Certificate of Completion: Tableau Essential Training **| LinkedIn Learning** – 2019

Certificate of Completion: Data Science Foundations: Python Scientific Stack **| LinkedIn Learning** – 2019

Certificate of Completion: Data Science Foundations: The Data Science of Healthcare, Medicine, and Public Health, with Barton Poulson **| LinkedIn Learning** – 2019

Certificate of Completion: Design Thinking **| Marsilius-Kolege, Germany:** 2017

Certificate of Completion: Prototyping **| Marsilius-Kolege, Germany:** 2017

Certificate of Proficiency: Project Management**| Project Management Institute:** 2017

Certificate of Completion: Entrepreneurship | **Handong Global University, Korea:** 2014

Certificate of Completion: Scientific Writing | **University of Ghana, Legon:** 2014

Certificate of Completion: Conflict Resolution and Mediation | **Fordham University:** 2012

Certificate of Completion: Learning to Listen, Learning to Teach| **Global Learning Partners:** 2005

PROFESSIONAL AFFILIATIONS

Member (2101441) | Project Management Institute, Global: **2017 – Present**

Member (2101441) | Project Management Institute, Ghana: **2017 - Present**

Member |Ghana Health Informatics Association (GHIA): 2010 – **Present**

Member | American Health Information Managers Association: 2010 – 2014

REFERENCES

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EIDESSTATTLICHE VERISCHERUNG (AFFIDAVIT)

1. Bei der eingereichten Dissertation zu dem Thema

CONCEPTUALISING THE MATURITY OF CITIZENS FOR CONSUMER HEALTH INFORMATICS IN LOW AND MIDDLE-INCOME COUNTRIES: EMPIRICAL ANALYSIS OF CHILE, GHANA, IRAQ, KOSOVO, TURKEY, AND UKRAINE.

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