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Friend or foe? How innovative digital technologies affect motivational work characteristics and employees' perceived job insecurity

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Summary

The rising distribution of smart technology, artificial intelligence, robotics, algorithms, and automation (STARA) in today's world of work has the potential to revolutionize what, how, where, and when humans work by supplementing and substituting work processes. However, it is largely unclear how these technological changes affect employees. While employees may benefit from the substitution of tedious and dangerous, they may suffer from STARA creating micro-jobs, polarizing required skill levels, and evoking job insecurity. Although these rapid technological changes have crucial implications for employee outcomes, empirical evidence of their effects on employees is surprisingly scarce. Neglecting to investigate these effects could result in poorly designed, demotivating workplaces of the future.

Building on the integration of numerous theoretical models and frameworks, this dissertation examines how the introduction of intelligent assistance systems (IASs) modifies motivational work characteristics in modern assembly. It considers various scenarios, such as the assembly of simple products, the assembly of more complex products, and the assembly with intensified product changes. Applying online experiments with vignette methodology, we experimentally manipulated hypothetical assembly workstations and instructed participants to rate them regarding motivational work characteristics. In the first online experiment (N_1 = 203 German and British blue-collar workers) participants were randomly assigned to one of three conditions (work without vs. work with vs. work with voluntary use of IASs). Results indicated enhanced feedback from job and information processing when working with IASs in the assembly of simple products. Thus, they highlight the purely positive effects of IASs on motivational work characteristics.

Transferring these findings to the assembly of more complex products in the second online experiment (work without vs. work with IASs, N_2 = 169 German workers) was limited. Findings illuminated that IASs restrict work scheduling, decision-making, and work methods autonomy besides increasing feedback from job and information processing. Therefore, they indicate the contradictory effects of IASs on motivational work characteristics. In a third online experiment (N_3 = 176 German workers) we also manipulated the extent of task rotation (no task rotation vs. task rotation after one hour). We fully replicated the results highlighting the contradictory role of IASs, regardless of the extent of task rotation.

This dissertation further illuminates how employees appraise STARA to threaten their employment by contributing a thorough construct validation of affective automation-related job insecurity, a refinement of the STARA Awareness construct (Brougham & Haar, 2018). Findings from two cross-sectional studies (N_4 = 215, N_5 = 224 German employees) and one longitudinal study with a total time lag of one year (N_6 = 233 German employees) demonstrated a fluctuating fit of the measurement model of STARA Awareness between independent samples. With the exclusion of cognitive elements and the inclusion of the substitution of core tasks within jobs, we reconceptualized

the construct, renamed it to affective automation-related job insecurity, and adapted its measurement. While affective automation-related job insecurity is weakly associated with cognitive and affective job insecurity, and negatively with core self-evaluations, it exhibits unique associations with indicators of technological change (positive relations with objective substitution potential and use of STARA). Moreover, we identified rising levels of affective automation-related job insecurity over time for employees with moderate use of STARA, and decreasing levels for employees with low and high use of STARA.

Overall, this dissertation provides vital empirical evidence on the beneficial and detrimental effects of STARA on workplaces and employees in today's world of work. Its findings represent a firm foundation for fruitful research in digital work design, human-machine interaction, and related fields. Finally, considering these findings contributes to the human-centered development, implementation, and use of STARA to maintain a healthy and motivated workforce.

Keywords: digitalization, intelligent assistance systems, work design, motivational work characteristics, assembly, task rotation, substitution potential, core self-evaluations, STARA Awareness, cognitive and affective job insecurity, affective automation-related job insecurity

Zusammenfassung

Die zunehmende Verbreitung von intelligenter Technologie, künstlicher Intelligenz, Robotik, Algorithmen und Automatisierung (STARA) in der heutigen Arbeitswelt hat das Potenzial, zu revolutionieren, was, wie, wo und wann Menschen arbeiten, indem sie Arbeitsprozesse ergänzen und ersetzen. Es ist jedoch weitgehend unklar, wie sich diese technologischen Veränderungen auf Arbeitnehmende auswirken. Während Arbeitnehmende von der Ersetzung mühsamer und gefährlicher Arbeit profitieren können, leiden sie möglicherweise darunter, dass STARA Mikrojobs schafft, die erforderlichen Qualifikationsanforderungen polarisiert und Arbeitsplatzunsicherheit hervorruft. Obwohl diese raschen technologischen Veränderungen entscheidende Konsequenzen auf die Arbeitsergebnisse haben, gibt es überraschend wenige empirische Belege für ihre Effekte auf Arbeitnehmende. Die Vernachlässigung der Untersuchung solcher Auswirkungen könnte zu mangelhaft gestalteten, demotivierenden Arbeitsplätzen der Zukunft führen.

Aufbauend auf der Integration zahlreicher theoretischer Modelle und Rahmenkonzepte wird in dieser Dissertation untersucht, wie die Einführung intelligenter Assistenzsysteme (IAS) die motivationalen Arbeitsplatzmerkmale in der modernen Montage verändert. Dabei werden verschiedene Szenarien betrachtet wie die Montage einfacher Produkte, die Montage komplexerer Produkte und die Montage mit verstärktem Produktwechsel. In Online-Experimenten mit Vignettenmethodik haben wir hypothetische Montagearbeitsplätze experimentell manipuliert und die Teilnehmenden aufgefordert, dieser hinsichtlich motivationaler Arbeitsplatzmerkmale zu bewerten. Im ersten Online-Experiment (N_1 = 203 deutsche und britische Industriearbeitende) wurden die Teilnehmenden zufällig einer von drei Bedingungen zugewiesen (Arbeit ohne vs. Arbeit mit vs. Arbeit mit freiwilliger Nutzung von IAS). Die Ergebnisse zeigten, dass die Arbeit mit IAS bei der Montage einfacher Produkte zu einer erhöhten Rückmeldung durch die Tätigkeit und Informationsverarbeitung führt. Sie unterstreichen somit die rein positiven Auswirkungen von IAS auf motivationale Arbeitsplatzmerkmale.

Die Übertragung dieser Ergebnisse auf die Montage komplexerer Produkte im zweiten Online-Experiment (Arbeit ohne vs. Arbeit mit IAS, N_2 = 169 deutsche Berufstätige) war eingeschränkt. Die Ergebnisse zeigen, dass IAS die Planungs-, Entscheidungs- und Methodenautonomie einschränken und gleichzeitig die Rückmeldung durch die Tätigkeit und die Informationsverarbeitung erhöhen. Sie weisen daher auf die widersprüchlichen Auswirkungen von IAS auf motivationale Arbeitsplatzmerkmale hin. In einem dritten Online-Experiment (N_3 = 176 deutsche Berufstätige) manipulierten wir zusätzlich das Ausmaß der Aufgabenrotation (keine Aufgabenrotation vs. Aufgabenrotation nach einer Stunde). Wir konnten die Ergebnisse vollständig replizieren, welche die widersprüchliche Rolle von IAS unabhängig vom Ausmaß der Aufgabenrotation aufzeigen.

Diese Dissertation beleuchtet weiter, wie Arbeitnehmende STARA als Bedrohung ihres Arbeitsplatzes einschätzen, indem sie eine ausführliche Konstruktvalidierung der affektiven automatisierungsbezogenen Arbeitsplatzunsicherheit, eine Weiterentwicklung des Konstrukts STARA-

Bewusstsein (Brougham & Haar, 2018), beiträgt. Die Ergebnisse aus zwei querschnittlichen Studien ($N_4 = 215$, $N_5 = 224$ deutsche Arbeitnehmende) und einer Längsschnittstudie mit einem zeitlichen Abstand von einem Jahr ($N_6 = 233$ deutsche Arbeitnehmende) zeigten eine schwankende Passung des Messmodells von STARA-Bewusstsein zwischen unabhängigen Stichproben. Mit dem Ausschluss kognitiver Elemente und der Einbeziehung der Ersetzung von Kernaufgaben innerhalb von Arbeitsplätzen haben wir das Konstrukt neu konzeptualisiert, es in affektive automatisierungsbezogene Arbeitsplatzunsicherheit umbenannt und seine Messinstrumente angepasst. Während die affektive automatisierungsbezogene Arbeitsplatzunsicherheit schwach mit der kognitiven und affektiven Arbeitsplatzunsicherheit und negativ mit der zentralen Selbsteinschätzung assoziiert ist, weist sie einzigartige Assoziationen mit Indikatoren des technologischen Wandels auf (positive Beziehungen mit dem objektiven Ersetzungspotenzial und der Nutzung von STARA). Darüber hinaus haben wir festgestellt, dass die affektive automatisierungsbezogene Arbeitsplatzunsicherheit mit Arbeitnehmenden mit moderater Nutzung von STARA im Laufe der Zeit zunimmt und bei Arbeitnehmenden mit geringer und hoher Nutzung von STARA abnimmt.

Insgesamt liefert diese Dissertation wichtige empirische Belege für die positiven und negativen Auswirkungen von STARA auf Arbeitsplätze und Arbeitnehmende in der heutigen Arbeitswelt. Die Ergebnisse bilden eine solide Grundlage für fruchtbare Forschung in der digitalen Arbeitsgestaltung, der Mensch-Maschine-Interaktion und verwandten Bereichen. Schließlich trägt die Berücksichtigung dieser Erkenntnisse zu einer menschenzentrierten Entwicklung, Implementierung und Nutzung von STARA bei, um eine motivierte und gesunde Belegschaft zu bewahren.

Schlüsselbegriffe: Digitalisierung, intelligente Assistenzsysteme, Arbeitsgestaltung, motivationale Arbeitsplatzmerkmale, Montage, Aufgabenrotation, Ersetzungspotenzial, zentrale Selbsteinschätzungen, STARA-Bewusstsein, kognitive und affektive Arbeitsplatzunsicherheit, affektive automatisierungsbezogene Arbeitsplatzunsicherheit

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Chapter 1 – General Introduction

"I think there is a world market for about five computers" (Carr, 2008, para. 1). This quote from 1943 is commonly credited to Thomas J. Watson, the former CEO of IBM, which is now a world-renowned IT company for hard- and software (Dornberger et al., 2018). Less than a century after this alleged quote, 62% of the workforce in member countries of the OECD regularly uses computers at work (OECD, 2023). Particularly, in Germany, computers have found their way into 96% of organizations (Statistisches Bundesamt, 2022). Thus, it is fair to state that even leading figures in the development of digital *information and communication technologies* (ICTs) like Thomas J. Watson drastically underestimated their worldwide potential and how the everyday use of all sorts of ICTs would shape our today's working lives.

Since the beginning of the industrial revolution, the development of new technologies and their introduction at work fundamentally altered, what, how, where, and when humans worked. Consequently, the implementation of exemplarily industrial machines in agriculture, and manufacturing simultaneously fostered productivity and cut costs by substituting manual human labor (Cascio & Montealegre, 2016). This led to shrinking numbers of employees in primary (agriculture and mining) and secondary (manufacturing) sectors and, hence, vast shifts of the labor force to the tertiary (service) sector (Brougham & Haar, 2018). The implementation of computers (Dornberger et al., 2018) in the digital era brought further changes to the global labor market that is now built on and connected through digital data, knowledge, and information, enabling new ways of work (e.g., progressive automation in manufacturing or virtual teams) (Cascio & Montealegre, 2016).

As part of today's fourth wave of the industrial revolution, advanced computer programs and large language models based on artificial intelligence (AI) continue to drive innovation in all sectors (Brougham & Haar, 2018; Parker & Grote, 2022a) which was even accelerated during the Covid-19-pandemic (Tang et al., 2022). Progress is made apparent in a wide variety of innovative ICTs that differ in their application settings, technological functions, and organizational purposes, for example, self-checkout in retail, chatbots in customer service, or wearable devices like smartwatches and glasses, or collaborative robots in manufacturing (Brougham & Haar, 2018; Cascio & Montealegre, 2016; Faccio et al., 2023). Modern assembly is also subject to technological advances. *Intelligent assistance systems* are progressively implemented in today's assembly to support workers in an increasingly complex work environment (Egger-Lampl et al., 2019; Faccio et al., 2023). Brougham and Haar (2018) refer to this range of innovative ICTs as smart technologies, artificial intelligence, robotics, and algorithms (*STARA*)[1]. STARA lead to a unique fusion of the physical and virtual worlds in which objects, technical systems, networks, and people are interconnected (Cascio & Montealegre, 2016), facilitating "the creation of a ubiquitous computing environment at work" (Fraccaroli et al., 2024, p. 314). This is

[1] Given that the authors also included "automation" in a later article (Brougham & Haar, 2020), further use of the term STARA also refers to automation.

enabled by vast improvements in hardware and software, the ubiquitous collection of data, and its analysis and use in organizational practice in real-time. Hence, STARA also continue to alter what, how, where, and when humans work. Several scholars expect STARA to have bigger impacts on the global labor market than technologies from previous waves of industrial revolution by increasingly substituting nonroutine tasks (e.g., data analysis, programming, or management) beyond manual and cognitive routine tasks like before (Brougham & Haar, 2018; Brynjolfsson & McAfee, 2011; Cameron, 2017; Dengler & Matthes, 2018; Fraccaroli et al., 2024; Parker & Grote, 2022b; Schwab, 2017). However, it remains unclear whether employees benefit or suffer from the implementation of STARA in a rapidly changing world of work.

On the bright side, STARA have the potential for essential benefits for a variety of employee outcomes like motivation, health, and safety by substituting “dull, dirty, and dangerous work” (Walsh & Strano, 2018, p. xix). STARA’s technological possibilities also enable novel ways of collaboration with AI, robots, and machines (Cascio & Montealegre, 2016; Faccio et al., 2023). The successful collaboration between human and non-human workers could foster digital competencies (Oberländer et al., 2020), knowledge acquisition and sharing (Golden & Raghuram, 2010; Trenerry et al., 2021), and therefore, contribute to further qualifications (*general upskilling*) of the workforce (Pedota et al., 2023). For instance, assembly workers can gain important digital competencies through working with intelligent assistance systems (Blumberg & Kauffeld, 2020). The enhanced skill levels required for the successful execution of the work tasks in turn lead to improvements in employee outcomes (Humphrey et al., 2007).

On the dark side, following the substitution of previous human labor STARA could create jobs with low task and skill variety that consist exclusively of “micro-tasks” (Parker & Grote, 2022a, p. 1176) such as monitoring technological processes executed by non-human workers. Lacking task and skill variety in jobs consisting of micro-tasks in turn deteriorates a variety of vital employee outcomes (Parker & Grote, 2022a). In the context of modern assembly, workers might experience the deterioration of a variety of positive employee outcomes by working with intelligent assistance systems as their use could reduce skill variety by substituting cognitive work tasks (Blumberg & Kauffeld, 2020). However, besides the reduced variety of tasks and required skills (Parker & Grote, 2022a), STARA could simultaneously create a higher number of highly demanding jobs. The resulting greater levels of complexity and speed of today’s world of work (Cascio & Montealegre, 2016) could potentially leave parts of the labor force with deficits in required (digital) competencies behind (Brougham & Haar, 2018). Thus, the rising introduction of STARA into modern workplaces could be accompanied by an increasing polarization of required skills (i.e., more jobs that require low and high skill levels, and fewer jobs that require moderate skill levels). As complementations are expected for high-skilled workers, and substitutions for low-skilled workers due to technological innovations (Autor et al., 2003), “many commentators [are] especially concerned about the effects of digitalization on the less skilled workforce” (Parker & Grote, 2022a, p. 1172).

The introduction of STARA into modern workplaces is not only altering the content of humans' work and the way they perform it but might also have the potential to eliminate jobs completely (Brougham & Haar, 2018; Gödöllei, 2022). For instance, organizations intend to implement robots in their work processes to enhance decrease while also cutting personnel costs (Brougham & Haar, 2018; Yam et al., 2023). Although technological progress in previous waves of industrial revolution has caused a large number of jobs to become obsolete over the last decades, mass unemployment due to the substitution of human labor has not yet occurred. Workers have switched to new jobs created by technology, typically with higher skill levels (Autor, 2015; Cascio & Montealegre, 2016). Nevertheless, it remains unclear whether this can be transferred to STARA, given significantly faster development cycles and their introduction in branches in which previously only humans have worked (Brynjolfsson & McAfee, 2011; Gödöllei, 2022). Recent articles (Wang et al., 2023; Yam et al., 2023) also stress that employees appraise the implementation of robots at work as threatening to their employment. Thus, it is also important to consider the essential effect of STARA on employees beyond technology-related changes in what, how, where, and when employees work.

Considering that digitalization does not show any signs of stagnation, it becomes more and more crucial to understand how the implementation of STARA at work supplements and substitutes human work processes, thus affecting workplaces and the employees who work there (Parker & Grote, 2022a). This dissertation primarily focuses on two issues: first, the effects of intelligent assistance systems on motivational work characteristics in modern assembly, a work environment that is characterized by increasing complexity (Egger-Lampl et al., 2019; Faccio et al., 2023) but a traditionally low-skilled workforce (Maxwell, 2006); second, the valid assessment of how employees across various occupational groups and sectors appraise the effect of STARA on their employment. As this dissertation considers both the digital transformation of workplaces and the potential substitution of individual jobs, it illuminates the effects of STARA in a modern world of work in a comprehensive framework to promote research on digital work design and human-machine interaction as well as their human-centered development, implementation, and use in organizational practice.

1. How digitalization shapes motivational work characteristics

As outlined above, several scholars agree that the implementation of STARA alters profoundly which, how, where, and when work was executed by humans, i.e. *work design* in recent decades (e.g., Cascio & Montealegre, 2016; Fraccaroli et al., 2024; Gagné et al., 2022; Parker et al., 2017; Parker & Grote, 2022a). Work design is defined as "the content and organization of one's work tasks, activities, relationships, and responsibilities" (Parker, 2014, p. 662), comprising a variety of different *work characteristics*. Numerous theoretical approaches from the *job characteristics model* (Hackman & Oldham, 1975) to the recently published integrative *SMART model* (Parker & Knight, 2023) postulate a decisive role of work characteristics in promoting employee outcomes. For instance, the job characteristics model proposes that five core work characteristics (*job autonomy*, *task identity*, *task significance*, *feedback from the job*, and *skill variety*) evoke three critical psychological states (*experienced responsibility*, *meaningfulness*, and *knowledge of results*) which then affect work-related outcomes like motivation and job satisfaction of employees (Hackman & Oldham, 1975). With more than 17,000 research articles on work design over the last one hundred years, scholars documented the importance of work characteristics (primarily as a predictor) for a wide range of outcomes of employees including behavioral (e.g., *job performance*, *absenteeism*), attitudinal (e.g., *job satisfaction*, *organizational commitment*, *work motivation*), role perception (e.g., *role conflict*) or well-being outcomes (e.g., *anxiety*, *stress*, *burnout*) extensively (Fraccaroli et al., 2024; Humphrey et al., 2007).

Integrating different work design theories and models, the *work design questionnaire* (WDQ) represents the most extensive instrument for assessing work characteristics. It distinguishes between 21 work characteristics which can be differentiated into four main types of work characteristics: *task*, *knowledge*, *social*, and *contextual characteristics* (Morgeson & Humphrey, 2006). Task characteristics focus particularly on the scope and type of tasks and the way these tasks are performed and include three subdimensions of *job autonomy* (*work scheduling*, *decision-making*, and *work methods autonomy*), *task variety*, *task significance*, *task identity*, and *feedback from job*. Knowledge characteristics describe requirements for knowledge, skills, and abilities that the tasks within a job place on job holders. These comprise *job complexity*, *information processing*, *problem solving*, *skill variety*, and *specialization*. As task and knowledge characteristics explain up to 34% of the variance in work-related outcomes like motivation, job performance, and job satisfaction based on meta-analytic results (Humphrey et al., 2007), they are also collectively referred to as *motivational work characteristics* (Morgeson & Humphrey, 2006). Although the majority of work design research is correlational in nature, a systematic review by Knight and Parker (2021) indicates that work characteristics affect work-related outcomes. The authors found that interventions aimed at redesigning work impact both employees' motivation and job performance via altered perceptions of (motivational) work characteristics. Building on their substantial relevance for work-related outcomes and given that scholars expect significant changes due to the ongoing digital transformation of the labor market (Parker & Grote, 2022a; Wang et al., 2020), this dissertation focuses on motivational work characteristics.

Whereas the relationship between work characteristics and employee outcomes has been thoroughly examined so far (Fraccaroli et al., 2024), empirical studies investigating the implementation of digital technologies at work as an antecedent of work characteristics are surprisingly scarce (Cascio & Montealegre, 2016; Parker & Grote, 2022a; Parker & Grote, 2022b). To provide initial empirical evidence on the frequently postulated changing world of work by ICTs, Wegman and colleagues (2018) conducted a cross-temporal meta-analysis. They included 102 studies with 107 independent samples from the US that were published between 1975 and 2011 that measured at least one work characteristic outlined in the job characteristics model using the *Job Diagnostic Survey* (Hackman & Oldham, 1975) or its revised form (Idaszak & Drasgow, 1987). The authors identified largely increased mean levels of skill variety and moderately increased mean levels of job autonomy from 1975 to 2011. However, Fraccaroli and colleagues (2024) state that "causal attributions for these changes in job perception [on implemented digital technologies] is purely speculative" (p. 311). Additionally, it remains unclear whether these findings can be extended to further work characteristics that are outlined in the WDQ, and transferred to other cultural contexts, and new types of digital technologies like STARA that were introduced after 2011 (Fraccaroli et al., 2024).

Scholars discuss the potential contradictory effects of STARA on motivational work characteristics (Cascio & Montealegre, 2016; Fraccaroli et al., 2024; Parker & Grote, 2022a). If automation substitutes manual and cognitive routine tasks that require low knowledge, skills, and abilities, employees will have more spare resources (time and energy) for demanding non-routine tasks, creative and social tasks, suggesting rising levels of skill variety or other knowledge characteristics (Parker & Grote, 2022a). However, if automation leads to the "move from active use of skills to mostly passive monitoring jobs" (Parker & Grote, 2022a, p. 1182), knowledge characteristics like skill variety will decrease with growing automation. These proposed contradictory effects of STARA on skill variety can be transferred and extended to other motivational work characteristics like job autonomy or feedback from job. Parker and Grote (2022a) listed both potential positive and negative effects of AI, robots, and algorithms on other work characteristics in a comprehensive review. However, empirical evidence for most theoretical arguments is scarce (Parker & Grote, 2022b). Peeters and Plomp (2022) recently demonstrated that workplace automation is negatively related to work engagement mediated by decreased job autonomy and skill variety in a sample of 420 employees in a Dutch ministry. Empirical evidence from the aviation industry shows that pilots' manual flying skills reduce with a heightened level of automation of the flying processes (Casner et al., 2014; Haslbeck & Hoermann, 2016), indicating decreased knowledge characteristics like skill variety (Parker & Grote, 2022a) or specialization. Thus, preliminary findings primarily stress the negative impact of STARA on motivational work characteristics but they are either limited due to a cross-sectional study design or very specific contexts. Especially, experimental and longitudinal studies with large time intervals which are necessary to understand whether digital technologies either supplement or substitute work tasks, resulting in positive or negative effects on motivational work characteristics, respectively, are missing (Knight & Parker, 2021).

Scarce empirical evidence on the effects of ICTs on work design could be attributed to the lack of comprehensive theories, frameworks, and models that specify the role of digital technologies in shaping modern workplaces and affecting employee outcomes via altering work characteristics (Gagné et al., 2022). Recently, Gagné and colleagues (2022) proposed a novel model for the future of work design. Building on the premise that implemented digital technologies differ in how they shape work characteristics, the authors presume that technological changes do not affect work design deterministically. Rather, they postulate that *technology design* (e.g., the extent of worker control) and *organizational implementation factors* (e.g., the extent of training that workers receive during implementation) moderate the effect of technological changes on work characteristics. Based on previously mentioned models, work design then influences work motivation via the satisfaction of psychological needs. Integrating the role of workers, Gagné and colleagues (2022) postulate that work motivation can result in proactive behavior and job crafting of employees who then shape both technology design and organizational implementation factors as well as work design directly. However, by neglecting further specifications in definitions of technology design and organizational implementation factors, and affected work characteristics (instead of work design in general), the model by Gagné and colleagues (2022) appears to be highly general. To investigate how intelligent assistance systems or STARA in general continue to impact work design, the model urgently needs refinements in crucial technology design and organizational implementation factors as well as affected work characteristics. The scientific consensus is that the implementation of STARA leads to work-related changes by, for example, fostering human-machine and human-AI interaction (Gagné et al., 2022; Parker & Grote, 2022a). While this means that these jobs remain to exist with alteration due to STARA, some scholars even postulate that STARA will substitute parts of jobs or whole jobs (Brougham & Haar, 2018; Frey & Osborne, 2017).

2. How digitalization affects employees' perceived job insecurity

In their pioneering work, Frey and Osborne (2017) calculated that 47% of US employees were at risk of losing their jobs within the next two decades resulting from the substitution of human labor by automation. Their approach was built on the premise that automation is able to substitute whole jobs. Their article fueled debates on the substitution potential of jobs and occupations due to the increasing implementation of STARA in the modern world of work. Subsequent studies transferred this alarming number to other OECD countries (e.g., Dengler & Matthes, 2018) but strongly criticized that automation rather leads to the substitution of specific tasks within occupations than to the substitution of whole jobs. In the so-called *task-approach*, Dengler and Matthes (2018) yielded strongly reduced numbers for the substitution risk in Germany. They calculated that as of 2013, 15% of the German workforce was at high risk of being substituted by automation, meaning that at least 70% of the core tasks within the occupation can be substituted by automation. Nevertheless, both approaches indicate the immense potential of STARA to substitute work that was previously executed by human employees. Considering the increasing technological advances of STARA in recent years, even more employees might work in occupations with a high substitution risk of core tasks.

Beyond demonstrating the objective substitution risk due to the implementation of STARA, recent frameworks (e.g., Shoss, 2017) and studies (e.g., Wang et al., 2023; Yam et al., 2023) also highlight workers' perceived *job insecurity*, defined as "a perceived threat to the continuity and stability of employment as it is currently experienced" (Shoss, 2017, p. 1914). Including the comprehensive literature on job insecurity, the *conceptual model of antecedents and outcomes of job insecurity* (Shoss, 2017) postulates a variety of antecedents that evoke job insecurity. For instance, it incorporates national or macro-economic factors (like industry decline or technological change) and vulnerable personality traits (low core self-evaluations) that increase job insecurity. In a current article, Yam and colleagues (2023) support the job insecurity-evoking effect of robots. The authors investigated whether physical or virtual exposure to robots evokes job insecurity in employees. Drawing from the *cognitive appraisal theory of stress* (Lazarus & Folkman, 1984), Yam and colleagues (2023) presumed that employees appraise robots to be incongruent with their goals and are perceived as threatening since robots already exceed humans in efficiency and competence in a variety of tasks, allowing for the substitution of human labor (Brougham & Haar, 2018; Yam et al., 2023). Moreover, while human knowledge acquisition as well as the development of abilities and skills have their natural limit, ongoing technological advances will contribute to further discrepancies in the performance of humans and robots in favor of the latter, even in domains in which humans currently still outperform robots (Yam et al., 2023). Therefore, employees' limited coping potential (in terms of knowledge acquisition or training) results in employees' perceived job insecurity. The authors provided multimethod evidence from a total of six studies with independent samples that supports that physical and virtual exposure to robots evokes job insecurity. Thus, they illuminate that the implementation of robots at work is accompanied by unintended negative effects on employees regarding their perceived job insecurity (Yam et al., 2023) which in turn is extensively linked to a variety of detrimental outcomes (Shoss, 2017).

Although Brougham and Haar (2018) emphasize that this effect is not limited to robots but generalizable to STARA, research on this matter is still scarce. To facilitate research on the unintended negative effects of STARA on employees regarding the perceived continuity of their employment, namely the substitution of one's job by STARA, Brougham and Haar (2018) developed a novel construct called *STARA Awareness*. They defined it as "the extent to which an employee views the likelihood of [STARA] impacting on their future career prospects" (p. 241). First empirical evidence demonstrates that STARA Awareness is primarily associated with negative outcomes (e.g., Brougham & Haar, 2018; 2020). Considering that a profound construct validation of STARA Awareness is still pending, the increasing application of the construct might lead to misinterpreted findings instead of the nuanced understanding of how employees appraise STARA to impact their employment it was originally developed for.

3. Research gaps and contributions

As outlined above, it remains largely unclear how the implementation of STARA in the modern labor market already alters and will continue to alter how, where, and when humans execute their work, and how human workers appraise STARA's increasing implementation in terms of their employment. This dissertation tackles these issues in the following ways: Based on the assumption that technologies differ in how they affect work design depending on technology design and organizational implementation factors (Gagné et al., 2022), and integration of theoretical approaches (e.g., Autor et al., 2003; Waschull et al., 2020), it focuses on how intelligent assistance systems shape motivational work characteristics in assembly. Today's modern assembly is characterized by growing complexity resulting from frequent changes in individualized assembly products. To alleviate those rising cognitive demands for traditionally low-skilled workers in assembly, intelligent assistance systems are increasingly implemented in organizational practice for assistance during frequent product changes (Egger-Lampl et al., 2019). Common technology design factors of intelligent assistance systems include the projection of context-sensitive in-situ operating instructions and feedback for subsequent assembly steps (Apt et al., 2018). These aim to evoke numerous benefits like the cognitive support of assembly workers in training phases and the long-term, shortened training phases, the inclusion of non-native speakers and low-skilled workers, the reduction of human errors and uncertainties, and increased productivity (Apt et al., 2018; Mark et al. 2019). Despite their growing use in organizational practice (Bortolini et al., 2021), it is yet unclear how their implementation in assembly alters affected workplaces, i.e., motivational work characteristics. Indeed, this knowledge is crucial considering the well-documented downstream effects of work design on employee outcomes (Parker et al., 2017).

For this reason, the first aim of this dissertation is to investigate whether the use of intelligent assistance systems yields its intended objectives in terms of altered motivational work characteristics (e.g., increased feedback from job, decreased job complexity), or whether this use evokes unintended negative effects on motivational work characteristics. Such potential negative effects comprise the restriction of autonomy or systematic deskilling of employees by completely taking over cognitive tasks, as mentioned in qualitative studies (Baethge-Kinsky, 2020; Blumberg & Kauffeld, 2020).

The second aim of this dissertation is to explore the possibility of preventing these potential negative effects of the intelligent assistance system on motivational work characteristics in terms of restricted autonomy and systematic deskilling of assembly workers. Assembly workers might recognize that the intelligent assistance system has the potential to deteriorate employee outcomes via the reduction of motivational work characteristics. In turn, they might primarily use it when it is specifically needed such as in training phases and during the first times of the assembly of new products. This dissertation illuminates the *voluntary use* of the intelligent assistance system as an essential implementation factor that buffers the negative impacts of the system on work design. Thus, it aims to provide an implementation measure to promote the beneficial impact of using intelligent assistance systems in organizational practice.

The third research aim is to examine whether the identified effects are transferrable to more complex assembly sequences. By ruling out that the identified effects of the intelligent assistance system on motivational work characteristics are an artifact of the assisted assembly sequence, the generalizability to other assembly sequences ensures the validity of the effects. This aims to avoid the precipitous assessment of the impact of intelligent assistance systems.

Fourth, drawing from the model by Gagné and colleagues (2022) that specifically postulates a moderation of the effect of technological changes on work design by organizational implementation factors, we investigate whether the extent of alternations between assembly products moderates the effect the intelligent assistance system on motivational work characteristics. Hence, this dissertation contributes to the development and refinement of a work design theory that describes and specifies how the implementation of novel digital technologies (like intelligent assistance systems) alters motivational work characteristics. Additionally, by highlighting subjective human factors in the implementation of intelligent assistance systems in assembly, it provides vital insights for their human-centered development and motivational assembly workplaces in the future.

The fifth research aim of this dissertation is to provide a thorough construct validation of STARA Awareness that was neglected by Brougham and Haar (2018). Specifically, this includes the investigation of its internal structure, the extension of its definition, the empirical separation from established *cognitive* and *affective job insecurity*, the identification of potential antecedents in terms of indicators of technological change, and *core self-evaluations*, a higher-order personality trait consisting of generalized self-efficacy, self-esteem, locus of control and neuroticism (Judge, 2009), and finally, the investigation of its temporal stability. This thorough construct validation enables a nuanced understanding of how employees appraise STARA to affect the continuity of their employment by substituting human labor, and the integration of the construct into the extensive job insecurity literature (Shoss, 2017). This further contributes to the development of a comprehensive theory that depicts how employees appraise STARA in today's digitalized labor market.

Sixth, given that the developed questionnaire by Brougham and Haar (2018) only considers the substitution of whole jobs, we provide an extension of the questionnaire that takes into account that STARA also substitute core tasks within jobs. Consequently, the extended questionnaire captures the expected technological changes in the labor market (Dengler & Matthes, 2018) more realistically. Extending both the construct definition and measurement instrument enables the nuanced application and assessment of STARA Awareness for research and organizational practice. Therefore, the three articles included in this dissertation offer a holistic framework that sheds light on both the digital transformation of workplaces in assembly and the possible replacement of jobs due to STARA.

4. Summary of the included articles

To achieve the proposed research aims, this dissertation includes three articles with a total of three conducted online experiments, two cross-sectional and one longitudinal study. Table 1 depicts the respective research aims, study variables, methods, and samples of the studies included in these three articles. Figure 1 displays a graphic overview of the articles' thematic relationships. The included articles constitute the forthcoming chapters 2, 3, and 4.

Paper 1: Investigating the effect of intelligent assistance systems on motivational work characteristics in assembly

Intelligent assistance systems are supposed to assist assembly workers cognitively during frequently changing assembly products (Egger-Lampl et al., 2019). Due to the lack of specific theoretical models and empirical evidence on how intelligent assistance systems alter workplaces by impacting motivational work characteristics, it is unclear whether their use induces the intended effects or causes unintended, negative effects. These negative effects include the restriction of autonomy and the systematic deskilling of employees which have been pointed out in qualitative studies (Baethge-Kinsky, 2020; Blumberg & Kauffeld, 2020). Therefore, we conducted an online experiment with vignette methodology in which we manipulated a hypothetical assembly workstation (without intelligent assistance system vs. with intelligent assistance system vs. with voluntary use of intelligent assistance system), depicting a simple assembly task that rotates every two hours. We instructed 203 German and British blue-collar workers to rate the presented assembly workstation in terms of motivational work characteristics. The results demonstrated significantly higher ratings in feedback from job and information processing for the workstation with the intelligent assistance system compared with the workstation without the intelligent assistance system. Given that the manipulation for the voluntary use of the intelligent assistance system failed, it precluded the exploration of a buffering effect. Therefore, the experiment in Paper 1 showcases exclusively positive effects of the use of the investigated intelligent assistance system with respect to motivational work characteristics. As we did not find any decreases in other knowledge characteristics (job complexity, problem solving, skill variety, or specialization), the results indicate the investigated intelligent assistance systems neither reaches its main purpose of providing cognitive support nor systematically deskills employees. However, floor effects in motivational work characteristics ratings may have prevented the identification of negative effects of the intelligent assistance system. The general low ratings in motivational work characteristics – apart from feedback from job – could be attributed to a highly simplified assembly process and infrequent rotations of assembly products. Nevertheless, this experiment contributes the first causal evidence on how the implementation of intelligent assistance systems shapes motivational work design in assembly, specifically enhancing feedback from job and information processing.

Paper 2: Blessed be intelligent assistance systems at high task rotation? The effect on motivational work design in assembly

Building on the results from Paper 1, we further challenged the purely positive effect of intelligent assistance systems on motivational work characteristics (increasing feedback from job and information processing) in Paper 2. We conducted two online experiments with vignette methodology to rule out whether the missing negative effects in Paper 1 are attributable to potential floor effects in the motivational work characteristics ratings. In Study 1, we experimentally manipulated the use of an intelligent assistance system in assembly (work with vs. work without the intelligent assistance system) and transferred the findings from Paper 1 to a more complex assembly process. In Study 2, we experimentally manipulated both technology design and organizational implementation factors outlined in the model by Gagné and colleagues (2022) by varying the use of the intelligent assistance system (as in Study 1) and the extent of task rotation (alternation between assembly products after one hour vs. no alternation), respectively. Results from both online experiments (N_1 = 169, N_2 = 176 German workers) demonstrated significant main effects of the intelligent assistance system on motivational work characteristics in terms of increased feedback from job and information processing, and decreased work scheduling, decision-making, and work methods autonomy compared with working without the intelligent assistance system. Task rotation did not exert main effects or interaction effects with the intelligent assistance system on the examined motivational work characteristics. By showing both increases and decreases in motivational work characteristics, the two experiments contribute the first experimental evidence on the contradictory effects of intelligent assistance systems on work design, regardless of the alternations between assembly products. Given the differences between the effects on autonomy between Paper 1 and Paper 2, the difficulty of the assisted assembly task seems to have vital implications for the implementation of intelligent assistance systems in assembly.

Paper 3: One, two, new technology is coming for you – Construct validation of job insecurity due to smart technology, artificial intelligence, robotics, and automation

Innovative technologies like STARA continue to profoundly alter the global labor market by not only complementing but also substituting human labor. Brougham and Haar (2018) introduced the construct STARA Awareness to assess how employees appraise STARA to affect their employment regarding substituting their jobs but disregarded a thorough construct validation. To enable a nuanced application of STARA Awareness in future studies, we provide a comprehensive construct validation (investigation of internal structure, extension of definition and measurement, empirical differentiation from cognitive and affective job insecurity, identification of potential antecedents, and exploration of temporal stability) by conducting two cross-sectional studies (N_1 = 215; N_2 = 224) and one longitudinal study over one year (N_3 = 233) with German employees from different branches. Our findings demonstrate that the fit of the measurement model of STARA Awareness fluctuates strongly between independent samples. As a first step to tackle this issue, we renamed the construct to *affective automation-related job insecurity*, and adapted its definition and the associated measurement instrument by excluding cognitive components and incorporating the substitution of core tasks in a job. Hence, the development of affective automation-related job insecurity captures a digitalization-specific form of job insecurity that reflects the expected changes in the modern world of work more realistically. Although affective automation-related job insecurity is positively related to cognitive and affective job insecurity, it is uniquely related to indicators of technological change. Our findings indicate that core-self evaluations represent a protective higher-order personality trait for affective automation-related job insecurity as well as the established cognitive and affective job insecurity. Our longitudinal data demonstrate that affective automation-related job insecurity increases for employees with moderate use of STARA but decreases for employees with low or high use of STARA. Finally, these three studies provide evidence of the importance of a digitalization-specific construct that captures how employees appraise how STARA affects their employment. We contribute to the crucial understanding of how the implementation of STARA in the modern world of work impacts employees` perceived job insecurity beyond changing how, where, and when we work.

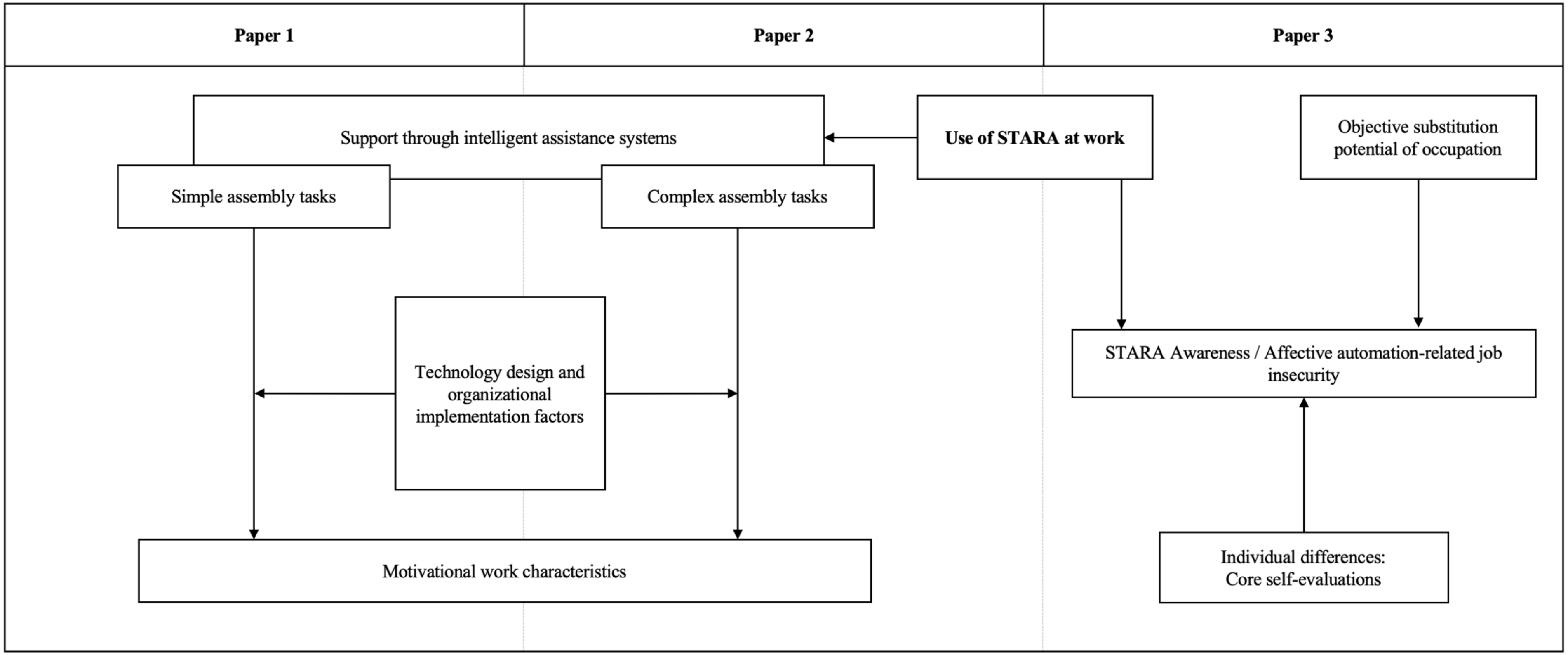
Table 1
Overview of the included articles

	Research aims	**Study variables**	**Research design and samples**
Paper 1	Examining the effect of an IAS on motivational work characteristics in assembly Explore a buffering effect of voluntary use of IAS on potential reductions in motivational work characteristics	Motivational work characteristics - Work scheduling, decision-making, work methods autonomy - Feedback from job - Job complexity - Problem solving - Information processing - Skill variety - Specialization	One-factorial experiment with between-subjects design using experimental vignette methodology - Work without IAS vs. work with IAS vs. work with voluntary use of IAS - N = 203 German and British blue-collar workers
Paper 2	Transfer of the effect of an IAS to a more complex assembly product Investigating the effect of the intelligent assistance system depending on the extent of task rotation	Motivational work characteristics - Work scheduling, decision-making, work methods autonomy - Feedback from job - Job complexity - Problem solving - Information processing - Skill variety - Specialization Task rotation	Study 1: One-factorial experiment with between-subjects design - Work without IAS vs. work with IAS - N_1 = 169 German workers Study 2: Two-factorial experiment with between-subjects design - Work without IAS vs. work with IAS - Task rotation every hour vs. no task rotation - N_2 = 176 German workers
Paper 3	Construct validation of affective automation-related job insecurity - Examining the internal structure - Extending the construct definition - Separating from established job insecurity - Identifying antecedents - Investigating temporal stability Further developing of a proposed scale to measure affective automation-related job insecurity	STARA Awareness / Affective automation-related job insecurity Cognitive and affective job insecurity Objective substitution potential of occupation Use of STARA Core self-evaluations	Two cross-sectional studies - N_1 = 215 German employees - N_2 = 224 German employees One longitudinal study with three measurement points and total time lag of one year - N_3 = 233 German employees

Notes. IAS = Intelligent assistance system. STARA = Smart technology, artificial intelligence, robotics, algorithms, and automation.

Figure 1

Graphic overview of included papers



Notes. STARA = Smart technology, artificial intelligence, robotics, algorithms, and automation

Chapter 2 – Paper 1

Investigating the effect of intelligent assistance systems on motivational work characteristics in assembly

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Abstract

Intelligent assistance systems (IAS) are designed to counteract rising cognitive demands caused by increasingly individualized manufacturing processes in assembly. How IAS affect *work characteristics* which are crucial for promoting work motivation of employees is yet unclear. Based on the *cyber-physical systems transformation framework*, the *model of routine-biased technological change*, and a comprehensive model of work design, we expected in- and decreases in *motivational work characteristics* (MWC) when working with IAS. Furthermore, we posited a buffering effect of the option of voluntary use on decreasing knowledge characteristics. Applying an online case study with *experimental vignette methodology* (EVM) allowed us to identify effects of the IAS on MWC before it is widely implemented. 203 German and British blue-collar workers evaluated an assembly workplace according to three experimental conditions (work without IAS, work with IAS, work with voluntary use of IAS). We identified enhanced feedback from the job and information processing in work with IAS in contrast to a traditional assembly workplace but found no restrictions (or elevations) in terms of other task (i.e., autonomy) or knowledge characteristics (i.e., job complexity, problem solving, specialization, skill variety). Thus, our results indicate that the IAS improves some motivational work characteristics of the assembly workplace, although it misses the primary goal of cognitive relief. Our study highlights the need for work design theories that specify the effect of IAS on motivational work characteristics and the potential benefit of IAS in assembly of the future.

Keywords: *intelligent assistance systems, work design, motivational work characteristics, voluntary use, assembly*

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Investigating the effect of intelligent assistance systems on motivational work characteristics in assembly

Despite technological advancements in today's workplaces like additive manufacturing (Zhang et al., 2017) or collaborative robots (Faccio et al., 2023), assembly processes carried out by humans will remain indispensable in the digital factory of the future (Pfeiffer, 2016). Assembly work even becomes increasingly complex due to highly variable, individualized manufacturing processes (Egger-Lampl et al., 2019; Faccio et al., 2023). Various *intelligent assistance systems* (IAS) have been developed to effectively support assembly workers in their mostly monotonous but concentration-demanding jobs with the intention to reduce cognitive workload, and increase quality (Egger-Lampl et al., 2019; Kang et al., 2016; Stockinger et al., 2021). Although the (cognitive) support of assembly workers by such systems is intended (Berkers et al., 2022), the research field lacks specific theories and causal evidence on how IAS shape *motivational work characteristics* (MWC) (Baethge-Kinsky, 2020; Egger-Lampl et al., 2019). These are crucial for promoting work motivation, job satisfaction, and performance (Parker et al., 2017). Such insights are needed, given that the distribution of IAS is accelerated by the Covid-19 pandemic (Krzywdzinski et al., 2022), and several scholars have outlined potential risks of the implementation of IAS, such as restricted autonomy, or systematic de-skilling of employees (e.g., Blumberg & Kauffeld, 2020; Dostert & Müller, 2020).

Therefore, the aim of the current case study is twofold. First, using *experimental vignette methodology* (EVM) (Aguinis & Bradley, 2014), we are – to our knowledge – the first to systematically examine the causal effects of an exemplary projection-based, cognitive-assistive IAS on MWC to identify positive and negative effects before the IAS is implemented in practice. Second, we investigate whether potential negative effects can be mitigated by the voluntary use of IAS. By this, our study provides important contributions to theory and practice. On the one hand, our study aims to contribute to theory development with regard to the role of technology for work design models by shedding light on motivational effects of IAS. Furthermore, by focusing on the consequences of IAS for employees, we stress the importance of the still neglected, subjective human factors (Faccio et al., 2023) in the implementation of IAS in assembly. By examining subjective factors, we essentially extend current research on IAS which mainly focuses on objective evaluation indicators (Keller et al., 2019; Lampen et al., 2019). On the other hand, with regard to practice, our EVM study design provides a valuable tool to test the effect of specific (future) technologies on MWC. Overall, our case study offers valuable practical recommendations for human-centered design and implementation of IAS to create motivating workplaces in assembly of the future.

To make our expectations and contribution clear, we first introduce intelligent assistance systems (IAS) and their intended function in supporting assembly workers. In detail, we then define motivational work characteristics (MWC) and review the existing literature and theoretical models how IAS might affect MWC. Subsequently, we postulate and explain our expectations on the effect of a projection-based, cognitive-assistive IAS on nine different MWC. Then, we present the used methods, in particular outlining the implemented experimental vignette methodology (EVM). We then present the results of our hypothesis testing, and finally discuss the implications of our findings for theory and practice.

Theoretical Background

Intelligent Assistance Systems at work

Technical systems that support people in carrying out activities by taking in and processing information from the environment or by inputting information are defined as intelligent assistance systems (IAS) (Hinrichsen, 2020). IAS represents an umbrella term covering a wide range of technical systems from wearables, including smart watches or data glasses (Blumberg & Kauffeld, 2020), to exoskeletons. Accordingly, IAS can be differentiated in their level of support or demand (low, medium, high, variable), type of support (physical, sensory, cognitive), and objective (compensatory, maintenance, enhancement) (see Apt et al., 2018 for a comprehensive overview of types of IAS).

In the current study, we focus on stationary, cognitive-assistive IAS with a low level of assistive performance, which will play an increasingly crucial role in modern assembly in tomorrow's smart factory (Apt et al., 2018). Such IAS are supposed to support workers cognitively by, for example, providing context-sensitive in-situ projection, or presenting work instructions and assembly information to reduce training times, workers' uncertainties, avoid incorrect assembly steps, and consequently increase work productivity (Apt et al., 2018). They should also support the inclusion of non-native speakers to the workforce, low-skilled people, and those with other deficits through visual, language-independent instructional materials (Apt et al., 2018; Mark et al., 2019).

The IAS in our study (see Jung et al., 2022 for further technical characteristics of the IAS) consists of a 3D camera and a projector mounted overhead above the assembly workstation and an industrial PC. Furthermore, eye-trackers are integrated that allow tracking eye movements of employees during task execution. The system architecture consists of an information system with a semantically structured knowledge database and a control system. The 3D camera captures image and depth data and thus the hand movements of the assembly workers. With the help of algorithms, the hands are recognized in different levels of detail, and videos are converted into time series of position data. Activities are derived from further analysis of the time series. Machine learning principles enable work processes to be autonomously taught to the system by having the system repeatedly record a previously unknown assembly process. Automatically generated instructional material is projected onto the work surface in-situ as augmented reality via the projector. Thus, the IAS intends to support and cognitively relieve assembly workers by instructing each assembly step. A picture of the investigated intelligent assistance system as well as a text description of the presented job, assembly workplace, and functions of the system can be found in the ESM on the Open Science Framework (OSF). We used this information to introduce participants to the hypothetical assembly workplace in our empirical study.

Although such systems are not only developed but already used in practice, current research on IAS largely neglects the effects of these systems on human factors (Egger-Lampl et al., 2019; Faccio et al., 2023). Comprehensive models of how IAS shape the work design in assembly are still missing. Suggestions about the impact of IAS on work outcomes stem from the related field of *information and communication technology* (ICT). For example, researchers have reported contradictory impacts of ICT at work, for example, on motivation (Baethge-Kinsky, 2020; Day et al., 2019; Parker & Grote, 2022; Wang et al., 2020; Waschull et al., 2020). On the one hand, ICTs have the potential to replace dull routine work with algorithms and automation, giving workers more time to complete creative and cognitively demanding tasks, thereby increasing skill variety and motivation (Parker & Grote, 2022). On the other hand, ICTs could lead to a systematic de-skilling of employees by increasing automation of cognitively demanding work (Blumberg & Kauffeld, 2020; Parker & Grote, 2022). In turn, these reductions in skills can lead to lower motivation and learning-related outcomes (Parker & Grote, 2022). Still, current research on IAS largely neglects the effects of these systems on human factors despite its growing importance (Egger-Lampl et al., 2019; Faccio et al., 2023).

Motivational work characteristics

Work design is defined as “the study, creation, and modification of the composition, content, structure, and environment within which jobs and roles are enacted” (Morgeson & Humphrey, 2008, p. 47), and has been shown to have a substantial impact on important outcome variables at work, such as work motivation, job satisfaction, or performance (Morgeson & Humphrey, 2006; Parker et al., 2017). Numerous theories and models have been suggested and tested in the last decades, to specify which work characteristics are linked to which work-related outcomes. For example, the *job characteristics model* (JCM) is one of the most influential theories in work design and motivation literature (Hackman & Oldham, 1976; Parker et al., 2017). It distinguishes five core job characteristics (job variety, job autonomy, job feedback, job significance, and job identity) which trigger three critical psychological states (experiencing meaning, feeling responsible for outcomes, and understanding the results of their efforts) which in turn have a positive impact on motivation (Hackman & Oldham, 1976; Parker, 2014).

Resulting from a review of different theories and empirical studies investigating work and job design, the *work design questionnaire* (WDQ) (Morgeson & Humphrey, 2006) is the most comprehensive and integrative instrument to capture work characteristics (Parker et al., 2017). Identifying key, yet distinct work characteristics, it includes aspects from established models such as the JCM (Hackman & Oldham, 1976), as well as further relevant identified work characteristics (Parker et al., 2017). The 21 work characteristics encompassed in the instrument have been shown to fall into four categories, namely *task*, *knowledge, social,* and *contextual work characteristics* (Morgeson & Humphrey, 2006). First, task characteristics capture the five JCM characteristics (Parker, 2014), which mainly refer to the execution of work and the “range and nature of tasks associated with a particular job“ (Morgeson & Humphrey, 2006, p. 1323). In total, three facets of autonomy are separated (*work scheduling*, *decision-making,* and *work methods autonomy).* Further relevant task characteristics identified are *task variety, task significance, task identity,* and *feedback from the job*. Second, knowledge characteristics comprise knowledge, skills, and abilities needed for the execution of a job, and include *job complexity*, *problem solving*, *information processing*, *skill variety*, and *specialization* (Morgeson & Humphrey, 2006). Because of their positive relation with motivation, task and knowledge characteristics are also referred to as motivational work characteristics (Morgeson & Humphrey, 2006; Parker, 2014; Stegmann et al., 2010). Providing evidence for their relevance, Humphrey et al. (2007) showed in their meta-analysis that these motivational characteristics together can explain up to 34% of the variance in job performance, job satisfaction, internal work motivation, or organizational commitment. Third, the WDQ also covers social and contextual characteristics, which refer to the social environment in which the work is embedded and the physical nature of the work environment, respectively (Morgeson & Humphrey, 2006). In our current study, we focus on the motivational work characteristics because of their importance for work motivation, and their fundamental changes due to technological changes at work (Parker & Grote, 2022; Wang et al., 2020).

Altered work design characteristics due to the implementation of IAS

Although the WDQ provides an organizing framework of work characteristics and has stimulated research about the effects of motivational, social, and context characteristics at work, specific theories and empirical evidence on how work characteristics are altered by the introduction of technology in the workplace are missing. This could be because the effect of technology on work characteristics depends, among other things, on the specific type and design of technology (Parker & Grote, 2022). Gagné and colleagues (2022) state that digital technologies have the potential to in- and decrease motivational work characteristics, as “there is no deterministic relationship between technology and work design; instead the effect of new technology on work design, and hence motivation, depends on various moderating factors” (p. 6), such as the employees’ skills or organizational implementation factors. Therefore, the existing literature on the effects on work design appears to be too general for a generalization to stationary IAS in assembly. For example, wearables enable time- and location-flexible working and thus increase an employee’s autonomy (Parker & Grote, 2022). However, in contrast, such effects seem not easily transferable to stationary IAS, as they do not support such work arrangements. This highlights the importance of technology-specific studies; in our case, this is a stationary, cognitive-assistive IAS.

On a general level, different theoretical models or frameworks stemming from various fields (i.,e. industrial engineering, or economics) might help to explain some of the motivational effects on task and knowledge characteristics when introducing IAS at work. First, the *CPS transformation framework* by Waschull et al. (2020) is based on the WDQ (Morgeson & Humphrey, 2006). It postulates that job autonomy, job complexity, and skill variety in industrial production are affected by the introduction of cyber-physical systems, for example, IAS (Drossel et al., 2018). In detail, the authors expect an increase in job complexity as simple tasks will be eliminated by increasing automated information collection and analysis, whereas complex tasks will continue to exist. This framework also postulates significant increases in skill variety, especially in occupations that require high levels of information processing. For low-skilled and middle-skilled jobs like jobs in assembly (Maxwell, 2006), the authors suggest reductions in autonomy, as technologies might limit decision-making freedom, clock and standardize work (Waschull et al., 2020). Although this framework allows postulating specific effects of the introduction of IAS on task and knowledge characteristics, so far empirical evidence for these postulations in a comprehensive work design model is – to our knowledge – still missing.

Second, Autor et al. (2003) developed the *model of routine-biased technological change*, which postulates a polarization of jobs in the form of an increasing number of low-skilled and high-skilled jobs as the number of middle-skilled jobs decreases due to the introduction of digital technologies. It differentiates between manual and cognitive as well as routine tasks – tasks that “can be performed by machines according to explicitly programmed rules” (Autor et al., 2003, p. 1283) – and non-routine tasks. While increasing automation through new digital technologies is expected for manual and cognitive routine tasks, the model posits strong complementarities for non-routine cognitive tasks as well as limited opportunities for substitution or complementarities for non-routine manual tasks (Autor et al., 2003). Based on this model, Mlekus (2021) empirically showed that the relationship between digitization level in the workplace and competency requirements is indeed moderated by the context (stronger focus on nonroutine manual vs. nonroutine cognitive tasks). Whereas she found a positive correlation between digitalization level and competence requirements in the domain of production (stronger focus on nonroutine cognitive tasks), a negative correlation between digitization level and competence requirements in the domain of logistics was evident (stronger focus on nonroutine manual tasks) (Mlekus, 2021). Modern assembly is characterized by nonroutine cognitive and nonroutine manual tasks due to the highly frequent switching of assembly processes due to highly variable, individualized manufacturing processes (Egger-Lampl et al., 2019; Faccio et al., 2023). The implementation of IAS in assembly should therefore not only increase the digitalization level in the workplace but also shift the focus to nonroutine manual tasks since employees are cognitively supported by the use of IAS so that nonroutine cognitive tasks play a subordinate role. Consequently, the model of routine-biased technological change suggests a reduction of knowledge characteristics while working with IAS, while it is unclear yet which particular aspects are indeed positively or negatively affected.

Overview of present research and hypotheses

In sum, in the context of IAS at work, there are mainly theoretical considerations about the extent to which motivational work characteristics will be transformed instead of empirical evidence. Existing findings regarding IAS apply to wearables such as smart watches or smart glasses (Blumberg & Kauffeld, 2020; Paruzel et al., 2020). Hence, we aim to provide the first systematic investigation of the effects of stationary IAS on motivational work characteristics within a comprehensive framework of work design. Based on the CPS transformation framework and the model of routine-biased technological change framework, we suggest that IAS not only affect motivational work characteristics positively but also carry the risk of detrimental effects (see Table 1 for an overview of the closely related empirical work on IAS and motivational work characteristics). Furthermore, we propose that the voluntary use of IAS can mitigate negative effects on knowledge characteristics.

First, with regard to the task characteristics included in the WDQ, we expected distinct effects of the introduction of IAS on autonomy and feedback. Taking a closer look at the three facets of autonomy, work scheduling autonomy refers to "the extent to which a job allows freedom, independence, and discretion to schedule work" (Morgeson & Humphrey, 2006, p. 1323), whereas decision-making autonomy reflects the degree to which a job allows incumbents to make decisions on their own. The facet of work methods autonomy is defined as the extent to which a job allows workers to choose methods to perform their tasks themselves (Morgeson & Humphrey, 2006). IAS are introduced with the overall goal to standardize work by specifying and providing information about subsequent work steps, detailed sequences of individual assembly steps, instruments or tools to be used for specific tasks, as well as solutions to problems at each point in the execution of activities (Blumberg & Kauffeld, 2020; Dostert & Müller, 2020; Waschull et al., 2020). Therefore, their introduction at the workplace suggests reductions in all three autonomy facets. Such an expectation is supported by the qualitative studies (cf. Table 1) by Blumberg and Kauffeld (2020) and Berkers and colleagues (2022). Several interview participants highlighted the decline of autonomy as a central risk of the implementation of data glasses and tablets as IAS at work (Blumberg & Kauffeld, 2020), and the implementation of robots in logistics (Berkers et al., 2022). However, causal evidence for such an effect for IAS in assembly is so far missing. Furthermore, specifying the effects of the implementation of IAS on all three different autonomy facets seems necessary, as these facets are differently related to work outcomes (Humphrey et al., 2007).

Hypothesis 1: a) Work scheduling autonomy b) Decision-making autonomy c) Work methods autonomy is significantly lower in work with IAS than in work without IAS.

With regard to feedback from the job, defined as "the degree to which the job provides direct and clear information about the effectiveness of task performance" (Morgeson & Humphrey, 2006, p. 1323), significant increases can be expected through the implementation of IAS, as they provide feedback on every assembly step and can be used specifically for learning a specific task or job (Apt et al., 2018).

Hypothesis 2: Feedback from job is significantly higher in work with IAS than in work without IAS.

Concerning further task characteristics included in the WDQ, we expect neither positive nor negative effects of IAS on task variety, task significance, and task identity, since the individual work steps and thus the work as a whole remain largely unchanged. The individual work steps are merely assisted by the IAS. This is supported by findings based on qualitative interviews with production workers from Baethge-Kinsky (2020), who reported that work with IAS still has the same features (high monotony, routine tasks, and few opportunities for technically demanding activities) as work without IAS unless the work is extended through work design interventions.

Second, we expected all five knowledge characteristics to be affected by the introduction of IAS. First, job complexity describes how complex and difficult the tasks that the job holder has to perform are (Morgeson & Humphrey, 2006). The two general frameworks do not convey in this regard: While the CPS transformation framework (Waschull et al., 2020) postulates significant increases, reductions can be expected based on the routine-biased technological change model (Autor et al., 2003). However, as the IAS intends to support employees cognitively, it can be expected that job complexity decreases as it provides precise instructions for each assembly step (Apt et al., 2018). Furthermore, such systems have been associated with the risk of long-term systematic de-skilling of employees by taking over the mental work (Baethge-Kinsky, 2020; Blumberg & Kauffeld, 2020; Parker & Grote, 2022). Also, Lampen and colleagues (2019) showed that the cognitive workload learning a new task can be significantly reduced by an IAS compared to a paper instruction. Therefore, we expected that job complexity will be reduced while working with an IAS.

Hypothesis 3: Job complexity is significantly lower in work with IAS than in work without IAS.

Second, problem solving describes “the degree to which a job requires unique ideas or solutions and reflects the more active cognitive processing requirements of a job” (Morgeson & Humphrey, 2006, p. 1323). Since IAS uses, for example, context-sensitive in-situ projections to instruct workers on subsequent assembly steps and identify incorrect activities as mistakes, problem solving is taken over by IAS so that workers no longer have to solve problems on their own (Dostert & Müller, 2020). Due to this, knowledge, skills, and abilities regarding problem solving can decrease in the long term, potentially leading to a systematic de-skilling of workers (Autor et al., 2003), a potential risk that was also mentioned by some interview participants in the study by Blumberg and Kauffeld (2020).

Hypothesis 4: Problem solving is significantly lower in work with IAS than in work without IAS.

Third, information processing refers to “the degree to which a job requires attending to and processing data or other information” (Morgeson & Humphrey, 2006, p. 1323). On the one hand, the IAS as another source of information in addition to the traditional workplace provides information that has to be monitored and processed by the employees, so the demands on information processing could increase through the introduction of IAS. On the other hand, there is also the possibility of a decrease in information processing because IAS aim to support the job incumbents cognitively and could take over the cognitive work entirely (Baethge-Kinsky, 2020; Blumberg & Kauffeld, 2020). This also seems plausible considering the strong intercorrelation of information processing with other knowledge characteristics, in terms of problem solving and complexity (Morgeson & Humphrey, 2006; Stegmann et al., 2010). Due to the plausibility of the two directions and the lack of empirical research regarding changes in information processing through the implementation of IAS, we suggest competing hypotheses for this work characteristic.

Hypothesis 5: Information processing is significantly a) lower b) higher in work with IAS than in work without IAS.

Fourth, skill variety reflects the necessary amount of skills that are required for the completion of the work (Morgeson & Humphrey, 2006). Similar to information processing, significant reductions or significant increases in the skill variety through the introduction of IAS seem plausible. On the one hand, IAS are specifically used to train non-native speakers and low-skilled persons and integrate them into the labor market (Apt et al., 2018; Mark et al., 2019), so that the skill variety could decrease significantly by taking over the cognitive work. This would again result in the risk of systematic de-skilling or general downgrading (Autor et al., 2003; Baethge-Kinsky, 2020; Blumberg & Kauffeld, 2020). On the other hand, in addition to the traditionally needed requirements, digital competencies are required for successful interaction with the IAS (Waschull et al., 2020), which will play an ever-increasing role in the context of digitalization, smart factory, and Industry 4.0 (Oberländer et al., 2020). This may even result in general upskilling (Baethge-Kinsky, 2020).

Hypothesis 6: Skill variety is significantly a) lower b) higher in work with IAS than in work without IAS.

Fifth, specialization refers to “the extent to which a job involves performing specialized tasks or possessing specialized knowledge and skill” (Morgeson & Humphrey, 2006, p. 1324). In terms of specialization, the introduction of IAS can be expected to lead to a deterioration, as, for example, the context-sensitive in-situ instructions allow non-native speakers and low-skilled individuals to be trained more quickly, thus requiring fewer specific skills and abilities (Apt et al., 2018), which could result in a systematic de-skilling of employees (Autor et al., 2003; Baethge-Kinsky, 2020; Blumberg & Kauffeld, 2020).

Hypothesis 7: Specialization is significantly lower in work with IAS than in work without IAS.

Besides investigating the effects of the introduction of IAS in assembly on core work characteristics, we were interested if the potential negative effects of using such a system (cf. our expected effects in terms of lowered knowledge characteristics outlined above), can be buffered in practice. Using the system voluntarily – allowing employees to use the system or not – could counteract systematic de-skilling of workers based on the model of routine-biased technology change (Autor et al., 2003). By preventing over-support and excessive takeover of cognitive work, modern assembly continues to include not only nonroutine manual but also nonroutine cognitive tasks for which the model expects strong complementarities in skills (Autor et al., 2003) which has been empirically supported (Mlekus, 2021). Therefore, we suggest, that using the system voluntarily could buffer potential negative effects of IAS on knowledge characteristics by preventing a shift in focus to nonroutine tasks.

Hypothesis 8: a) Job complexity b) problem solving c) information processing d) skill variety e) specialization is significantly higher in work with voluntary use of IAS than in work with IAS.

Method

In our experiment, we investigated the causal impact of a stationary, cognitive-assistive IAS on task and knowledge characteristics and the role of the voluntary use of IAS concerning knowledge characteristics. For this, we manipulated an assembly workstation using EVM in an online experiment realizing three experimental conditions (work without IAS vs. work with IAS vs. work with voluntary use of IAS).

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We pre-registered all procedures and hypotheses before data collection (https://osf.io/352zd/?view_only=5ff4cf3e692d44edbb0843418bb9bc26). The electronic supplementary material (ESM) including the presented hypothetical assembly workstation, information on the presented IAS, and additional analyses can be found in the OSF.

Experimental design and procedure

We manipulated the assembly workstation in an online study using a between-subjects design based on vignettes with three experimental conditions: work without IAS vs. work with IAS vs. work with voluntary use of IAS. Since the implementation of IAS in assembly is still in its infancy (Bortolini et al., 2021) which complicates the experimental investigation of the effect of such systems with samples in organizational practice, we chose an EVM study design. Such a study design is associated with several advantages. First, it allows the investigation of causal effects (high internal validity) using realistic (future) scenarios, maximizing the generalizability of experimental results (high external validity) (Aguinis & Bradley, 2014). Hence, our study enables the much-needed identification of potential opportunities and risks of such systems before they are implemented. Second, and in contrast to, for example, an investigation of the changes in work characteristics before and after the implementation of an IAS in one organization, the EVM allowed us to investigate employees from diverse organizations, thus increasing generalizability of our results. And implementing the exact same system in various organizations and investigating that across them seems not feasible, as different organizations would need to adapt the IAS to the specific needs of their particular assembly processes, which would systematically bias the results. In this way, the EVM study counteracts assembly process- and organization-specific effects, such as an organization's technology-averse tendency. Third, the EVM study design allows the pure investigation of the effect of the IAS on MWC without the impact of additional interferences, such as time delays or incorrect modeling which could occur in occupational practice (Tao et al., 2022; Xu et al., 2021).

In our realization of the EVM in an online study, we followed the best practice recommendations for designing and implementing such studies by Aguinis and Bradley (2014) and used baseline information, and combined text, picture and video material to maximize the level of immersion. Figure 1 includes a flow chart depicting procedure of the experiment. In the beginning, we asked all participants who agreed to participate to imagine a hypothetical work situation as an assembly worker in a medium-sized assembly company. Therefore, all participants read a three-sentence long baseline information on the situational context. Afterward, participants were randomly assigned to one of the three experimental conditions.

In the first condition, work without IAS, participants were given a page of text description of a traditional assembly workstation (including a picture of the workspace) without IAS as well as an approximately 1-minute long video of an exemplary assembly process without the support of the IAS.

In the second condition, work with IAS, and the third condition, work with voluntary use of IAS, participants were given a page of text description of an assembly workstation with IAS (again including a picture of the workspace) and additional information about the functions of the IAS. Also, the participants watched an approximately 1-minute long video of the exemplary assembly process with the support of the IAS. Conditions 2 and 3 differed only in that the participants in Condition 3 received the information that they could turn the IAS off and on at any time on a separate page. The IAS presented in the vignette is a projection-based, cognitive-assistive system that guides workers through each assembly step using short instructional videos projected onto the work surface. If the work steps are performed correctly, the projected video will light up green; if they are performed incorrectly, the video will light up red. The progress of work processes is displayed in the form of a progress bar above the videos with the assembly steps on the work surface. Alternative workflows and assembly sequences can be observed and taught automatically using machine learning. The basis of these functions lies in the recording of the hand and eye movements of the employees with the help of a 3D camera and three eye trackers (Jung et al., 2022). A translation of the description of the hypothetical workplace with IAS can be found in ESM (Appendix A). The video of the presented assembly process with(out) the support of the IAS can be found in the pre-registration in the Open Science Framework.

To ensure careful reading of the text description and observation of the assembly process, we included a time lag of one minute each before one could continue with the study in all conditions. Subsequently, participants rated the workplace according to their condition regarding task and knowledge characteristics in randomized order and finally answered some demographic information (age, sex, and prior experiences with IAS) about themselves.

Participants

For recruiting participants, we realized two approaches. First, we invited German blue-collar workers from our personal and professional networks from diverse fields via email and social media to participate in an online experiment. Blue-collar workers perform jobs relatively similar to assembly work, so they are able to adequately assess the work situation presented. The prerequisite for participation was a current job or prior work-related experience in the areas of manufacturing, assembly, or craftsmanship. We offered them a summary of the study results and an opportunity to enter a drawing for vouchers (5 x 20 Euro) for every 50 participants as incentives for participating. Within the collection period from October 2021 to April 2022, 1,041 people clicked on the link to the online experiment. 135 participants completed the survey (response rate of approximately 13%). We excluded six participants who failed the attention check (“Please tick answer option 1 ‘do not agree at all’ in this row”), five participants who had technical problems, and another 23 who classified their job as an office job and had no prior experience working in manufacturing, assembly, or craftsmanship from the analysis. This led to 101 German participants.

Second, we collected additional data from British blue-collar workers with an English version of our experiment in April 2022 using Prolific. We paid 2.20 GBP for participating. Of the 147 people who clicked on the link to the study, 127 participants completed the experiment (response rate of approximately 86%). We excluded two participants who failed one of two built-in attention checks. We further excluded 23 participants who reported that they were currently working in an office job or were students and did not have any prior work experiences in manufacturing, assembly, or crafting, resulting in 102 British participants.

Given the two different data collection efforts, we checked for potential differences in demographic variables. We did not find significant differences in age, $t(201) = -.826$, $p = .410$, $d = -.116$, sex, $\chi^2(2) = 0.334$, $p = .846$, $\varphi = .041$, or prior experience with working with IAS, $\chi^2(1) = 1.012$, $p = .314$, $\varphi = -.071$, between the German and British participants (ESM, Table 2). Furthermore, a chi-square difference test revealed no disproportionate allocation of the German or English subsample to one of the three experimental conditions, $\chi^2(1) = 1.159$, $p = .560$, Cramér's V = 0.076 (ESM, Table 2).

Therefore, we based our analysis on the combined data, resulting in a sample of $N = 203$. Ages ranged from 19 to 75 ($M = 37.54$, $SD = 12.01$). The majority of the participants were male (70.4%) and had no prior experience with IAS (87%). Among those 13% of participants with prior experience with IAS, virtual reality ($n = 10$), pick-by-light ($n = 6$), and augmented reality ($n = 3$) were the most common. The low number of participants with prior experience with working with IAS in our sample reflects the low use and distribution of IAS in German and British production companies, highlighting the importance of EVM study designs.

Manipulation checks

First, to ensure the successful manipulation of the assembly workstation, we asked participants in all three experimental conditions to rate *equipment use* in the hypothetical workplace immediately after reading the text description and watching the short video of an exemplary assembly process. For this, we used three items of a validated German version (Stegmann et al., 2010) ($\alpha = .76$) or the validated English version of the WDQ (Morgeson & Humphrey, 2006), with a five-point Likert scale ranging from *strongly disagree* (1) to *strongly agree* (5). We conducted a Helmert contrast to test whether the work without IAS differs significantly from the other two conditions (work with IAS and work with voluntary use of IAS). Equipment use was rated significantly lower in the condition of work without IAS ($M = 2.00$, $SD = 0.92$) than in the other two conditions (work with IAS: $M = 2.29$, $SD = 0.97$; work with voluntary use of IAS: $M = 2.26$, $SD = 0.86$), $F(2, 199) = 3.29$, $p = .039$, $\eta_p^2 = .032$, $C = -.314$, $p = .014$, indicating that our experimental manipulation of the assembly workstation was successful.

Second, to ensure the successful manipulation of voluntary use of the IAS, we asked participants to rate work methods autonomy ($\alpha = .91$) from the WDQ (Morgeson & Humphrey, 2006) to check our experimental manipulation of the voluntary use of IAS between conditions work with IAS and work with voluntary use of IAS. We used three validated items of the German version (Stegmann et al., 2010) or the English version (Morgeson & Humphrey, 2006) with the same five-point Likert scale as equipment use. A t-test indicated that the work with voluntary use of IAS condition ($M = 1.92$, $SD =$

0.97) did not differ significantly from the work with IAS condition (M = 1.62, SD = 0.87) in terms of work methods autonomy, $t(135) = -1.468$, $p = .144$, $d = -.251$, resulting in a failed manipulation of voluntary use. Hence, we combined the work with IAS and work with voluntary use of IAS into the work with IAS condition (see ESM, Table 4 for ANOVA results of all three experimental conditions). This precluded us from testing H8.

Measures

Task and knowledge characteristics. We measured the four task characteristics and the five knowledge characteristics based on the original English version of the WDQ (Morgeson & Humphrey, 2006) and its validated German version (Stegmann et al., 2010). In total, participants rated 32 items on a five-point Likert scale with the range from *strongly disagree* (1) to *strongly agree* (5). To cover the hypothetical job situation (and not the current job participants hold), we slightly altered the item wording of some German items (items including "my job" were changed to "the job"). This was not necessary for the English version by Morgeson and Humphrey (2006) where "the job" was already used. In detail, we measured work scheduling autonomy ("The job allows me to plan how I do my work", $\alpha = .86$), decision-making autonomy ("The job allows me to make a lot of decisions on my own", $\alpha = .89$), work methods autonomy ("The job allows me to make decisions about what methods I use to complete my work", $\alpha = .91$), and feedback from job ("The job itself provides feedback on my performance", $\alpha = .86$) with three items each. To capture the knowledge characteristics job complexity ("The tasks on the job are simple and uncomplicated", $\alpha = .86$), problem solving ("The job requires to be creative", $\alpha = .84$), information processing ("The job requires me to monitor a great deal of information", $\alpha = .91$), skill variety ("The job requires a variety of skills", $\alpha = .92$), and specialization ("The job requires a depth of knowledge and expertise", $\alpha = .91$), we used four items each. The internal consistency reliabilities (Cronbach's α) ranged from .79 to .92. Table 3 in the ESM also contains reliabilities of the German and English versions separately[2].

Results

Table 2 shows the descriptive statistics of the two experimental conditions work without IAS and work with IAS. The ratings of all motivational work characteristics are low across all conditions. A one-way MANOVA showed a significant difference between the two working conditions without and with IAS for all nine motivational work characteristics under investigation[3], $F(9, 193) = 6.441$, $p < .001$, $\eta_p^2 = .231$, Wilk's $\Lambda = .769$. Subsequently, we conducted t-tests for every motivational work characteristic separately according to our hypotheses (Table 2 and Figure 2). We did not find a significant difference between work without IAS and work with IAS in work scheduling autonomy, $t(201) = 1.909$, $p = .058$, $d = .286$, decision-making autonomy, $t(201) = -0.149$, $p = .882$, $d = -.022$, and work methods autonomy, $t(201) = 0.330$, $p = .742$, $d = .049$, thereby rejecting H1a-c. Feedback from

[2] Only in the German sample specialization showed rather low reliability (Cronbach's $\alpha = .61$).
[3] A one-way MANCOVA with sample origin as a covariate revealed identical results, $F(2, 192) = 5.530$, $p < .001$, $\eta_p^2 = .206$, Wilk's $\Lambda = .794$.

job was significantly higher in work with IAS than in work without IAS, $t(201) = -5.701$, $p < .001$, $d = -.854$, supporting H2. There was no significant difference between work without IAS and work with IAS in job complexity, $t(201) = -0.790$, $p = .430$, $d = -.118$, and problem solving, $t(201) = -0.728$, $p = .467$, $d = -.109$. Thus, we rejected H3 and H4. Information processing was significantly higher in work with IAS than in work without IAS, $t(201) = -2.205$, $p = .029$, $d = -.330$, supporting H5b. Finally, the two working conditions did not differ in skill variety, $t(201) = 0.369$, $p = .713$, $d = .055$, and specialization, $t(201) = -1.077$, $p = .283$, $d = -.161$. Hence, we rejected H6a, H6b, and H7.

Discussion

As prior research on IAS largely neglected human factors (Egger-Lampl et al., 2019; Faccio et al., 2023), our case study contributes to a human-centered design and integration of advanced technologies in assembly in two important ways. First, we were able to provide causal evidence for an increase in MWC feedback from job and information processing due to the implementation of a cognitive-assistive IAS in assembly. Whereas the effect of the IAS on information processing was rather weak, we found a strong effect on feedback from the job. As our results are based on a rather big sample stemming from two European countries highlights that such effects might not be bound to specific countries. Second, unfortunately, we were not able to provide insights into a potential buffering effect of voluntary use, as our manipulation of voluntary use failed. However, the results of our case study in this regard are also promising, since we were not able to identify any essential decrease in knowledge characteristics, indicating no negative consequences of working with IAS that should alarm practice. In sum, our results provide important insights into the work design and IAS literature as well as practical implications for the potential benefits of IAS in assembly.

Theoretical Implications

Although the CPS transformation framework (Waschull et al., 2020) postulates restrictions in autonomy in low- and middle-skilled jobs by clocking and standardizing work, we did not find reduced autonomy due to the IAS as suggested in qualitative studies (Berkers et al., 2022; Blumberg & Kauffeld, 2020). This applies to the three autonomy facets distinguished in the WDQ, extending the current state of limited research in which autonomy is considered a global construct without considering relevant autonomy facets (Blumberg & Kauffeld, 2020). The fact that the IAS does not seem to decrease perceived autonomy is probably attributable to the already highly standardized traditional assembly work. Additionally, in our description of the system, we also indicated that the system can adapt to alternative work processes using machine learning. For example, in the case of work scheduling autonomy, this could mean that alternative sequences in the assembly process preferred by employees may counteract decreases. It is not surprising that IAS can be used to foster immediate feedback from the job which highlights their importance in phases in which frequent and immediate feedback is needed. The model of routine-biased technological change (Autor et al., 2003) posits a reduction in knowledge characteristics due to new technologies, resulting in a de-skilling of employees in assembly by automating manual and cognitive routine tasks. However, our results indicate that the IAS will not establish a lower level of requirements on the assembly workers, since problem solving, skill variety, and specialization seem to be unaffected by the implementation of the IAS. The results also do not indicate a higher skill variety, for example, with an associated need for digital competencies (Oberländer et al., 2020) when working with IAS. These knowledge characteristics appear to be more dependent on the underlying assembly process than on the IAS. Given that job complexity is not lowered by the IAS investigated here either, it appears that the system is failing to achieve its primary goal of cognitive relief of employees (Egger-Lampl et al., 2019). The introduction of IAS even requires assembly workers to pay attention to an additional source of information and thus to process more information which is generally associated with positive work outcomes (Stegmann et al., 2010). Therefore, our results suggest an improvement regarding work motivation in the digitized assembly workplace, although the IAS does not provide the cognitive relief for which such systems were primarily developed. Overall, our results stress the importance of subjective human factors (Faccio et al., 2023) when implementing IAS in assembly.

The fact that the majority of our hypotheses had to be rejected highlights the need for theories targeting the specific impact of innovative technologies, such as IAS, on work characteristics. The CPS transformation framework and the model of routine-biased technological change did not provide either a suitable basis for predicting the influence of cognitive-assistive IAS on work design, as they do not take into account the specific technical design features (Gagné et al., 2022). However, by applying a case study on an exemplary IAS and its effect on motivational work characteristics, we contribute to the development of such theories.

Practical Implications

Although prior qualitative studies (e.g., Berkers et al., 2022; Blumberg & Kauffeld, 2020) mainly emphasized the negative sides of IAS, namely the risks of reduced autonomy and de-skilling of employees, our results indicate no such effects and even an improvement of certain aspects of the digitized assembly workplace. This could prove beneficial for reducing employees' resistance to change and support the introduction of such systems in practice. Assembly workers can benefit in terms of work-related outcomes, like motivation and job satisfaction, by using an IAS primarily through these two work design aspects. First, they profit from the strongly enhanced feedback from the job which is positively associated with motivation (Humphrey et al., 2007). The enhanced feedback implies that especially in the learning and training phases, assembly workers can benefit from the use of IAS (Doolani et al., 2020). Providing immediate feedback from the job by using IAS will also help in the long term if the work processes are characterized by individualized customer requests and the associated frequent product changes as in modern assembly. Second, assembly workers can benefit from increased information processing when working with the IAS compared to the traditional workplace which is positively associated with job satisfaction (Humphrey et al., 2007). Nevertheless, managers must be aware that the increased information processing may represent a double-edged sword. Since IAS also aim at the inclusion of low-skilled workers and workers with cognitive deficits (Apt et al., 2018; Mark et al., 2019), enhanced information processing could potentially lead to information overload. However, as we found a rather weak effect in terms of effect size, thus the additional source of information should not pose a great risk for employees without cognitive deficits.

On a more general level, the overall rather low ratings in MWC for both, the traditional and digitized workplace in our vignette emphasize the need for work design interventions in assembly, such as *task* or *job rotation* (Mlekus & Maier, 2021). Task rotation "refers to the alternation between tasks within a job that can require different skills and responsibilities but is not associated with a change to a different function or department" (Mlekus & Maier, 2021, p. 2), in this case, the alternation between assembly products. This task rotation is already an essential consequence of the individualized customer requests that characterize the digital factory of the future. Job rotation is defined as "a lateral transfer of employees within an organization without a change in salary or hierarchy" (Mlekus, 2021, p. 2) and can include rotations not only in departments but whole units (Mlekus & Maier, 2021). Applying job rotation on a larger scale will be more challenging than using task rotation in this assembly context. The implementation of our exemplary IAS as an innovative advanced technology could represent a first step in improving MWC of assembly workplaces.

Limitations and future research

Although our case study provides first causal insights into alterations in MWC by the implementation of a stationary, cognitive-assistive IAS in assembly, some limitations need to be acknowledged. First, our results might be limited due to the rather low ratings in the MWC across all experimental conditions. That we did not find any negative effects of the IAS on MWC might therefore also be due to potential floor effects in the ratings, as the presented assembly process was highly simplified. The investigation of the effect of IAS with more demanding assembly processes could counteract such effects, particularly for expected effects on knowledge characteristics.

Second, our manipulation of the voluntary use of IAS failed. Participants in the work with IAS condition may have implicitly assumed that they could turn the system off and on at any time. However, we did not include explicit coercion in this condition to avoid artificially biasing the study results, as some studies show that coercion elicits negative responses from employees (Hausman & Johnston, 2010; Yılmaz & Kılıçoğlu, 2013). Again, the investigated exemplary assembly process may also have contributed to this missing effect, as cognitive relief from the IAS is not essential for a highly simplified assembly process. This is also evident from technology acceptance models (Feng et al., 2021), where the perceived usefulness of a system is a key predictor of the intention to use it. Consequently, individuals may have thought that they could simply ignore the system if it did not fulfill the desired goal of cognitive relief. This may also be a potential reason why we found no negative consequences of the system on MWC. If employees assume over-simplified work processes with restricted autonomy when working with IAS, they will not use the system.

Third, the use of an EVM study design allowed causal investigation of the effect of the IAS on MWC, taking into account specific design features, such as autonomous teaching of the system through machine learning, even before the system is implemented in practice. Nonetheless, participants were not asked to work with the presented IAS, thus results may be biased by their expectations of such systems. However, given the experimental design of our study, the random assignment to one of the three conditions prevented at least systematic distortions of particular expectations. Future studies should assess MWC before and after implementing IAS on the work floor to investigate the specific effect of the system under more realistic conditions, over a longer time period. In addition, the EVM study design prevented us from collecting other (objective) assessment factors, such as the task completion time, or error count, which have already been investigated in other studies (Keller et al., 2019; Lampen et al. 2019). In future studies, subjective factors, as in our study, should be supplemented with objective factors to provide an even more comprehensive picture of the effect of IAS on motivational and performance-related outcomes in terms of quality and quantity.

Fourth, we explicitly omitted sources of interference in the representations of the assembly workplace with IAS to investigate its pure effect on MWC. However, interferences, such as time delays or modeling errors (Tao et al., 2022; Xu et al., 2021), can be expected to occur in operational practice in assembly process planning (Qian et al., 2023) when working with IAS, which could alter the experiences of workers with such systems. Depending on whether assembly workers need to fix certain malfunctions on their own, knowledge characteristics could increase by using IAS, for example, because programming skills are needed to fix interferences but are not necessary for the majority of daily assembly processes. Thus, the role of such additional factors needs to be investigated in future studies.

Fifth, since the effects of advanced technologies on work design depend on its specific design features (Gagné et al., 2022), the generalizability of the results to other stationary, cognitive-assistive IAS needs to be investigated. Nevertheless, due to similar instructional materials for assembly processes, our results appear to be transferable, for example, to pick-to-light systems, augmented reality-based, and other projection-based IAS. Future studies should examine the role of specific design features and the generalizability of our study results.

Conclusion

Our study contributes to the development of theories on the effect of innovative advanced technologies on work design by considering specific design features of an exemplary cognitive-assistive IAS in assembly (Gagné et al., 2022). We demonstrated the benefit of IAS for modern assembly workplaces in terms of enhanced feedback from the job and information processing. Particularly, our study emphasizes the benefit of IAS in employees' daily work contrary to qualitative studies in which employees mentioned risks of restricted autonomy or systematic de-skilling when using IAS (Baethge-Kinsky, 2020; Blumberg & Kauffeld, 2020). Future studies should test if our results are transferable to other cognitive-assistive IAS.

References

Aguinis, H., & Bradley, K. J. (2014). Best Practice Recommendations for Designing and Implementing Experimental Vignette Methodology Studies. *Organizational Research Methods*, *17*(4), 351-371. https://doi.org/10.1177/1094428114547952

Apt, W., Bovenschulte, M., Priesack, K., & Hartmann, E. A. (2018). *Einsatz von digitalen Assistenzsystemen im Betrieb* [*Use of digital assistance systems in practice*]. Bundesministerium für Arbeit und Soziales. https://www.iit-berlin.de/iit-docs/0b0ab71d0ed949269fa39e2b38665fde_Einsatz-von-digitalen-Assistenzsystemen-im-Betrieb.pdf

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly journal of economics*, *118*(4), 1279-1333. https://doi.org/10.1162/003355303322552801

Baethge-Kinsky, V. (2020). Digitized Industrial Work: Requirements, Opportunities, and Problems of Competence Development. *Frontiers in Sociology*, *5*, 33. https://doi.org/10.3389/fsoc.2020.00033

Berkers, H. A., Rispens, S., & Le Blanc, P. M. (2022). The role of robotization in work design: A comparative case study among logistic warehouses. *The International Journal of Human Resource Management*, 1-24. https://doi.org/10.1080/09585192.2022.2043925

Blumberg, V. S. L., & Kauffeld, S. (2020). Anwendungsszenarien und Technologiebewertung von digitalen Werkerassistenzsystemen in der Produktion – Ergebnisse einer Interview-Studie mit Experten aus der Wissenschaft, der Politik und der betrieblichen Praxis [Application scenarios and technology assessment of smart wearables and mobile smart devices in industrial practice]. *Gruppe. Interaktion. Organisation. Zeitschrift für Angewandte Organisationspsychologie (GIO)*, *51*(1), 5-24. https://doi.org/10.1007/s11612-020-00506-0

Bortolini, M., Faccio, M., Galizia, F. G., Gamberi, M., & Pilati, F. (2021). Adaptive Automation Assembly Systems in the Industry 4.0 Era: A Reference Framework and Full-Scale Prototype. *Applied Sciences*, *11*(3), 1256. https://doi.org/10.3390/app11031256

Day, A., Barber, L. K., & Tonet, J. (2019). Information Communication Technology and Employee Well-Being: Understanding the “iParadox Triad” at Work. In R. N. Landers (Ed.), *The Cambridge Handbook of Technology and Employee Behavior* (p. 580-607). Cambridge University Press. https://doi.org/10.1017/9781108649636.022

Doolani, S., Wessels, C., Kanal, V., Sevastopoulos, C., Jaiswal, A., Nambiappan, H., & Makedon, F. (2020). A Review of Extended Reality (XR) Technologies for Manufacturing Training. *Technologies*, *8*(4), 77. https://doi.org/10.3390/technologies8040077

Dostert, J., & Müller, R. (2020). Motivational assistance system design for industrial production: From motivation theories to design strategies. *Cognition, Technology & Work, 23*(3), 507-535. https://doi.org/10.1007/s10111-020-00643-y

Drossel, W.-G., Ihlenfeldt, S., Langer, T., & Dumitrescu, R. (2018). Cyber-Physische Systeme [Cyber-physical systems].. In R. Neugebauer (Ed.), *Digitalisierung* (p. 197-222). Springer. https://doi.org/10.1007/978-3-662-55890-4_12

Egger-Lampl, S., Gerdenitsch, C., Deinhard, L., Schatz, R., & Hold, P. (2019, June). Assembly Instructions with AR: Towards measuring Interactive Assistance Experience in an Industry 4.0 Context. In *2019 Eleventh International Conference on Quality of Multimedia Experience (QoMEX)*, (p. 1-3). IEEE. https://doi.org/10.1109/QoMEX.2019.8743266

Faccio, M., Granata, I., Menini, A., Milanese, M., Rossato, C., Bottin, M., Minto, R., Pluchino, P., Gamberini, L., Boschetti, G., & Rosati, G. (2023). Human factors in cobot era: A review of modern production systems features. *Journal of Intelligent Manufacturing*, *34*, 85-106. https://doi.org/10.1007/s10845-022-01953-w

Feng, G. C., Su, X., Lin, Z., He, Y., Luo, N., & Zhang, Y. (2021). Determinants of Technology Acceptance: Two Model-Based Meta-Analytic Reviews. *Journalism & Mass Communication Quarterly*, *98*(1), 83-104. https://doi.org/10.1177/1077699020952400

Gagné, M., Parker, S. K., Griffin, M. A., Dunlop, P. D., Knight, C., Klonek, F. E., & Parent-Rocheleau, X. (2022). Understanding and shaping the future of work with self-determination theory. *Nature Reviews Psychology*, 1-15. https://doi.org/10.1038/s44159-022-00056-w

Hackman, J. R., & Oldham, G. R. (1976). Motivation through the design of work: Test of a theory.

Organizational Behavior and Human Performance, *16*(2), 250-279. https://doi.org/10.1016/0030-5073(76)90016-7
Hausman, A., & Johnston, W. J. (2010). The impact of coercive and non-coercive forms of influence on trust, commitment, and compliance in supply chains. *Industrial Marketing Management*, *39*(3), 519-526. https://doi.org/10.1016/j.indmarman.2009.05.007
Hinrichsen, S. (2020). Informatorische Gestaltung der Montage mittels Assistenzsystemen [Informational design of assembly using assistance systems]. In M. Bornewasser & S. Hinrichsen (Eds.), *Informatorische Assistenzsysteme in der variantenreiche Montage: Theorie und Praxis* (p. 29-42). Springer. https://doi.org/10.1007/978-3-662-61374-0
Humphrey, S. E., Nahrgang, J. D., & Morgeson, F. P. (2007). Integrating motivational, social, and contextual work design features: A meta-analytic summary and theoretical extension of the work design literature. *Journal of Applied Psychology*, *92*(5), 1332-1356. https://doi.org/10.1037/0021-9010.92.5.1332
Jung, J., Hubert, A., Doll, K., Kröhn, M., & Stadler, J. (2022, March 9-11). *Prozessinnovation: Selbstlernendes Assistenzsystem für die manuelle Montage* [*Process innovation: Self-learning assistance system for manual assembly*]. 18. AALE-Konferenz, Pforzheim. https://doi.org/10.33968/2022.20
Kang, H. S., Lee, J. Y., Choi, S., Kim, H., Park, J. H., Son, J. Y., Kim, B. H., & Noh, S. D. (2016). Smart Manufacturing: Past Research, Present Findings, and Future Directions. *International journal of precision engineering and manufacturing-green technology*, *3*(1), 111-128. https://doi.org/10.1007/s40684-016-0015-5
Keller, T., Bayer, C., Bausch, P., & Metternich, J. (2019). Benefit evaluation of digital assistance systems for assembly workstations. *Procedia CIRP*, *81*, 441-446. https://doi.org/10.1016/j.procir.2019.03.076
Krzywdzinski, M., Butollo, F., Flemming, J., Gerber, C., Wandjo, D., Delicat, N., Herzog, L., Bovenschulte, M., & Nerger, M. (2022). *The Growing Gap Between Pioneers and Laggards: Digitalization, automation, and organizational change in the wake of the COVID-19-crisis in Germany*. https://doi.org/10.34669/WI.WS/25
Lampen, E., Teuber, J., Gaisbauer, F., Bär, T., Pfeiffer, T., & Wachsmuth, S. (2019). Combining Simulation and Augmented Reality Methods for Enhanced Worker Assistance in Manual Assembly. *Procedia CIRP*, *81*, 588-593. https://doi.org/10.1016/j.procir.2019.03.160
Mark, B. G., Hofmayer, S., Rauch, E., & Matt, D. T. (2019). Inclusion of workers with disabilities in production 4.0: Legal foundations in Europe and potentials through worker assistance systems. *Sustainability*, *11*(21), 5978. https://doi.org/10.3390/su11215978
Maxwell, N. L. (2006). *The Working Life: The Labor Market for Workers in Low-Skilled Jobs*. WE Upjohn Institute.
Mlekus, L. (2021). Work design in times of digitalization: Challenges of advanced technologies at work with job and task rotation as potential remedies (Publication No. 2956391) [Doctoral dissertation, Bielefeld University].
Mlekus, L., & Maier, G. W. (2021). More hype than substance? A meta-analysis on job and task rotation. *Frontiers in psychology*, *12*. 633530. https://doi.org/10.3389/fpsyg.2021.633530
Morgeson, F. P., & Humphrey, S. E. (2006). The Work Design Questionnaire (WDQ): Developing and validating a comprehensive measure for assessing job design and the nature of work. *Journal of Applied Psychology*, *91*(6), 1321-1339. https://doi.org/10.1037/0021-9010.91.6.1321
Morgeson, F. P., & Humphrey, S. E. (2008). Job and team design: Toward a more integrative conceptualization of work design. In J. Martoccio (Ed.) *Research in Personnel and Human Resources Management* (p. 39-91). Emerald Group Publishing Limited https://doi.org/10.1016/S0742-7301(08)27002-7
Oberländer, M., Beinicke, A., & Bipp, T. (2020). Digital competencies: A review of the literature and applications in the workplace. *Computers & Education*, *146*, 103752. https://doi.org/10.1016/j.compedu.2019.103752
Parker, S. K. (2014). Beyond Motivation: Job and Work Design for Development, Health, Ambidexterity, and More. *Annual Review of Psychology*, *65*(1), 661-691. https://doi.org/10.1146/annurev-psych-010213-115208

Parker, S. K., & Grote, G. (2022). Automation, Algorithms, and Beyond: Why Work Design Matters More Than Ever in a Digital World. *Applied Psychology*. https://doi.org/10.1111/apps.12241

Parker, S. K., Morgeson, F. P., & Johns, G. (2017). One hundred years of work design research: Looking back and looking forward. *Journal of Applied Psychology*, *102*(3), 403-420. https://doi.org/10.1037/apl0000106

Paruzel, A., Bentler, D., Schlicher, K. D., Nettelstroth, W., & Maier, G. W. (2020). Employees First, Technology Second: Implementation of Smart Glasses in a Manufacturing Company. *Zeitschrift Für Arbeits- und Organisationspsychologie A&O*, *64*(1), 46-57. https://doi.org/10.1026/0932-4089/a000292

Pfeiffer, S. (2016). Robots, Industry 4.0 and Humans, or Why Assembly Work Is More than Routine Work. *Societies*, *6*(2), 16. https://doi.org/10.3390/soc6020016

Qian, J., Zhang, Z., Shi, L., & Song, D. (2023). An assembly timing planning method based on knowledge and mixed integer linear programming. *Journal of Intelligent Manufacturing, 34*, 429-453. https://doi.org/10.1007/s10845-021-01819-7

Stegmann, S., Dick, R. van, Ullrich, J., Charalambous, J., Menzel, B., Egold, N., & Wu, T. T.-C. (2010). Der Work Design Questionnaire: Vorstellung und erste Validierung einer deutschen Version [The Work Design Questionnaire: Introduction and validation of a German version]. *Zeitschrift für Arbeits- und Organisationspsychologie A&O*, *54*(1), 1-28. https://doi.org/10.1026/0932-4089/a000002

Stockinger, C., Stuke, F., & Subtil, I. (2021). User-centered development of a worker guidance system for a flexible production line. *Human Factors and Ergonomics in Manufacturing & Service Industries*, *31*(5), 532-545. https://doi.org/10.1002/hfm.20901

Tao, H., Cheng, L., Qiu, J., & Stojanovic, V. (2022). Few shot cross equipmet fault diagnosis method based on parameter optimization and feature mertic. *Measurement Science and Technology* *33*(11), 115005.

Wang, B., Liu, Y., & Parker, S. K. (2020). How Does the Use of Information Communication Technology Affect Individuals? A Work Design Perspective. *Academy of Management Annals*, *14*(2), 695-725. https://doi.org/10.5465/annals.2018.0127

Waschull, S., Bokhorst, J. A. C., Molleman, E., & Wortmann, J. C. (2020). Work design in future industrial production: Transforming towards cyber-physical systems. *Computers & Industrial Engineering*, *139*. https://doi.org/10.1016/j.cie.2019.01.053

Xu, Z., Li, X, & Stojanovic, V. (2021). Exponential stability of nonlinear state-dependent impulsive systems with applications. *Nonlinear Analysis: Hybrid Systems, 42*. https://doi.org/10.1016/j.nahs.2021.101088

Yılmaz, D., & Kılıçoğlu, G. (2013). Resistance to change and ways of reducing resistance in educational organizations. *European journal of research on education, 1*(1), 14-21.

Zhang, Y., Bernard, A., Harik, R., & Karunakaran, K. P. (2017). Build orientation optimization for multi-part production in additive manufacturing. *Journal of Intelligent Manufacturing*, *28*, 1393-1407. https://doi.org/10.1007/s10845-015-1057-1

Table 1

Closely related empirical work on intelligent assistance systems (IAS) and motivational work characteristics (MWC)

Authors (Year)	Method and sample	Relevant findings with regard to MWC
Blumberg & Kauffeld (2020)	Interview study with 76 German experts from science, politics, and industrial practice	Experts indicate risks of restricted autonomy and systematic de-skilling of employees when using smart watches or data glasses in industrial practice.
Berkers et al. (2022)	Interview study with 24 Dutch employees and managers from six logistic organizations	Warehouse workers cite the fear of restricted autonomy by implementation of robots in logistic warehouses.
Lampen et al. (2019)	Experiment with 24 German students and research engineers realizing a within-subject design (3 instructions: Pictorial paper-based, 3D in-situ-visual cues, human simulation approach)	Cognitive workload in learning new tasks is significantly reduced by using the 3D in-situ-visual cues instruction compared to the pictorial paper-based instruction.
Paruzel et al. (2020)	Cross-sectional survey with 14 German employees in manufacturing company on expectations and fears of the implementation of smart glasses	The employees expect potential positive and negative effects of smart glasses on work characteristics (e.g., increased and decreased job complexity).

Table 2

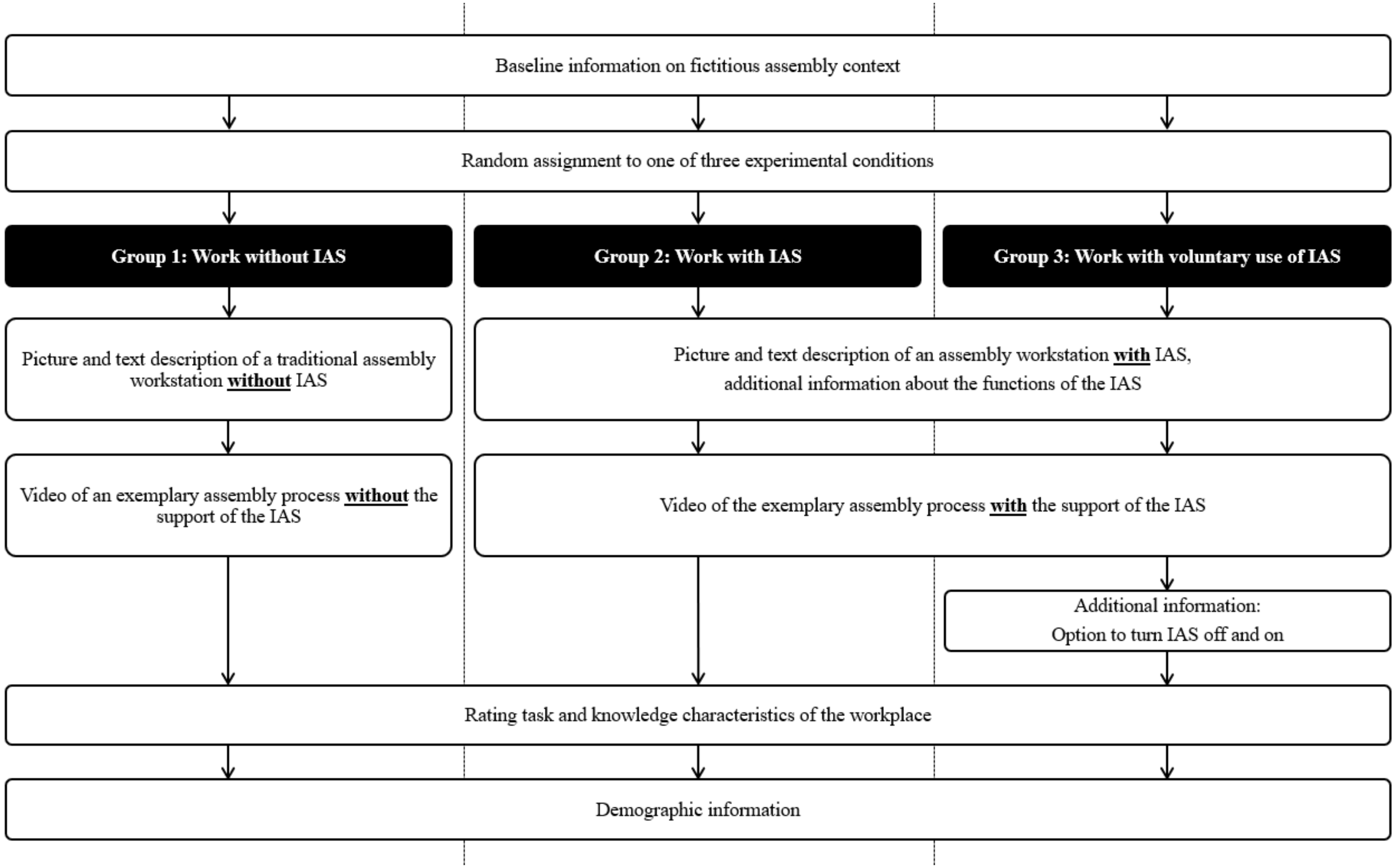
Cell means and standard deviation of motivational work characteristics in work without IAS and work with IAS

	Work without IAS n = 66		Work with IAS n = 137			
	M	*SD*	*M*	*SD*	t-test	Hypothesis
Work scheduling autonomy	2.13	0.99	1.85	0.96	$t(201) = 1.909, p = .058, d = .286$	1a
Decision-making autonomy	1.70	0.96	1.73	0.91	$t(201) = -0.149, p = .882, d = -.022$	1b
Work methods autonomy	1.80	0.96	1.76	0.92	$t(201) = 0.330, p = .742, d = .049$	1c
Feedback from job	2.87	1.14	3.76	0.99	$t(201) = -5.701, p < .001, d = -.854$***	2
Job complexity	1.60	0.87	1.69	0.72	$t(201) = -0.790, p = .430, d = -.118$	3
Problem solving	1.55	0.69	1.62	0.73	$t(201) = -0.728, p = .467, d = -.109$	4
Information processing	1.75	0.91	2.06	0.94	$t(201) = -2.205, p = .029, d = -.330$*	5a/b
Skill variety	1.94	0.94	1.89	0.86	$t(201) = 0.369, p = .713, d = .055$	6a/b
Specialization	2.02	0.87	2.16	0.83	$t(201) = -1.077, p = .283, d = -.161$	7

Notes. IAS = Intelligent assistance system. * $p < .05$. *** $p < .001$.

Figure 1

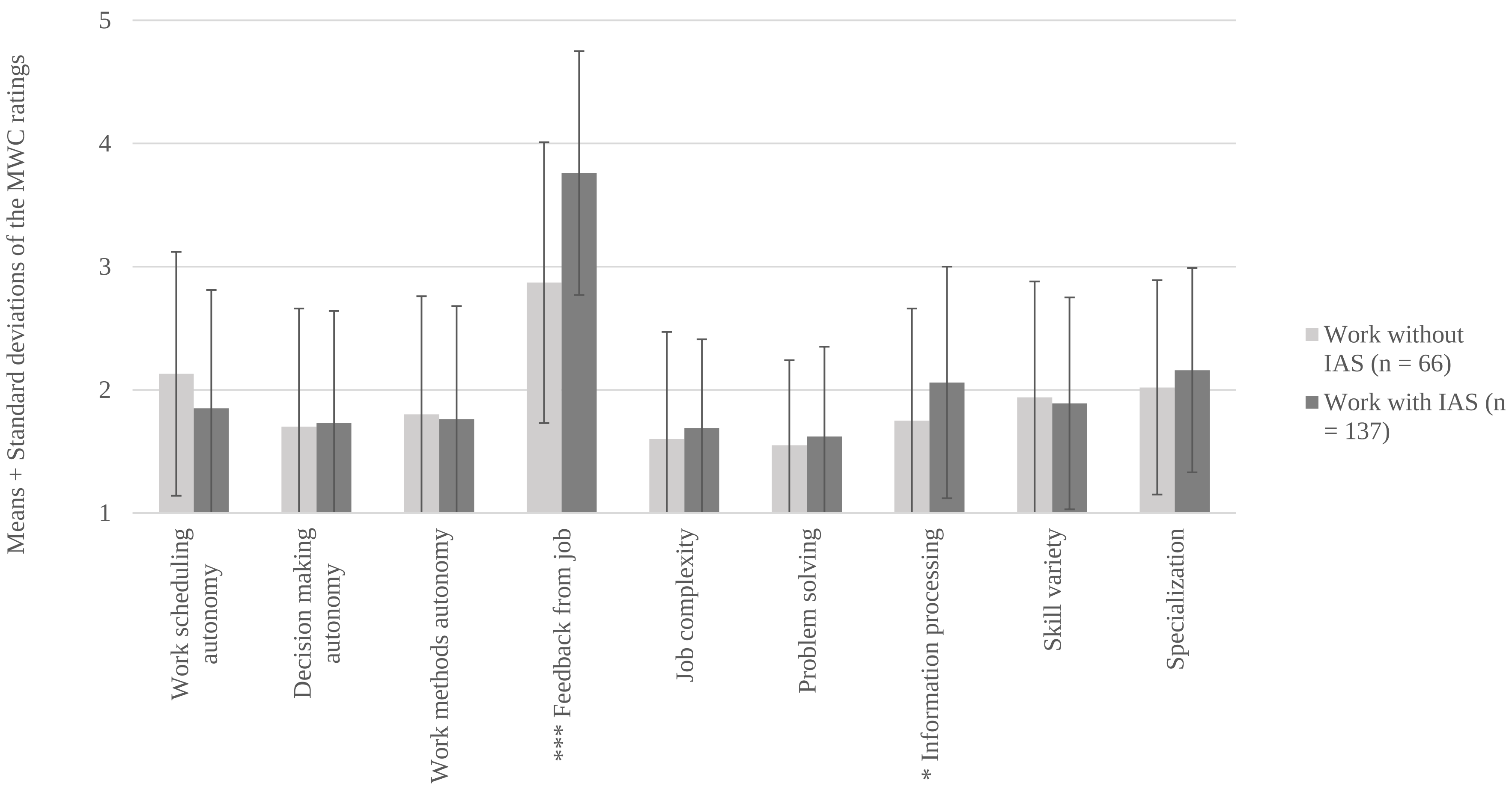
Flow chart of the study with three experimental groups (Group 1: Work without IAS, Group 2: Work with IAS, Group 3: Work with voluntary use of IAS)



Notes. IAS = Intelligent assistance system.

Figure 2

Ratings of motivational work characteristics in work without IAS and work with IAS



Notes. IAS = Intelligent assistance system. MWC = Motivational work characteristics. * $p < .05$. *** $p < .001$.

Electronic Supplementary Material (ESM)

Table 1

Differences in demographic variables of German and English subsamples

Scale	German		British		Test
	M	SD	M	SD	
Sex	1.26	0.46	1.29	0.48	$\chi^2(2) = 0.334$, $p = .846$, $\varphi = .041$
Age	30.47	29.19	33.84	29.09	$t(201) = -.826$, $p = .410$
Prior experience with IAS	1.89	0.31	1.84	0.37	$\chi^2(1) = 1.012$, $p = .314$, $\varphi = -.071$

Notes. IAS = Intelligent assistance system.

Table 2

Distribution of the German and English subsample into the three experimental conditions

Condition	German subsample (n = 101)	English subsample (n = 102)	Total sample (N = 203)
Work without IAS	31	35	66
Work with IAS	40	33	73
Work with voluntary use of IAS	30	34	64

Notes. IAS = Intelligent assistance system. A chi-sqaure test showed no significant differences in the distribution of the German and English subsamples into the three experimental conditions, $\chi^2(1) = 1.159$, $p = .560$, Cramér's V = 0.076.

Table 3

Internal consistencies (Cronbach's α*) of the study variables by German and English subsamples and total sample*

	Scale	German subsample (n = 101)	English subsample (n = 102)	Total sample (N = 203)
1	Equipment use	.73	.72	.76
2	Work scheduling autonomy	.79	.91	.86
3	Decision-making autonomy	.86	.89	.89
4	Work methods autonomy	.85	.92	.91
5	Feedback from job	.88	.83	.86
6	Job complexity	.87	.85	.86
7	Problem solving	.88	.80	.84
8	Informat. processing	.90	.92	.91
9	Skill variety	.90	.93	.92
10	Specialization	.61	.89	.79

Notes. The English version of the motivational work characteristics was assessed with the validated version of the Work Design Questionnaire (WDQ) (Morgeson & Humprhey, 2006). The German version was assessed by the validated German version of the WDQ (Stegmann et al., 2010).

Table 4

Cell means and standard deviation of equipment use and motivational work characteristics according to experimental conditions

	Work without IAS n = 66		Work with IAS n = 73		Work with voluntary use of IAS n = 64		
	M	SD	M	SD	M	SD	ANOVA
Work scheduling autonomy	2.13	0.99	1.73	0.96	1.99	0.94	$F(2,200) = 3.109$, $p = .047$, $\eta^2 = .030$*
Decision making autonomy	1.70	0.96	1.62	0.96	1.84	0.84	$F(2,200) = 1.048$, $p = .353$, $\eta^2 = .010$
Work methods autonomy	1.80	0.96	1.62	0.87	1.92	0.97	$F(2,200) = 1.829$, $p = .163$, $\eta^2 = .018$
Feedback from job	2.87	1.14	3.88	0.97	3.61	0.99	$F(2,200) = 17.483$, $p < .001$, $\eta^2 = .149$***
Job complexity	1.60	0.87	1.73	0.66	1.65	0.78	$F(2,200) = 0.482$, $p = .618$, $\eta^2 = .005$
Problem solving	1.55	0.69	1.65	0.83	1.59	0.61	$F(2,200) = 0.370$, $p = .691$, $\eta^2 = .004$
Information processing	1.75	0.91	2.13	1.02	1.99	0.85	$F(2,200) = 2.804$, $p = .063$, $\eta^2 = .027$
Skill variety	1.94	0.94	2.00	0.95	1.78	0.74	$F(2,200) = 1.115$, $p = .330$, $\eta^2 = .011$
Specialization	2.02	0.87	2.21	0.86	2.10	0.79	$F(2,200) = 0.857$, $p = .426$, $\eta^2 = .008$

Notes. IAS = Intelligent assistance system. * $p < .05$ *** $p < .001$.

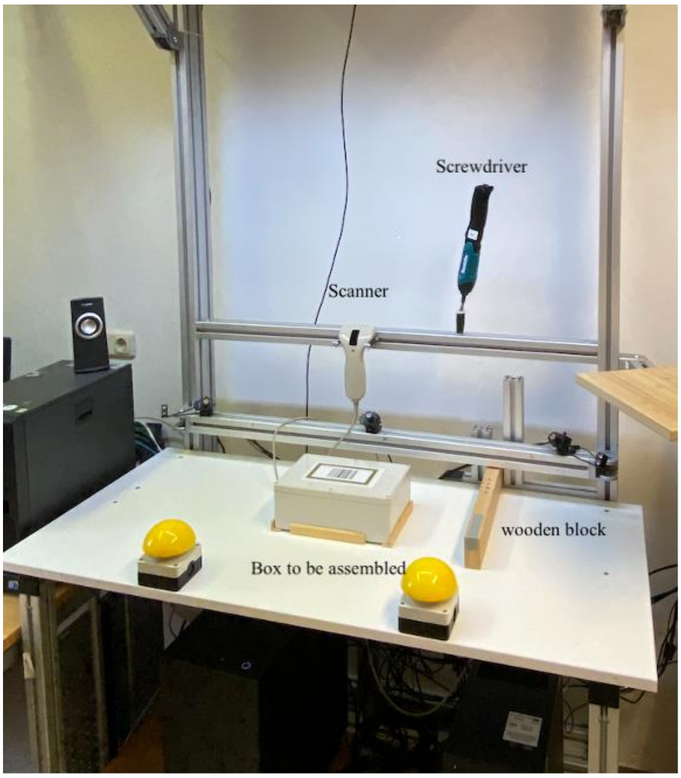
Appendix A

Vignette of the condition work without IAS (translated from German)

Read the following job description carefully. Look at the fictitious workplace and try to put yourself in the situation.

Imagine you are an employee in a medium-sized company, the Montage GmbH. You work in the assembly department and assemble boxes at the assembly workstations in the production halls of Montage GmbH.

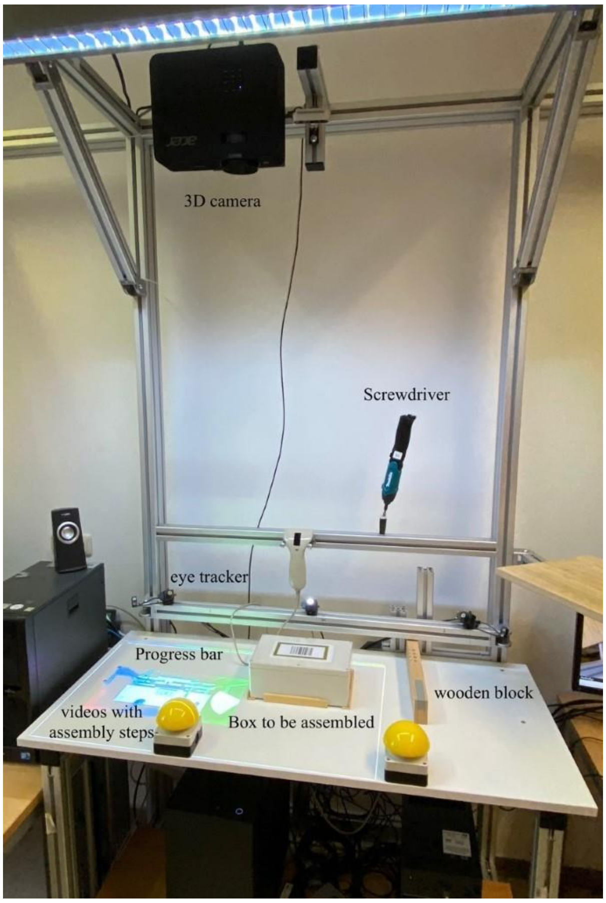
The picture shows an exemplary assembly workstation. On the work surface there is the box to be assembled and a wooden block with the required screws. The work is performed with a screwdriver and a scanner. After every 2 hours you assemble a different product.



Appendix B

Vignette of the conditions work with IAS and work with voluntary use of IAS (translated from German)

Read the following job description carefully. Look at the fictitious workplace and try to put yourself in the situation.



Imagine you are an employee in a medium-sized company, the Montage GmbH. You work in the assembly department and assemble boxes at the assembly workstations in the production halls of Montage GmbH.

The picture shows an exemplary assembly workstation. On the work surface there is the box to be assembled and a wooden block with the required screws. The work is performed with a screwdriver and a scanner. After every 2 hours you assemble a different product.

You will be supported by a digital assistance system while performing your job.

It has the following features**:**

- It guides you through each assembly step with the help of short videos, which are displayed on the work surface with the help of a beamer.
- For this purpose, your hand and eye movements are recorded using a 3D camera and three small, black eye-tracking cameras.
- If the assembly steps are performed correctly, the video lights up green on the work surface; if they are performed incorrectly, the video lights up red.
- The progress of your workflows is displayed in the form of a progress bar above the videos with the assembly steps on the work surface.
- Alternative workflows and assembly sequences can be automatically observed and taught using machine learning and artificial intelligence. This allows the system to constantly adapt to the user and other work steps, so that the system and the user can learn from each other.

Chapter 3 – Paper 2

Blessed be intelligent assistance systems at high task rotation? The effect on motivational work design in assembly

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Abstract

We aimed to provide causal evidence on the contradictory effects of projection-based intelligent assistance systems (IASs) for nine motivational work characteristics (MWCs). IASs are increasingly implemented in assembly to counteract rising cognitive workload due to individualized manufacturing processes. However, how IASs enhance or restrict MWCs is largely unknown. We conducted two studies with experimental vignette methodology. In Study 1 (N_1 = 169 German employees), we manipulated an assembly workplace (with IAS vs. without IAS) and tested whether findings indicating only positive effects of IASs in the support of a simple assembly process can be transferred to more complex assembly processes. In Study 2 (N_2 = 176 German employees), we manipulated again the assembly workplace (with IAS vs. without IAS) and in addition the dynamic of product changes (task rotation after 1 h vs. no task rotation). Analyzing the data with SPSS 27, we found increased feedback from job and information processing and decreased work scheduling, decision-making, and work methods autonomy when working with IAS. In Study 2, we did not find the main or interaction effects of task rotation on MWCs. Our experimental evidence suggests that working with IASs represents a double-edged sword regarding MWCs and that the effect of task rotation is limited. Hence, our results provide vital theoretical implications for a much-needed work design theory that delineates how new technologies shape work design and practical implications for modern assembly.

Keywords: *assembly, intelligent assistance systems, motivational work characteristics, task rotation*

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Introduction

To counteract rising complexity in assembly due to individual customer requests (Egger-Lampl et al., 2019), *intelligent assistance systems* (IASs) are increasingly implemented, even further pushed by the Covid-19 pandemic (Krzywdzinski et al., 2022). However, the effect of these systems on workplaces and thus workplace characteristics in assembly is largely unclear. Not only is there a lack of theories explaining and predicting how technologies affect *motivational work characteristics* (MWCs) (Gagné et al., 2022) but also empirical evidence on the effect of specific technologies such as IASs is scarce, and prior findings show contradicting results. For example, on the one hand, Walczok and Bipp (2023) recently found that IASs increase feedback from job and information processing, and thus could have a motivation-enhancing effect. On the other hand, findings of qualitative studies (e.g., Blumberg & Kauffeld, 2020) suggest the risk of restricted autonomy and systematic deskilling when working with IASs.

Therefore, the aim of our current study is twofold. First, we aim to provide much-needed empirical evidence for the positive and/or negative effects of IASs on MWCs in complex assembly processes (Study 1). Second, we investigate the interaction effect of IASs and *task rotation* on MWCs as IASs are increasingly important in highly dynamic work environments characterized by frequent product changes (Study 2). We contribute to the postulation of work design theories that emphasize the role of new technologies as determinants of work characteristics and their interaction with established work design interventions (Gagné et al., 2022). By highlighting human factors in the implementation of innovative technologies, we point out the positive and negative effects of IAS before they are widely implemented in practice. Hence, we help organizations to react to anticipated changes when implementing IASs in assembly, enabling motivating workplaces in smart factories of the future by amplifying the user-centered design of those systems (Stockinger et al., 2021).

A model of the future of work design

Even though the effects of technologies on work design are evident, comprehensive theories that describe and explain the impact of technological changes in the workplace on work design are still lacking (Gagné et al., 2022; Walczok & Bipp, 2023). Recently, Gagné and colleagues (2022) propose a novel model, stating that technological changes in the workplace directly affect the design of work by either in- or decreasing MWCs, leading to psychological need (for autonomy, competence, relatedness) satisfaction, and therefore (indirectly) affecting work motivation. As findings on the impact of technologies on work design are inconsistent, they postulate that “there is no deterministic relationship between technology and work design; instead, the effect of new technology on work design, and hence on motivation, depends on various moderating factors” (p. 383). They suggest that technology design and organizational implementation factors moderate the direct effect of technological changes on work design, hence leading to positive or negative motivational effects. On the one hand, technologies have the potential to replace routine cognitive tasks and automate “dull, dangerous, and dirty” (Walsh & Strano, 2018, p. XIX) work. The remaining tasks are characterized by high standardization, including increased monitoring of technologies, and lack of job autonomy, task variety, and skill variety (Blumberg & Kauffeld, 2020; Gagné et al., 2022; Parker & Grote, 2022). On the other hand, technologies can also have a positive impact on MWCs by automating simple tasks, resulting in the execution of more complex tasks, increasing job complexity, skill variety, and problem solving (Gagné et al., 2022; Waschull et al., 2020).

Given that a direct test of the theoretical suggestions of Gagne et al. (2022) is missing so far, we explicate the effect of the previously presented IASs on MWCs in assembly by taking into account technological design factors of IASs as well as frequent product changes as organizational implementation factor into account (Figure 1). In detail, we relied on MWCs (*task* and *knowledge characteristics*) that are outlined in the *work design questionnaire* (WDQ) as a comprehensive model of work characteristics (Morgeson & Humphrey, 2006). We focus on task and knowledge characteristics as meta-analytical findings indicate positive associations of these MWCs with favorable work outcomes (e.g., work motivation) (Humphrey et al., 2007) (see Table 1 for definitions and exemplary items of investigated MWCs). Beyond cross-sectional study evidence on the relationship between MWCs and work outcomes, the results of a systematic review by Knight and Parker (2021) demonstrate that work redesign interventions (like task rotation) lead to changes in employees' perceptions of MWCs and motivation with positive downstream effects on job performance. To prevent unintended negative effects of the implementation of new technologies at work, MWCs need to be considered throughout the whole digitalization process, starting with a user-centered development of these technologies (Mlekus et al., 2022; Stockinger et al., 2021).

Technology design factors of an IAS in assembly

IASs represent a broad range of technical systems from wearables (Javdan et al., 2023), robotic exoskeletons (Luger et al., 2023), virtual or augmented reality (Marklin et al., 2022) to projection-based assistance systems (Mark et al., 2022). Different classification systems exist for the categorization of IASs, which subdivide those systems either in terms of the level of support or demand, type of support, and objectives (Apt et al., 2018), or attribute categories and capability parameters (Mark et al., 2022). In the current study, we investigate the effects of a cognitive-assistive projection-based IAS with a low level of support which is used for quality assessment and verification of assembly steps. By presenting context-sensitive in situ projections on the work surface, the projection-based assistance system is intended to guide and cognitively relieve assembly workers during assembly processes. With the help of feedback symbols, including a green tick and a red cross, the IAS gives immediate feedback to the worker when an assembly step is performed correctly or incorrectly, respectively. Machine learning allows the IAS to intelligently and automatically learn new assembly sequences for already known and new, varying products (Jung et al., 2022; Walczok & Bipp, 2023). The technical components of this IAS are discussed in detail by Jung et al. (2022). With this set of functions, the IAS represents a common IAS in industrial applications (Jetter et al., 2018).

The use of language-independent instruction material is supposed to facilitate the inclusion of, for example, nonnative speakers, persons with low skill levels, or with cognitive deficits into the labor market (Apt et al., 2018; Mark et al., 2019). Nevertheless, IASs are also intended to be used in the long term by assembly workers after the learning phases, especially in very dynamic work environments characterized by frequent changes of products (such as modern assembly, in which products rotate resulting from individual customer requests). In this way, those systems should ensure long-term, cognitive relief for assembly workers (Egger-Lampl et al., 2019). However, this means that IASs transform workplaces by altering MWCs.

The first causal evidence on how a cognitive-assistive IAS modifies task and knowledge characteristics stems from Walczok and Bipp (2023). They presented 203 German and British blue-collar workers with a hypothetical assembly workstation and an exemplary, simple work process (assembly of a box) with or without the support of the IAS. Walczok and Bipp (2023) expected an increase in feedback from job as the IAS provides assembly workers with more and immediate feedback for every assembly step in the form of a green tick or a red cross, respectively. Thus, the feedback function as a technological design factor of the IAS leads to higher feedback from job compared with working without IAS. They postulated contradicting effects on information processing. On the one hand, the cognitive support of assembly workers and the takeover of cognitive tasks by instructing assembly steps could decrease assembly workers' information processing. On the other hand, higher information processing could be increased due to the necessity that employees need to monitor and process additional information (due to feedback and instruction functions of the IAS) when working with IAS compared with working without the support of IAS. Indeed, Walczok and Bipp (2023) identified increased feedback from job (d = 0.85), and information processing (d = 0.33) when working with IAS compared with working without the support of the IAS, but no differences in other MWCs. These findings suggest the impact of IASs on MWCs is purely positive.

H1. Feedback from job is significantly higher in work with IASs than in work without IASs.

H2. Information processing is significantly higher in work with IASs than in work without IASs.

However, such effects seem contrary to prior qualitative studies which propose negative effects on MWCs, such as reduced autonomy or a systematic deskilling of workers (e.g., Blumberg & Kauffeld, 2020). Also, Walczok and Bipp (2023) criticize that their findings might be restricted by general low ratings in MWCs (floor effects) with a "highly simplified" (p. 12) work process in their study, resulting in limited opportunities for the identification of reduced MWCs due to the IAS. Hence, to rule out this alternative explanation, we tested for such negative effects of an IAS in a more complex assembly process. Since the instruction function of the IAS as a technological design factor strictly standardizes assembly processes by instructing workers through the projection of upcoming assembly steps, the IAS specifies the order of assembly steps and which tools to use. Hence, working with IASs should reduce all three autonomy facets based on the WDQ, namely, work scheduling, decision-making, and work methods autonomy. This is also in line with the *cyber-physical systems transformation framework by*

Waschull et al. (2020) postulates restricted autonomy due to technological advances in manufacturing settings by standardizing work processes. Furthermore, qualitative studies indicate decreased autonomy as a potential risk of IASs (Baethge-Kinsky, 2020; Blumberg & Kauffeld, 2020). However, to date, to our knowledge, no quantitative study has provided empirical support for such an effect.

H3a. Work scheduling autonomy is significantly lower in work with IASs than in work without IASs.

H3b. Decision-making autonomy is significantly lower in work with IASs than in work without IASs.

H3c. Work methods autonomy is significantly lower in work with IASs than in work without IASs.

Furthermore, the design factors of the IAS should lead to reductions of other knowledge characteristics, such as job complexity, problem solving, and *specialization*. By instructing assembly workers on all assembly steps through the use of context-sensitive in situ projections of the subsequent work steps, the IAS is intended to teach new employees and workers without prior assembly experiences (Apt et al., 2018). Thus, the instruction function of the IAS can lead to the takeover of the cognitive work and problem solving, so that assembly workers primarily perform the remaining manual tasks. Accordingly, qualitative studies stress the risk of systematic deskilling of workers when introducing IASs at work as a result of the takeover of cognitive tasks (Baethge-Kinsky, 2020; Blumberg & Kauffeld, 2020). Consequently, assembly workers need to have fewer skills, knowledge, and abilities to complete assembly processes, particularly cognitive skills (Walczok & Bipp, 2023).

H4a. Job complexity is significantly lower in work with IASs than in work without IASs.

H4b. Problem solving is significantly lower in work with IASs than in work without IASs.

H4c. Specialization is significantly lower in work with IASs than in work without IASs.

Existing frameworks like the cyber-physical systems transformation framework (Waschull et al., 2020) propose contradicting effects of new technologies in manufacturing on skill variety. On the one hand, the instruction function of the IAS could potentially take over cognitive work completely and reduce the need for cognitive skills by instructing assembly workers, therefore leading to a reduction in skill variety. For the context of aviation, Volz and colleagues (2016) demonstrated that automation leads to decreases of cognitive skills in the long term. On the other hand, the instruction function of the IAS could also increase the need for new skills, such as digital competencies to effectively use IASs. Building up on a framework model of digital competencies of employees (Oberländer et al., 2020), these could refer to the evaluation of digitalized information in the form of projected videos and basic knowledge about how the IAS works to handle potential false positive or false negative feedback on individual assembly steps (Oberländer et al., 2020). Consequently, we anticipate contradictory effects of IASs on skill variety, and propose competing hypotheses.

H5a. Skill variety is significantly lower in work with IASs than in work without IASs.

H5b. Skill variety is significantly higher in work with IASs than in work without IASs.

Organizational implementation factor: Task rotation

As modern assembly is characterized by frequent changes in assembly products due to individualized customer requests (Egger-Lampl et al., 2019), assembly often incorporates task rotation as an “alternation between tasks within a job that can require different skills and responsibilities but is not associated with a change to a different function or department” (Mlekus & Maier, 2021, p. 2). IASs are not only designed to support assembly workers at high task rotation but several scholars postulate that task rotation could counteract negative impacts on work design and motivation, such as monotony and boredom that result from technologies taking over cognitive tasks (e.g., Mlekus et al., 2022). Hence, task rotation could represent a vital organizational implementation factor that affects the impact of technological changes in the workplace on work design (Gagné et al., 2022; Mlekus et al., 2022).

In their meta-analysis, Mlekus and Maier (2021) found a positive relationship between task rotation and attitudinal work outcomes (e.g., job satisfaction) which they suggest to be due to modified MWCs. They postulate that task rotation not only increases task variety per definition but also skill variety as the execution of numerous tasks requires a higher number of skills compared with jobs in which fewer tasks are executed (Mlekus & Maier, 2021). The proposed effects of task rotation on task and skill variety and work outcomes were supported by findings by Mlekus and colleagues (2022). In two studies, they presented a hypothetical assembly workplace with a digital assistance system (which strongly resembles the IAS we focus on in its functions) to participants. The authors manipulated task rotation (no task rotation vs. task rotation) in a between-subjects design. In both experiments, task rotation elevated task and skill variety which in turn positively influenced work outcomes.

In the case of task rotation in assembly, we also anticipate positive effects of task rotation (alone and in combination with IASs) on MWCs. When working with task rotation, assembly workers execute a higher number of diverse assembly products resulting in a higher perceived task variety compared with working without task rotation. Hence, the successful assembly of diverse products requires a higher skill variety, primarily manual skills by manually operating with different assembly parts, materials, and tools, and learning numerous assembly processes.

H6. Skill variety is significantly higher when working with task rotation than when working without task rotation.

In addition to the impact of task rotation also postulated by Mlekus and Maier (2021), we propose that task rotation in assembly furthermore leads to higher information processing, as assembly workers learn and perform more diverse assembly processes in their daily work, and thus have to process more information than when no task rotation is implemented.

H7. Information processing is significantly higher when working with task rotation than when working without task rotation.

Since we anticipate that working with IASs and task rotation leads to enhanced information processing compared with working without IASs or task rotation, respectively, we postulate that a combination of both, working with IASs with task rotation, maximizes the amount of information that assembly workers need to process. This requires the processing of numerous, varying instructions that are projected by the IAS, and using varying tools, materials, mounting parts, and products.

H8. A combination of work with IASs and task rotation leads to higher information processing compared with other working conditions.

Given that we expect contradictory effects of the IASs on skill variety (cf. competing H5a and H5b), we investigate how the combination of IASs and task rotation impacts skill variety exploratively in a research question. On the one hand, an enhanced variability in assembly products by frequent task rotation could promote, for example, manual skills which could in turn counteract the reduction of required cognitive skills. On the other hand, both working with IASs and task rotation could boost digital competencies and manual skills, respectively.

RQ: How does the combination of work with IAS and task rotation impact skill variety?

Additionally, Mlekus and Maier (2021) postulate that task rotation will decrease work scheduling autonomy if "employees might be required to follow a fixed rotation roster" (p. 3), and will increase *task identity* if task rotation leads to the execution of subsequent tasks that result in a holistic work process. However, we do not postulate an effect of task rotation on work scheduling autonomy or task identity. First, neither assembly workers who need to follow a fixed rotation schedule nor workers who continuously assemble identical products (no task rotation) can choose a desired order of tasks or products. Second, task rotation does not necessarily lead to the assembly of numerous assembly products that are further processed into a final overall product. Third, we do not anticipate that the IAS affects task identity as the assembly work as a whole remains largely unchanged (Baethge-Kinsky, 2020).

Study 1: Working with IAS in a complex assembly process

To test H1-5 and the transferability of the effect of the IAS on MWCs by Walczok and Bipp (2023), we apply an *experimental vignette methodology* (EVM) studywith two experimental conditions (work without IAS vs. work with IAS) and used a more complex assembly process which is also used in practice. This assembly process (twist stop) is characterized by a higher number (20) and more diverse assembly steps (Keller et al., 2019) which require more components and tools than the assembly of the simple box that was used in Walczok and Bipp (2023). Thereby, we postulate higher mental work, resulting in a higher degree of difficulty (Radowski et al., 2015).

Materials and methods

Experimental design and procedure

We applied an online EVM (between-subject) study design in resemblance to Walczok and Bipp (2023) to test the causal effects of the IAS on MWCs. EVM study designs represent established methods in work design research as they have been applied by several scholars (e.g., Bipp et al., 2021; Mlekus et al., 2022). These designs enable the investigation of research questions with simultaneously high internal validity (causality) and high external validity (generalizability). Currently, working with IASs in organizational practice often entails disturbances like modeling errors and time delays of such systems (Tao et al., 2022; Walczok & Bipp, 2023; Xu et al., 2021). Assembly workers could evaluate working with IASs negatively, not because of its functions or how it is used but because of these disturbances. By presenting working with IAS without disturbances, this EVM study design allows us to investigate the pure effect of IASs on MWCs without contributing, negative factors that decrease with further development cycles. We manipulated a hypothetical assembly station with two experimental conditions: Work without IAS and work with IAS. Following best practice recommendations (Aguinis & Bradley, 2014) to maximize internal and external validity, we aimed to maximize the level of immersion by presenting the hypothetical situation with text, picture, and video material. Participants were randomly assigned to one of the two conditions. First, all participants received a short text about a hypothetical situation. They were instructed to imagine themselves working as assembly workers in the production halls of an assembly company. Next, we presented a hypothetical assembly workplace using a short text and a picture with IAS for participants in the work with IAS condition and without IAS for participants in the work without IAS condition. Additionally, participants in the IAS condition received information on the functions of the IAS. Then, all participants watched a short video of the assembly of a twist stop, again with or without the support of the IAS, according to their experimental condition. Participants in both experimental conditions were informed that the product to be assembled would change every 2 h. Finally, participants rated the presented assembly workplace from their condition in terms of equipment use, and MWCs, and provided demographic information. This procedure builds up on the notion that job analysis is possible through observation (Dierdorff & Wilson, 2003).

Participants

We invited German blue-collar workers, employees with prior work experience in manufacturing, and novices (workers from other fields and without prior work experience in manufacturing) from our professional and personal networks to participate in our online experiment. As IASs should assist people with low skills in training phases, we included novices as a specific target group of IASs (Doolani et al., 2020). We donated 0.50€ per participant to a charitable organization. In total, 223 participants completed our study from November to December 2022. We excluded two participants who reported having technical issues, eight participants who failed the built-in attention check ("Please tick answer option 1 ' strongly disagree' in this row to demonstrate your attention"), five participants who reported "student" as their current job, 14 participants with missing values in demographics, and 25 participants who reported difficulties placing themselves in the hypothetical work situation[4]. This resulted in a final sample of 169 participants (76 in the work without IAS condition and 93 in the work with IAS condition) including 22 assembly workers from a German technical ceramics and plastics producing company that plans to implement the IAS in assembly. Specifically, 73 participants worked (at least partly) in manufacturing (43.2%), further 23 had prior work experiences in manufacturing but currently had another job (13.6%), and 73 participants were novices (43.2%). Age

[4] They answered the item "How easy was it for you to put yourself in the situation presented" with *very difficult* (1), *difficult* (2), or *rather difficult*.

ranged from 18 to 68 years (M = 37.37, SD = 13.71). The majority of the sample was female (53.3%). The minority had prior work experience with IASs (12.4%).

Manipulation check

To ensure that we successfully manipulated the assembly workstation, the participants rated the equipment use using a validated German version (Stegmann et al., 2010) of the WDQ (Morgeson & Humphrey, 2006) on a five-point Likert scale ranging from *strongly disagree* (1) to *strongly agree* (5). We adapted the items for the manipulation check and MWCs ratings by switching from "my job" to "the job" in both studies to refer to the presented work situation. Equipment use (α = .73) was significantly higher in work with IASs (M = 2.20, SD = 0.84) than in work without IASs (M = 1.91, SD = 0.75), $t(167)$ = -2.330, p = .021, d = -0.360, suggesting that the manipulation was successful.

Measures

We measured MWCs using the validated German version (Stegmann et al., 2010) of the WDQ (Morgeson & Humphrey, 2006), again on a five-point Likert scale (Table 1). Internal consistency reliabilities varied from .66 (specialization) to .87 (feedback from job).

Results and Discussion Study 1

Table 2 and Figure 2 show the descriptive results of the two experimental conditions. In general, on a descriptive level, low ratings in all MWCs – except feedback from job – are visible. One-way multivariate analysis of variance (MANOVA) indicated a significant difference between the two experimental conditions work with IASs and work without IASs across all nine MWCs, $F(9, 159)$ = 5.305, p < .001, η_p^2 = 0.231. One-way MANCOVA with expertise level (prior or current work experiences in manufacturing vs. no experiences in manufacturing) as covariate yielded identical results, $F(9, 158)$ = 5.288, p < .001, η_p^2 = 0.231, as experts and novices did not significantly differ in their ratings of MWCs according to their experimental condition, $F(9, 158)$ = 0.849, p = .572, η_p^2 = 0.046.

We conducted subsequent t-tests for the MWCs separately to test our hypotheses. We found significantly higher feedback from job in work with IASs than in work without IASs, $t(167)$ = -3.709, p < .001, d = -0.573, supporting H1. Information processing was also significantly higher in work with IASs than in work without IASs, $t(167)$ = -1.984, p = .049, d = -0.307, supporting H2. We found significantly lower work scheduling autonomy, $t(146.69)$ = 3.347, p = .001, d = 0.527, decision-making autonomy, $t(100.15)$ = 3.887, p < .001, d = 0.643, and work methods autonomy, $t(124.98)$ = 3.346, p = .001, d = 0.538, in work with IASs than in work without IASs, supporting H3a-c. We did not identify any significant differences between work with IASs and work without IASs in job complexity, $t(167)$ = -0.127, p = .899, d = -0.020, problem solving, $t(167)$ = 0.270, p = .787, d = 0.042, or specialization, $t(167)$ = 0.382, p = .703, d = 0.059, rejecting H4a-c. Finally, we did not find a significant difference in skill variety between both experimental conditions, $t(167)$ = 0.667, p = .506, d = 0.103, rejecting H5a and H5b.

In Study 1, we investigated whether we can transfer prior findings on the effect of IASs on MWCs by Walczok and Bipp (2023) to a more complex assembly process. In line with prior findings, we identified moderately higher feedback from job and weakly higher information processing when working with IASs compared with working without IASs. In contrast to prior findings, our current study provides evidence for restricted autonomy (in all three investigated autonomy facets) when working with IASs to a moderate degree. Consequently, the results of our first study suggest that the implementation of IASs in assembly represents a double-edged sword in terms of MWCs. On the one hand, assembly workers benefit from the increased feedback from job and information processing as long as higher information processing does not lead to information overload (Walczok & Bipp, 2023). On the other hand, the restricted autonomy facets could counteract these two positive effects of IASs on MWCs, hence, questioning the added value of IASs. Therefore, our study is the first to provide causal evidence on the contradictory effects of IASs on MWCs. We partially transferred prior findings to a more complex assembly process, further highlighting the importance of their degree of difficulty for the evaluation of IASs and resulting effects on MWCs.

Since we did not find any differences in the remaining knowledge characteristics (job complexity, problem solving, specialization, skill variety) between both experimental conditions, our results reinforce prior findings that the investigated IAS seems to fail to cognitively assist assembly workers (Walczok & Bipp, 2023). Thus, the absence of cognitive relief despite the in situ step-by-step instructions by the IAS remains. To achieve this desired positive effect of the technological design factors on work design, we need to take organizational implementation factors and their interaction with technological design factors into consideration as outlined in the model by Gagné and colleagues (2022). As IASs are mainly used for learning new assembly processes (Egger-Lampl et al., 2019), which frequently change due to individual customer requests, high task rotation could play a fundamental role in the beneficial role of IASs with regard to work motivation. Although in the current study, all participants received the information that the task would change after 2 h, this description of potential task rotation might have been too abstract or discreet, or the used time interval of 2 h to the next rotation might be too long for the cognitive relief by the IAS. This is also in line with research by Watson and colleagues (2010) who demonstrated drastic reductions in build times of small-scale assembly tasks depending on the number of performed assembly processes with the beginning of stagnation after only three assembly runs. This suggests that cognitive assistance in assembly tasks is specifically needed in highly frequent product changes. More rapid product changes (higher task rotation) could therefore be a prerequisite for IASs to be considered as cognitive relief. Therefore, we experimentally manipulated task rotation (in combination with the use of the IAS) in our second study.

Study 2: The role of task rotation

In our second EVM study with German employees, we investigated the effect of IASs, task rotation, and their interaction on MWCs (H1-H8, RQ) to further stress the importance of the highly dynamic product changes caused by individual customer requests. We preregistered the hypotheses and procedure before data collection and uploaded the used material to the Open Science Framework (https://osf.io/kteqy?view_only=44ac9c4d661348c9b8902312f4a2036b).

Materials and methods

Experimental design and procedure

We applied a 2 x 2 EVM (between-subject) study design with manipulation of the assembly workplace (work without IAS vs. work with IAS) and the task rotation (no task rotation vs. task rotation), resulting in four experimental conditions. We extended the study design from Study 1 and used the same instructions and baseline information. We presented participants from all experimental conditions with the hypothetical assembly workstation and the assembly of the twist stop. Besides the use of IAS (the assembly process was or was not supported by the IAS), task rotation was experimentally manipulated. Participants in the high task rotation conditions were informed that after every hour they would switch with a colleague to a nearby assembly station to carry out individual customer requests. After another hour, they switch again to assemble a different product. To amplify the illustration, we presented participants in the task rotation conditions a new assembly workstation with(out) IAS as well as the assembly of a box with(out) the assistance of the IAS from Walczok and Bipp (2023).

Participants

As in Study 1, we invited German employees from professional and personal networks and used a donation of 0.75€ per participant to a charitable organization as an incentive. In total, 229 participants completed the experiment from December 2022 to February 2023. We excluded three participants with technical issues during the presentation of the hypothetical workplace, five participants who failed the built-in attention checks, two participants with missing information in demographics, and nine who reported "student" as their current job from the analysis. Additionally, we excluded 34 participants who reported difficulties placing themselves in the presented situation. The final sample includes 176 participants who were randomly assigned to one of the four experimental groups including 83 participants who worked at least partly in manufacturing (47.2%), further 30 with prior work experience in manufacturing (17.0%), and 63 novices (35.8%). Age ranged from 18 to 66 years (M = 38.97, SD = 13.57). Most participants were male (51.7%). Only 32 participants had prior work experience with IASs (18.2%).

Manipulation checks

To ensure that the experimental manipulations of the assembly workstation and task rotation were successful, participants rated the equipment use and task variety, respectively, with the validated German version (Stegmann et al., 2010) of the WDQ (Morgeson & Humphrey, 2006). Comparing the ratings across the conditions supported that our manipulation was successful. First, equipment use (α = .70) was significantly higher in the conditions with IASs (M = 2.14, SD = 0.79) than without IASs (M = 1.84, SD = 0.72), $t(174) = -2.689$, $p = .008$, $d = -0.407$. Second, task variety (α = .87) was significantly higher in conditions with task rotation (M = 1.94, SD = 0.81) than in conditions without task rotation (M = 1.58, SD = 0.67), $t(174) = -3.249$, $p = .001$, $d = -0.490$.

Measures

As in Study 1, we measured MWCs with the validated German version (Stegmann et al., 2010) of the WDQ (Morgeson & Humphrey, 2006). Internal consistency reliabilities ranged from .65 (specialization) to .89 (skill variety).

Results and Discussion Study 2

Table 3 and Figure 3 display the descriptive results of the four experimental conditions. Again, on a descriptive level, all MWCs ratings —expect feedback from job —were on the lower end of the scale in all conditions. A two-way MANOVA pointed out significant differences between the four experimental conditions with a significant main effect of IASs on MWCs, $F(9, 164) = 8.109$, $p < .001$, $\eta_p^2 = 0.308$. Neither did we find a significant main effect of task rotation on MWCs, $F(9, 164) = 0.646$, $p = .757$, $\eta_p^2 = 0.034$, nor a significant interaction effect of IASs and task rotation on MWCs, $F(9, 164) = 0.283$, $p = .979$, $\eta_p^2 = 0.015$. Considering the expertise level as a covariate in a two-way MANCOVA yielded identical results with a significant main effect of IASs on MWCs, $F(9, 163) = 7.920$, $p < .001$, $\eta_p^2 = 0.304$, and again a nonsignificant main effect of task rotation on MWCs, $F(9, 163) = 0.759$, $p = .654$, $\eta_p^2 = 0.040$, and interaction effect of IASs and task rotation on MWCs, $F(9, 163) = 0.311$, $p = .970$, $\eta_p^2 = 0.017$. Furthermore, our results further support that experts and novices did not significantly vary from each other in the MWCs ratings of the hypothetical assembly workstation, $F(9, 163) = 1.400$, $p = .192$, $\eta_p^2 = 0.072$.

We conducted a series of ANOVAs to test our hypotheses (Table 4). In line with H1, we identified significantly higher feedback from job in work with IASs than in work without IASs, $F(1, 172) = 39.216$, $p < .001$, $\eta_p^2 = 0.186$. We also found significantly higher information processing in work with IASs than in work without IASs, $F(1, 172) = 4.345$, $p = .039$, $\eta_p^2 = 0.025$, supporting H2. In congruence with H3a-c, our results indicate significantly lower work scheduling autonomy, $F(1, 172) = 12.734$, $p < .001$, $\eta_p^2 = 0.069$, decision-making autonomy, $F(1, 172) = 5.210$, $p = .024$, $\eta_p^2 = 0.029$, and work methods autonomy, $F(1, 172) = 5.878$, $p = .016$, $\eta_p^2 = 0.033$, in work with IASs than in work without IASs. We did not find any significant differences between work with IASs and work without IASs in job complexity, $F(1, 172) = 0.915$, $p = .340$, $\eta_p^2 = 0.005$, problem solving, $F(1, 172) = 0.810$, $p = .369$, $\eta_p^2 = 0.005$, or specialization, $F(1, 172) = 1.959$, $p = .163$, $\eta_p^2 = 0.011$, providing no evidence for H4a-c. We also found no significant difference in skill variety between work with IASs and work without IASs, $F(1, 172) = 0.809$, $p = .370$, $\eta_p^2 = 0.005$, rejecting H5a and H5b. In terms of task rotation, we did not identify significant main effects on skill variety, $F(1, 172) = 0.007$, $p = .931$, $\eta_p^2 = 0.000$, or information processing, $F(1, 172) = 0.102$, $p = .750$, $\eta_p^2 = 0.001$, rejecting H6 and H7, respectively. Contrary to H8, we found no significant interaction effect of IASs and task rotation on information processing, $F(1, 172) = 0.001$, $p = .976$, $\eta_p^2 = 0.000$. Finally, with regard to our RQ, we did not identify a significant interaction effect of IASs and task rotation on skill variety, $F(1, 172) = 0.128$, $p = .721$, $\eta_p^2 = 0.001$.

Besides examining the impact of IASs on work design, we investigated how high task rotation as an organizational implementation factor interacts with the effect of IASs on MWCs in assembly in

Study 2. As we found the main effects of IASs in terms of increased feedback from job and information processing as well as restricted work scheduling, decision-making, and work methods autonomy in working with IASs (compared with working without IAS), the results of Study 2 reinforce the notion of IASs as a double-edged sword regarding MWCs. Whereas the largely increased feedback from job and the weakly enhanced information processing have a motivation-enhancing effect, the moderately restricted work scheduling autonomy as well as weakly reduced decision-making and work methods autonomy counteract these positive motivational effects.

Again, the IAS did not affect other knowledge characteristics, therefore not changing requirements in skills, abilities, and knowledge that assembly workers need to successfully perform assembly work daily. Hence, the results of Study 2 demonstrate that the investigated IAS does not lead to the intended cognitive relief. This is further stressed by the fact that knowledge characteristics are not affected by the implementation of task rotation or IAS with high task rotation in combination. Thus, our results refute the potential benefits (enhancing skill variety by promoting both manual skills and digital competencies) of IASs in the cognitive support of assembly workers in highly frequent product changes caused by individual customer requests.

Moreover, surprisingly, the rotation of assembly products after every hour did not lead to a significant increase in skill variety as postulated by Mlekus and Maier (2021) or information processing and did not enhance the positive effect of IASs on information processing. Thereby, our results suggest that task rotation has limited potential to valorize work design in assembly or counteract the negative effects of technologies on MWCs, besides simply enhancing task variety.

Finally, the MWCs ratings in all four experimental conditions were low except for feedback from job. In particular, skill variety and information processing were also low, even in conditions with task rotation. This study stresses the importance of work design interventions other than task rotation in assembly to improve MWCs, and hence, the motivation of assembly workers.

General Discussion

Applying EVM study designs across two German samples, we tested the effect of the IAS on MWCs in assembly by taking technological design factors and task rotation into account as an organizational implementation factor (Figure 1) based on the suggested model by Gagne et al. (2022). In detail, we provided causal evidence on the contradictory effects of IASs regarding MWCs by examining whether prior findings on the impact of IASs on MWCs in assembly (Walczok & Bipp, 2023) are transferable to more complex assembly processes and depend on the extent of task rotation. Our results fully replicate across our two studies: We found causal evidence for the effect of IASs in terms of increased feedback from job and information processing as well as restricted work scheduling, decision-making, and work methods autonomy by working with IASs in both of our studies. Therefore, our results imply that working with IASs represents a double-edged sword regarding MWCs. On the one hand, assembly workers receive more immediate feedback throughout the assembly process, which also increases the amount of information that needs to be perceived and processed and satisfies the need for competence as outlined in self-determination theory (Deci & Ryan, 1985), thereby increasing motivation. On the other hand, higher standardization of work processes by instructing workers with context-sensitive in situ projections results in decreased different facets of autonomy, hampering the satisfaction of the need for autonomy, and thus motivation (Gagné et al., 2022). As Walczok and Bipp (2023) only identified enhanced feedback from job and information processing when executing a simple assembly task with the support of IASs, our results obtained with a more complex assembly process emphasize how the perception of IASs depends on the difficulty of the supported assembly tasks. If IASs are used for support in the execution of more objectively difficult assembly processes, contradictory effects on motivation were visible in our current study. Additionally, our results imply that the extent of task rotation is negligible when it comes to the perception of IASs and their impact on MWCs in assembly. Consequently, task rotation does not represent an adequate work design intervention to valorize MWCs in assembly or to boost positive effects of technologies —in our case information processing. By this, our causal evidence contributes to the postulation of work design theories that highlight the role of technological changes in the workplace (Gagné et al., 2022) and provides much-needed practical implications for the implementation of IASs in modern assembly.

Theoretical implications

Although we found significant effects of IASs on work design based on its specific technological design factors, the model proposed by Gagné and colleagues (2022) seems to be too general to test how technologies change the way work is perceived and executed. We successfully identified increased feedback by working with IASs as it provides immediate feedback to individual assembly steps. Respectively, we found significantly enhanced information processing since workers need to perceive and process context-sensitive in situ projections in addition to traditional assembly work. Further and in line with qualitative studies (e.g., Blumberg & Kauffeld, 2020), we found restricted autonomy in all facets by working with IASs, resulting from the higher standardization of assembly processes and specification of assembly steps. However, since the IAS could potentially take over cognitive processes, we anticipated decreases in knowledge characteristics, namely, job complexity, problem solving, specialization, and skill variety. This implies that assembly workers gain similar knowledge, skills, and abilities by learning on the job despite the cognitive assistance from the IAS. Thus, our results contradict the anticipated systematic deskilling by the use of IASs which is crucial considering that the majority of organizational learning (estimations range from 70 to90%) occurs informally through learning on the job (Cerasoli et al., 2018). Novel theories that acknowledge the impact of technologies on work design should consider which skills remain relevant and which skills are negligible in work with innovative technologies due to automation. These should integrate existing frameworks such as the cyber-physical systems transformation framework by Waschull and colleagues (2020) which highlights the contradictory effects of innovative technologies on the substitution and creation of tasks in light of automation, thereby leading to enriched, simplified, and substituted jobs.

Additionally, we did not find any evidence that task rotation alters investigated MWCs besides task variety or interacts with technological design factors of the IAS. This emphasizes the requirement to specify in detail which technological design and organizational implementation factors (and both in combination) modify work design. Since the terms technological design and organizational implementation factors remain rather vague and the model by Gagné and colleagues (2022) neglects further determinations of which functions of technologies have specific effects on work design, the results of our two studies contribute to the further specification of this framework. By demonstrating that task rotation as an organizational implementation factor does neither improve MWCs nor boost the positive effects of IASs on MWCs, we highlight the need to extend the postulated framework.

Gagne and colleagues (2022) state "[h]ighly skilled individuals or those with proactive personalities might actively shape the technology and/or craft their work design to better meet their needs and increase their motivation" (p. 383). By statistically controlling for the participants ' expertise level, we have first indications that the skill level in terms of prior experience in manufacturing does not play a fundamental role in how IASs are perceived. Thus, our results stress the importance of specific theories and models that allow to predict and test how new technologies (e.g., IASs) shape MWCs, and that human-centered design and potential effects on MWCs should be considered during the development of technologies.

Our findings show that besides task variety, MWCs remained unchanged by the implementation of task rotation challenges the notion that IASs are developed to intelligently support workers in highly dynamic product changes and questions the benefit of this work design intervention. Missing and small effects of task rotation in the meta-analysis by Mlekus and Maier (2021) on attitudinal work, learning, and psychological health outcomes could be attributed to the fact that task rotation has weaker impacts on MWCs than expected, especially on skill variety.

Practical implications

Our studies provide practical implications for the implementation of IASs in assembly. Contrary to the results by Walczok and Bipp (2023) who emphasize a motivation-enhancing effect of IAS by increasing feedback from job and information processing, our two studies show contradictory results. As indicated in qualitative studies (Baethge-Kinsky, 2020; Blumberg & Kauffeld, 2020), we identified restricted autonomy, specifically work scheduling, decision-making, and work methods autonomy by working with IASs. Practitioners should therefore not expect purely positive effects of IASs on MWCs in assembly and ensure that workers perceive autonomy in other ways, for example, through flexible shift starts. To avoid the negative long-term effects of IASs on autonomy, practitioners should consider self-adaptive IAS (Yigitbas et al., 2023) that reduces the level of support with increasing skill level. Although we identified reduced autonomy in all facets when working with the investigated self-adaptive IAS, the option of high self-adaption may nevertheless represent a promising solution to counteract negative effects on autonomy. By reducing the projection of instructions with increasing execution of identical assembly products and thus gaining skills, the self-adaption of IASs enables the execution of assembly steps in preferred ways. However, this could counteract the positive effects of enhanced feedback from job and information processing as these decrease with reduced support of the IAS, too.

Replicating prior findings (Walczok & Bipp, 2023), the IAS does not impact further knowledge characteristics job complexity, problem solving, specialization, and skill variety, our results refute the risk of systematic deskilling of employees (Baethge-Kinsky, 2020; Blumberg & Kauffeld, 2020) through cognitive support by the IAS. Nevertheless, this also indicates that cognitive support as its primary goal is not achieved by the investigated cognitive-assistive IAS. Practitioners should consider the missing decreases in knowledge characteristics when implementing IASs in assembly. Given that IASs should have the potential to reinforce the inclusion of workers with cognitive deficits (Mark et al., 2019), our findings imply that IASs are not suitable for doing so. Particularly, increased information processing could result in information overload (Walczok & Bipp, 2023). Roetzel (2019) argues that information overload frequently results from the misuse of ICT technologies at work which leads to decreased decision-making performance, resulting in hampered performance when working with IASs. A higher amount of information could pose further problems, such as reduced IAS acceptance and use if its output was perceived as complex (Javdan et al., 2023).

Although IASs are developed to support workers cognitively in highly dynamic product changes, our results suggest that the extent of task rotation does not affect the contradictory effects of IASs regarding MWCs. Consequently, our results suggest that IASs are not an adequate technology to cognitively assist workers in highly dynamic product changes due to individual customer requests. Equally, our results indicate that task rotation does not represent an appropriate work design intervention to improve work design in assembly besides promoting task variety. Thus, also task rotation and working with IASs do not lead to an overall increased skill variety by boosting manual skills and digital competencies. Practitioners who aim to improve MWCs should therefore rely on other work design interventions. Employees can also proactively alter MWCs after the implementation of new technologies using job crafting as outlined by Gagné and colleagues (2022).

Limitations and future research

Although the results of our two studies provide implications for the use of IASs and work design theory, we have to acknowledge several limitations. First, while EVM study designs have the potential to maximize internal and external validity, thereby providing causality and high generalizability of findings (Aguinis & Bradley, 2014), studies examining how accurately our results translate to a real-life setting need to be conducted. Therefore, we recommend the investigation of work design in an assembly setting before and after the IAS is implemented, and its consequences for attitudinal work outcomes, such as work motivation or job satisfaction. This would also allow investigation of how technological interferences of the system that affect productivity and accuracy (Bortolini et al., 2021) influence the perception of IASs (Walczok & Bipp, 2023). Furthermore, future studies in a real production setting might investigate whether and how employees proactively react to adapt work design after the implementation of innovative technologies (Gagné et al., 2022).

Second, despite presenting a more complex assembly process, MWCs ratings were low across all experimental conditions in both studies. Even more difficult assembly processes should be used in future studies to further counteract floor effects in MWCs ratings. However, these did not prevent us from identifying reductions in the already low autonomy (in the work without IASs) by the implementation of IASs. The restricting effect of IAS on autonomy could be even stronger in magnitude in more difficult assembly processes that also provide more autonomy. Additionally, subsequent studies should focus on how self-adaptive IASs that reduce the level of support based on workers ' skill level provides a solution to counteract restricted autonomy.

Third, although we measured MWCs with a validated German version of the WDQ (Stegmann et al., 2010), internal consistency reliabilities were low for work scheduling autonomy in Study 1, and specialization in both studies. Hence, results regarding work scheduling autonomy and specialization should be interpreted with caution.

Fourth, the generalizability of the effect of the investigated IAS on MWCs to other IASs remains an empirical question. Given that we based our hypotheses on the functions of the specific IAS in question, the generalizability of the results may be limited to other cognitive-assistive IASs with a low level of support that are characterized by similar functions (providing feedback for subsequent assembly steps and instructing assembly workers with sensitive in situ material). These might include pick-to-light systems or projection- and augmentation-based IASs (Walczok & Bipp, 2023). Finally, we encourage the experimental manipulation of technological design factors (such as the extent of feedback and in situ projections) to attribute specific effects to specific functions of technologies.

Conclusion

By identifying enhanced feedback from job and information processing, as well as restricted work scheduling, decision-making, and work methods autonomy by working with a cognitive-assistive IAS in assembly, our two studies provide vital causal evidence of their contradictory effects regarding motivational work design. Our results suggest no effect of the IAS on the knowledge characteristics job complexity, problem solving, specialization, and skill variety. Despite being developed to support assembly workers in highly dynamic product changes due to individual customer requests, the effect of IASs on MWCs does not interact with the extent of task rotation. Our results stress the importance of technology for work design and highlight the need for further refinement of work design theories to make accurate predictions of positive and/or negative effects.

References

Aguinis, H., & Bradley, K. J. (2014). Best practice recommendations for designing and implementing experimental vignette methodology studies. *Organizational Research Methods, 17*(4), 351-371. https://doi.org/10.1177/1094428114547952

Apt, W., Bovenschulte, M, Priesack, K., & Hartmann, E. A. (2018). *Einsatz von digitalen Assistenzsystemen im Betrieb* [*Use of digital assistance systems in practice*]. Bundesministerium für Arbeit und Soziales. https://www.iit-berlin.de/iit-docs/0b0a71d0ed949269fa39e2b38555fde_Einsatz-von-digitalen-Assistenzsystemen-im-Betrieb.pdf

Baethge-Kinsky, V. (2020). Digitized Industrial Work: Requirements, Opportunities, and Problems of Competence Development. *Frontiers in Sociology*, *5*, 33. https://doi.org/10.3389/fsoc.2020.00033

Bipp, T., Oberländer, M., & Walczok, M. (2021). *The dark side of autonomy: The role of autonomy facets and work intensification*. Paper presented at the Academy of Management Meeting, 2021, Seattle.

Blumberg, V. S. L., & Kauffeld, S. (2020). Anwendungsszenarien und Technologiebewertung von digitalen Werkerassistenzsystemen in der Produktion – Ergebnisse einer Interview-Studie mit Experten aus der Wissenschaft, der Politik und der betrieblichen Praxis [Application scenarios and technology assessment of smart wearables and mobile smart devices in industrial pracice]. *Gruppe. Interaktion. Organisation. Zeitschrift für Angewandte Organisationspsychologie (GIO)*, *51*(1), 5-24. https://doi.org/10.1007/s11612-020-00506-0

Bortolini, M., Faccio, M., Galizia, F. G., Gamberi, M., & Pilati, F. (2021). Adaptive automation assembly systems in the industry 4.0 era: A reference framework and full-scale prototype. *Applied Sciences*, *11*(3), 1256. https://doi.org/10.3390/app11031256

Cerasoli, C., P., Alliger, G. M., Donsbach, J. S., Mathieu, J. E., Tannenbaum, S. I., & Orvis, K. A. (2018). Antecedents and outcomes of informal learning behaviors: A meta-analysis. *Journal of Business and Psychology, 33*, 203-230. https://doi.org/10.1007/s10869-017-9492-y

Deci, E. L., & Ryan, R., M. (1985). *Intrinsic Motivation and Self-Determination in Human Behavior*. Springer. https://doi.org/10.1007/978-1-4899-2271-7

Dierdorff, E. C., & Wilson, M. A. (2003). A meta-analysis of job analysis reliability. *Journal of Applied Psychology*, *88*(4), 635-646. https://doi.org/10.1037/0021-9010.88.4.635

Doolani, S., Wessels, C., Kanal, V., Sevastopoulos C., Jaiswal, A., Nambiappan, H., & Makedon, F. (2020). A Review of Extended Reality (XR) Technologies for Manufacturing Training. *Technologies*, *8*(4), 77. https://doi.org/10.3390/technologies8040077

Egger-Lampl, S., Gerdenitsch, C., Deinhard, L., Schatz, R., & Hold, P. (2019, June). Assembly Instructions with AR: Towards measuring Interactive Assistance Experience in an Industry 4.0 Context. In *2019 Eleventh International Conference on Quality of Multimedia Experience (QoMEX)*, (pp.1-3). IEEE. https://doi.org/10.1109/QoMEX.2019.8743266

Gagné, M., Parker, S. K., Griffin, M. A., Dunlop, P. D., Knight, C., Klonek, F. E., & Parent-Rocheleau, X. (2022). Understanding and shaping the future of work with self-determination theory. *Nature Reviews Psychology*, 1-15. https://doi.org/10.1038/s44159-022-00056-w

Humphrey, S. E., Nahrgang, J. D., & Morgeson, F. P. (2007). Integrating motivational, social, and contextual work design features: A meta-analytic summary and theoretical extension of the work design literature. *Journal of Applied Psychology*, *92*(5), 1332-1356. https://doi.org/10.1037/0021-9010.92.5.1332

Javdan, M., Ghasemaghaei, M., & Abouzahra, M. (2023). Psychological barriers of using wearable devices by seniors: A mixed-methods study. *Computers in Human Behavior*, *141*. https://doi.org/10.1016/j.chb.2022.107615

Jetter, J., Eimecke, J., & Rese, A. (2018). Augmented reality tools for industrial applications: What are potential key performance indicators and who benefits?. *Computers in Human Behavior*, *87*, 13-33. https://doi.org/10.1016/j.chb.2018.04.054

Jung, J., Hubert, A., Doll, K., Kröhn, M., & Stadler, J. (2022, March 9-11). *Prozessinnovation: Selbstlernendes Assistenzsystem für die manuelle Montage* [*Process innovation: Self-learning assistance system for manual assembly*]. 18. AALE-Konferenz, Pforzheim. https://doi.org/10.33968/2022.20

Keller, T., Bayer, C., Bausch, P., & Metternich, J. (2019). Benefit evaluation of digital assistance systems for assembly workstations. *Procedia CIRP, 81*, 441-446. https://doi.org/10.1016/0030-5073(83)90118-6
Knight, C., & Parker, S. K. (2021). How work redesign interventions affect performance: An evidence-based model from a systematic review. *Human relations, 74*(1), 69-104. https://doi.org/10.1177/0018726719865604
Krzywdzinski, M., Butollo, F., Flemming, J., Gerber, C., Wandjo, D., Delicat, N., Herzog, L., Bovenschulte, M., & Nerger, M. (2022). *The Growing Gap Between Pioneers and Laggards: Digitalization, automation, and organizational change in the wake of the COVID-19-crisis in Germany*. 25, Weizenbaum Series. Berlin: Weizenbaum Institute for the Networked Society. https://doi.org/10.34669/WI.WS/25
Luger, T., Bär, M., Seibt, R., Rieger, M. A., & Steinhilber, B. (2023). Using a back exoskeleton during industrial and functional tasks – Effects on muscle activitiy, posture, performance, usability, and wearer discomfort in a laboratory trial. *Human Factors, 65*(1), 5-21. https://doi.org/10.1177/00187208211007267
Mark, B. G., Hofmayer, S., Rauch, E., & Matt, D. T. (2019). Inclusion of workers with disabilities in production 4.0: Legal foundations in Europe and potentials through worker assistance systems. *Sustainability, 11*(21), 5978. https://doi.org/10.3390/su11215978
Mark, B. G., De Marchi, M., Rauch, R., & Matt, D.T. (2022). Expert-based Classification of Worker Assistance Systems in Manufacturing Considering the Human. In *Proceedings of the 3rd Internation Conference on Innovative Intelligent Industrial Production and Logistics (IN4PL 2022)* (pp. 184-191). https://doi.org/10.5220/0011591200003329
Marklin Jr, R. W., Toll, A. M., Bauman, E. H., Simmins, J. J., LaDisa Jr, J. F., & Cooper, R. (2022). Do Head-Mounted Augmented Reality Devices Affect Muscle Activity and Eye Strain of Utility Workers Who Do Procedural Work? Studies of Operators and Manhole Workers. *Human Factors, 64*(2), 305-323. https://doi.org/10.1177/0018720820943710
Mlekus, L., & Maier, G. W. (2021). More hype than substance? A meta-analysis on job and task rotation. *Frontiers in Psychology, 12*. 633530. https://doi.org/10.3389/fpsyg.2021.633530
Mlekus, L., Lehmann, J., & Maier, G. W. (2022). New work situations call for familiar work design methods: Effects of task rotation and how they are mediated in a technology-supported workplace. *Frontiers in Psychology, 13*, 1-21. https://doi.org/10.3389/fpsyg.2022.935952
Morgeson, F. P., & Humphrey, S. E. (2006). The Work Design Questionnaire (WDQ): Developing and validating a comprehensive measure for assessing job design and the nature of work. *Journal of Applied Psychology, 91*(6), 1321-1339. https://doi.org/10.1037/0021-9010.91.6.1321
Oberländer, M., Beinicke, A., & Bipp, T. (2020). Digital competencies: A review of the literature and applications in the workplace. *Computers & Education, 146*, 103752. https://doi.org/10.1016/j.compedu.2019.103752
Parker, S. K., & Grote, G. (2022). Automation, Algorithms, and Beyond: Why Work Design Matters More Than Ever in a Digital World. *Applied Psychology*. https://doi.org/10.1111/apps.12241
Radowski, R., Herrema, J., & Oliver, J. (2015). Augmented reality-based manual assembly support with visual features for different degrees of difficulty. *International Journal of Human-Computer Interaction, 31*(5), 337-349. https://doi.org/10.1080/10447318.2014.994194
Roetzel, P. G. (2019). Information overload in the information age: a review of the literature from business administration, business psychology, and related disciplines with a bibliometric approach and framework development. *Business research, 12*(2), 479-522. https://doi.org/10.1007/s40685-018-0069-z
Stegmann, S., Dick, R., van, Ullrich, J., Charalambous, J., Menzel, B., Egold, N., & Wu T. T.-C. (2010). Der Work Design Questionnaire: Vorstellung und erste Validierung einer deutschen Version [The Work Design Questionnaire: Introduction and validation of a German version]. *Zeitschrift für Arbeits- und Organisationspsychologie A&O, 54*(1), 1-28. https://doi.org/10.1026/0932-4089/a000002
Stockinger, C., Stuke, F., & Subtil, I. (2021). User-centered development of a worker guidance system for a flexible production line. *Human Factors and Ergonomics in Manufacturing & Service Industries, 31*(5), 532-545. https://doi.org/10.1002/hfm.20901
Tao, H., Cheng, L., Qiu, J., & Stojanovic, V. (2022). Few shot cross equipmet fault diagnosis method

based on parameter optimization and feature mertic. *Measurement Science and Technology 33*(11), 115005.

Volz, K., Yang, E., Dudley, R., Lynch, E., Dropps, M., & Dorneich, M. C. (2016, September). An evaluation of cognitive skill degradation in information automation. *Proceedings of the human factors and ergonomics society annual meeting*, *60*(1), 191-195. https://doi.org/10.1177/1541931213601043

Walczok, M., & Bipp, T. (2023). Investigating the effect of intelligent assistance systems on motivational work characteristics in assembly. *Journal of Intelligent Manufacturing*, 1-14. https://doi.org/10.1007/s10845-023-02086-4

Walsh, S. M., & Strano, M. S. (2018). *Robotic systems and autonomous platforms: Advances in materials and manufacturing.* Woodhead Publishing.

Waschull, S., Bokhorst, J. A. C., Molleman, E., & Wortmann, J. C. (2020). Work design in future industrial production: Transforming towards cyber-physical systems. *Computers & Industrial Engineering, 139*, 105679. https://doi.org/10.1016/j.cie.2019.01.053

Watson, G., Butterfield, J., Curran, R., & Craig, C. (2010). Do dynamic work instructions provide an advantage over static instructions in a small scale assembly task?. *Learning and Instruction, 20*(1), 84-93. https://doi.org/10.1016/j.learninstruc.2009.05.001

Xu, Z., Li, X, & Stojanovic, V. (2021). Exponential stability of nonlinear state-dependent impulsive systems with applications. *Nonlinear Analysis: Hybrid Systems, 42,* 101088. https://doi.org/10.1016/j.nahs.2021.101088

Yigitbas, E., Sauer, S., & Engels, G. (2023). Self-Adaptive Digital Assistance Systems for Work 4.0. In B. Vogel-Heuser, & M. Wimmer (Eds.) *Digital Transformation: Core Technologies and Emerging Topics from a Computer Science Perspective* (pp. 475-496). Springer. https://doi.org/10.1007/978-3-662-65004-2_19

Table 1

Definition and exemplary items for investigated motivational work characteristics (MWCs) based on the work design questionnaire (WDQ)

	Definition and exemplary items (Morgeson & Humphrey, 2006, pp. 1323-1338)
Task characteristics	
Feedback from job	"degree to which the job provides direct and clear information about the effectiveness of task performance" *"The job itself provides feedback on my performance."*
Work scheduling autonomy	"extent to which a job allows freedom independence, and discretion to schedule work" *"The job allows me to plan how I do my work."*
Decision-making autonomy	"extent to which a job allows freedom independence, and discretion to […] make decisions" *"The job allows me to make a lot of decisions on my own."*
Work methods autonomy	"extent to which a job allows freedom independence, and discretion to […] choose the methods used to perform tasks" *"The job allows me to decide on my own how to go about doing my work"*
Knowledge characteristics	
Information processing	"degree to which a job requires attending to and processing data or other information" *"The job requires me to analyze a lot of information."*
Job complexity	"extent to which the tasks on a job are complex and difficult to perform" *"The job comprises relatively uncomplicated tasks." (r)*
Problem solving	"degree to which a job requires unique ideas or solutions" *"The job requires me to be creative."*
Specialization	"extent to which a job involves performing specialized tasks or possessing specialized knowledge and skill" *"The job requires a depth of knowledge and expertise."*
Skill variety	"extent to which a job requires an individual to use a variety of different skills to complete the work" *"The job requires a variety of skills."*

Notes. (r) = reverse scored. Exemplary items in italics. Definitions (pp. 1323-1324) and exemplary items (pp. 1337-1338) stem from Morgeson and Humphrey (2006).

Table 2

Reliabilities, cell means, and standard deviations in motivational work characteristic ratings in work without IAS and work with IAS (Study 1)

	Work without IAS (n = 76)		Work with IAS (n = 93)		
	M	*SD*	*M*	*SD*	Hypothesis and t-test
Feedback from job (.87)	3.50	1.01	4.03	0.82	**H1:** $t(167) = -3.709$, $p < .001$, $d = -0.573$***
Information processing (.81)	1.84	0.70	2.06	0.75	**H2:** $t(167) = -1.984$, $p = .049$, $d = -0.307$*
Work scheduling autonomy[a] (.68)	1.93	0.78	1.55	0.66	**H3a:** $t(146.69) = 3.347$, $p = .001$, $d = 0.527$**
Decision-making autonomy[a] (.82)	1.55	0.74	1.19	0.33	**H3b:** $t(100.15) = 3.887$, $p < .001$, $d = 0.643$***
Work methods autonomy[a] (.79)	1.55	0.64	1.27	0.42	**H3c:** $t(124.98) = 3.346$, $p = .001$, $d = 0.538$**
Job complexity (.83)	1.70	0.67	1.72	0.79	**H4a:** $t(167) = -0.127$, $p = .899$, $d = -0.020$
Problem solving (.78)	1.38	0.52	1.35	0.45	**H4b:** $t(167) = 0.270$, $p = .787$, $d = 0.042$
Specialization (.66)	2.08	0.69	2.04	0.63	**H4c:** $t(167) = 0.382$, $p = .703$, $d = 0.059$
Skill variety (.82)	1.79	0.58	1.73	0.66	**H5a/b:** $t(167) = 0.667$, $p = .506$, $d = 0.103$

Notes. Cronbach's alpha in parentheses. Abbreviation: IAS, Intelligent assistance system. [a] We conducted the Welch tests to test differences in autonomy facets between work without IAS and work with IAS since variance homogeneity was not given. $N = 169$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table 3

Reliabilities, cell means, and standard deviations in motivational work characteristic ratings in the four experimental conditions (Study 2)

	Conditions								
	Work without IAS		Work with IAS		Overall means				
	No TR *M* (SD)	TR *M* (SD)	No TR *M* (SD)	TR *M* (SD)	Work without IAS *M* (SD)	Work with IAS *M* (SD)	No TR *M* (SD)	TR *M* (SD)	Overall mean *M* (SD)
n	51	40	41	44	91	85	92	84	176
FB (.86)	3.17 (1.09)	3.21 (1.13)	4.00 (1.02)	4.29 (0.74)	3.19 (1.10)	4.15 (0.89)	3.54 (1.13)	3.77 (1.09)	3.65 (1.11)
IP (.80)	1.64 (0.68)	1.61 (0.67)	1.85 (0.66)	1.82 (0.70)	1.63 (0.67)	1.84 (0.68)	1.74 (0.68)	1.72 (0.69)	1.73 (0.68)
WSA (.74)	1.80 (0.71)	1.70 (0.72)	1.42 (0.68)	1.36 (0.57)	1.76 (0.71)	1.39 (0.62)	1.63 (0.72)	1.52 (0.66)	1.58 (0.69)
DMA (.86)	1.41 (0.55)	1.39 (0.65)	1.19 (0.58)	1.23 (0.47)	1.40 (0.59)	1.21 (0.52)	1.32 (0.57)	1.31 (0.56)	1.31 (0.57)
WMA (.86)	1.51 (0.60)	1.48 (0.70)	1.27 (0.59)	1.27 (0.51)	1.49 (0.64)	1.27 (0.55)	1.40 (0.61)	1.37 (0.61)	1.39 (0.61)
JC (.82)	1.58 (0.53)	1.69 (0.89)	1.57 (0.67)	1.51 (0.57)	1.63 (0.71)	1.54 (0.62)	1.58 (0.59)	1.60 (0.74)	1.59 (0.66)
PS (.70)	1.40 (0.54)	1.39 (0.52)	1.34 (0.45)	1.32 (0.37)	1.40 (0.53)	1.33 (0.41)	1.37 (0.50)	1.35 (0.45)	1.36 (0.47)
SP (.65)	1.84 (0.59)	1.96 (0.65)	2.00 (0.53)	2.07 (0.69)	1.90 (0.62)	2.03 (0.62)	1.91 (0.57)	2.02 (0.67)	1.96 (0.62)
SV (.89)	1.72 (0.66)	1.68 (0.77)	1.59 (0.65)	1.62 (0.64)	1.70 (0.71)	1.61 (0.64)	1.66 (0.66)	1.65 (0.70)	1.65 (0.67)

Notes. Cronbach's alpha is in parentheses in the first column. Abbreviations: IAS, intelligent assistance system; TR,task rotation; FB, feedback from job; IP, information processing; WSA, work scheduling autonomy; DMA, decision-making autonomy; WMA, work methods autonomy; JC, job complexity; PS, problem solving; SP, specialization; SV, skill variety.

Table 4

ANOVA results for motivational work characteristics (Study 2)

ANOVA results	Factor		
	IAS	Task rotation	Interaction IAS x Task rotation
Feedback from job	**H1:** $F(1, 172) = 39.216$, $p < .001$, $\eta_p^2 = 0.186$***	$F(1, 172) = 1.145$, $p = .286$, $\eta_p^2 = 0.007$	$F(1, 172) = 0.669$, $p = .414$, $\eta_p^2 = 0.004$
Information processing	**H2:** $F(1, 172) = 4.345$, $p = .039$, $\eta_p^2 = 0.025$*	**H7:** $F(1, 172) = 0.102$, $p = .750$, $\eta_p^2 = 0.001$	**H8:** $F(1, 172) = 0.001$, $p = .976$, $\eta_p^2 = 0.000$
Work scheduling autonomy	**H3a:** $F(1, 172) = 12.734$, $p < .001$, $\eta_p^2 = 0.069$***	$F(1, 172) = 0.705$, $p = .402$, $\eta_p^2 = 0.004$	$F(1, 172) = 0.034$, $p = .855$, $\eta_p^2 = 0.000$
Decision-making autonomy	**H3b:** $F(1, 172) = 5.210$, $p = .024$, $\eta_p^2 = 0.029$*	$F(1, 172) = 0.014$, $p = .906$, $\eta_p^2 = 0.000$	$F(1, 172) = 0.125$, $p = .724$, $\eta_p^2 = 0.001$
Work methods autonomy	**H3c:** $F(1, 172) = 5.878$, $p = .016$, $\eta_p^2 = 0.033$*	$F(1, 172) = 0.028$, $p = .868$, $\eta_p^2 = 0.000$	$F(1, 172) = 0.046$, $p = .831$, $\eta_p^2 = 0.000$
Job complexity	**H4a:** $F(1, 172) = 0.915$, $p = .340$, $\eta_p^2 = 0.005$	$F(1, 172) = 0.056$, $p = .813$, $\eta_p^2 = 0.000$	$F(1, 172) = 0.818$, $p = .367$, $\eta_p^2 = 0.005$
Problem solving	**H4b:** $F(1, 172) = 0.810$, $p = .369$, $\eta_p^2 = 0.005$	$F(1, 172) = 0.032$, $p = .858$, $\eta_p^2 = 0.000$	$F(1, 172) = 0.000$, $p = .984$, $\eta_p^2 = 0.000$
Specialization	**H4c:** $F(1, 172) = 1.959$, $p = .163$, $\eta_p^2 = 0.011$	$F(1, 172) = 1.000$, $p = .319$, $\eta_p^2 = 0.006$	$F(1, 172) = 0.074$, $p = .785$, $\eta_p^2 = 0.000$
Skill variety	**H5a/b:** $F(1, 172) = 0.809$, $p = .370$, $\eta_p^2 = 0.005$	**H6:** $F(1, 172) = 0.007$, $p = .931$, $\eta_p^2 = 0.000$	**RQ:** $F(1, 172) = 0.128$, $p = .721$, $\eta_p^2 = 0.001$

Notes. $N = 176$. Abbreviations: ANOVA, analysis of variance; IAS, intelligent assistance system.

Figure 1

The research model based on parts of the theoretical model by Gagné et al. (2022)

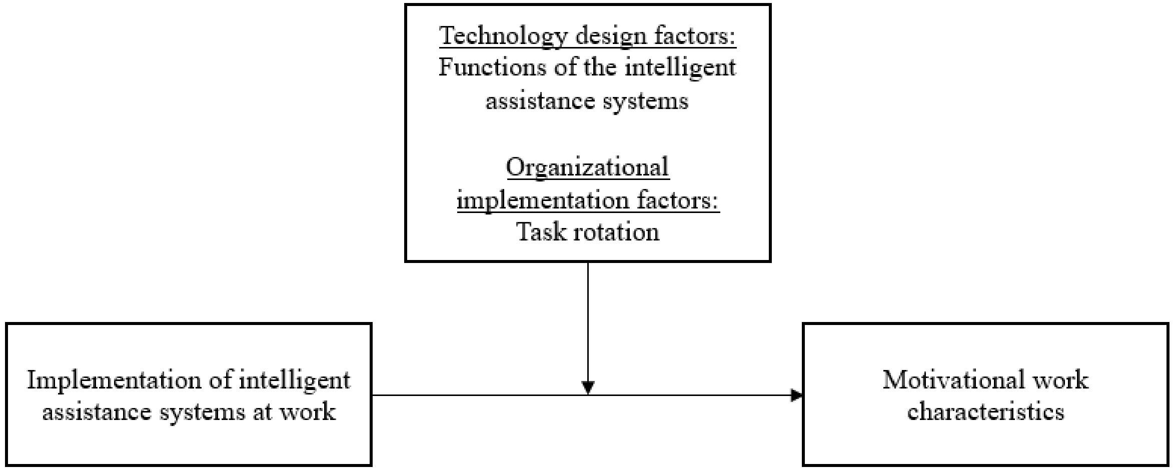
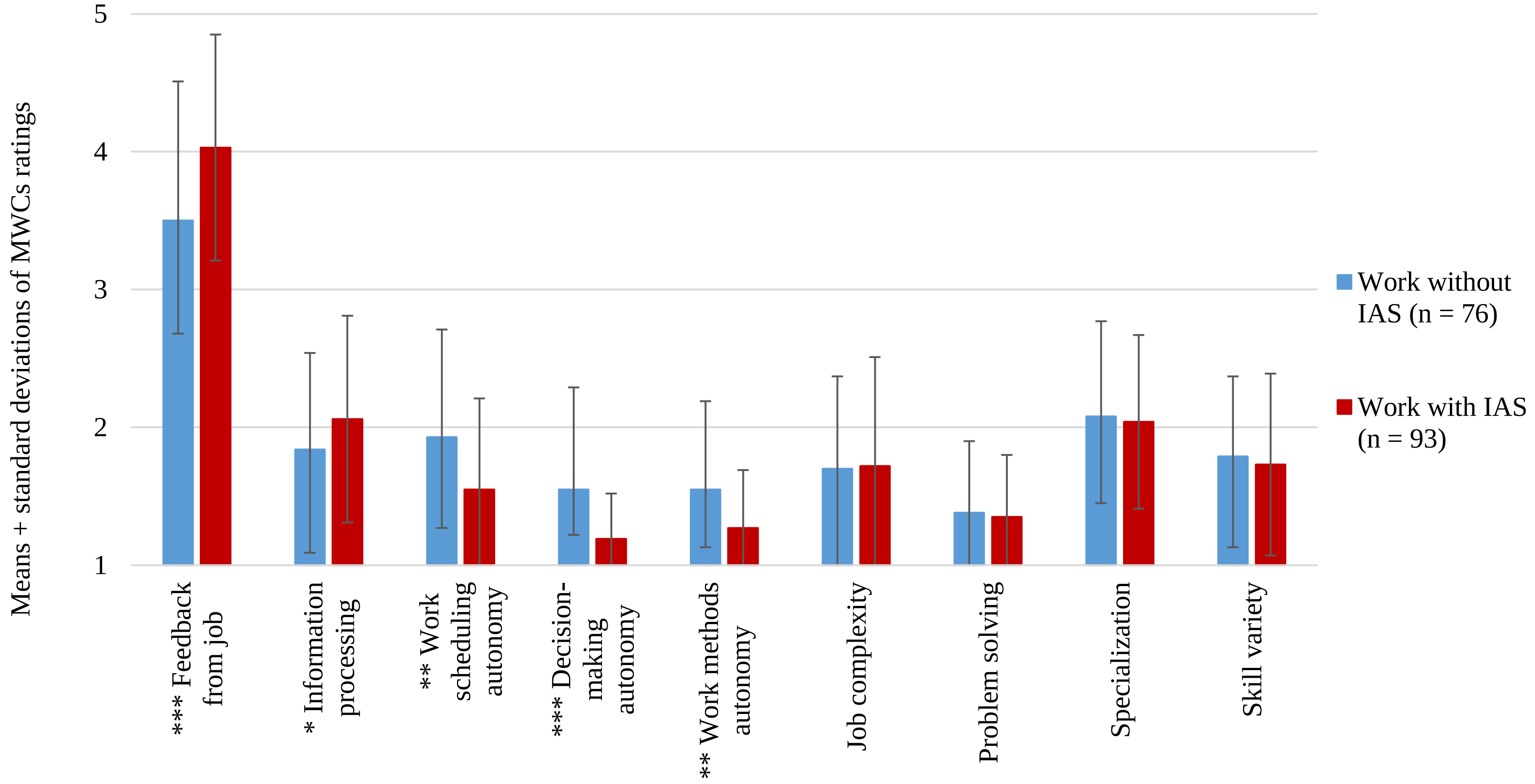


Figure 2

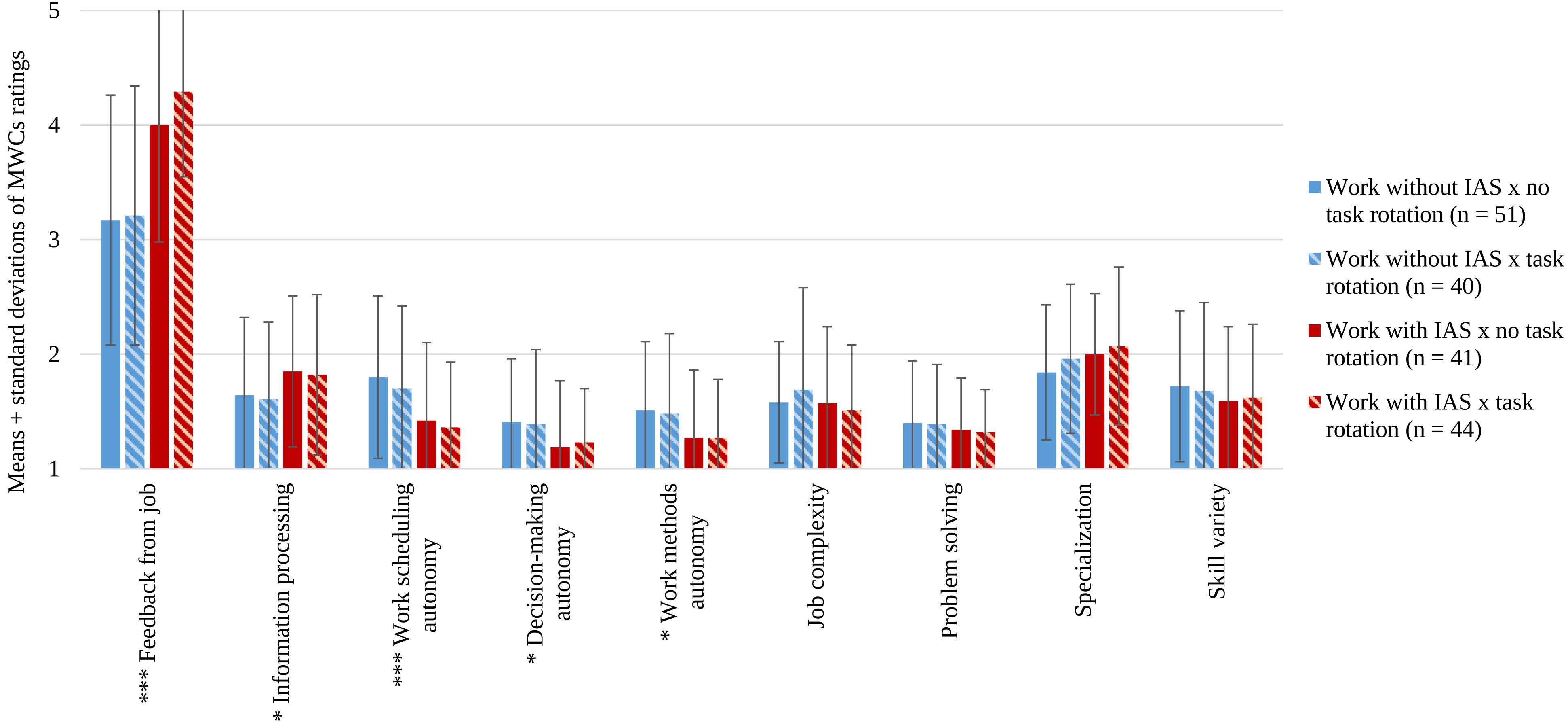
Motivational work characteristics ratings according to the experimental conditions (Study 1)



Notes. Error bars display standard deviations. * $p < .05$. ** $p < .01$. *** $p < .001$. Abbreviations: IAS, Intelligent assistance system; MWCs, motivational work characteristics.

Figure 3

Motivational work characteristic ratings according to the experimental conditions (Study 2)



Notes. Flagged variables represent the main effects of the IAS. Error bars display standard deviations. * $p < .05$. *** $p < .001$. Abbreviations: IAS, intelligent assistance system; MWCs, motivational work characteristics.

Electronic Supplementary Material (ESM)

Appendix A

Study 1: Vignette of the condition work without IAS (translated from German)

Read the following job description carefully. Look at the fictitious workplace and try to put yourself in the situation.

Imagine you are an employee in a medium-sized company, the Montage GmbH. You work in the assembly department and assemble boxes at the assembly workstations in the production halls of Montage GmbH.

The picture shows an exemplary assembly workstation. On the work surface there is the box to be assembled and a wooden block with the required screws. The work is performed with a screwdriver and a scanner. After every 2 hours you assemble a different product.

Appendix B

Study 1: Vignette of the conditions work with IAS (translated from German)

Read the following job description carefully. Look at the fictitious workplace and try to put yourself in the situation.

Imagine you are an employee in a medium-sized company, the Montage GmbH. You work in the assembly department and assemble boxes at the assembly workstations in the production halls of Montage GmbH.

The picture shows an exemplary assembly workstation. On the work surface there is the box to be assembled and a wooden block with the required screws. The work is performed with a screwdriver and a scanner. After every 2 hours you assemble a different product.

You will be supported by a digital assistance system while performing your job.

It has the following features:

- It guides you through each assembly step with the help of short videos, which are displayed on the work surface with the help of a beamer.
- For this purpose, your hand and eye movements are recorded using a 3D camera and three small, black eye-tracking cameras.
- If the assembly steps are performed correctly, the video lights up green on the work surface; if they are performed incorrectly, the video lights up red.
- The progress of your workflows is displayed in the form of a progress bar above the videos with the assembly steps on the work surface.
- Alternative workflows and assembly sequences can be automatically observed and taught using machine learning and artificial intelligence. This allows the system to constantly adapt to the user and other work steps, so that the system and the user can learn from each other.

Appendix C

Study 2: Vignette of the condition work without IAS (translated from German)

Read the following job description carefully. Look at the fictitious workplace and try to put yourself in the situation.

Imagine you are an employee in a medium-sized company, the Montage GmbH. You work in the assembly department and assemble boxes at the assembly workstations in the production halls of Montage GmbH.

The picture shows an exemplary assembly workstation. On the work surface there is the box to be assembled and a wooden block with the required screws. The work is performed with a screwdriver and a scanner.

Appendix D

Study 2: Vignette of the conditions work with IAS (translated from German)

Read the following job description carefully. Look at the fictitious workplace and try to put yourself in the situation.

Imagine you are an employee in a medium-sized company, the Montage GmbH. You work in the assembly department and assemble boxes at the assembly workstations in the production halls of Montage GmbH.

The picture shows an exemplary assembly workstation. On the work surface there is the box to be assembled and a wooden block with the required screws. The work is performed with a screwdriver and a scanner.

You will be supported by a digital assistance system while performing your job.

It has the following features:

- It guides you through each assembly step with the help of short videos, which are displayed on the work surface with the help of a beamer.
- For this purpose, your hand and eye movements are recorded using a 3D camera and three small, black eye-tracking cameras.
- If the assembly steps are performed correctly, the video lights up green on the work surface; if they are performed incorrectly, the video lights up red.
- The progress of your workflows is displayed in the form of a progress bar above the videos with the assembly steps on the work surface.
- Alternative workflows and assembly sequences can be automatically observed and taught using machine learning and artificial intelligence. This allows the system to constantly adapt to the user and other work steps, so that the system and the user can learn from each other.

Appendix E

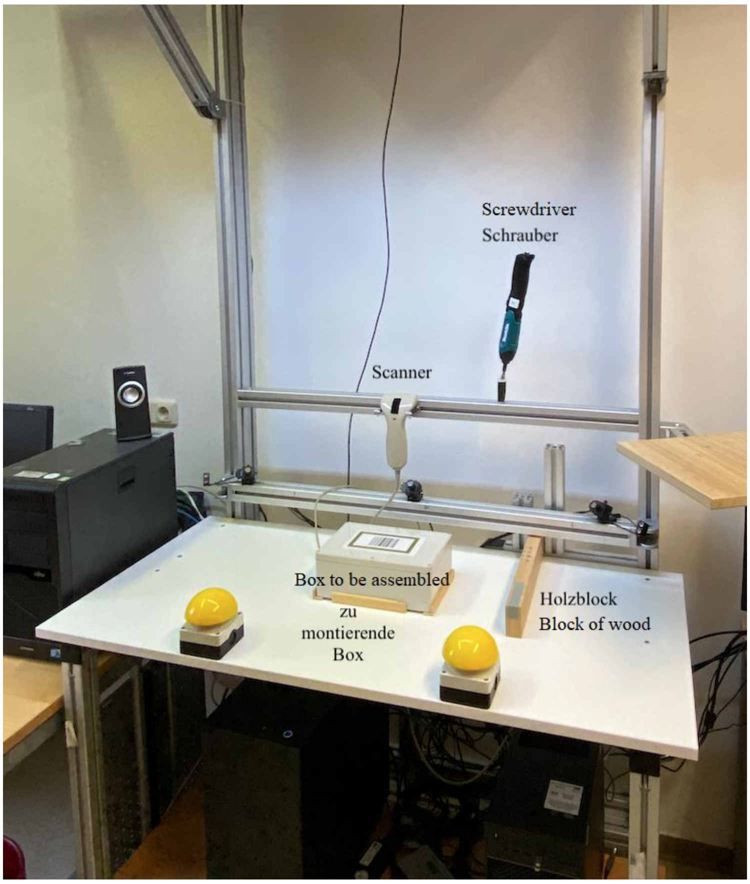
Study 2: Vignette of the condition work without IAS and task rotation (translated from German)

Read the following job description carefully. Look at the fictitious workplace and try to put yourself in the situation.

Imagine you are an employee in a medium-sized company, the Montage GmbH. You work in the assembly department and assemble boxes at the assembly workstations in the production halls of Montage GmbH.

The picture shows an exemplary assembly workstation. On the work surface there is the box to be assembled and a wooden block with the required screws. The work is performed with a screwdriver and a scanner.

After one hour each, you switch with a colleague to a neighboring assembly station and assemble a different product in order to process individual customer requests. After one hour, you switch again with another colleague and assemble another product. Your second station looks like this:



Now there is a box to be assembled and a block of wood with the necessary screws on the work surface. The work is done with a screwdriver and a scanner.

Appendix F

Study 2: Vignette of the conditions work with IAS and task rotation (translated from German)

Read the following job description carefully. Look at the fictitious workplace and try to put yourself in the situation.

Imagine you are an employee in a medium-sized company, the Montage GmbH. You work in the assembly department and assemble boxes at the assembly workstations in the production halls of Montage GmbH.

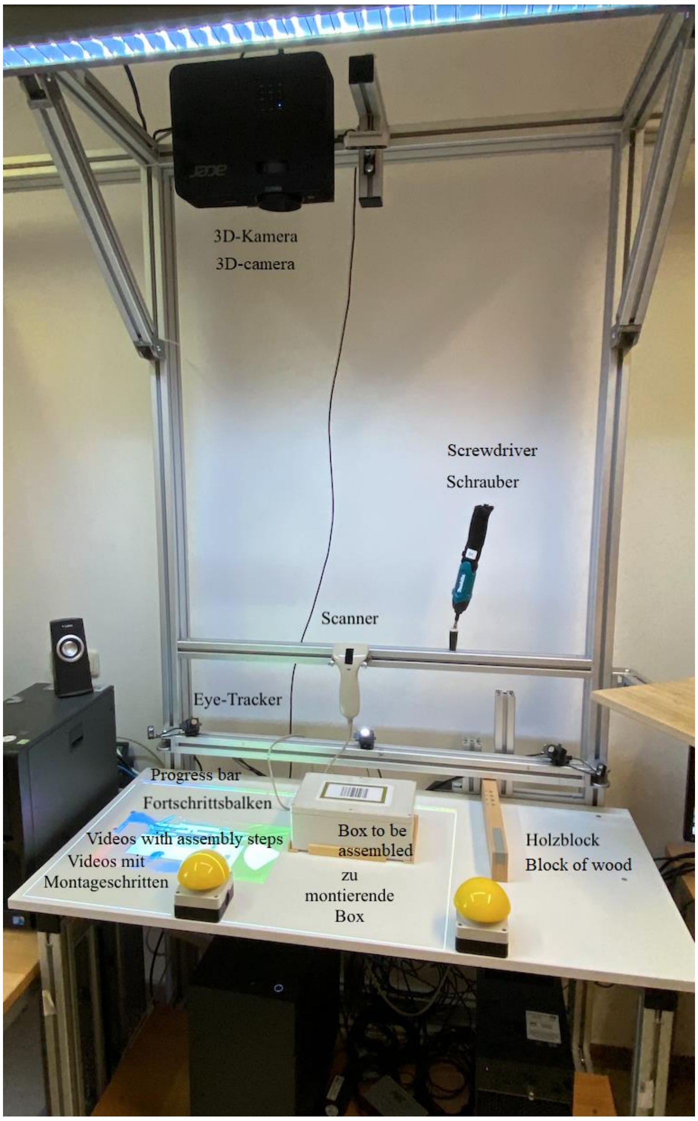
The picture shows an exemplary assembly workstation. On the work surface there is the box to be assembled and a wooden block with the required screws. The work is performed with a screwdriver and a scanner.

You will be supported by a digital assistance system while performing your job.

It has the following features:

- It guides you through each assembly step with the help of short videos, which are displayed on the work surface with the help of a beamer.
- For this purpose, your hand and eye movements are recorded using a 3D camera and three small, black eye-tracking cameras.
- If the assembly steps are performed correctly, the video lights up green on the work surface; if they are performed incorrectly, the video lights up red.
- The progress of your workflows is displayed in the form of a progress bar above the videos with the assembly steps on the work surface.
- Alternative workflows and assembly sequences can be automatically observed and taught using machine learning and artificial intelligence. This allows the system to constantly adapt to the user and other work steps, so that the system and the user can learn from each other.

After one hour each, you switch with a colleague to a neighboring assembly station and assemble a different product in order to process individual customer requests. After one hour, you switch again with another colleague and assemble another product. Your second station looks like this:



Now there is a box to be assembled and a block of wood with the necessary screws on the work surface. The work is done with a screwdriver and a scanner.

You will again be supported by the digital assistant system when performing the activity. It has the same functions as in the previous workflow.

Chapter 4 – Paper 3

One, two, new technology is coming for you – Construct validation of job insecurity due to smart technology, artificial intelligence, robotics, and automation

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Abstract

Smart technologies, artificial intelligence, robotics, and automation (STARA) can revolutionize the labor market by substituting human labor. STARA Awareness has been introduced to capture employees' affective appraisal of the impact of STARA on their employment without a thorough validation and overarching theoretical framework. Therefore, we examined the internal structure of the suggested measurement instrument, the differentiation from cognitive and affective job insecurity (JI), potential antecedents, and its long-term trend. We conducted two cross-sectional (N_1 = 215, N_2 = 224) and one longitudinal study (N_3 = 233) with German employees from diverse branches. Based on content criticism and poor measurement model fit in Study 1, we adapted the questionnaire and redefined the construct in terms of affective automation-related job insecurity (AAJI). Our results indicate that AAJI is weakly positively related to cognitive and affective JI but empirically different. We identified the objective substitution potential of occupation, the use of STARA as positive predictors, and core self-evaluations as a negative predictor of AAJI. Latent growth curve models reveal no linear change of AAJI over one year but different trajectories as a function of use of STARA. Thus, AAJI represents a novel construct with its distinct nomological net and high stability.

Keywords: *STARA Awareness, job insecurity, affective automation-related job insecurity, substitution potential, core self-evaluations*

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One, two, new technology is coming for you – Construct validation of job insecurity due to smart technology, artificial intelligence, robotics, and automation

From autonomous self-service checkouts in retail, algorithmic decision making, autonomous buses and trains to ChatGPT – smart technologies, artificial intelligence, robotics, and automation (STARA) (Brougham & Haar, 2018; 2020) have the potential to fundamentally revolutionize the labor market. Contrary to previous waves of industrialization, in which primary and secondary sectors were mainly affected by downsizing (Dennis, 1978), the tertiary sector is increasingly downsized by changes in Industry 4.0 too (Brynjolfsson & McAfee, 2011). The automation of work processes was further accelerated in the wake of the COVID-19 pandemic (Krzywdzinski et al., 2022). Building on evidence by Yam and colleagues (2023) that exposure to robots triggers employee's *job insecurity* (JI), the ongoing digitalization does not only change the labor market but also fundamentally affects central employee attitudes. To capture how employees appraise the impact of new technologies on their employment, Brougham and Haar (2018) introduced the concept of *STARA Awareness*. While they provided initial empirical insights into correlations of this affective and cognitive elements encompassing construct with negative work-related outcomes (e.g., burnout, turnover intentions), thorough research on the nature of this construct, its nomological net including antecedents, and its temporal stability is still scarce. The number of publications on this timely construct and its outcomes is rising, while a rigorous construct validation and separation from closely related constructs is missing so far. In addition, as STARA Awareness focusses on the substitution of whole jobs, it provides an oversimplistic view on the digital transformation of the labor market, as it does not consider the changes of individual work tasks due to new technologies. Therefore, an in-depth investigation and refinement of this suggested construct is necessary to develop a nuanced understanding of how technological advances impact employees.

Therefore, we conducted three studies with the overall aim to validate the timely STARA Awareness and provide a theoretical basis by applying a comprehensive model of JI (Shoss, 2017) to the construct. First, we examine its internal structure and provide an extension of the construct and questionnaire by also including the substitution of core tasks within an occupation instead the substitution of whole jobs. Second, we separate STARA Awareness from the established, constructs of cognitive and affective JI, given the suggested overlap of the constructs. Third, we investigate whether we can transfer antecedents (indicators for technological change and individual differences) from JI research to STARA Awareness. Fourth, we examine its long-term trend over one year by shedding light on how potential antecedents predict the intercept and trajectory.

By this, we contribute to the nuanced understanding of STARA Awareness and to the development of a comprehensive theory that advances research focusing on how humans perceive technologies in an increasingly digitalized world of work. Following the suggestions by Yam and colleagues (2023) we do not only consider "robots with physical forms" (Yam et al., 2023, p. 851) as a trigger of concern and anxiety of job loss to STARA but also innovative technologies in their scope including disembodied algorithms and automation processes. Furthermore, as Yam and colleagues (2023) exclusively investigated JI as the outcome of robot exposure, we expand the range of outcomes by examining STARA Awareness, indicating that the effect is not an artefact of the used JI measure. Lastly, we provide an adapted valid, short questionnaire for use in research and practice that allows to specifically capture employees' concern, worry and anxiety about losing job or core tasks within a job due to the substitution of work processes due to new technologies.

STARA Awareness

Brougham and Haar (2018) defined STARA Awareness as "the extent to which an employee views the likelihood of Smart Technology, Artificial Intelligence, Robotics and Algorithms impacting on their future career prospects" (p. 3). Later labeled as *threat of technological disruption*, Brougham and Haar (2020) extended its definition by the inclusion of automation and redefined the construct as "an employee's appraisal of technology (e.g., threat of smart technology, artificial intelligence, automation, robotics, and algorithms) as potentially affecting their current work through radical technological changes" (p. 3). Even though STARA Awareness represents a timely construct with essential practical implications, we suggest refinements on the following two theoretical critiques. First, although the term Awareness suggests that especially cognitive aspects of STARA are covered, the questionnaire developed by Brougham and Haar (2018; 2020). Taking a look at the proposed questionnaire suggests that besides assessing the perceived possibility of job substitution due to increasing implementation of STARA in one item ("I think my job could be replaced by STARA", Brougham & Haar, 218, p. 246), the remaining three items explicitly concern the affective appraisal. One exemplary item reads "I am personally worried that what I do now in my job will be able to be replaced by STARA" (Brougham & Haar, 2018, p. 246). Therefore, this questionnaire mainly seems to capture a STARA-driven form of job insecurity in the modern world of work as also suggested by Gödöllei (2022). The focus on the affective component raises serious questions about the fit of the construct definition and the developed measurement instrument. Going forward, the derivation of hypotheses considers this affective component that is strongly focused in the developed questionnaire by Brougham and Haar (2018). Second, both definitions provided by Brougham and Haar (2018, 2020) neglect that innovative technologies have the potential to substitute core tasks within a job which in turn causes fundamental changes in tasks instead of substituting whole jobs (Dengler & Matthes, 2018). In both of their studies, STARA Awareness represents a global construct that refrains from differentiating cognitive and affective components.

In addition to criticism concerning its definition and measurement, an overarching theoretical model is missing so far. Brougham and Haar (2018) stated that STARA Awareness is theoretically based on the career planning literature (Greenhaus & Kopelman, 1981) and the boundaryless career concept (Arthur & Rousseau, 2001). STARA could potentially automate specific occupations and lead to technological disruption and a downsizing of a variety of sectors (Dengler & Matthes, 2018; Frey & Osborne, 2017). Therefore, STARA will increasingly affect the individual's career planning process by altering workplaces and employment settings (Brougham & Haar, 2018). Although a thorough construct validation of STARA Awareness is missing, several scholars already adapted versions like *AI Awareness* (Kong et al., 2021; Liang et al., 2022) or *automation-related job insecurity* (Gödöllei, 2022).

To date, only a few cross-sectional findings exist that provide insights into the relationship between STARA Awareness and work-related outcomes. For example, STARA Awareness correlates positively with burnout (Brougham & Haar, 2018; Kong et al., 2021) and turnover intentions (Brougham & Haar, 2018, 2020; Gödöllei, 2022; Kurniawan et al., 2022; Li et al., 2019), or negatively with organizational commitment, career satisfaction (Brougham & Haar, 2018) and work engagement (Gödöllei, 2022).

The correlations reported so far in the literature highlight the relevance of the construct. However, all these correlations have also been reported for related constructs, such as JI (Brougham & Haar, 2018; Greenglass & Burke, 2000; Staufenbiel & König, 2011), which raises the question about the validity of this construct. Overall, research so far has focused on a few potential consequences, and findings suggest detrimental relations of STARA Awareness with varying outcome variables, while researchers completely neglected the investigation of antecedents. Therefore, we aim in the current study not only to provide insights into the nature of this construct by separating it from related constructs but also to suggest a specific theoretical framework that helps to identify and test potential antecedents of it. We suggest, that taking into account framework models about the conceptually similar construct of JI (Shoss, 2017) could prove useful in developing a comprehensive theory on STARA Awareness. In particular, insights about potential antecedents are needed, as they may allow to identify employees with high risk of experiencing STARA Awareness to counteract and to prevent detrimental consequences reported in prior studies.

Differentiating STARA Awareness from Job Insecurity

Given the striking similarity of the STARA Awareness construct with already existing constructs, in particular JI, it is surprising that – to our knowledge – no prior research has provided empirical insights if these constructs can be separated. On the one hand, STARA Awareness and JI seem to share similarities in terms of content as the STARA Awareness questionnaire by Brougham and Haar (2018) is based on the job insecurity questionnaire by Armstrong-Stassen (2001). JI is defined as “the degree to which employees perceive their jobs, or important features of their jobs, to be threatened and to which they perceive themselves to be powerless to do anything” (Huang et al., 2010, p. 21). Therefore, the two constructs align in the content through a perceived threat to the current job as well as employees’ powerlessness (Brougham & Haar, 2020; Huang et al., 2010). This seems to be reflected in prior empirical findings, demonstrating (partly) strong intercorrelations of $r = .51$ (Brougham & Haar, 2020), or $r = .71$ (Lingmont & Alexiou, 2020). On a theoretical level, some researchers consider STARA Awareness as an antecedent of JI which mediates the effects of STARA Awareness on work outcomes (Brougham & Haar, 2020; Kurniawan et al., 2022; Lingmont & Alexiou, 2020).

On the other hand, STARA Awareness includes a digitalization context explicitly in its definition and measurement (STARA substituting work processes, therefore leading to a downsizing in organizations and industries), whereas JI is defined in general terms (causes of job insecurity are not explicitly stated in definition and measurement). Additionally, the two constructs differ in terms of their abstraction level with reference to one's job or organization and industry. While STARA Awareness is operationalized by the substitution of one's job and jobs in one's organization and industry, JI only considers an individual's perceived threat of the current job (Brougham et al., 2018). Given these differences, empirical findings also provide initial hints that STARA Awareness can be separated from JI. In their first study about the construct, Brougham and Haar (2018) did not find a significant correlation in a sample of 120 employees. However, to our knowledge, no prior study has provided direct empirical evidence that the two constructs are distinct on a measurement level.

In contrast to the global STARA Awareness construct, JI has in prior research been further differentiated into two highly intercorrelated factors (r = .53, Jiang & Lavaysee, 2018), namely *cognitive* and *affective JI* (Huang et al., 2012). Cognitive JI captures the "perception of the likelihood of negative changes to one's job, (e.g., losing the job or losing attractive job features) while affective JI captures the affective elements of the JI experience, such as being concerned, worried, or anxious about losing the job or particular job features" (Huang et al., 2010, p. 22). However, in prior studies on STARA Awareness, JI was operationalized as a global construct and not differentiated into cognitive and affective JI, thus it is not clear yet if both JI aspects are comparably related to it. Given the substantial construct overlap in the content of STARA Awareness, cognitive JI, and affective JI, and the fact that STARA Awareness captures both cognitive and affective components, we postulate that they are positively related, yet clearly differentiated from one another empirically.

Hypothesis 1: A three-factor model separating STARA Awareness, cognitive and affective JI fits better than a one-factor model subsuming all constructs.

Hypothesis 2: STARA Awareness is positively related to a) cognitive and b) affective JI.

A theoretical framework for the postulation of antecedents of STARA Awareness

Shoss' (2017) *Conceptual Model of Antecedents and Outcomes of Job Insecurity*, which combines the two perspectives of psychological contract (Ashford et al., 1989) and stress research (Sverke et al., 2002), provides a detailed overview of antecedents and outcomes of JI based on comprehensive empirical findings. In this model, antecedents range from national/macro-economic factors (i.e. industry decline, technological change) to individual characteristics (i.e. *core self-evaluations*, CSE). Given the conceptual overlap of the two constructs, we suggest Shoss' (2017) model as a theoretical framework to also explain antecedents of STARA Awareness. In detail, we examine potential antecedents on different levels according to this model: On the national/macro-economic level, we investigate the objective substitution potential of occupation and the use of STARA as indicators for the technological change, as these increase directly by implementing STARA in the workplace. On the individual level, we consider CSE as the only listed personality trait in Shoss' (2017) model to investigate whether STARA Awareness also depends on personal vulnerabilities, not just work-related technological changes.

First, at the national/macro-economic level, the model postulates that industry decline, shrinking demands, and technological change trigger employee's JI by generating changes that jeopardize jobs as organizations vie for survival and act as distant indicators of future vulnerabilities (Shoss, 2017). Indirect empirical support for this anticipated link stems from a study by Roskies and Louis-Guerin (1990) who showed that perceived changes in business or the technological environment significantly predict JI. Due to the increasing implementations of STARA in the modern world of work (Brougham & Haar, 2018), the substitution of occupations and core tasks will lead to a growing industry decline and shrinking demands, and thus an increasing unemployment rate in specific sectors and occupations (Dengler & Matthes, 2018; Frey & Osborne, 2017). Therefore, we expect an increasing substitution potential of occupation to stimulate job-threatening changes and to be associated with higher STARA Awareness.

Hypothesis 3: The objective substitution potential of occupation is positively related to STARA Awareness.

We theorize that the use of STARA as an indicator for technological change based on Shoss' (2017) model acts as a distal warning sign for the growing substitution of occupations, hence fostering STARA Awareness. By using STARA in their jobs, employees recognize the potential of STARA to outperform and substitute human workers in specific work tasks. In fact, STARA can already outperform human workers in a whole variety of cognitive and manual tasks and is "poised to outperform them in the near future" (Yam et al., 2023, p. 851). Additionally, organizations that implement STARA recognize its potential to substitute human work. Thus, use of STARA can act as a proxy variable for the willingness of organizations to automate work processes, resulting in higher substitution risks and in turn higher STARA Awareness for employees who use STARA in their daily work compared to those who do not. Partial empirical support for this stems from recent findings by Yam and colleagues (2023) who demonstrated that the exposure to robots increases employees' JI.

Hypothesis 4: Use of STARA is positively related to STARA Awareness.

Second, at the individual level, Shoss' (2017) model posits CSE – a higher-order personality trait comprised of neuroticism, self-esteem, self-efficacy, and locus of control (Judge, 2009) – as an antecedent of JI. Low CSE, characterized by low emotional stability, low self-esteem, low self-efficacy, and high external locus of control, promotes JI. In detail, the tendency to view oneself as unable and worthless, to evaluate events as negative and uncontrollable, and to perceive one's environment as threatening triggers JI (Shoss, 2017). In a meta-analysis, Jiang et al. (2021) corroborated an average correlation of CSE with JI of r = -.42. Based on this negative association between CSE and JI, we hypothesize that individuals with low CSE will also perceive the introduction of STARA and its impact on the future of their individual jobs as negative, threatening, and uncontrollable. Recent findings by Truța and colleagues (2023) indicate that CSE play a central protective role for negative affects (like technostress when using technology), as individuals with high levels of CSE tend to appraise technologies as beneficial for optimizing their performance.

Hypothesis 5: CSE is negatively related to STARA Awareness.

Study 1: Validation of a German STARA Awareness Scale

In our first cross-sectional study with German employees, we translate the STARA Awareness questionnaire by Brougham and Haar (2018) into German and validate it by investigating its internal structure, separating it from cognitive and affective JI (H1-H2), and identify potential antecedents of STARA Awareness based on JI models (H3-5).

Method

Procedure and Participants

We invited German employees from our personal and professional networks from various branches and organizations via e-mail and social media accounts to an online survey. For participating, the respondents had to work at least part-time. We offered two incentives in return for participation (summary of the study results, opportunity to win one of five 20€ vouchers). We measured the included variables in randomized order – except for the objective substitution potential that was measured at the very end of the questionnaire. During the data collection from March to April 2021, 661 people clicked on starting page of the survey. Participants who did not finish the study or with missing values on the study variables were excluded from the analysis, leaving 219 participants (response rate approximately 33%). Another four participants were excluded from the analysis because they failed the built-in attention check ("Please tick answer option 1 'strongly disagree' in this row"). The final sample consisted of N = 215 participants (63% female). On average, they were 31.53 years old (SD = 9.23). While 49% of the respondents reported a university degree as their highest level of education, 30% reported an apprenticeship, resulting in a disproportionately highly academically educated German sample. The participants stemmed from diverse branches (22% from manufacturing, 14% from healthcare, 8% from science), including occupations with strongly varying substitution potentials and use of STARA. Due to the COVID-19 pandemic, 19% of respondents reported currently working short-time.

Measures

STARA Awareness. STARA Awareness was measured using the 4-item scale by (Brougham & Humphrey, 2018). For the scope of this study, the scale was translated into German by two independent researchers, and accuracy was confirmed through back translation by a native English speaker. We adapted the items following the development of the construct suggested by Brougham and Haar (2020) by including the word "automation" in the items. However, we left algorithms out as these form the basis for smart technologies, artificial intelligence, robotics, and automation (and are therefore already covered). One exemplary adapted item is "I am personally worried about my future in my organization due to smart technology, artificial intelligence, robotics and automation replacing employees" (original item: I am personally worried about my future in my organization due to smart technology, artificial intelligence, robotics and algorithms replacing employees). All items were answered as for the original scale on a five-point Likert scale ranging from *completely disagree* (1) to *completely agree* (5). Internal consistency in the current sample was good (Cronbach's α = .87, McDonald's Ω = .87).

Job insecurity (JI). Cognitive and affective JI were measured using a validated German translation (Staufenbiel & König, 2011) of the job insecurity scales by Borg and Elizur (1992). Cognitive JI was measured by four (e.g., "My job is secure"), affective JI by three items (e.g., "The thought of losing my job troubles me"). Responses were made on a scale from *strongly disagree* (1) to *strongly agree* (7). Affective JI demonstrated very good internal consistency (α = .93, McDonald's Ω = .93), whereas cognitive JI showed good internal consistency (α = .85, McDonald's Ω = .86).

Objective substitution potential. The substitution potential of the occupation of participants was determined using the Job Futuromat website by the German Institute for employment research (https://job-futuromat.iab.de). The substitution potential is based on task profiles of occupations and indicates for the selected occupation which and how many core tasks of the occupation could be performed fully automatically by a computer or a computer-controlled machine as of 2019. The substitution potential presents the relative number of core tasks of occupation that can be automated and varies between zero and 100 percent. As the system differentiates various jobs within occupational types, we instructed participants to follow the link to this website and let themselves find the accurate job description for their current job.

Use of STARA. Use of STARA was assessed with a single item ("Please estimate the percentage of your weekly work time in which you have contact with smart technology, artificial intelligence, robotics, and automation"). Respondents answered on a scale of zero to 100 percent in steps of 10 percent.

CSE. CSE was measured with the validated German version (Stumpp et al. 2010) of the twelve-item scale originally developed by Judge et al. (2003). One exemplary item was "When I try, I generally succeed." Participants answered on a five-point Likert scale ranging from *strongly disagree* (1) to *strongly agree* (5). The overall scale yielded good reliability (α = .86, McDonald's Ω = .86).

Analytic Approach

We performed all statistical analyses using JASP 0.17.1 (JASP Team, 2023). For the measurement models, we compared a *one-factor model* to a *three-factor model,* using confirmatory factor analyses (CFA). In the one-factor model, all STARA Awareness items, as well as all cognitive and affective JI items load onto one general factor. The three-factor model represents three different, but intercorrelated factors STARA Awareness, cognitive JI, and affective JI. We based our evaluations of the model fit on the recommendations by Hooper et al. (2008) and West et al. (2012) by using the comparative fit index (CFI > .95), root mean square error of approximation (RMSEA < .06), and standardized root-mean-square residual (SRMR < .08). Moreover, we report the Akaike information criterion (AIC). We also report the average variance extracted (AVE) of STARA Awareness and its shared variance (SV) with cognitive and affective JI. If the AVE score exceeds the SV scores, the analyses support the discriminant validity of STARA Awareness (Farrell, 2010).

Results & Discussion Study 1

Table 1 lists the results of the measurement model of STARA Awareness alone (see factor loadings in Figure 1 in the ESM), and the two CFAs comparing STARA Awareness, and cognitive and affective JI. Although CFI and SRMR suggest a good fit of the STARA Awareness measurement model for our translated measurement instrument, the RMSEA indicates a poor fit based on the aforementioned recommendations with the item containing cognitive components exhibiting the lowest factor loading. However, in line with our expectations, a three-factor model separating STARA Awareness, cognitive and affective JI fits the data better than the one-factor model, thereby supporting H1.

Table 2 displays descriptive statistics and spearman intercorrelations of the variables in Study 1 (none of the variables was normally distributed as assessed by Shapiro-Wilk tests, $p < .001$). In line with our expectations, STARA Awareness was positively related to cognitive as well as affective JI in a comparable height, supporting H2a and H2b. As the AVE (.620) of STARA Awareness exceeded its SV with cognitive (.029) and affective JI (.026), the analyses support the discriminant validity of STARA Awareness. Furthermore, the substitution potential of occupation and use of STARA were both positively associated with STARA Awareness, supporting H3 and H4. Unexpectedly, CSE and STARA Awareness were not significantly related, $r = -.12$, $p = .07$, thereby rejecting H5. In contrast to STARA Awareness, we did not find a significant relationship between substitution potential and affective JI, $r = -.03$, $p = .63$, or between use of STARA and cognitive JI, $r = -.08$, $p = .22$, or affective JI, $r = .00$, $p = .97$. Substitution potential and cognitive JI were even negatively related. CSE was negatively related to cognitive and affective JI.

In our first study, we successfully translated and adapted the existing STARA Awareness measurement instrument by Brougham and Haar (2018). Similar to the studies by Brougham and Haar (2018; 2020) in the USA, Australia, and New Zealand, STARA Awareness is low in magnitude in our German sample. This suggests a successful transfer of the construct to the German context with our sample including participants with various occupations and objective substitution potential. Additionally, we clearly separated STARA Awareness from cognitive and affective JI on the measurement level, even though they are weakly related to one another. The low magnitude of the correlations seems striking, as theoretical considerations suggested substantial overlap between the constructs. The relationships between STARA Awareness and cognitive and affective JI are much weaker than in prior studies which examined JI globally (Brougham & Haar, 2020; Lingmont & Alexiou, 2020). Even though STARA Awareness is largely affective in nature, it is similarly related to cognitive and affective JI.

With regard to potential antecedents, we demonstrated most of the expected correlations based on Shoss' (2017) model. Although these findings seem to support that the model can be transferred to STARA Awareness, comparing the correlation pattern of this construct with (cognitive and affective) JI indicated substantial differences. Compared to JI, STARA Awareness seems to be more strongly associated with national/macro-economic factors than with personality factors, such as CSE. That STARA Awareness rises with increasing use of STARA suggests that fears of job loss due to the implementation of STARA at work are not reduced by the mere use of these technologies. Rather, this is a growing concern in an increasingly digitized work environment. Hence, STARA Awareness represents a distinct construct with its own nomological net. Therefore, our study provides valuable information for the theoretical and practical added value of the timely STARA Awareness construct.

However, our results for the measurement model indicate the need for a revision of the original questionnaire. In line with the original scale by Brougham and Haar (2018), the item that contains the cognitive component exhibits the factor loading. Hence, the (partly) poor model fit can presumably be attributed to the neglection of a differentiated and balanced consideration of cognitive and affective elements, comparable to research on JI (Staufenbiel & König, 2011). Additionally, the affective items assess concerns about the substitution of jobs on varying levels (individual, organizational and industrial level), whereas the cognitive item only captures the perceived possibility of the substitution of one's job at the individual level. However, the introduction of STARA in the modern world of work will not only lead to the complete substitution of jobs, but also to the substitution of individual tasks and thus to job-related changes (Dengler & Matthes, 2018), which is not captured in the definition or original measurement of STARA Awareness (Brougham & Haar, 2018, 2020). Substituting core tasks within a job due to STARA could result in a reduction in the quality of a job. In the JI literature, this process is partly covered by *qualitative job insecurity* defined as perceived threats of valued job features (Shoss, 2017). Given the current questionnaire primarily focuses on affective components, and the substantial theoretical and weak empirical overlap between STARA Awareness and cognitive and affective JI, we propose the renaming of the construct and its consideration as specific subdimension of JI with digitalization context, which has also been suggested by other authors (Gödöllei, 2022). Consequently, we suggest a revision of the (original) questionnaire in accordance to research on JI, and to define and assess cognitive and affective components of automation-related JI separately. We define *cognitive automation-related job insecurity* (CAJI) as the employees' perceived possibility of STARA-driven task and job substitution. Relatedly, we define *affective automation-related job insecurity* (AAJI) as employees' affective appraisal (concern, worry, anxiety) of STARA-driven task and job substitution.

Study 2: Separation of cognitive and affective automation-related JI

In a second cross-sectional study with German employees, we address the aforementioned content criticism of the construct. In detail, we expand the limited STARA Awareness construct by adding cognitive and affective items that capture components at the individual, organizational, and industrial levels, as well as taking the substitution of individual core tasks into account. We investigate whether we can separate STARA Awareness into CAJI and AAJI. Additionally, we aim to replicate our validation hypotheses (H1-5) from Study 1.

Hypothesis 6: A two-factor model of CAJI and AAJI fits better than a one-factor model.

Method

Procedure and Participants

Again, we invited German employees from our personal and professional networks from various sectors and organizations via e-mail and social media accounts for a short online study with a cross-sectional design. For participating, they had to work at least part-time. Again, we rewarded the participants with a summary of the central study results as well as the opportunity to win one of five 20€ vouchers. As in Study 1, we assessed the variables in randomized order but collected the objective substitution potential at the end of the questionnaire. Initially, 571 people clicked on the link to the study, which took place within three weeks in October 2021. We excluded 344 participants who did not finish the questionnaire, leaving 227 participants (response rate of approximately 40%). Moreover, we excluded one person who reported “student” as current job, one person who reported having simply looked through the questionnaire, another one for working under 16 hours per week, leaving 224 participants. The majority of our sample was female (58%). One participant indicated diverse as their gender. On average, the participants were 33.08 years old (*SD* = 10.26). 63% of the participants had a university degree, whereas 23% completed an apprenticeship, again resulting in a sample with an above-average number of academics. As in Study 1, the participants worked in diverse branches (14% from healthcare, 14% from public administration and government, 9% from science). Due to the COVID-19 pandemic, 14% of the respondents worked short-time.

Measures

We assessed cognitive and affective JI, the substitution potential, the use of STARA, and CSE with the same methods used in Study 1.

STARA Awareness. We assessed STARA Awareness with the same four items which we used in Study 1.

Cognitive and affective automation-related job insecurity. To extend the construct, we followed the recommendations by Hinkin (1998) and Schwab (1980) and generated 26 new items based on the STARA Awareness definition and the aforementioned theoretical and measurement criticism (see Figure 1 a visualization of the item adaption process). After screening our generated items regarding redundancy and representativeness (Ferris et al., 2008), we excluded seven items, resulting in twelve cognitive and seven affective items that represented STARA Awareness on the individual, organizational and industrial levels as well as the substitution of individual tasks. Following the recommendations by Clark and Watson (1995), the original items and the items we generated were then evaluated by two research associates and one research assistant for how close they fit the construct definition on a five Likert-scale from *strongly disagree* (1) to *strongly agree* (5). Based on these ratings, we excluded six cognitive and three affective items, resulting in the four original (one cognitive and three affective items), six new cognitive, and four new affective items. In our second study, we tested these 14 items empirically (see item formulation and factor loadings in Table 1 in the ESM).

Analytic Approach

Again, we performed all statistical analyses using JASP 0.17.1 (JASP Team, 2023), including the measurement model of the original STARA Awareness scale, exploratory factor analyses (EFAs), and CFAs of the modified scale and intercorrelations of our study variables, and report AVE and SV scores. We used the same recommendations for model fit as in Study 1.

Results & Discussion Study 2

In contrast to our findings in Study 1, all model fit indices of the measurement model of the original STARA Awareness scale suggest a perfect model fit (Table 3, see factor loadings in Figure 2 in ESM). Considering our criticism on its content and poor psychometric properties, we adapted the scale by Brougham and Haar (2018). Therefore, we conducted an EFA using maximum likelihood and promax rotation (Cureton & Mulaik, 1975) with all 14 items, which suggested the extraction of two factors, thereby supporting H6. However, contrary to our expectations, all items except three cognitive items and showed substantial estimated factor loadings on factor 1 (factor loadings > 0.4), whereas one inverted affective item did not show a substantial estimated factor loading on either of the two factors. To further investigate the factor structure and potential separation of CAJI and AAJI, we contrasted a one-factor model to a two-factor model with all 14 items (Table 3). In the one-factor model (see factor loadings in Figure 3 in ESM), all seven cognitive and seven affective items loaded on a single factor, while in the two-factor model (see factor loadings in Figure 4 in ESM), the cognitive items and the affective loaded on separate factors. Contrary to H6, the two-factor model did not fit significantly better than the one-factor model ($\Delta\chi^2(1) = 1.09$, $p = .30$). All model fit indices suggest a poor model fit for both models including all 14 items. To improve model fit, we tried to reduce the number of cognitive and affective items. Based on item statists and content consideration, also an alternative model including only 8 items did not lead to satisfactory fit for two separate scales to assess CAJI and AAJI (see factor loadings in Figures 5 and 6 in ESM). Hence, we failed to differentiate separate factors for assessing cognitive and affective components. Consequently, and in contrast to JI, these results indicate that employees do not differentiate between the perceived possibility of job loss or core tasks within the job and emotions like concern, worry, and anxiety about losing the job or core tasks within a job due to STARA substituting work processes in organizations and industries.

However, as the model fit indices of the original STARA Awareness scale varied strongly between our studies, we adapted the original four-item scale to address the content criticism (neglecting to differentiate cognitive and affective components and neglecting the ability to automate individual core tasks within a job) and the poor model fit in Study 1. To reach higher construct clarity, we removed the sole cognitive item and instead added an affective item that takes the substitution of individual tasks into account. Additionally, we replaced one affective item with a new item so that the item stem varied stronger. The model fit indices of the measurement model of our new scale to capture AAJI, focusing solely on affective elements encompassing four items suggested a perfect model fit (Table 3, see factor loadings in Figure 7 in ESM). Table 1 in ESM displays the items of the adapted questionnaire in German and English. Given the minor changes, the original scale by Brougham and Haar (2018) and our revised scale are highly intercorrelated, $r = .92$, $p < .001$.

Table 3 also lists the results of the two CFAs comparing AAJI, and cognitive and affective JI. Again, in line with our expectations and results for the original scale in Study 1, all model fit indices of the one-factor model indicate a poor model fit, whereas the three-factor model, which separates AAJI, cognitive and affective JI, fits significantly better than the one-factor model. All model fit indices of the three-factor model suggest a very good model fit, thereby supporting H1 also for the AAJI scale. Moreover, the AVE score of AAJI (.677) exceeds the SV with cognitive (.020) and affective JI (.023), indicating discriminant validity of AAJI.

Table 4 lists descriptive statistics and spearman intercorrelations of the variables in Study 2 (again, all variables were not normally distributed as assessed by Shapiro-Wilk tests, $p < .001$). Supporting H2a and H2b, AAJI was positively associated with cognitive and affective JI. In line with our expectations in H3 and H4, the substitution potential of occupation and use of STARA were both positively related to AAJI. Contrary to Study 1, CSE and AAJI were as expected negatively associated, supporting H5. In contrast to AAJI and in line with Study 1, the substitution potential was not significantly related to affective JI, $r = -.06$, $p = .39$, while use of AAJI was not related to cognitive JI, $r = -.09$, $p = .18$, and affective JI, $r = .04$, $p = .55$. Again, the substitution potential and cognitive JI were negatively related. Additionally, CSE was again negatively associated with cognitive and affective JI.

In sum, in our second study, we adapted the STARA Awareness questionnaire by Brougham and Haar (2018) addressing the aforementioned content criticism. Although we failed to separate aspects of CAJI and AAJI, we provided a revision and validation of the questionnaire that now considers the ability to automate individual tasks instead of whole occupations and is exclusively affective in nature. However, we have to note, that the model fit indices of the original scale by Brougham and Haar (2018) and our revised scale indicate a perfect fit of the measurement models in Study 2. The better model fit of the original scale could be (partly) attributed to potential range restrictions in the current study, given that Franco-Martínez and colleagues (2022) showed that especially the CFI is largely affected by it. Therefore, our revised scale needs to be cross-validated in further studies.

Furthermore, we have almost completely replicated our previous results on potential antecedents using our revised version of the questionnaire. AAJI was more strongly related to national/macro-economic factors than JI. This suggests that the continuing digitalization of the modern world of work will strongly trigger AAJI (and not higher general JI), underlining the additional value of the construct. Consequently, the results of both studies suggest that AAJI is triggered by the use of STARA at work. In contrast to Study 1 and in line with JI, we identified CSE as a potentially protective personality trait against AAJI. This relationship probably emerged due to the now purely affective nature of our revised construct. Since our two studies so far are limited by their cross-sectional design, we need longitudinal study designs to empirically test whether the potential antecedents predict the starting point and the trajectory of the construct.

Study 3: The stability and change of affective automation-related job insecurity

We conducted a third, longitudinal study over one year with three measurement points and time lags of six months each. Our aim was threefold. First, we cross-validate our AAJI scale. Second, we investigate the long-term trend of the construct in the context of the COVID-19 pandemic characterized by the acceleration of technological implementations at work. Third, we provide insights into how the potential antecedents predict the starting point (intercept) and trajectory (slope) of AAJI over time. Besides the postulated hypotheses 1-5 that we tested in Studies 1 and 2, we propose and test two further hypotheses in Study 3.

As in Studies 1 and 2, we anticipate that the objective substitution potential of occupation and the use of STARA are positively and CSE are negatively related to AAJI, thereby determining the starting level (intercept) of AAJI at T1.

Hypothesis 7: Substitution potential, use of STARA and CSE will predict AAJI at the starting point of the study (intercept) such that higher scores on substitution potential (H7a) and use of STARA (H7b), and lower scores on CSE (H7c) are associated with higher initial AAJI levels.

Further, we postulate that the use of STARA does not only influence the intercept but also a positive growth trajectory of AAJI as employees progressively experience the rising efficiency and competence of STARA due to ongoing technological advances and implementation at work by using them in daily work activities. Consequently, employees realize the possibility of STARA substituting work processes as new technologies are "poised to outperform them in the near future" (Yam et al., p. 851). The perception of increasing efficiency and comparison of STARA compared to human skills should trigger AAJI over time by the mere use.

Hypothesis 8: Use of STARA will predict positive growth in AAJI (slope) such that higher scores on the use of STARA are associated with higher positive growth in AAJI.

Method

Open Science

We pre-registered all procedures and hypotheses before data collection (https://osf.io/f6gd2/?view_only=09de1c92118448d89d2c723c57364163).

Procedure and Participants

As in our prior studies, we invited German employees from diverse sectors and organizations via e-mail and social media accounts for a short longitudinal online study with three measurement points over one year with a time-lag of six months, similar to longitudinal studies on antecedents of JI (Huang et al., 2012; Kinnunen et al., 2014). The participants had to work at least part-time. We rewarded participants at the first measurement point with work and organizational psychology tips for remote work, at the second measurement point with individual feedback on their work motivation (assessed at T1), and at the third and final measurement point with the chance to win one of 20 vouchers (10€). For each person who participated in all three measurement points, we donated 1€ to a charitable organization. Again, we collected the objective substitution potential at the end of the questionnaire from T1.

From the 2339 people who clicked on the starting page of the survey in the first wave from January to March 2022, 498 participants completed T1 (response rate approximately 21%) and were automatically invited to the following measurement point six months later. We excluded 34 participants who failed the built-in attention check ("Please tick answer option 5 'strongly agree' in this row."), eight participants who worked less than 16 hours per week, four participants who stated "student" as their current job as well as four participants with missing values in the objective substitution potential from the statistical analysis. Furthermore, we excluded participants who changed jobs (n = 41) between T1 and T3, resulting in 406 participants that we included in T1. Of the 406 participants at T1, 261 completed T2 who were automatically invited to the final measurement point (T3) six months later. Of the 261 participants from T2, 233 participants also completed T3. To investigate potential systematic drop-out we tested for differences in our study variables (AAJI, objective substitution potential, use of STARA, and CSE) in participants who completed all three measurement points (N = 233) from participants who did not participate in T2 and/or T3 (N = 173) using MANOVA. Results indicated no systematic dropout based on our study variables, $F(4, 401) = 1.21$, $p = .31$.

The final sample included 117 women (50%), 114 men (49%), one diverse, and one participant who did not state gender. The average age was 37.31 years (SD = 12.13). With 58% of participants with a university degree and 26% with an apprenticeship as their highest level of education, the sample is disproportionately highly academically educated. Again, participants stemmed from diverse branches (16% from healthcare, 15% from manufacturing, and 10% from science) and occupations. Due to COVID-19, 14% of the participants at T1, 11% of participants at T2, and 12% of the participants at T3 worked short-time.

Measures

We assessed the substitution potential, the use of STARA, and CSE with the identical methods used in Studies 1 and 2. We used our modified scale from Study 2 to measure AAJI. In addition, we assessed and individually reported back work engagement using a German version of the ultra-short measure for work engagement (Schaufeli et al., 2017) to reward participants.

Analytical Approach

We tested the measurement model of the AAJI scale at all three measurement points and evaluated the model fit based on the previously used recommendations (Hooper et al., 2008; West et al., 2012). To test H7-H8, we performed latent growth curve models (LCM) using R and the package lavaan (Rosseel, 2012). Contrary to basic regression models with fixed effects which postulate that participants do not differ in their starting point (intercept) or change rate (slope), LCM considers that participants vary in their intercept and slope by adding random-effects terms (Curran et al., 2010). By performing LCM, we investigated the relationship of the three potential antecedents (objective substitution potential of occupation, use of STARA, and CSE) and AAJI at the starting point of the study (intercept) and the growth trajectory (slope) of AAJI over the three measurement points. For this, we followed the recommendation by Curran and colleagues (2010). First, we test a baseline model (M0) and evaluate its model fit. This baseline model postulates a linear positive trajectory of AAJI without the between-person predictor variables and incorporates fixed and random effects. The fixed effects include the estimation of the mean intercept and the mean slope. The random effects include estimates of the variance in intercept and slope, "referring to between-person variability around the mean intercept and mean slope" (Apers et al., 2019, p. 220). Second, we postulate a second model (M1) that incorporates between-person predictor variables at T1 (objective substitution potential of occupation, use of STARA, and CSE) to predict the individual variability in the intercept and use of STARA to predict the individual variability in the slope of AAJI and evaluate the model fit (Apers et al., 2019; Curran et al., 2010) to test H7-8.

Results & Discussion Study 3

Table 5 displays the measurement model of AAJI at the three measurement points. Whereas the CFI and SRMR indicate a good model fit of AAJI at all three measurement points, the RMSEA suggests a poor model fit at T1 and T3, and a good model fit at T2 (see factor loadings in Figures 8-10 in ESM). Table 6 shows descriptive statistics and Spearman intercorrelations of the variables in Study 3 (again, none of the variables were normally distributed according to Shapiro-Wilk tests, $p < .05$). Since we identified significant positive relations between the objective substitution potential of occupation and the use of STARA with AAJI at all three measurement points, our results support H3 and H4. In line with Study 2, we also found significant negative relations between CSE and AAJI at all three measurement points, supporting H5.

Table 7 displays the LCM results for the baseline model (Model M0) and the model including predictors for the intercept and slope (Model M1) which provides the basis for testing hypotheses 7 and 8. Model fit indices for M0 suggested an acceptable fit to the data except RMSEA, Normed χ^2= 6.817, df = 1, p = .009, CFI = .980, TLI = .941, RMSEA = .158, SRMR = .031, AIC = 1298.361. Thereby, the results indicate that AAJI is constant both between participants and over time. M0 revealed no linear change in AAJI throughout the three measurement points (Figure 2). The mean intercept which displays the average AAJI level at T1 was b = 1.688, $t(1)$ = 32.791, p < .001. The mean slope which displays the average rate of AAJI growth over the three measurement points was nonsignificant, b = 0.001, $t(1)$ = 0.060, p = .953. Intercept variance was significant, $\sigma^2_{intercept}$ = 0.463, $t(1)$ = 6.942, p < .001. Slope variance was nonsignificant, σ^2_{slope} = 0.041, $t(1)$ = 1.635, p = .102. Intercept and slope were strongly negatively related, r = -.49, p = .032, indicating that the higher the starting point the lower the change in AAJI.

Including the predictors for the intercept and slope in M1 yielded a good model fit according to the model fit indices, Normed χ^2= 12.705, df = 8, p = .122, CFI = .987, TLI = .981, RMSEA = .050, SRMR = .029, AIC = 1230.235, allowing the examination of the parameter estimations. M1 revealed no linear positive trajectory of AAJI, too, b = -0.004, $t(1)$ = -0.166, p = .868, but slope variance was significant, σ^2_{slope} = 0.037, $t(1)$ = 2.754, p = .006. Intercept and slope were strongly negatively related again, $r = -.48$, $p = .007$. Although all model fit indices were better on a descriptive level, M1 did not significantly differ from M0, $\chi^2(7) = 5.888$, $p = .533$. The inclusion of predictors for the intercept and slope revealed the objective substitution potential, $\beta = .271$, $p < .001$ (H7a), and use of STARA, $\beta = .131$, $p = .005$ (H7b), as significant positive predictors and CSE, $\beta = -.136$, $p < .001$ (H7c), as a significant negative predictor of the intercept variability of AAJI, supporting H7. Thus, participants with higher objective substitution potential and use of STARA reported higher levels of AAJI at the starting point of the study. Contrary, participants with higher CSE reported lower levels of AAJI at the starting point. Although use of STARA was a significant predictor of slope variability of AAJI, we identified a negative prediction weight, $\beta = -.055$, $p = .016$, therefore rejecting H8. This indicates that the higher the use of STARA at T1, the lower the change in AAJI over the course of one year. Plotting the trajectory of AAJI over the course of the three measurement points for different levels of use of STARA at T1 displays a slight increase for moderate levels of use of STARA but slight decreases for both high (M + SD) and low levels (M - SD) (Figure 3).

Applying a longitudinal study design with a total time lag of one year, our contributions to the emerging research field are threefold. First, we cross-validated our AAJI scale. Although our CFA results demonstrate a varying model fit over the three measurement points, all indices suggest a better model fit than the original scale in Study 1. Second, since scholars have investigated the underlying construct STARA Awareness in cross-sectional studies, we are the first to examine the long-term trend of AAJI. Instead of an expected linear positive growth trajectory, we provided evidence for a rather high stability over the period of one year. The high correlations of AAJI between the three measurement points are comparable to studies on JI which used the same total time lag (Kinnunen et al., 2014), suggesting equivalent stability for the two constructs. Third, we demonstrated that the objective substitution potential of occupation and the use of STARA positively predicted the intercept whereas CSE negatively predicted the intercept. Noting that we found evidence for different levels of AAJI as a function of the objective substitution potential of occupation, use of STARA, and CSE in a multimethod approach strengthens the robustness of our results. Since the intercept variance was significant, we showed that participants differed in their (relatively low) starting point of their AAJI. However, taking a closer look at the change trajectories over time, we found no indication for a general – positive or negative linear - trend which indicates that the majority of employees in our sample stagnated in their AAJI during the investigated time frame (on a rather low level). Nevertheless, our analysis revealed also a more complex pattern, as such that change in AAJI is associated with the initial level of use of innovative technologies at work.

General Discussion

The findings of our two cross-sectional studies and one longitudinal study with the overall aim to validate the construct of AAJI contribute to the emerging research field on how humans perceive the implementation of new technologies in four important ways. First, building up on the work of Brougham and Haar (2018), we further developed the construct of STARA Awareness to address the substitution of core tasks, adapted and validated a measure. In addition to the content criticism, we identified a fluctuating (and partly poor) fit of the measurement model of the original construct, thereby indicating low validity. Although we failed to separate cognitive and affective subdimensions of the original construct, we adapted the original questionnaire to incorporate the substitution of core tasks within a job by STARA. We redefined the construct called *affective automation-related job insecurity* (AAJI) as a digitalization-specific form of job insecurity based on empirical results of the measurement model and criticism of the content. Overall, our analyses indicate a good internal structure of the revised questionnaire. Further, we cross-validated the structure of the adapted questionnaire to assess AAJI. In sum, our adapted construct addresses how employees perceive the impact of technological changes on their employment in an ever increasingly digitalized world of work in a more adequate way. We also provide a short and valid questionnaire to capture AAJI for use in research and practice.

Second, we contribute to the investigation of the nomological net of AAJI, as we were able to differentiate it from the related constructs of cognitive and affective JI. Therefore, AAJI represents a novel, contextualized measure that is only weakly related to job insecurity. This emphasizes the relevance of this discrete construct, as giving participants a digitalization frame alters their perception of job insecurity in today's world of work.

Third, drawing upon the conceptual model by Shoss (2017) for general JI, we investigated the objective substitution of occupation, use of STARA, and CSE as potential antecedents, essentially expanding knowledge about antecedents of AAJI. Our findings support the notion that indicators for technological change play an essential role for the development of AAJI. In line with the model by Shoss (2017), we found a protective function of CSE as a higher-order personality trait.

Fourth, we provided insights into the rather high stability of the construct over one year during the COVID-19 pandemic. Although not all our hypotheses were confirmed in LCM, we found evidence that the substitution potential, the use of STARA and CSE determine the starting level of AAJI. Employees who work in occupation with high objective substitution, use more STARA at work, and score low on CSE represent risk groups to experience high levels of AAJI. Moreover, our results indicate that the trajectory of AAJI depends on the extent to which employees use STARA at work. Especially, as employees with moderate use of STARA at work exhibit slightly increased levels of AAJI over time, makes them a particular critical group for interventions. Hence, our work suggests vital implications for theory and practice.

Theoretical Implications

Our research contributes to a comprehensive theory on AAJI by separating it from the well-known construct of JI, the investigation of potential subdimensions, antecedents that were neglected in prior research, and the examination of the long-term trend of AAJI. Based on the original STARA Awareness construct, our findings led to the clear conceptualization and validated assessment of AAJI, that enables the development of a theoretical foundation to foster future human-technology interaction research.

Our results support the transfer of indicators of technological change and higher-order personality traits as antecedents postulated in the conceptual model of JI (Shoss, 2017) to the novel construct AAJI. That we consistently identified a positive relationship between the objective substitution potential of occupation and AAJI in three studies indicates that there seems to be (at least in parts) a rational basis for employees' concern, worry or anxiety in terms of actual risk of being substituted. Hence, employees working in occupations with high substitution risk represent a risk group of AAJI which in turn can undermines their well-being and positive work outcomes (Brougham & Haar, 2018; Li et al., 2019; Kong et al., 2021). Additionally, as the use of STARA was positively linked to AAJI, strengthens the notion that working with new technologies triggers AAJI which remains highly stable over time and is neither accumulated through the continued use of STARA at work nor reduced by the mere use of these technologies. That is also in line with Yam and colleagues (2023) who demonstrated that robot exposure leads to JI (even when robot implementation does not lead to higher unemployment rates). By broadening the technologies under consideration (no restriction to robots), our work provides essential insights into how STARA affect employees' perception of their future employment or career. Following Yam and colleagues' (2023) recommendation to consider further outcomes besides JI – in our case AAJI – our work strengthens that employees tend to appraise the implementation of new technologies negatively as they fear potential job substitution. Thus, not only the exposure to robots but also the use of STARA is related to unintended detrimental effects on employee attitudes. Eventually, our findings indicate the high relevance of national/macro-economic factors that depict the technological change for AAJI.

Surprisingly, besides an even negative relation between the substitution potential and cognitive JI, we did not find any correlations between the indicators of technological change (as a national/macro-economic factor) and (cognitive and affective) JI. This suggests that the underlying model by Shoss (2017) needs further refinements to account for the role of technological advances in the workplaces and its effect on cognitive and affective JI. In addition, the differences in the correlation patterns between JI and AAJI demonstrate that AAJI constitutes a novel construct with its unique nomological net including indicators stemming particularly from the digitalization context which will be increasingly crucial to account for the substitution of human labor.

However, AAJI and JI resemble each other in some aspects. First, CSE seem to represent a protective higher-order personality trait for the experience of cognitive and affective JI (Jiang et al., 2021) as well as AAJI. Therefore, our findings highlight the importance of individual differences for the emerging field of a AAJI. Appraising oneself as worthy, competent, and capable (Stumpp et al., 2010) affects how employees experience their employment also in times of technological change. These findings are aligned with Yam and colleagues (2023) who demonstrated that self-affirmation can buffer the detrimental effects of robot exposure on JI.

Second, AAJI exhibits comparably high stability as JI (Kinnunen et al., 2014). Whether this translates into chronic detrimental consequences, remains to be investigated. The slight decline of AAJI among employees with high use of STARA may be because they hold jobs like computer scientists or engineers and thus actively shape the technological change; employees who do not use STARA at work may underestimate the potential impact of STARA in the long run, also resulting in slight decreases. Summarized, we propose that the novel construct of AAJI represents a specific subdimension of JI that is uniquely related to indicators for technological changes of the labor market and occupations (Dengler & Matthes, 2018). Although prior empirical findings suggest that AAJI and JI may share similar detrimental outcomes, our results show that they are determined by different factors. This further highlights the relevance of a digitalization-fixed construct and measure to adequately assess employees' appraisal of the impact of new technologies on their employment.

Practical Implications

We provide a reliable and valid questionnaire that measures AAJI, that considers that new technologies at work often have the potential to substitute single work processes and not eliminate whole jobs (Dengler & Matthes, 2018). Practitioners who intend to capture employees' affective appraisal of new technologies on their employment should therefore rely on our adapted scale to assess AAJI instead, for example, of general JI scales.

Furthermore, practitioners need to consider certain risk groups when implementing STARA at work. Our findings demonstrate that employees who face the real threat of job loss to STARA, who use STARA in their daily work, and who have low levels of CSE experience significantly more AAJI than employees in "automation-proof" occupations, who do not use STARA at work, or with high levels of CSE. Our studies suggest that CSE represent a vital higher-order personality trait for the context of personnel selection, especially in work environments that are characterized by dynamic technological advances. Although Judge et al. (2003) originally proposed CSE as a stable trait, several scholars postulate that CSE can also represent a state, meaning "individuals with positive state CSE appraise themselves in a positive manner in a specific situation" (Nübold et al., 2013, p. 31), not across diverse situations. Building up on findings that indicate that performance feedback triggers (state) CSE (Schinkel et al., 2004), practitioners may increase employees' state CSE and reduce AAJI as a downstream effect by implementing frequent and immediate feedback. This is also partially supported by experimental evidence by Yam and colleagues (2023) who demonstrated that self-affirmation can counteract JI caused by exposure to robots. However, since AAJI showed high stability over one year, practitioners should not expect decreases in AAJI by the mere use or growing familiarity with new technologies over time.

Limitations and Future Research

Although our results offer much-needed insights into the construct of AAJI, we have to acknowledge several limitations of our studies. First, although our adapted scale to measure AAJI demonstrates better model fit indices than the translation of the original STARA Awareness scale by Brougham and Haar (2018), the model fit still fluctuates between the three measurement points in Study 3. To enable a more reliable and valid measurement of AAJI, we suggest further adaptations of the questionnaire in the future (e.g., replacing “STARA” with “automation” in the item formulation since the automation of work processes is the key mechanism). Furthermore, future research should elaborate more on the validity and nomological net of the construct, by, for example, explicitly test the cross-cultural measurement invariance of our revised questionnaire (Miller & Scheu, 2008).

Second, AAJI is characterized by potential variance restrictions which limit the generalizability of our findings, even though we investigated employees from diverse branches and occupations in Germany. While by the time of our studies, the German public discourse might have been preoccupied with other topics than automatization at work (e.g., COVID-19, climate crisis), we are convinced, that AAJI will be of rising significance with the ongoing digitalization, especially with the rise of language models like ChatGPT. On the bright side, our results also indicate that employees’ affective appraisal of new technologies as threatening to their employment is currently confined in Germany.

Third, while the assessment of the substitution potential of occupations strengthens the validity of our findings with objective data, the data might be slightly dated as they originate from the year 2019 considering the rapid development of new technologies in recent years. Thus, we stress the replication of our findings with more current objective data if available.

Fourth, we used a self-developed single-item measure to capture the extent to which employees use STARA at work since established, validated questionnaires are missing to date. Also, future research should consider that employees can differ in their appraisal of STARA as either a resource, challenge, or hindrance which implies besides negative also positive effects for work outcomes. Several scholars (e.g., Gödöllei, 2022) emphasize the crucial role of appraisal of STARA as technologies can improve performance by substituting “dull, dangerous, and dirty” (Walsh & Strano, 2018, p. XIX) work.

Fifth, as we identified factors that uniquely determine AAJI and therefore emphasize the relevance of this construct in the digitalized world of work, future research is urged to investigate its incremental validity for outcomes in the digitalized work context, for example, in terms of technology acceptance or trust in automation. Furthermore, AAJI should also be empirically differentiated from the recently introduced related construct of *occupation insecurity* (Roll et al., 2023).

Finally, it largely remains unclear what organizations can do to reduce AAJI of and the associated negative impact on health and work outcomes of affected employees. Therefore, we encourage the development and evaluation of interventions (e.g., increasing state CSE) and the role of coping (El Khwali et al., 2022) to help employees with high levels of AAJI in organizational practice in the long run.

Conclusion

In sum, our findings essentially contribute to research on the AAJI as an important construct to capture employees' affective appraisal of new technologies at work impacting their employment. We shed light on its construct validity, by taking a closer look at the internal structure, its nomological net, tested for antecedents (in terms of indicators of technological change and personality traits), and outline its long-term trend. As we continue to face rapid technological advances in basically all work environments, this timely construct and our validated measurement instrument contribute to much-needed research and practical applications.

References

Apers, C., Lang, J. W., & Derous, E. (2019). Who earns more? Explicit traits, implicit motives and income growth trajectories. *Journal of Vocational Behavior, 110*, 214-228. https://doi.org/10.1016/j.jvb.2018.12.004

Armstrong-Stassen, M. (2001). Reactions of older employees to organizational downsizing: The role of gender, job level, and time. *The Journals of Gerontology Series B: Psychological Science and Social Sciences*, *56*(4), 234-243. https://doi.org/10.1093/geronb/56.4.P234

Arthur, M. B., & Rousseau, D. M. (2001). *The boundaryless career: A new employment principle for a new organizational era.* Oxford University Press.

Ashford, S. J., Lee, C., & Bobko, P. (1989). Content, causes, and consequences of job insecurity: A theory-based measure and substantive test. *Academy of Management Journal*, *32*(4), 803-829. https://doi.org/10.5465/256569

Borg, I., & Elizur, D. (1992). Job insecurity: Correlates, moderators and measurement. *International Journal of Manpower, 13*(2), 13-26. https://doi.org/10.1108/01437729210010210

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization*, *24*(2), 239-257. https://doi.org/10.1017/jmo.2016.55

Brougham, D., & Haar, J. (2020). Technological disruption and employment: The influence on job insecurity and turnover intentions: A multi-country study. *Technological Forecasting and Social Change, 161*. https://doi.org/10.1016/j.techfore.2020.120276

Brynjolfsson, E., & McAfee, A. (2011). *Race against the machine: How the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy*. Digital Frontier Press.

Clark, L. A., & Watson, D. (1995). Constructing validity: Basic issues in objective scale development. *Psychological assessment, 7*(3), 309-319. https://doi.org/10.1037/1040-3590.7.3.309

Cureton, E. E., & Mulaik, S. A. (1975). The weighted varimax rotation and the promax rotation. *Psychometrikra, 40*(2), 183-195. https://doi.org/10.1007/BF02291565

Curran, P. J., Obeidat, K., & Losardo, D. (2010). Twelve frequently asked questions about growth curve modeling. *Journal of Cognitive Development*, *11*(2), 121-136. https://doi.org/10.1080/15248371003699969

Dengler, K., & Matthes, B. (2018). The impacts of digital transformation on the labour market: Substitution potentials of occupations in Germany. *Technological Forecasting and Social Change*, *137*, 304-316. https://doi.org/10.1016/j.techfore.2018.09.024

Dennis, R. (1978). The decline of manufacturing employment in Greater London: 1966-74. *Urban Studies 15*(1), 63-73. https://doi.org/10.1080/713702294

El Khwali, E., Keller, A. C., Agostini, M., Gützkow, B., Kreienkamp, J., Leander, N. P., & Scheibe, S. (2022). The rise and fall of job insecurity during a pandemic: The role of habitual coping. *Journal of Vocational Behavior*, 139. https://doi.org/10.1016/j.jvb.2022.103792

Farrell, A. M. (2010). Insufficient discriminant validity: A comment on Bove, Pervan, Beatty, and Shiu (2009). *Journal of Business Research, 63*(3), 324-327. https://doi.org/10.1016/j.jbusres.2009.05.003

Ferris, D. L., Brown, D. J., Berry, J. W., & Lian, H. (2008). The development and validation of the Workplace Ostracism Scale. *Journal of Applied Psychology*, *93*(6), 1348-1366. https://doi.org/10.1037/a0012743

Franco-Martínez, A., Alvarado, J. M., & Sorrel, M. A. (2023). Range restriction affects factor analysis: Normality, estimation, fit, loadings, and reliability. *Educational and Psychological Measurement*, *83*(2), 262-293. https://doi.org/10.1177/00131644221081867

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerization? *Technological Forecasting and Social Change*, 114, 254-280. https://doi.org/10.1016/j.techfore.2016.08.019

Gödöllei, A. (2022). *Hoping for the Best, Preparing for the Worst: Employee Reactions to Automation at Work* [Doctoral dissertation, University of Waterloo]. https://uwspace.uwaterloo.ca/bitstream/handle/10012/18431/Godollei_Anna.pdf?sequence=3&isAllowed=y

Greenglass, E. R., & Burke, R. J. (2000). Hospital downsizing, individual resources, and occupational stressor in nurses. *Anxiety, Stress and Coping*, *13*(4), 371-390. https://doi.org/10.1080/10615800008248342

Greenhaus, J., & Kopelman, R. (1981). Conflict between work and nonwork roles: Implications for the career planning process. *Human Resource Planning, 4*(1), 1-10.

Hinkin, T. R. (1998). A brief tutorial on the development of measures for use in survey questionnaires. *Organizational research methods, 1*(1), 104-121.

Hooper, D., Coughlan, J., & Mullen, M. (2008). Structural equation modelling: Guidelines for determining model fit. *Electronic Journal of Business Research Methods, 6*(1), 53-60. https://doi.org/fv2d

Huang, G. H., Lee, C., Ashford, S., Chen, Z., & Ren, X. (2010). Affective job insecurity: A mediator of cognitive job insecurity and employee outcomes relationships. *International Studies of Management & Organization*, *40*(1), 20-39. https://doi.org/10.2753/IMO0020-8825400102

Huang, G. H., Niu, X., Lee, C., & Ashford, S. J. (2012). Differentiating cognitive and affective job insecurity: Antecendents and outcomes. *Journal of Organizational Behavior, 33*(6), 752-769. https://doi.org/10.1002/job.1815

JASP Team (2023). *JASP* (Version 0.17.1) [Computer software]. JASP Team. https://jasp-stats.org

Jiang, L., & Lavaysee, L. M. (2018). Cognitive and affective job insecurity: A meta-analysis and a primary study. *Journal of Management*, *44*(6), 2307-2342. https://doi.org/10.1177/0149206318773853

Jiang, L., Xu, X., & Wang, H. J. (2021). A resources-demands approach to sources of job insecurity: A multilevel meta-analytic investigation. *Journal of Occupational Health Psychology, 26*(2), 108-126. https://doi.org/10.1037/ocp0000267

Judge, T. A. (2009). Core self-evaluations and work success. *Current directions in psychological science*, *18*(1), 58-62. https://doi.org/10.1111/j.1467-8721.2009.01606.x

Judge, T. A., Erez, A., Bono, J. E., & Thoresen, C. J. (2003). The Core Self-Evaluations Scale: Development of a measure. *Personnel Psychology*, *56*, 303-331. https://doi.org/10.1111/j.1744-6570.2003.tb00152.x

Kinnunen, U., Mäkikangas, A., Mauno, S., De Cuyper, N., & De Witte, H. (2014). Development of perceived job insecurity across two years: associations with antecedents and employee outcomes. *Journal of Occupational Health Psychology, 19*(2), 243-258. https://doi.org/10.1037/a0035835

Kong, H., Yuan, Y., Baruch, Y., Bu, N., Jiang, X., & Wang, K. (2021). Influences of artificial intelligence (AI) awareness on career competency and job burnout. *International Journal of Contemporary Hospitality Management, 33*(2), 717-734. https://doi.org/10.1108/IJCHM-07-2020-0789

Krzywdzinski, M., Butollo, F., Flemming, J., Gerber, C., Wandjo, D., Delicat, N., Herzog, L., Bovenschulte, M., Nerger, M. (2022). *The Growing Gap Between Pioneers and Laggards: Digitalization, automation, and organizational change in the wake of the COVID-19-crisis in Germany*. Weizenbaum Institute for the Networked Society – The German Internet Insititute. https://doi.org/10.34669/WI.WS/25

Kurniawan, D. T., Prameka, A. S., Praktikto, H. (2022, September). STARA is in Sight: The Effect of STARA on Job Outcome through Job Insecurity Perception about Future Workplace on Private Companies in East Java, Indonesia. *In 2022 3rd International Conference on Big Data Analytics and Practices (IBDAP)* (pp. 52-56). IEEE. https://doi.org/10.1109/IBADP55587.2022.9907292

Lazarus, R. S., & Folkman, S. (1984). *Stress, appraisal, and coping*. Springer Publishing Company.

Li, J. J., Bonn, M. A., & Ye, B. H. (2019). Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: The moderating roles of perceived organizational support and competitive psychological climate. *Tourism Management, 73*, 172-181. https://doi.org/10.1016/j.tourman.2019.02.006

Lingmont, D. M., & Alexiou, A. (2020). The contingent effect of job automating technology awareness on perceived job insecurity: Exploring the moderating role of organizational culture. *Technological Forecasting and Social Change, 161*. https://doi.org/10.1016/j.techfore.2020.120302

Liang, X., Guo, G., Shu, L., Gong, Q., & Luo, P. (2022). Investigating the double-edged sword effect of AI awareness on employee's service innovative behavior. *Tourism Management*, *92*. https://doi.org/10.1016/j.tourman.2022.104564

Miller, M. J., & Sheu, H. B. (2008). Conceptual and measurement issues in multicultural psychology research. In S. D. Brown, & R. W. Lent (Eds.), *Handbook of Counseling Psychology* (pp. 103-120). John Wiley & Sons Inc.

Nübold, A., Muck, P. M., & Maier, G. W. (2013). A new substitute for leadership? Followers' state core self-evaluations. *The Leadership Quarterly*, *24*(1), 29-44. https://doi.org/10.1016/j.leaqua.2012.07.002

Roll, L. C., De Witte, H., & Wang, H. J. (2023). Conceptualization and Validation of the Occupation Insecurity Scale (OCIS): Measuring Employees' Occupation Insecurity Due to Automation. *International Journal of Environment Research and Public Health*, *20*(3), 2589. https://doi.org/10.3390/ijerph20032589

Roskies, E., & Louis-Guerin, C. (1990). Job insecurity in managers: Antecedents and consequences. *Journal of Organizational Behavior*, *11*(5), 345-359. https://doi.org/10.1002/job.4030110503

Rosseel, Y. (2012). lavaan: An R Package for Structural Equation Modeling. *Journal of Statistical Software*, *48*(2), 1-36. https://doi.org/10.18637/jss.v048.i02

Schaufeli, W. B., Shimazu, A., Hakanen, J., Salanova, M., & De Witte, H. (2017). An ultra-short measure for work engagement. *European Journal of Psychological Assessment*, *35*, 577-591. https://doi.org/10.1027/1015-5759/a000430

Schinkel, S., Van Dierendonck, D., & Anderson, N. (2004). The impact of selection encounters on applicants: An experimental study into feedback effects after a negative selection decision. *International Journal of Selection and Assessment*, *12*(1-2), 197-205. https://doi.org/10.1111/j.0965-075X.2004.00274.x

Schwab, D. P. (1980). Construct validity in organization behavior. In B. M. Staw & L. L. Cummings (Eds.), *Research in organizational behavior* (Vol. 2, pp.3-43). CT: JAI.

Shoss, M. K. (2017). Job insecurity: An integrative review and agenda for future research. *Journal of Management*, *43*(6), 1911-1939. https://doi.org/10.1177/0149206317691574

Staufenbiel, T., & König, C. J. (2011). An evaluation of Borg's cognitive and affective job insecurity scales. *International Journal of Business and Social Science*, *2*(20).

Stumpp, T., Muck, P. M., Hülsheger, U. R., Judge, T. A., Maier, G. W. (2010). Core Self-Evaluations in Germany: Validation of a German Measure and its Relationships with Career Success. *Applied Psychology: An International Review*, *59*(4), 674-700. https://doi.org/10.1111/j.1464-0597.2010.00422.x

Sverke, M., Hellgren, J., & Näswall, K. (2002). No security: a meta-analysis and review of job insecurity and its consequences. *Journal of Occupational Health Psychology*, *7*(3), 242-264. https://doi.org/10.1037//1076-8998.7.3.242

Truta, C., Maican, C. I., Cazan, A. M., Lixandroiu, R. C., Dovleac, L., Maican, M. A. (2023). Always connected @ work. Technostress and well-beings with academics. *Computers in Human Behavior*, *143*. https://doi.org/10.1016/j.chb.2023.107675

Walsh, S. M., & Strano, M. S. (2018). *Robotic systems and autonomous platforms: Advances in materials and manufacturing.* Woodhead Publishing.

West, S. G., Taylor, A. B., & Wu, W. (2012). Model fit and model selection in structural equation modeling. In R. H. Hoyle (Ed.), *Handbook of structural equation modeling* (pp.209-231). The Guilford Press.

Yam, K., C., Tang, P. M., Jackson, J. C., Su, R., & Gray, K. (2023). The rise of robots increases job insecurity and maladaptive workplace behaviors: Multimethod evidence. *Journal of Applied Psychology*, *108*(5), 850-870. https://doi.org/10.1037/apl0001045

Table 1

Fit indices of the CFA models of STARA Awareness, cognitive and affective JI and average variance extracted (Study 1)

Model	χ^2	*df*	χ^2/df	$\Delta\chi^2(\Delta df)$	CFI	RMSEA	SRMR	AIC	AVE
STARA Awareness measurement model	17.442	2	8.72		.965	.190	.037	42.442	.620
Model Comparisons (including items for cognitive and affective job insecurity)									
One-factor model	1083.377	44	24.62		.311	.332	.255	1149.377	
Three-factor model	111.770	41	2.73	971.68(3)***	.953	.090	.065	183.770	

Notes. $N = 215$. Chi-square difference test compares to the previous model. *** $p < .001$. AVE = Average variance extracted.

Table 2

Descriptive statistics and bivariate Spearman intercorrelations of study variables (Study 1)

	Variables	*M*	*SD*	1	2	3	4	5	6
1	STARA Awareness	1.83	0.80	(.87)					
2	Cognitive JI	2.82	1.30	.17*	(.85)				
3	Affective JI	3.12	1.75	.16*	.25***	(.93)			
4	SP	35.39	31.40	.34***	-.16*	-.03	-		
5	Use of STARA	32.42	28.62	.21**	-.08	.00	.35***	-	
6	CSE	3.76	0.58	-.12	-.19**	-.32***	.04	.11	(.86)

Notes. $N = 215$. Cronbach's alpha in brackets. JI = Job insecurity. SP = Substitution potential. CSE = Core self-evaluations. Responses in SP and Use of STARA in percent. *$p < .05$. **$p < .01$. ***$p < .001$. SP is stronger related to STARA Awareness than to cognitive JI, $z = 6.208$, $p < .001$, and affective JI, $z = 4.446$, $p < .001$. Use of STARA is stronger related to STARA Awareness than to cognitive JI, $z = 3.402$, $p < .001$, and affective JI, $z = 2.428$, $p = .015$. CSE is not stronger related to cognitive JI than to STARA Awareness, $z = -0.812$, $p = .417$, but stronger related to affective JI than to STARA Awareness, $z = -2.373$, $p = .018$.

Table 3

Fit indices of the CFA models of STARA Awareness, cognitive and affective STARA Awareness, cognitive and affective JI and average variance extracted (Study 2)

Model	χ^2	*df*	χ^2/df	$\Delta\chi^2(\Delta df)$	CFI	RMSEA	SRMR	AIC	AVE
STARA measurement model	0.435	2	0.218		1.000	.000	.005	1767.049	.652
14 Items Model comparison (including items for cognitive and affective STARA Awareness)									
One-factor model	501.581	77	6.514		.794	.157	.095	7235.522	
Two-factor model	412.133	76	5.423	1.091(1)	.837	.141	.085	7148.074	
AAJI measurement model	1.895	2	0.948		1.000	.000	.010	1660.406	.677
Model Comparisons (AAJI and cognitive and affective JI)									
One-factor model	1143.900	44	25.793		.339	.333	.264	7712.084	
Three-factor model	49.960	41	1.22	1084.94(3)***	.995	.031	.035	6633.144	

Notes. $N = 224$. Chi-square difference test compares to the previous model. AVE = Average variance extracted. STARA = STARA Awareness. AAJI = Affective automation-related job insecurity. *** $p < .001$.

Table 4

Descriptive statistics and bivariate Spearman intercorrelations of study variables (Study 2)

Variables		*M*	*SD*	1	2	3	4	5	6
1	AAJI	1.62	0.71	(.89)					
2	Cognitive JI	2.61	1.35	.14*	(.87)				
3	Affective JI	2.95	1.73	.15*	.33***	(.94)			
4	SP	32.22	27.89	.35***	-.24***	-.06	-		
5	Use of STARA	27.63	25.96	.33***	-.09	.04	.28***	-	
6	CSE	3.78	0.63	-.15*	-.25**	-.32***	.07	.08	(.87)

Notes. N = 224. Cronbach's alpha in brackets. AAJI = Affective automation-related job insecurity. JI = Job insecurity. SP = Substitution potential. CSE = Core self-evaluations. Responses in SP and Use of STARA in percent. *p < .05. **p < .01. ***p < .001. SP is stronger related to AAJI than to cognitive JI, z = 7.568, p < .001, and affective JI, z = 5.039, p < .001. Use of STARA is stronger related to AAJI than to cognitive JI, z = 5.124, p < .001, and affective JI, z = 3.503, p < .001. CSE is not stronger related to cognitive JI than to STARA Awareness, z = -1.179, p = .238, but stronger related to affective JI than to AAJI, z = -2.051, p = .040.

Table 5

Fit indices of the CFA models of affective automation-related job insecurity and average variance extracted at three measurement points (Study 3)

Measurement Point	$\chi 2$	*df*	χ^2/df	CFI	RMSEA	SRMR	AIC	AVE
T1 (N = 406)	12.893	2	6.447	.989	.116	.018	3267.072	.723
T2 (N = 261)	2.912	2	1.456	.998	.042	.011	2012.554	.655
T3 (N = 233)	7.854	2	3.927	.988	.112	.020	1768.053	.645

Notes. AVE = Average variance extracted.

Table 6

Descriptive statistics and bivariate Spearman intercorrelations of study variables at three measurement points (Study 3)

Variables			*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12
T1	1	AAJI	1.71	0.79	(.90)											
	2	SP	36.09	29.74	.35***	-										
	3	Use of STARA	33.98	28.76	.20***	.23***	-									
	4	CSE	3.68	0.61	-.25***	-.05	.07	(.85)								
T2	5	AAJI	1.63	0.73	.64***	.45***	.20**	-.21**	(.88)							
	6	SP	38.09	29.85	.40***	-	.25***	-.04	.45***	-						
	7	Use of STARA	34.56	28.43	.30***	.44***	.64***	-.03	.34***	.44***	-					
	8	CSE	3.72	0.63	-.14*	.04	.07	.74***	-.17**	.04	.01	(.87)				
T3	9	AAJI	1.71	0.70	.57***	.36***	.18**	-.18**	.65***	.36***	.26***	-.12	(.88)			
	10	SP	38.78	30.17	.36***	-	.30***	-.02	.44***	-	.46***	.03	.36***	-		
	11	Use of STARA	33.05	26.60	.27***	.33***	.65***	.02	.33***	.33***	.70***	.03	.27***	.33***	-	
	12	CSE	3.72	0.61	-.17*	.00	.06	.74***	-.18**	.00	.07	.75***	-.19**	.00	.04	(.88)

Notes. N_{T1} = 406. N_{T2} = 261. N_{T3} = 233. Participants with changes in objective substitution potential (by changes in jobs) were excluded. Cronbach's alpha in brackets. AAJI = Affective automation-related job insecurity. SP = Substitution potential. CSE = Core self-evaluations. Responses in SP and Use of STARA in percent. *$p < .05$. **$p < .01$. ***$p < .001$.

Table 7

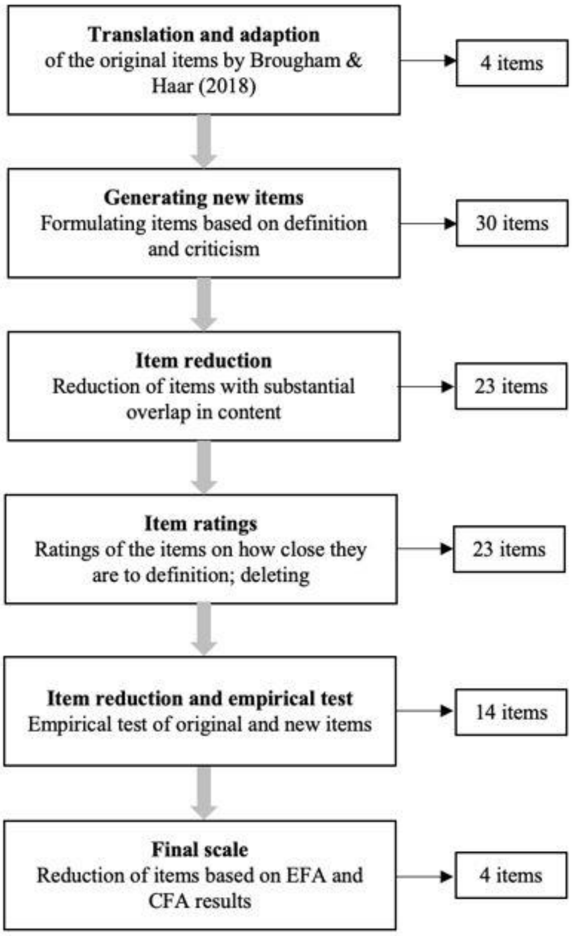
LCM results for baseline model (M0) and with predictors (M1) with criterium affective automation-related job insecurity (Study 3)

	M0		M1	
	β	*SE*	β	*SE*
Effects of predictors on intercept				
SP			.271***	0.038
Use of STARA			.131**	0.046
CSE			-.136***	0.037
Effects of predictors on slope				
Use of STARA			-.055*	0.023
Variance components				
Intercept	0.463		0.324	
Slope	0.041		0.037	
$r_{\text{intercept, slope}}$	-.49*		-.48**	
R^2				
Intercept			.288	
Slope			.074	
Model fit indices				
Normed χ^2	6.817		12.705	
CFI	.980		.987	
TLI	.941		.981	
RMSEA	.158		.050	
SRMR	.031		.029	
AIC	1298.361		1230.235	

Notes. N = 233. Predictors were z-standardized. SP = Substitution potential. CSE = Core self-evaluations. $*p < .05$. $**p < .01$. $***p < .001$.

Figure 1

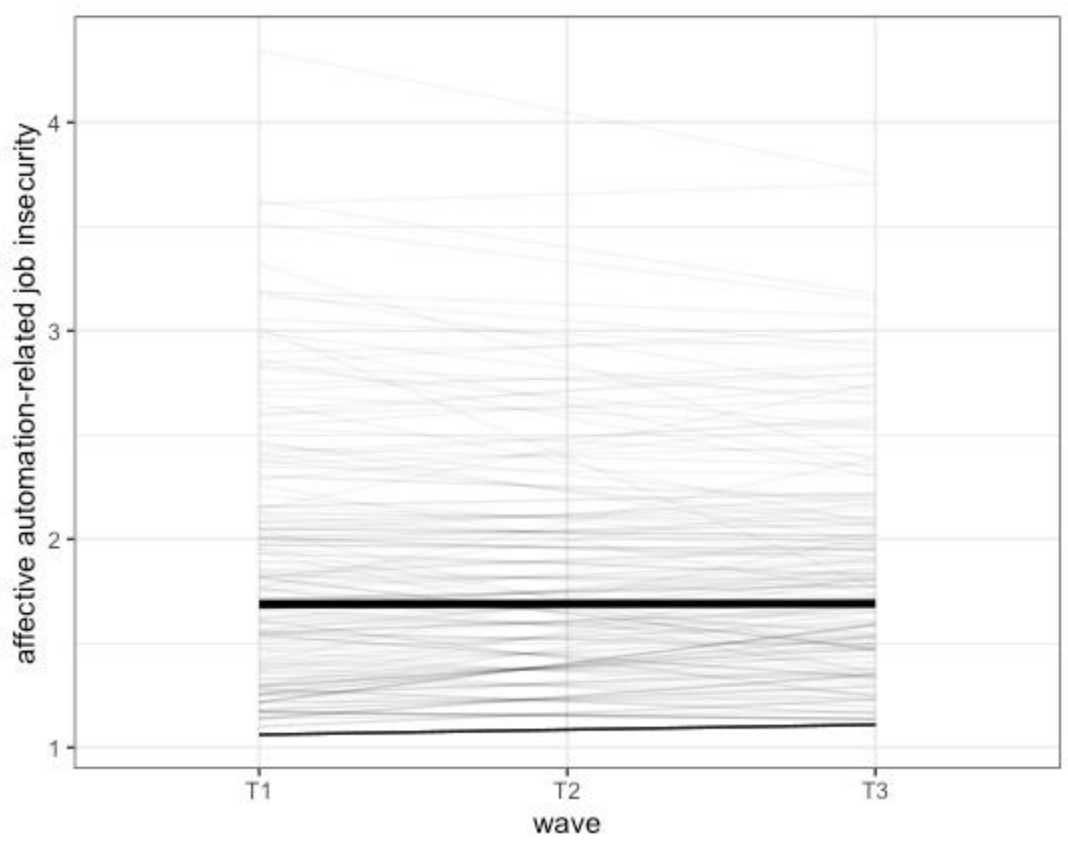
Item generation and reduction process (automation-related job insecurity)



Notes. EFA = Exploratory Factor Analysis. CFA = Confirmatory Factor Analysis.

Figure 2

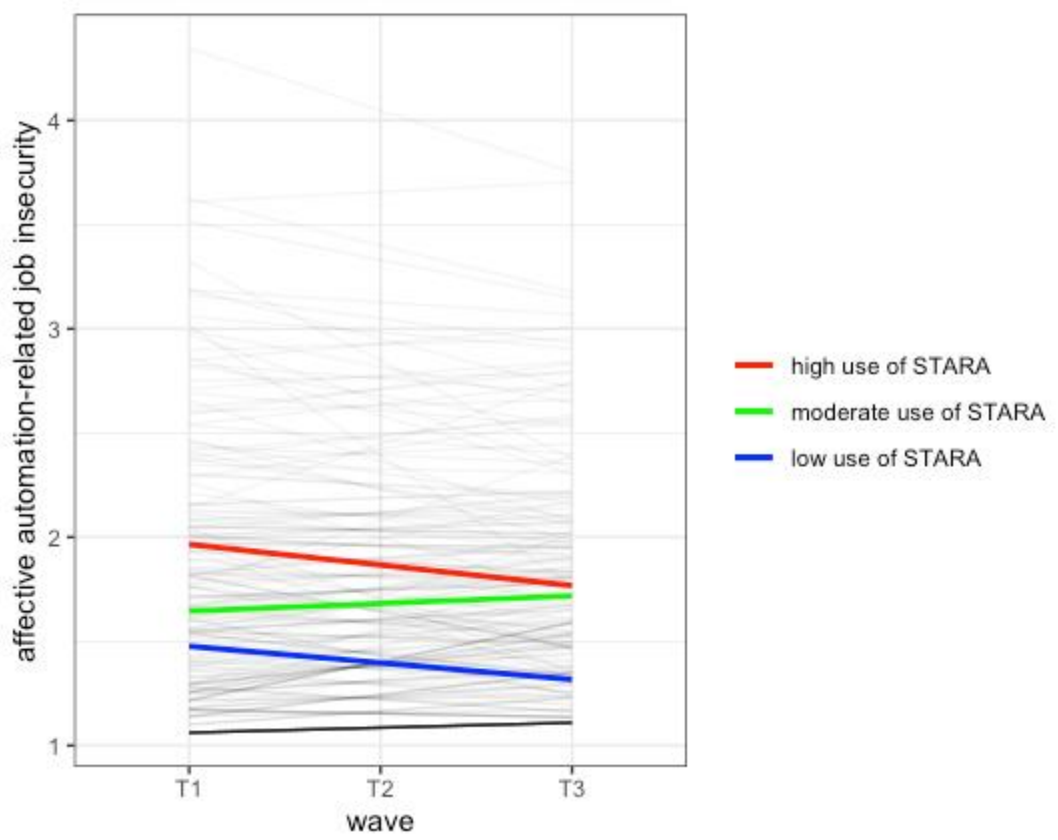
Baseline model M0: The trajectory of affective automation-related job insecurity over the three measurement points (Study 3)



Notes. N = 233. The bold line represents the average intercept and slope in affective automation-related job insecurity over one year. Gray lines represent regression lines for every participant.

Figure 3

M1: Change of affective automation-related job insecurity over the three measurement points as a function of use of STARA (Study 3)



Notes. N = 233. The colored lines represent separate regression lines in affective automation-related job insecurity over one year for participants with low, moderate and high use of STARA, respectively. Gray lines represent regression lines for every participant.

Electronic Supplementary Material (ESM)

Table 1

Factor Loadings from the Exploratory Factor Analysis of the 14-Item to capture cognitive and affective JI (EFA Model 2, Study 2)

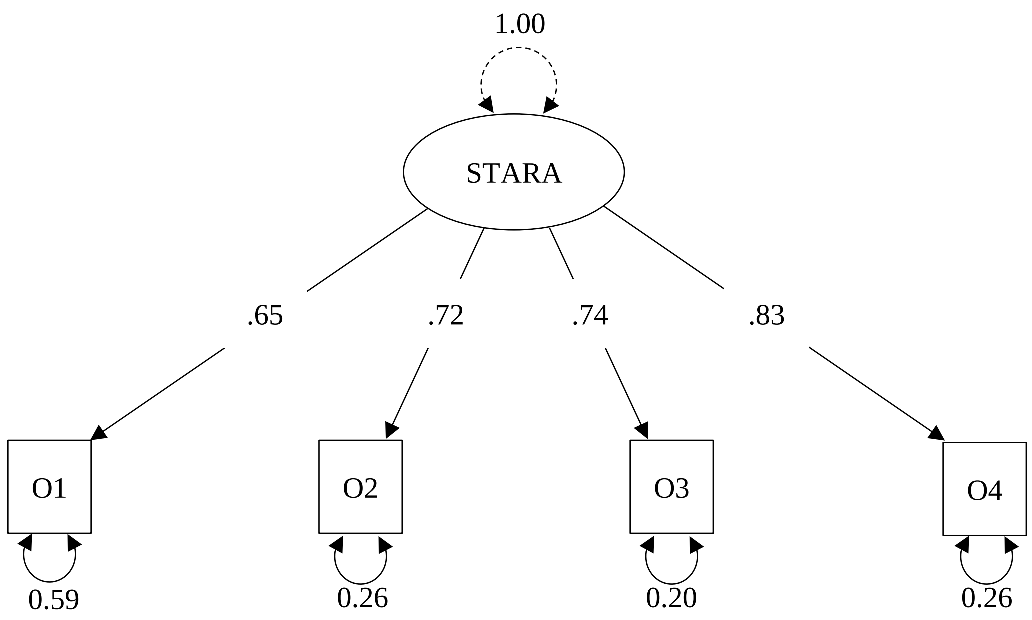
Item	German version *English version (translated)*	Factor loading 1	Factor loading 2
O1	Ich denke, meine Arbeit könnte durch intelligente Technologie, Automatisierung, Robotik und künstliche Intelligenz ersetzt werden. *I think my job could be replaced by smart technology, artificial intelligence, robotics and automation.*	**.72**	.08
O2	Ich persönlich mache mir Sorgen, dass es möglich sein wird, dass das, was ich jetzt in meinem Job mache, durch intelligente Technologie, Automatisierung, Robotik und künstliche Intelligenz ersetzt werden kann. *I am personally worried that what I do now in my job will be able to be replaced by smart technology, artificial intelligence, robotics and automation.*	**.93**	-.12
O3	**Ich persönlich mache mir Sorgen über meine Zukunft in meinem Unternehmen, da intelligente Technologie, Automatisierung, Robotik und künstliche Intelligenz Mitarbeiter ersetzt.** ***I am personally worried about my future in my organisation due to smart technology, artificial intelligence, robotics and automation replacing employees***.	**.79**	.02
O4	**Ich persönlich mache mir Sorgen über meine Zukunft in meiner Branche, da intelligente Technologie, Automatisierung, Robotik und künstliche Intelligenz Mitarbeiter ersetzt.** ***I am personally worried about my future in my industry due to smart technology, artificial intelligence, robotics and automation replacing employees.***	**.86**	-.07
C1	Mein Beruf wird trotz Entwicklungen in intelligenter Technologie, Automatisierung, Robotik und künstlicher Intelligenz weiterhin bestehen. (R) *My occupation will continue to remain despite developments in smart technology, artificial intelligence, robotics and automation. (R)*	**.49**	.06
C2	Ich denke, intelligente Technologie, Automatisierung, Robotik und künstliche Intelligenz werden zentrale Aspekte meines Berufs ersetzen. *I think smart technology, artificial intelligence, robotics and automation will replace central aspects of my occupation.*	**.63**	.14
C3	Ich denke, intelligente Technologie, Automatisierung, Robotik und künstliche Intelligenz werden zentrale Aufgaben in meinem Beruf ersetzen. *I think smart technology, artificial intelligence, robotics and automation will replace central tasks of my occupation.*	**.64**	.14
C4	Ich denke, intelligente Technologie, Automatisierung, Robotik und künstliche Intelligenz werden Arbeitsplätze in meinem Unternehmen ersetzen. *I think smart technology, artificial intelligence, robotics and automation will replace jobs in my organisation.*	.03	**.80**

C5	In meinem Unternehmen werden Arbeitsplätze durch intelligente Technologie, Automatisierung, Robotik und künstliche Intelligenz wegfallen. *In my organization, jobs will be lost to smart technology, artificial intelligence, robotics and automation.*	-.07	**.96**
C6	In meiner Branche werden Arbeitsplätze durch intelligente Technologie, Automatisierung, Robotik und künstliche Intelligenz abgebaut. *In my industry, jobs are being cut due to smart technology, artificial intelligence, robotics and automation.*	-.02	**.86**
A1	**Ich befürchte, dass intelligente Technologie, Automatisierung, Robotik und künstliche Intelligenz einen Großteil meiner aktuellen Arbeit übernehmen werden.** ***I fear that smart technology, artificial intelligence, robotics and automation will take over the majority of my current work.***	**.83**	.03
A2	Dass intelligente Technologie, Automatisierung, Robotik und künstliche Intelligenz wichtige Tätigkeiten meines Berufs ersetzen werden, ängstigt mich. *The fact that smart technology, artificial intelligence, robotics and automation will replace important activities in my occupation scares me.*	**.82**	-.12
A3	Ich bin unbesorgt, dass mein Beruf vollständig automatisiert wird. (R) *I am unconcerned that my occupation will be completely automated. (R)*	.27	.06
A4	**Ich habe Angst, meinen Job durch intelligente Technologie, Automatisierung, Robotik und künstliche Intelligenz zu verlieren.** ***I'm afraid of losing my job to smart technology, artificial intelligence, robotics and automation.***	**.89**	-.10

Note. $N = 224$. O = original items, C = cognitive items, A = affective items. English translations of the original items are adapted from Brougham & Haar (2018). Applied rotation method is promax. Factor loadings above .40 are in bold. Reverse-scored items are denoted with an (R). The final items of the questionnaire to assess affective automation-related job insecurity are in bold.

Figure 1

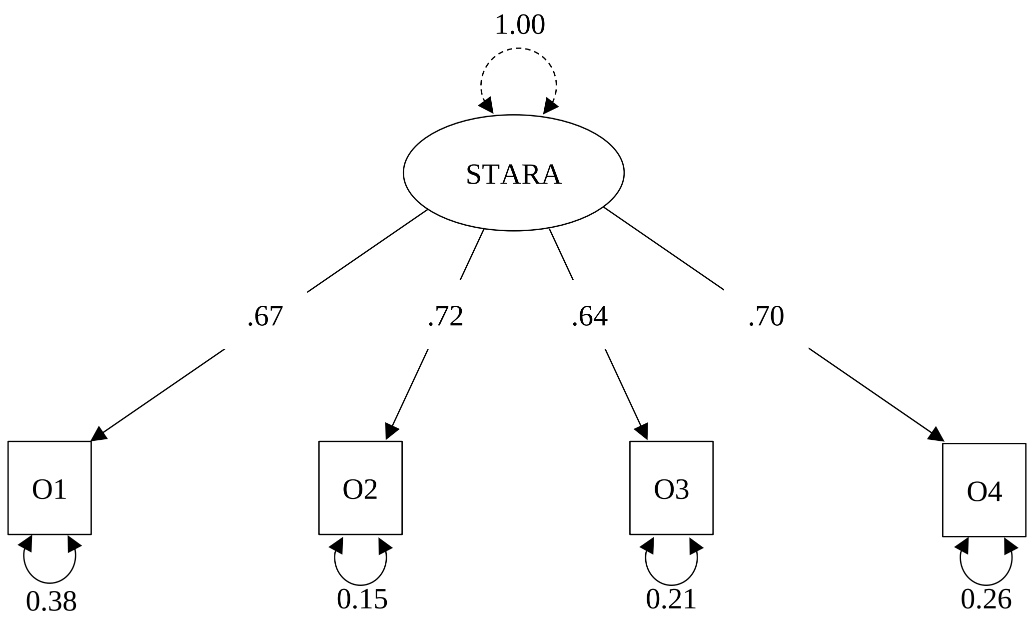
Model Plot for the original STARA Awareness Items with one Factor (Study 1)



Note. *N* = 215. STARA = STARA Awareness.

Figure 2

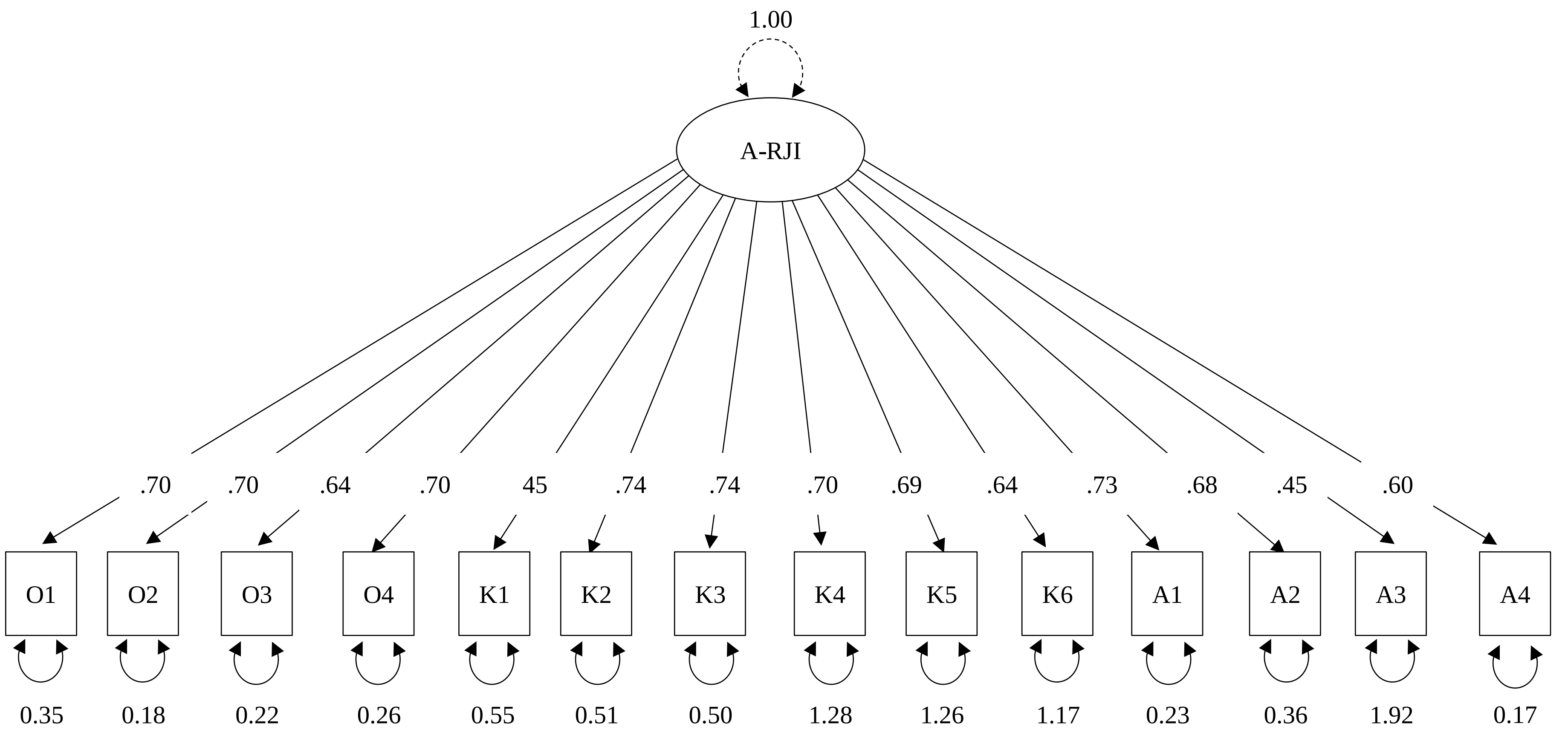
Model Plot for the original STARA Awareness Items with one Factor (*Study 2)*



Note. *N* = 224. STARA = STARA Awareness.

Figure 3

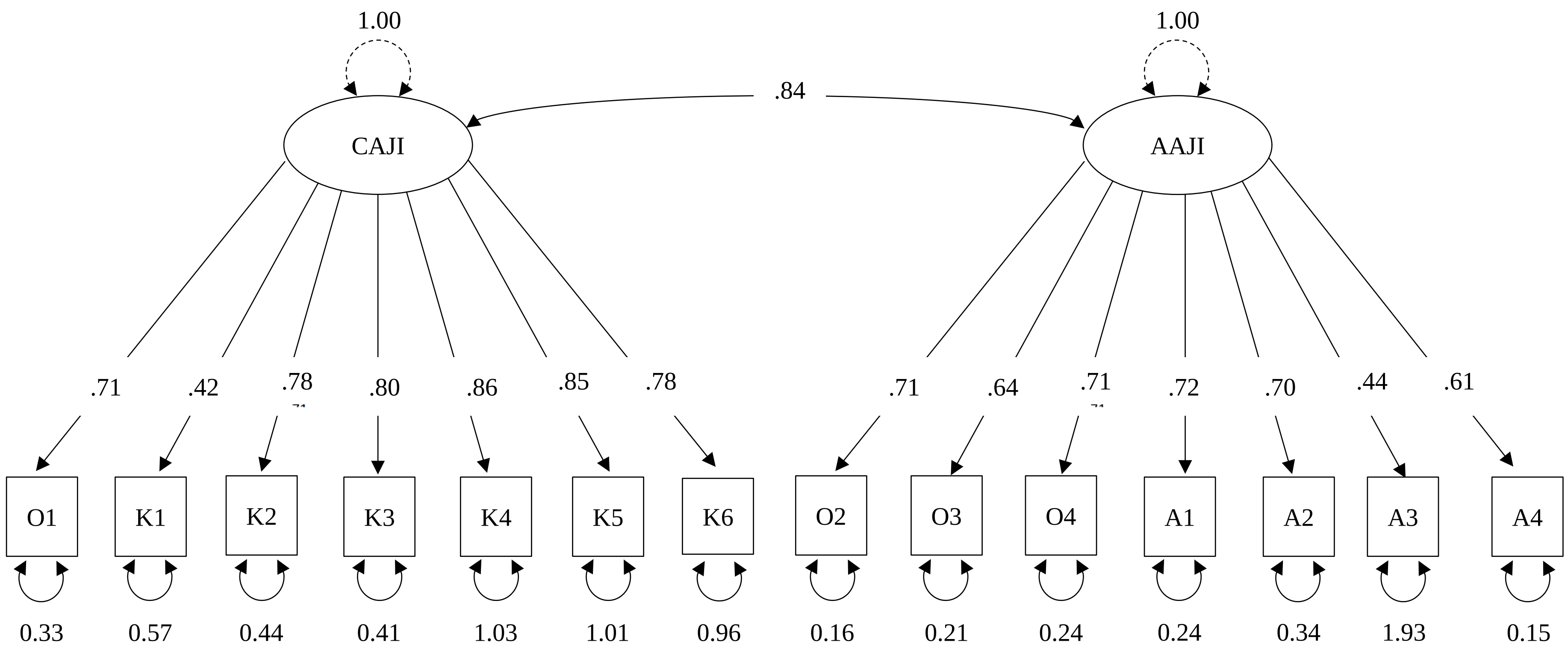
Model Plot for the 14 Items to capture automation-related job insecurity (A-RJI) with one Factor (Study 2)



Note. *N* = 224.

Figure 4

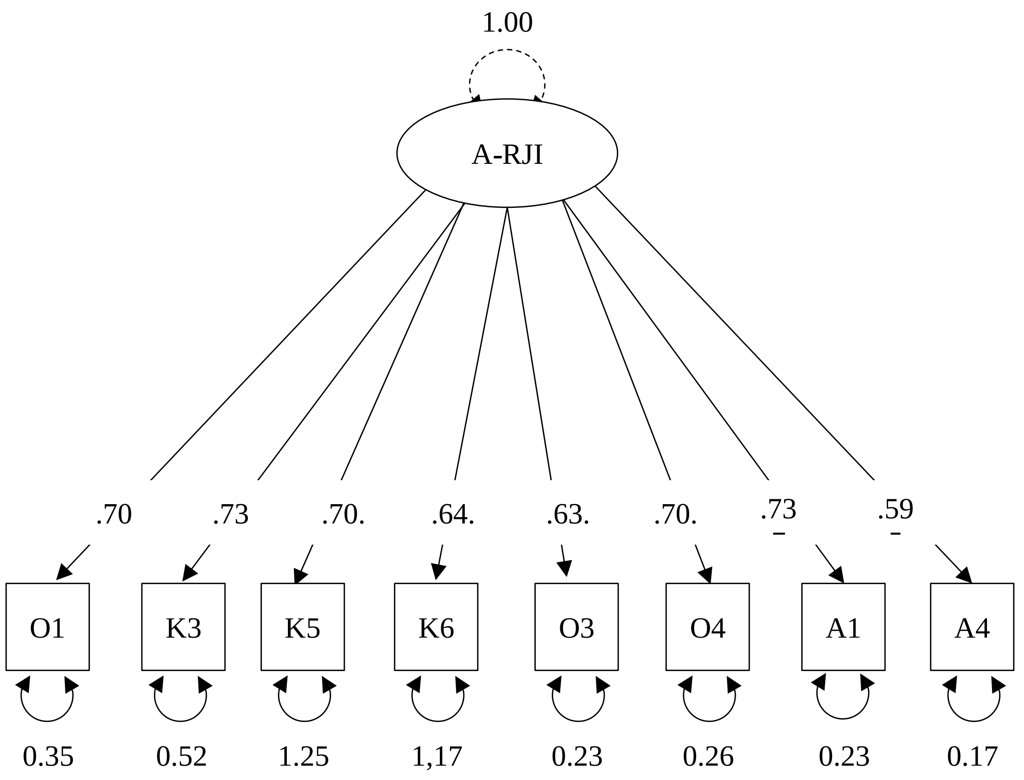
Model Plot for the 14 Items to capture automation-related job insecurity (A-RJI) with two Factors (Study 2)



Notes. *N* = 224. CAJI = Cognitive automation-related job insecurity. AAJI = Affective automation-related job insecurity.

Figure 5

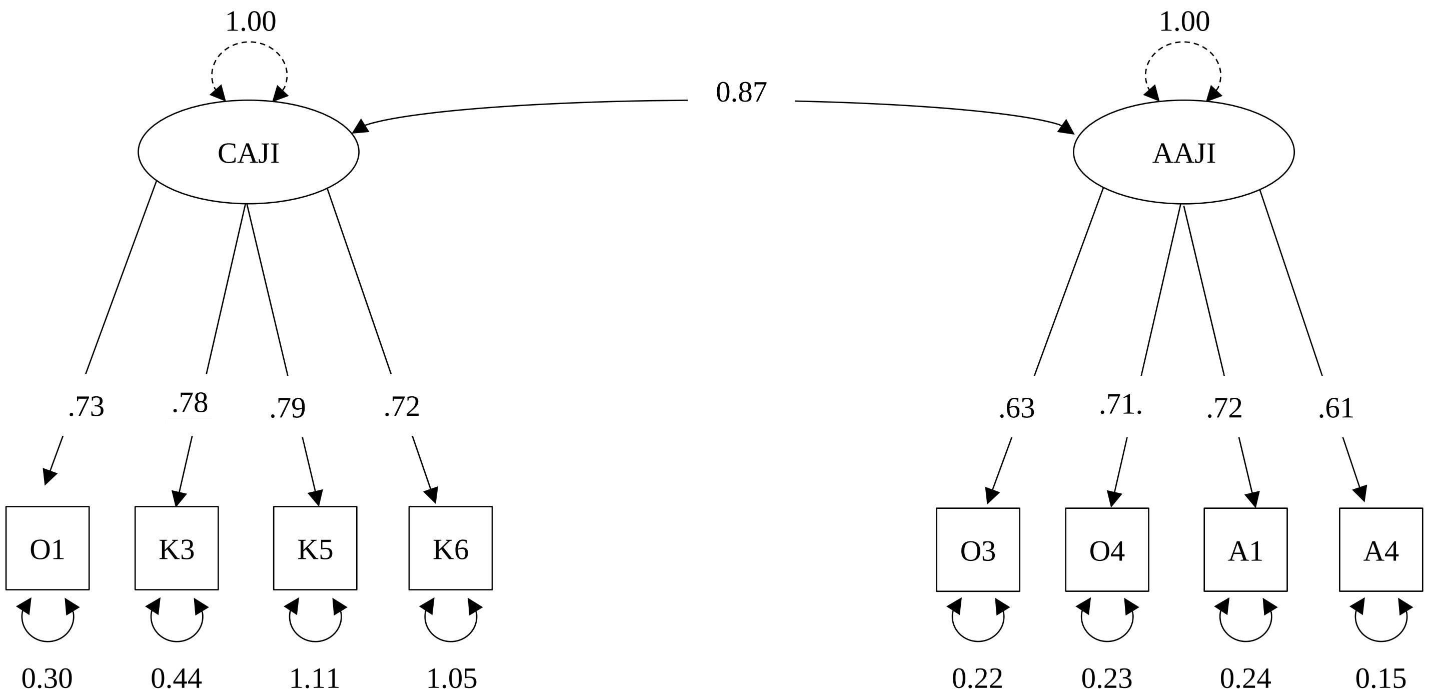
Model Plot for the 8 Items to capture automation-related job insecurity (A-RJI) with one Factor (*Study 2)*



Note. N = 224.

Figure 6

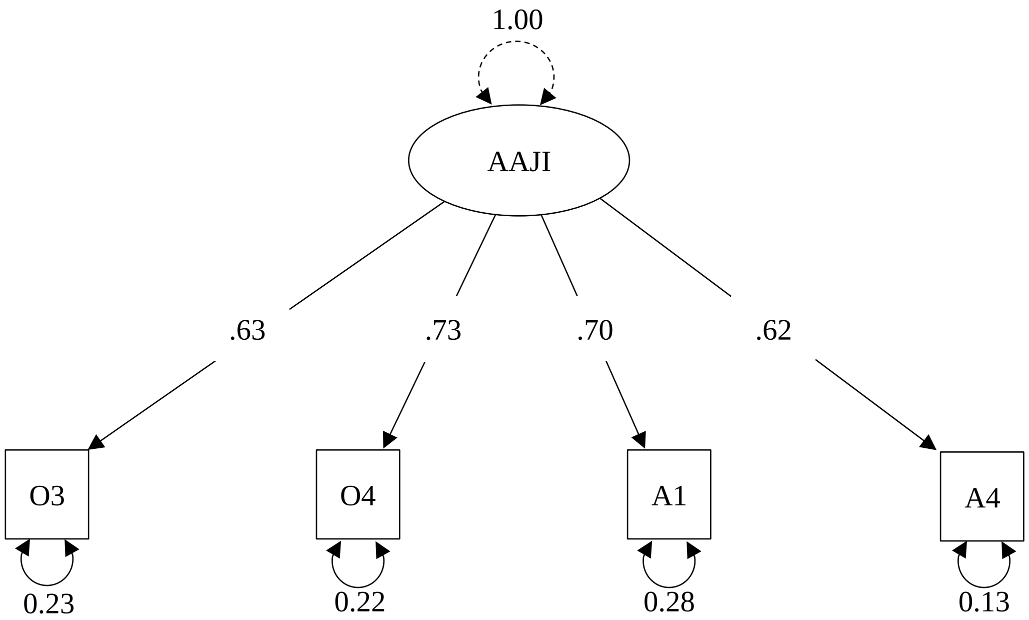
Model Plot for the 8 Items to capture automation-related job insecurity with two Factors (Study 2)



Note. N = 224. CAJI = Cognitive automation-related job insecurity. AAJI = Affective automation-related job insecurity.

Figure 7

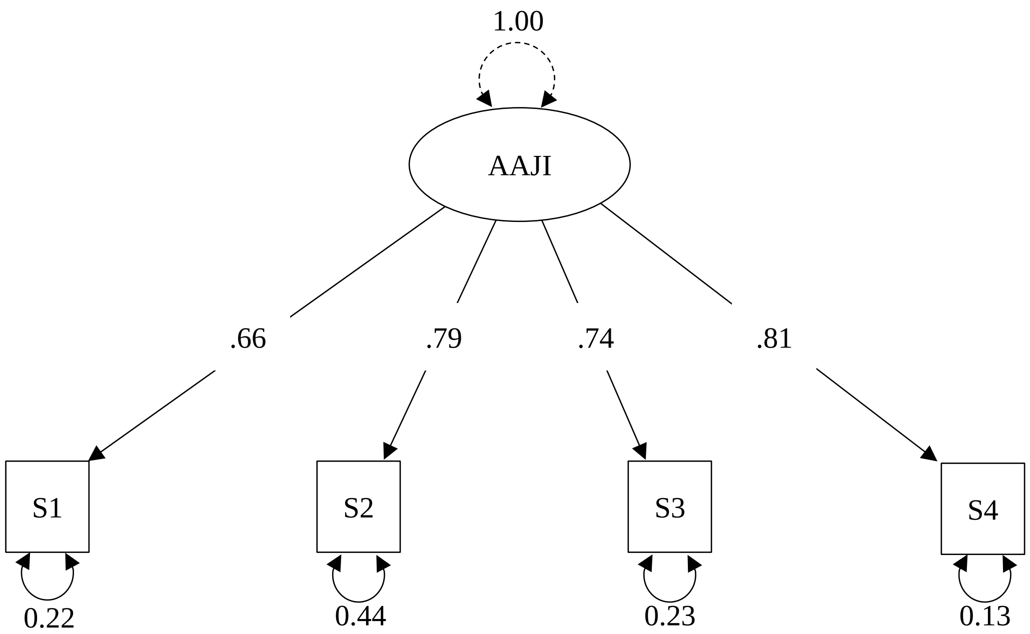
Model Plot for the revised scale to capture affective automation-related job insecurity (AAJI) (Study 2)



Note. *N* = 224.

Figure 8

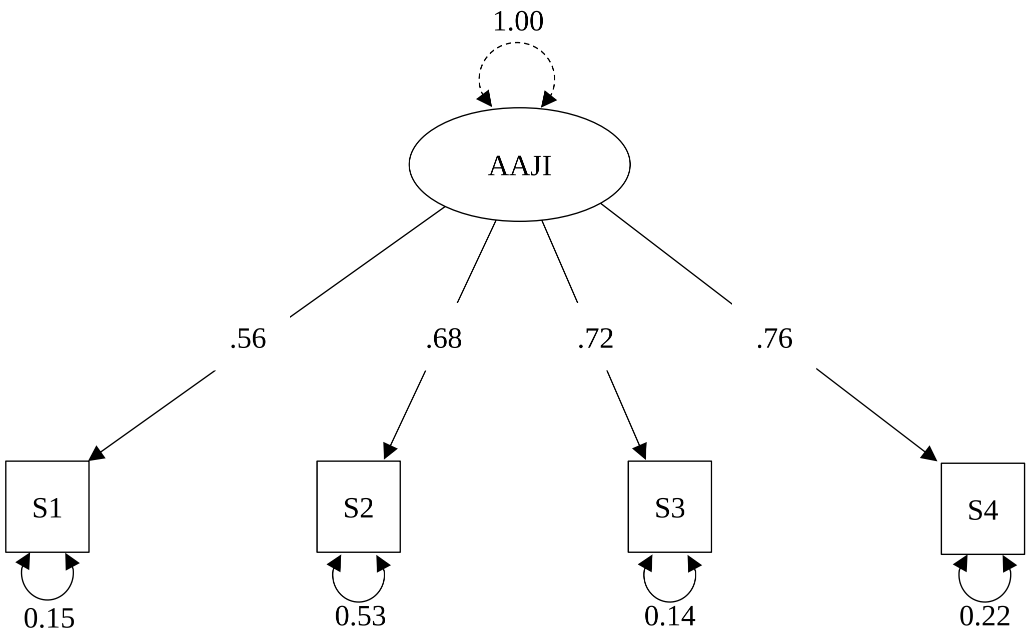
Model Plot for the revised scale to capture affective automation-related job insecurity (AAJI) at T1 (*Study 3)*



Note. *N* = 406.

Figure 9

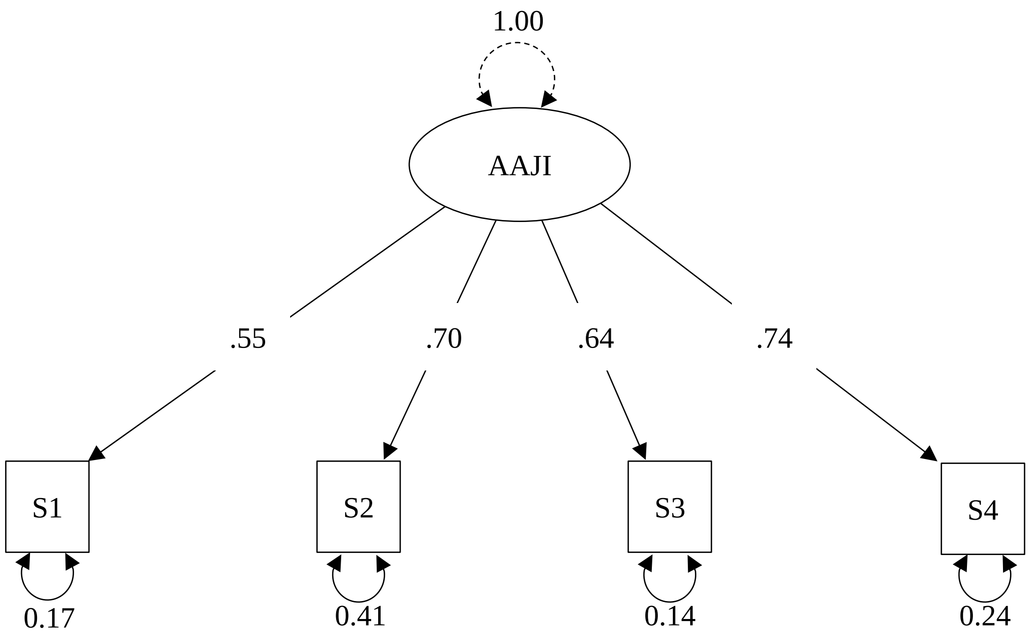
Model Plot for the revised scale to capture affective automation-related job insecurity (AAJI) at T2 (*Study 3)*



Note. *N* = 261.

Figure 10

Model Plot for the revised scale to capture affective automation-related job insecurity (AAJI) at T3 (Study 3)



Note. *N* = 233.

Chapter 5 – General Discussion

To achieve formulated research aims, we conducted a total of six empirical data collections with German and English samples (either blue-collar workers or employees with various occupational backgrounds), specifically three online experiments with vignette methodology, two cross-sectional studies, and one longitudinal study with a total time lag of one year. The following is a summary of our multi-method study results that are contained in the three articles included in this dissertation concerning the research goals.

First, the implementation of intelligent assistance systems as part of today's novel digital technologies (STARA) significantly alters modern workplaces in assembly by modifying motivational work characteristics. The use of the investigated intelligent assistance system for cognitive assistance of simple assembly sequences (assembly of a simple box) yields significant improvements in motivational work characteristics by increasing feedback from job and information processing compared with the work without the intelligent assistance system.

Second, we were precluded from testing a buffering effect of the voluntary use of intelligent assistance systems for two reasons: We did not identify any negative effects in terms of reductions in motivational work characteristics in the assembly of products due to the use of the intelligent assistance system. Moreover, our included manipulation check indicated that the experimental manipulation of the voluntary use in a dedicated experimental condition failed.

Third, the generalizability of the identified effects of the investigated intelligent assistance system on motivational work characteristics is limited. Our results indicate that these effects depend on the objective complexity of the assisted assembly process. When supporting an objectively more complex assembly process, the intelligent assistance system not only provides positive effects on motivational work characteristics in terms of enhanced feedback from job and information processing, but also negative effects in the form of restricted work scheduling, decision-making, and work methods autonomy.

Fourth, the extent of task rotation (alternation between assembly products) neither independently leads to improved motivational work characteristics in assembly – besides enhanced task variety – nor to modifications of the contrary effects that the intelligent assistance system exhibits. The contradictory effects that the intelligent assistance system induces on motivational work characteristics in the assistance of more complex assembly products remain unchanged, regardless of whether employees rotate frequently between assembly products or not.

Fifth, by providing a thorough construct validation and redefinition of STARA Awareness, we establish *affective automation-related job insecurity* as a digitalization-specific form of job insecurity. To enhance content clarity, we solely focused on the affective component and defined affective automation-related job insecurity as employees' affective appraisal (concern, worry, anxiety) of STARA-driven task and job substitution. It exhibits weak positive relations with cognitive and affective job insecurity but unique relations to indicators of technological change. With rising levels for specific subgroups (initial moderate use of STARA), affective automation-related job insecurity represents a novel and timely construct that captures how employees appraise the implementation of STARA in the modern world of work to impact their employment by substitution of human labor. However, as the fit indices of the measurement model using the original scale by Brougham and Haar (2018) strongly varied between independent samples, our results indicated the need for adaptations of the questionnaire.

Sixth, following our criticism on its content and psychometric properties, we adapted the original scale by Brougham and Haar (2018) by excluding cognitive components and including the substitution of core tasks within a job in the measurement instrument to enhance content clarity and consider the expected STARA-driven changes of the modern world of work more realistically (Dengler & Matthes, 2018; Parker & Grote, 2022a). In conclusion, we provided a short and valid scale to assess employees' affective automation-related job insecurity for application in research and organizational practice.

By answering the proposed research questions, this dissertation contributes vital theoretical and practical implications. It yields essential advances for the development of theories in industrial and organizational psychology that describe and explain how the implementation of STARA at work transforms workplaces and affects employees directly or via altering motivational work characteristics. By highlighting the contradictory effects of ongoing digitalization in our modern labor market on employees, this dissertation promotes the human-centered development, introduction, and use of STARA at work.

1. Theoretical Implications

With the integration of a variety of theoretical approaches, frameworks, and models including the routine-biased technological change (Autor et al., 2003), the cyber-physical systems transformation framework (Waschull et al., 2020), and the model on the future work design (Gagné et al., 2022) this dissertation provides causal evidence on the contradictory effects of increasingly digitalized workplaces on motivational work characteristics. Specifically, the empirical evidence highlights the increased feedback from job and information processing and decreased autonomy in all three differentiated facets (work scheduling, decision-making, and work methods autonomy) when working with intelligent assistance systems in assembly. While enhanced feedback from job and information processing imply positive effects, restricted autonomy implies negative effects on employee outcomes (Humphrey et al., 2007). This dissertation emphasizes the need for work design theories that describe and explain how the implementation of specific digital technologies shapes workplaces in our digitalized labor market. None of the previously mentioned theoretical approaches solely postulates our identified effects of the intelligent assistance system on motivational work characteristics: The existing approaches neither cover the variety of (motivational) work characteristics that are subject to technological change, nor postulate changes in specific characteristics. This complicates the derivation of hypotheses on how technologies affect work design. For instance, the cyber-physical systems transformation framework (Waschull et al.,

2020) only considers three motivational work characteristics that are outlined in the WDQ to be affected by the implementation of cyber-physical systems (e.g., intelligent assistance systems). Therefore, the positive effects of the investigated intelligent assistance system on feedback from job and information processing that we found in all three online experiments are not considered by this framework. The model on the future of work design (Gagné et al., 2022) lacks the required specificity as it only states that technological changes alter work design moderated by technology design and organizational implementation factors without providing explicit definitions. Regarding how intelligent assistance systems transform modern workplaces in assembly, the three online experiments contribute crucial insights into relevant factors. Our results illuminate that providing feedback and instructing employees by using step-by-step material represent crucial technology design factors. Further, our findings stress that task rotation is a neglectable organizational implementation factor for the effect of intelligent assistance systems. However, given that the results regarding autonomy facets varied between studies using different assembly sequences, we infer that the complexity of assisted tasks needs to be considered as an organizational implementation factor. Thus, by outlining a variety of substantial technology design and organizational implementation factors that moderate how technological changes shape motivational work characteristics, this dissertation contributes to the refinement of the model by Gagné and colleagues (2022).

However, the contribution of this dissertation is not limited to highlighting that the digital transformation of workplaces profoundly alters motivational work characteristics which have, in turn, vital downstream effects on employees (Parker & Grote, 2022a, 2022b; Wang et al., 2020). It indicates that the rising use of STARA in the modern world of work aiming for increased efficiency (Wang et al., 2022) is accompanied by an unintended, negative employee outcome, namely affective automation-related job insecurity. This dissertation contributes to research on affective automation-related job insecurity as an adaptation of STARA Awareness (Brougham & Haar, 2018) in two ways: First, the redefinition, comprehensive construct validation, and integration of affective automation-related job insecurity into the extensive job insecurity literature (Shoss, 2017) enable a better understanding of how employees appraise STARA to impact their employment. Applying a general model on job insecurity by Shoss (2017) we identified a unique nomological net of affective automation-related job insecurity in terms of indicators of technological change. Both an objectively high risk of being substituted by STARA and use of STARA at work are associated with high affective automation-related job insecurity but not with cognitive or affective job insecurity. Reinforced by the negative correlation of core self-evaluations with cognitive and affective (automation-related) job insecurity, our empirical evidence establishes Shoss' (2017) model as a theoretical foundation for the development and consequences of a timely digitalization-specific job insecurity. Although STARA enter all work areas (Brougham & Haar, 2018; Frey & Osborne, 2017), we identified rising levels of affective automation-related job insecurity for employees with an initial moderate use of STARA at work, while finding decreasing levels for employees with initial low or high use of STARA. Future research is required to shed light on the factors that contribute to the decline for low and high use of STARA. These could include the underestimation of the potential or limitations of STARA to substitute tasks and jobs, respectively. Despite these different trajectories of affective automation-related job insecurity, it remains a timely construct for a majority of the workforce which uses STARA to a significant extent in their working time.

Second, with the further development of the original questionnaire by Brougham and Haar (2018), this dissertation provides a short and valid affective automation-related job insecurity scale for future research to capture how employees appraise STARA to substitute their job as a whole or specific core tasks within their job. By also incorporating the latter, this scale captures the anticipated changing nature of work due to increasing digitalization more comprehensively (Dengler & Matthes, 2018; Parker & Grote, 2022a). It represents a crucial measurement instrument to detect interindividual differences in affective automation-related job insecurity of employees from different branches with a wide range of occupations and intraindividual differences, i.e. trajectories over time. Hence, the reconceptualization and adaption of measurement of affective automation-related job insecurity enable the exploration of specific dynamics and processes related to employees that start with digitalization-related changes at work. Given today’s increasingly rapid pace of technological innovations, the construct and the associated questionnaire will be an important asset in investigating employees’ affective appraisal of STARA with downstream effects on employee outcomes that complicate the successful interaction between human and non-human workers (Brougham & Haar, 2018, Yam et al., 2023).

Although our cross-sectional and longitudinal data demonstrate the considerable inter- and intraindividual variability in how employees appraise STARA to threaten their employment, they highlight the detrimental effects of implementing and using STARA on employees’ perceived job insecurity. Hence, our research is in line with recent articles that emphasize that the exposure to robots evokes job insecurity (Wang et al., 2023; Yam et al., 2023). This dissertation extends these articles by exploring protective (higher-order) personality traits. Therefore, it explores to whom these effects (do not) apply. Additionally, our results suggest that the effects of exposure to robots are transferable to the use of STARA. Consequently, this dissertation addresses both the positive and negative effects of STARA on workplaces and employees in a more extensive framework.

2. Practical Implications

Beyond theoretical implications, the three articles that are included in this dissertation provide vital practical implications for the implementation and use of STARA in rapidly changing modern workplaces by showcasing its benefits and challenges for workplaces and employees. Regarding workplaces in assembly, this dissertation demonstrates the merits of the introduction of intelligent assistance systems regarding motivational work characteristics. Enhanced feedback from job and information processing resulting from the use of intelligent assistance systems have the potential to boost outcomes like motivation, job satisfaction, and performance of assembly workers (Humphrey et al., 2007). Nevertheless, this dissertation also paints a more complex picture. Practitioners need to consider that the use of intelligent assistance systems in modern assembly has the following two downfalls: first, in the assembly of more complex products, their use restricts autonomy in all three investigated facets (work scheduling, decision-making, and work methods autonomy). Considering that autonomy is postulated to be a crucial antecedent of employee outcomes in a variety of theoretical frameworks (Hackman & Oldham, 1975; Parker & Knight, 2023) and that meta-analytic investigations support the essential relations of autonomy and its three facets with employee outcomes (Humphrey et al., 2007; Wegman et al., 2018) raises reason for concern. The restricted autonomy could counteract the positive effects (enhanced feedback from job and information processing) in terms of employee outcomes. Second, all three experiments on the effects of intelligent assistance systems on motivational work characteristics indicate that their use does not yield its intended effects of alleviating rising cognitive demands. As these systems are supposed to facilitate the inclusion of low-skilled workers into the labor market, this dissertation stresses the further development of their technology design factors to achieve this cognitive assistance. Thus, practitioners should not rely on the simple implementation of the investigated intelligent assistance system, even when assembly sequences are frequently rotating.

Besides intelligent assistance systems, the use of STARA at work is also accompanied by employees' perceived affective automation-related job insecurity. Practitioners who intend to implement STARA at work should therefore consider employees' appraisal of STARA as threatening to their employment. The results of this dissertation identified rising levels of affective automation-related job insecurity for employees who use STARA to a moderate extent, making those a special risk group to be monitored. The use of our refined measurement scale enables practitioners to monitor employees' affective automation-related job insecurity as a negative consequence of STARA holistically during digitalization processes. By relying on scales to assess cognitive or affective job insecurity, practitioners also capture other sources of job insecurity like temporary employment contracts (Shoss, 2017). Considering its negative downstream effects on employee outcomes that were already found in previous studies (e.g., Brougham & Haar, 2018; 2020), low levels of affective automation-related job insecurity remain integral for a healthy and productive workforce.

To achieve these low levels of affective automation-related job insecurity in the workforce, practitioners can apply the findings of this dissertation when hiring for open positions in their organizations. Given the negative relations between core self-evaluations and affective automation-related job insecurity, applicants' levels of core self-evaluations should be considered in recruiting and personnel selection processes for jobs that are characterized by rapid technological changes. Specifically, workers with high levels of core self-evaluations seem to appraise STARA to threaten their employment less than workers with low levels. Overall, this dissertation contributes to the human-centered development, implementation, and use of STARA in an increasingly digitalized world of work.

3. Limitations and future research

Despite vital implications for theory and practice, the articles included in this dissertation also exhibit some limitations. We found that the intelligent assistance system has both positive and negative effects on motivational work characteristics in the context of hypothetical assembly workstations and sequences that we experimentally manipulated and presented using vignette methodology. Although this design is used in work design research (e.g., Mlekus et al., 2022) and aims to maximize internal and external validity to gain causal evidence that is also generalizable (Aguinis & Bradley, 2014), it is limited. Given that the participants did not actually work at the presented assembly workstations, the results might differ in organizational practice due to other assembly sequences. Thus, future research should apply varying designs (e.g., cross-sectional and longitudinal studies) to provide multimethod evidence on the contradictory effects of intelligent assistance systems on motivational work characteristics in assembly. Considering that we found both positive and negative effects of the intelligent assistance system on motivational work characteristics, it remains unclear whether they compensate for each other. Building on the fact that we presented hypothetical assembly workstations, we refrained from including affective employee outcomes like work motivation as “research on *affective forecasting* has shown that people routinely mispredict how much pleasure or displeasure future events will bring” (Wilson & Gilbert, 2005, p. 131). Future studies should directly include the measurement of employee outcomes to examine the mediating role of altered motivational work characteristics due to technological changes. Also incorporating objective measures like the number of assembled products in a specific timeframe (Keller et al., 2019; Lampen et al., 2019) could yield an even more holistic understanding of how intelligent assistance systems affect assembly workers (Faccio et al., 2023).

Even though the investigated intelligent assistance system comprises the typical functions of such systems (Apt et al., 2018; Jung et al., 2022), empirical findings on the generalizability of our results to other intelligent assistance systems is missing so far. Drawing on the model by Gagné and colleagues (2022), transferring our results to intelligent assistance systems with similar technology design factors and to contexts with similar organizational implementation factors seems plausible. To gain insights into the generalizability of the findings, future studies should examine the influence of various intelligent assistance systems. Additionally, transferring our results that illuminate the contradictory effects of intelligent assistance systems on motivational work characteristics to technologies that provide different technology design factors (e.g., exoskeletons, ChatGPT) is not given. To identify technologies for which the effects are (not) generalizable, nuanced taxonomies that classify technologies based on technology design and organizational implementation factors seem essential. Based on the tenet that technologies differ in the effect on work design dependent on their technology design factors, Wang and colleagues (2022) recently introduced a first classification distinguishing between *assisting*, *arresting*, *augmenting*, and *automating* technologies to “facilitate practice-oriented technology research” (p. 477). However, the authors refrained from postulating specific effects on individual work characteristics for the four proposed categories. The fusion of such models and taxonomies that classify STARA by their technology design and organizational implementation factors could prove to be a major milestone for understanding how the increasing implementation of STARA at work shapes work design. All in all, this dissertation stresses the need for the integration and development of theories on how STARA impact work design based on a taxonomy of workplace technologies. Since Gagné and colleagues (2022) refrained from providing specific definitions for technology design and organizational implementation factors, future taxonomies benefit from further refinements. Regarding the context of intelligent assistance systems in assembly, our findings indicate that task rotation does not represent a crucial organizational implementation factor. However, they also hint that the objective complexity of assisted assembly sequences might be an important organizational implementation factor. To identify additional crucial technology design and organizational implementation factors that moderate how technological changes at work modify what, how, where, and when humans work, future research should consider their experimental manipulation. This allows the attribution of altered motivational work characteristics to individual factors. For instance, it seems plausible that the restrictions in work scheduling, decision-making, and work methods autonomy result from the increased standardization due to the use of step-by-step instructional material. Instead of attributing the reduced autonomy to this technology design factor, this dissertation only enables the attribution to the intelligent assistance system as a whole. Gaining those insights will prove to be beneficial for the development of further taxonomies.

Despite presenting a more objectively complex assembly sequence in Paper 2 compared with Paper 1, the ratings in motivational work characteristics remained low in all experimental conditions. Hence, floor effects might have counteracted the identification of further reductions in complexity, problem solving, specialization, and skill variety besides the identified restricted autonomy facets. Future studies should use even more complex assembly sequences characterized by higher quantity and variety of assembly steps (Keller et al., 2019) to rule out whether the intelligent assistance system does not reduce the remaining work characteristics only due to floor effects in the ratings.

This dissertation provides essential empirical evidence that working with intelligent assistance systems in assembly restricts work scheduling, decision-making, and work methods autonomy in more complex assembly sequences. Given the rising complexity of modern assembly, the support of the intelligent assistance system in more complex assembly sequences could be accompanied by negative downstream effects on employee outcomes (Humphrey et al., 2007; Morgeson & Humphrey, 2006). The present work does not offer any guidance on how practitioners can counteract the restriction of workers' autonomy. Therefore, future studies should illuminate countermeasures to prevent the reduction of autonomy and its negative downstream effects on employee outcomes like work motivation. For instance, extending the degree of self-adaptation of intelligent assistance systems in the form of successive reductions of instructional materials and feedback based on the quantity of assembled products and workers' increased skills could represent a starting point for further developments of intelligent assistance systems in assembly (Yigitbas et al., 2023).

With a thorough construct validation of affective automation-related job insecurity, this dissertation provides a solid base for fruitful research on how employees appraise the impact of STARA on their employment. However, it also displays some limitations. The adapted questionnaire for assessing affective automation-related job insecurity showcased a fluctuating fit of the measurement model between the various measurement points in the longitudinal study. To achieve measurement model fit indices that are in line with recommendations by Hooper and colleagues (2008) and West and colleagues (2012) this scale needs further adaptations. Nevertheless, our adaptations of the original scale by Brougham and Haar (2018) represent a crucial first step to tackle the valid assessment of the timely affective automation-related job insecurity in the modern world of work.

Building on the extended nomological net, this dissertation identified particular risk groups that experience affective automation-related job insecurity, namely employees with high objective substitution potential, employees who use STARA at work, and employees with low levels of core self-evaluations. Specifically, employees with a moderate use of STARA are a risk group of special interest since they showed increasing levels of affective automation-related job insecurity over time. Consequently, future research should focus on the outlined vulnerable groups and identify outcomes of affective automation-related job insecurity on the individual, group, and organizational levels. The emerging research on affective automation-related job insecurity primarily considers outcomes on the individual level like burnout, career satisfaction, or work engagement (Brougham & Haar, 2018; Gödöllei, 2022). However, the substitution of work tasks might also represent a crucial team phenomenon instead of only affecting individual employees within teams, as coworkers might resemble appraising the interaction with STARA as threatening to their employment and compete for the limited remaining positions in their team or organization (Lam et al., 2023; Yam et al., 2023). Affective automation-related job insecurity could therefore result in maladaptive work behavior towards coworkers and maladaptive team dynamics, which would be in line with a recent article on job insecurity (Yam et al., 2023).

The inclusion of objective data regarding the substitution potential of occupation beyond self-report data strengthens the validity of our findings by reducing common-method bias (Podsakoff et al., 2012). Nevertheless, as these objective data stem from 2019, they underestimate today's substitution potential of occupation in light of the fast-paced changing world of work. Thus, data on the objective substitution potential of occupation should be constantly updated and used in future studies.

Considering the rising levels of affective automation-related job insecurity for employees with moderate use of STARA at work and its relations with primarily negative well-being and work-related outcomes (Brougham & Haar, 2018, 2020; Gödöllei et al., 2022; Li et al., 2019), affective automation-related job insecurity will be an essential factor that prevents a healthy and motivated workforce in today's digitalized world of work. However, it remains unclear how practitioners can reduce employees' levels of affective automation-related job insecurity which makes the development of evidence-based interventions a crucial merit for maintaining healthy and motivated employees. Therefore, future research should empirically test the active mechanisms of how STARA evokes affective automation-related job insecurity. Yam and colleagues (2023) and Wang and colleagues (2023) postulate that employees recognize that robots exceed their performance, efficiency, and competence in specific tasks and therefore appraise robots as a threat to their employment. They also propose that employees realize that robots gain new knowledge, abilities, and skills at speeds and capacities unattainable by humans due to the rising distribution and development of robots. Finally, they suggest that the *perceived robot advantageousness* mediates the effect of the exposure to robots and job insecurity, but refrained from testing this empirically. Given the rapid technological advances, this potential mediating factor will become more and more important for how employees appraise STARA-driven task and job substitution. Nevertheless, the empirical testing of such mediating factors provides fundamental insights for the development of interventions that aim to reduce affective automation-related job insecurity.

Although this dissertation demonstrates that the use of STARA at work is related to the intercept and trajectory of affective automation-related job insecurity, it remains unclear which technologies that are included in the term STARA primarily drive affective automation-related job insecurity. Wang and colleagues (2023) show that robots that are visually reminiscent of humans especially evoke job insecurity. Thereby, they demonstrate that *robot anthropomorphism* defined as "the attribution of humanlike characteristics, intentions, motivations, or emotions to non-human agents" (Wang et al., 2023, p. 2) represents a key factor for employees appraising robots as threatening. Given that STARA can appear humanlike not only in terms of appearance but also in communication and movement (Roesler et al., 2021), the effects identified by Wang and colleagues (2023) might be extended to bodiless technologies like chatbots and virtual assistants. The extent to which STARA technologies differ in triggering affective automation-related job insecurity remains to be investigated (experimentally) in future studies to identify technologies with a high risk of evoking affective automation-related job insecurity.

While this dissertation highlights the unique nomological net of affective automation-related job insecurity in terms of potential antecedents, studies on affective automation-related job insecurity mainly investigated correlations with outcomes that were already examined in the context of job insecurity (e.g., Brougham & Haar, 2018; Gödöllei et al., 2022; Li et al., 2019). Thus, empirical evidence on the incremental validity of affective automation-related job insecurity beyond job insecurity is still pending. Especially, affective automation-related job insecurity could exhibit incremental validity on outcomes that focus on digitalization like *technology acceptance*.

4. General Conclusion

Building on the rising implementation of STARA at work, increasingly digitalized work environments have the potential to improve and deteriorate workplaces with positive and negative downstream effects on employees, respectively. As this dissertation contributes essential empirical evidence on the contradictory nature of intelligent assistance systems on motivational work characteristics, it sheds light on the understudied mediating mechanisms that may explain why the use of STARA can both promote and deteriorate employee outcomes. Drawing from a thorough construct validation of affective automation-related job insecurity, it facilitates the nuanced understanding of how employees appraise STARA to affect their employment. Rather than solely identifying the beneficial or detrimental effects of STARA in today's world of work, the findings of this dissertation demonstrate their contradictory nature, enabling innovative technologies to simultaneously act as friend or foe to employees. By advancing research in industrial and organizational psychology and related fields on the supplementation and substitution of work, this dissertation provides important links to fruitful future research on digital work design and the successful interaction between human and non-human workers.

References

Aguinis, H., & Bradley, K. J. (2014). Best practice recommendations for designing and implementing experimental vignette methodology studies. *Organizational Research Methods*, *17*(4), 351-371. https://doi.org/10.1177/1094428114547952

Apt, W., Bovenschulte, M., Priesack, K., & Hartmann, E. A. (2018). *Einsatz von digitalen Assistenzsystemen im Betrieb* [*Use of digital assistance systems in practice*]. Bundesministerium für Arbeit und Soziales. Retrieved from https://www.bundesregierung.de/breg-de/service/publikationen/einsatz-von-digitalen-assistenzsystemen-im-betrieb-1837856

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, *29*, 3-30. https://doi.org/10.1257/jep.29.3.3

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, *118*(4), 1279-1333. https://doi.org/10.1162/003355303322552801

Baethge-Kinsky, V. (2020). Digitized industrial work: Requirements, opportunities, and problems of competence development. *Frontiers in Sociology*, *5*, 33. https://doi.org/10.3389/fsoc.2020.00033

Blumberg, V. S. L., & Kauffeld, S. (2020). Anwendungsszenarien und Technologiebewertung von digitalen Werkerassistenzsystemen in der Produktion—Ergebnisse einer Interview-Studie mit Experten aus der Wissenschaft, der Politik und der betrieblichen Praxis [Application scenarios and technology assessment of smart wear- ables and mobile smart devices in industrial practice]. *Gruppe. Interaktion Organisation. Zeitschrift für Angewandte Organisationspsychologie (GIO)*, *51*(1), 5-24. https://doi.org/10.1007/s11612-020-00506-0

Bortolini, M., Faccio, M., Galizia, F. G., Gamberi, M., & Pilati, F. (2021). Adaptive automation assembly systems in the industry 4.0 era: A reference framework and full-scale prototype. Applied Sciences, 11(3), 1256. https://doi.org/10.3390/app11031256

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization*, *24*(2), 239-257. https://doi.org/10.1017/jmo.2016.55

Brougham, D., & Haar, J. (2020). Technological disruption and employment: The influence on job insecurity and turnover intentions: A multi-country study. *Technological Forecasting and Social Change*, *161*, 120276

Brynjolfsson, E., & McAfee, A. (2011). *Race against the machine: How the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy*. Digital Frontier Press.

Carr, N. (2008, February 08). How many computers does the world need? Fewer than you think. *The Guardian*. https://www.theguardian.com/technology/2008/feb/21/computing.supercomputers

Cascio, W. F., & Montealegre, R. (2016). How technology is changing work and organizations. *Annual Review of Organizational Psychology and Organizational Behavior*, *3*, 349-375. https://doi.org/10.1146/annurev-orgpsych-041015-062352

Casner, S.M., Geven, R.W., Recker, M.P., & Schooler, J.W. (2014). The retention of manual flying skills in the automated cockpit. *Human Factors*, *56*(8), 1506-1516. https://doi.org/10.1177/0018720814535628

Cameron, N. M. D. S. (2017). *Will robots take your job? A plea for consensus*. John Wiley & Sons.

Dengler, K., & Matthes, B. (2018). The impacts of digital transformation on the labour market: Substitution potentials of occupations in Germany. *Technological Forecasting and Social Change*, *137*, 304-316. https://doi.org/10.1016/j.techfore.2018.09.024

Dornberger, R., Inglese, T., Korkut, S., & Zhong, V. J. (2018). Digitalization: Yesterday, today and tomorrow. In R. Dornberger, (Ed.), *Business Information Systems and Technology 4.0: New trends in the Age of Digital Change*, (pp. 1-11). Springer. https://doi.org/10.1007/978-3-319-74322-6_1

Egger-Lampl, S., Gerdenitsch, C., Deinhard, L., Schatz, R., & Hold, P. (2019, June 5-7). *Assembly* *instructions with AR: Towards measuring inter- active assistance experience in an Industry 4.0 Context [Conference presentation]*. 2019 Eleventh International Conference on Quality of Multimedia Experience (QoMEX), Berlin, Germany. https://doi.org/10.1109/QoMEX.2019.8743266

Faccio, M., Granata, I., Menini, A., Milanese, M., Rossato, C., Bottin, M., Minto, R., Pluchino, P., Gamberini, L., Boschetti, G., & Rosati, G. (2023). Human factors in cobot era: A review of modern production systems features. *Journal of Intelligent Manufacturing, 34*, 85-106. https://doi.org/10.1007/s10845-022-01953-w

Fraccaroli, F., Zaniboni, S., & Truxillo, D. M. (2024). Challenges in the new economy: A new era for work design. *Annual Review of Organizational Psychology and Organizational Behavior*, *11*, 307-335. https://doi.org/10.1146/annurev-orgpsych-081722-053704

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerization? *Technological Forecasting and Social Change*, 114, 254-280. https://doi.org/10.1016/j.techfore.2016.08.019

Gagné, M., Parker, S. K., Griffin, M. A., Dunlop, P. D., Knight, C., Klonek, F. E., & Parent-Rocheleau, X. (2022). Understanding and shaping the future of work with self-determination theory. *Nature Reviews Psychology*, 1, 378-392. https://doi.org/10.1038/s44159-022-00056-w

Gödöllei, A. (2022). *Hoping for the best, preparing for the worst: Employee reactions to automation at work* [Doctoral dissertation, University of Waterloo]. https://uwspace.uwaterloo.ca/bitstream/handle/10012/18431/Godollei_Anna.pdf?sequence=3&isAllowed=y

Golden, T. D., & Raghuram, S. (2010). Teleworker knowledge sharing and the role of altered relational and technological interactions. *Journal of Organizational Behavior, 31*(8), 1061-1085. https://doi.org/10.1002/job.652

Hackman, J. R., & Oldham, G. R. (1975). Development of the Job Diagnostic Survey. *Journal of Applied Psychology*, *60*(2), 159-170. https://doi.org/10.1037/h0076546

Haslbeck, A., & Hoermann, H.-J. (2016). Flying the needles: Flight deck automation erodes fine-motor flying skills among airline pilots. *Human Factors*, *58*(4), 533-545. https://doi.org/10.1177/0018720816640394

Hooper, D., Coughlan, J., & Mullen, M. (2008). Structural equation modelling: Guidelines for determining model fit. *Electronic Journal of Business Research Methods, 6*(1), 53-60. https://doi.org/fv2d

Humphrey, S. E., Nahrgang, J. D., & Morgeson, F. P. (2007). Integrating motivational, social, and contextual work design features: A meta- analytic summary and theoretical extension of the work design literature. *Journal of Applied Psychology*, *92*(5), 1332-1356. https://doi.org/10.1037/0021-9010.92.5.1332

Idaszak, J. R., & Drasgow, F. 1987. A revision of the job diagnostic survey: Elimination of a measurement artifact. *Journal of Applied Psychology*, *72*(1), 69-74. https://doi.org/10.1037/0021-9010.72.1.69

Judge, T. A. (2009). Core self-evaluations and work success. *Current directions in Psychological Science*, *18*(1), 58-62. https://doi.org/10.1111/j.1467-8721.2009.01606.x

Jung, J., Hubert, A., Doll, K., Kröhn, M., & Stadler, J. (2022, March 9-11). *Prozessinnovation: Selbstlernendes Assistenzsystem für die manuelle Montage* [*Process innovation: Self-learning assistance system for manual assembly*]. 18. AALE-Konferenz, Pforzheim, Germany. https://doi.org/10.33968/2022.20

Keller, T., Bayer, C., Bausch, P., & Metternich, J. (2019). Benefit evaluation of digital assistance systems for assembly workstations. *Procedia CIRP*, *81*, 441-446. https://doi.org/10.1016/j.procir.2019.03.076

Knight, C., & Parker, S. K. (2021). How work redesign interventions affect performance: An evidence-based model from a systematic review. *Human Relations*, *74*(1), 69-104. https://doi.org/10.1177/0018726719865604

Lam, W., Chen, Z., Wu, W., & Lee, C. (2023). Transmitting affective job insecurity (AJI) within teams: Layoff effects of AJI convergence on intrateam power struggles and team outcomes. *Journal of Organizational Behavior*, *44*(7), 1078-1093. https://doi.org/10.1002/job.2726

Lampen, E., Teuber, J., Gaisbauer, F., Bär, T., Pfeiffer, T., & Wachsmuth, S. (2019). Combining

simulation and augmented reality methods for enhanced worker assistance in manual assembly. *Procedia CIRP*, *81*, 588-593. https://doi.org/10.1016/j.procir.2019.03.160
Lazarus, R. S., & Folkman, S. (1984). *Stress, appraisal, and coping*. Springer Publishing.
Li, J. J., Bonn, M. A., & Ye, B. H. (2019). Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: The moderating roles of perceived organizational support and competitive psychological climate. *Tourism Management, 73*, 172-181. https://doi.org/10.1016/j.tourman.2019.02.006
Mark, B. G., Hofmayer, S., Rauch, E., & Matt, D. T. (2019). Inclusion of workers with disabilities in Production 4.0: Legal foundations in Europe and potentials through worker assistance systems. *Sustainability, 11*(21), 5978. https://doi.org/10.3390/su11215978
Maxwell, N. L. (2006). *The working life: The labor market for workers in low-skilled jobs*. WE Upjohn Institute.
Mlekus, L., Lehmann, J., & Maier, G. W. (2022). New work situations call for familiar work design methods: Effects of task rotation and how they are mediated in a technology-supported workplace. *Frontiers in Psychology, 13*, 1-21. https://doi.org/10.3389/fpsyg.2022.935952
Morgeson, F. P., & Humphrey, S. E. (2006). The Work Design Questionnaire (WDQ): Developing and validating a comprehensive measure for assessing job design and the nature of work. *Journal of Applied Psychology, 91*(6), 1321-1339. https://doi.org/10.1037/0021-9010.91.6.1321
Oberländer, M., Beinicke, A., & Bipp, T. (2020). Digital competencies: A review of the literature and applications in the workplace. *Computers & Education, 146*, 103752. https://doi.org/10.1016/j.compedu.2019.103752
Organisation for Economic Co-operation and Development (2023). *ICT Access and Usage by Business*. https://shorturl.at/apEFO
Parker, S. K. (2014). Beyond motivation: Job and work design for development, health, ambidexterity, and more. *Annual Review of Psychology*, *65*(1), 661-691. https://doi.org/10.1146/annurev-psych-010213-115208
Parker, S. K., & Grote, G. (2022a). Automation, algorithms, and beyond: Why work design matters more than ever in a digital world. *Applied Psychology*, *71*(4), 1171-1204. https://doi.org/10.1111/apps.12241
Parker, S. K., & Grote, G. (2022b). More than 'more than ever': Revisiting a work design and sociotechnical perspective on digital technologies. *Applied Psychology*, *71*(4), 1215-1223. https://doi.org/10.1111/apps.12425
Parker, S. K., & Knight, C. (2023). The SMART model of work design: A higher order structure to help see the wood from the trees. *Human Resource Management*, 1-27. https://doi.org/10.1002/hrm.22200
Parker, S. K., Morgeson, F. P., & Johns, G. (2017). One hundred years of work design research: Looking back and looking forward. *Journal of Applied Psychology, 102*(3), 403-420. https://doi.org/10.1037/apl0000106
Pedota, M., Grilli, L., & Piscitello, L. (2023). Technology adoption and upskilling in the wake of Industry 4.0. *Technological Forecasting and Social Change*, *187*, 122085. https://doi.org/10.1016/j.techfore.2022.122085
Peeters, M. C., & Plomp, J. (2022). For better or for worse: The impact of workplace automation on work charac- teristics and employee well-being. In A. Petrillo, F. De Felice, M. V. Achim, & N. Mirza (Eds.), *Digital Transformation - Towards New Frontiers and Business Opportunities.* IntechOpen. https://doi.org/10.5772/intechopen.102980
Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology*, 63, 539-569. https://doi.org/10.1146/annurev-psych-120710-100452
Roesler, E., Manzey, D., & Onnasch, L. (2021). A meta-analysis on the effectiveness of anthropomorphism in human-robot interaction. *Science Robotics, 6*(58), eabj5425. https://doi.org/10.1126/scirobotics.abj5425
Schwab, K. (2017). *The fourth industrial revolution*. Crown Business.
Shoss, M. K. (2017). Job insecurity: An integrative review and agenda for future research. *Journal of Management*, *43*(6), 1911-1939. https://doi.org/10.1177/0149206317691574

Statistisches Bundesamt (2022). *IKT-Indikatoren für Unternehmen: Deutschland, Jahre* [*ICT indicators for businesses: Germany, years*]. https://shorturl.at/nrHKV

Tang, P. M., Koopman, J., Elfenbein, H. A., Zhang, J. H., De Cremer, D., Li, C. H., & Chan, E. T. (2022). Using robots at work during the COVID-19 crisis evokes passion decay: Evidence from field and experimental studies. *Applied Psychology*, *71*(3), 881-911. https://doi.org/10.1111/apps.12386

Trenerry, B., Chng, S., Wang, Y., Suhaila, Z. S., Lim, S. S., Lu, H. Y., & Oh, P. H. (2021). Preparing workplaces for digital transformation: An integrative review and framework of multi-level factors. *Frontiers in Psychology*, *12*, 620766. https://doi.org/10.3389/fpsyg.2021.620766

Walsh, S. M., & Strano, M. S. (2018). *Robotic systems and autonomous platforms: Advances in materials and manufacturing.* Woodhead Publishing.

Wang, B., Liu, Y., & Parker, S. K. (2020). How does the use of information communication technology affect individuals? A work design perspective. *Academy of Management Annals, 14*(2), 695-725. https://doi.org/10.5465/annals.2018.0127

Wang, B., Zhang, Y., & Li, B. (2022). Facilitating timelier research with a novel classification of workplace technology. *Industrial and Organizational Psychology*, *15*(3), 475-478. https://doi.org/10.1017/iop.2022.52

Wang, P. X., Kim, S., & Kim, M. (2023). Robot anthropomorphism and job insecurity: The role of social comparison. *Journal of Business Research*, *164*, 114003. https://doi.org/10.1016/j.jbusres.2023.114003

Waschull, S., Bokhorst, J. A. C., Molleman, E., & Wortmann, J. C. (2020). Work design in future industrial production: Transforming towards cyber-physical systems. *Computers & Industrial Engineering*, *139*. https://doi.org/10.1016/j.cie.2019.01.053

Wegman, L. A., Hoffman, B. J., Carter, N. T., Twenge, J. M., & Guenole, N. (2018). Placing job characteristics in context: Cross-temporal meta-analysis of changes in job characteristics since 1975. *Journal of Management*, *44*(1), 352-386. https://doi.org/10.1177/0149206316654545

West, S. G., Taylor, A. B., & Wu, W. (2012). Model fit and model selection in structural equation modeling. In R. H. Hoyle (Ed.), *Handbook of structural equation modeling* (pp. 209-231). The Guilford Press.

Wilson, T. D., & Gilbert, D. T. (2005). Affective forecasting: Knowing what to want. *Current Directions in Psychological Science*, *14*(3), 131-134. https://doi.org/10.1111/j.0963-7214.2005.00355.x

Yam, K., C., Tang, P. M., Jackson, J. C., Su, R., & Gray, K. (2023). The rise of robots increases job insecurity and maladaptive workplace behaviors: Multimethod evidence. *Journal of Applied Psychology*, *108*(5), 850-870. https://doi.org/10.1037/apl0001045

Yigitbas, E., Sauer, S., & Engels, G. (2023). Self-adaptive digital assistance systems for Work 4.0. In B. Vogel-Heuser, & M. Wimmer (Eds.) *Digital transformation: Core technologies and emerging topics from a computer science perspective* (pp. 475-496). Springer. https://doi.org/10.1007/978-3-662-65004-2_19

Appendix

Personal contribution to the included articles

Hereby, I declare that I have not submitted or had not submitted this dissertation in any form to another faculty.

Further, I certify that I have written this dissertation independently and without unauthorized assistance, that I have only used the sources indicated, and that I have indicated text passages taken verbatim or in spirit from the literature.

Moreover, I confirm that I have made the lead contribution to the articles produced under joint authorship included in this dissertation. For example, I wrote the first draft of every manuscript, did the formal data analysis, data curation, reviewing, and editing of the manuscripts, and made the lead contribution to conceptualization and methodology. Therefore, I am the first author of all three included articles.

Heidelberg, 01.02.2024

Dem Dekanat der Fakultät für Verhaltens- und Empirische Kulturwissenschaften liegt eine unterschriebene Version dieser Erklärung vom 01.02.2024 vor.

Declaration in accordance to § 8 (1) c) and d) of the doctoral degree regulation of the Faculty

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UNIVERSITÄT HEIDELBERG ZUKUNFT SEIT 1386

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