New Work and Digital Competencies with Aging Workforces

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Summary

The profound forces of digitalization, automation, and workplace flexibilization, often associated with the concept of New Work, are constantly reshaping organizations. As industries evolve, these trends require white- and blue-collar employees to adapt to new work environments and acquire additional competencies. At the same time, demographic change is transforming the workforce, with older workforces becoming more prominent due to increased life expectancy and declining birth rates. Therefore, this dissertation examines how aging white-collar and blue-collar employees react to the distinct challenges posed by these trends, and how organizations can support their successful adaptation to a changing world of work.

Study 1 investigates how digital fluency is distributed across different age groups in white-collar workers, using data from 1,007 employees with office jobs from a German industrial company. While the findings confirm a general age-related digital divide, negative age stereotypes and supervisor support moderate the age-digital fluency relationship. Study 2 examines the impact of remote work decision-making authority levels on employee well-being and performance. Based on data from 639 white-collar employees, this study finds that managerial control over remote work arrangements is associated with higher levels of employee exhaustion and loneliness, regardless of age. Study 3 investigates how blue-collar employees' readiness for digital change is influenced by their age, using data from 1,165 employees working at production sites of a German automotive supplier. While age is generally related to less readiness for change, technological insecurity moderates this effect. Finally, Study 4 examines intergenerational knowledge transfer among 868 blue-collar employees and finds that older employees are less engaged in both general and digital knowledge sharing and receiving, while employees' subjective age moderates these effects.

Overall, the findings of this dissertation offer critical insights into how aging employees in different occupational roles cope with the challenges of New Work, and how organizations can provide support.

Zusammenfassung

Die voranschreitende Digitalisierung, Automatisierung und Flexibilisierung der Arbeitswelt, welche oft durch „New Work“ zusammengefasst werden, prägen die Arbeitswelt grundlegend. Sowohl von Büromitarbeitenden als auch Beschäftigten in der Produktion wird erwartet, dass sie sich auf die vielfältigen Folgen dieser Trends einstellen und zusätzliche Kompetenzen erlernen. Gleichzeitig führt der demographische Wandel aufgrund steigender Lebenserwartung und sinkenden Geburtenraten zu einem Anstieg an älteren Beschäftigten. Die vorliegende Dissertation erarbeitet anhand vier empirischer Studien, wie Berufsgruppen verschiedenen Alters auf die wachsenden Herausforderungen reagieren und Organisationen durch Einflussmaßnahmen Unterstützung anbieten können.

Studie 1 untersucht anhand von 1.007 Büromitarbeitenden, inwiefern sich jüngere und ältere Beschäftigte in ihrer digitalen Gewandtheit unterscheiden. Während die Ergebnisse eine generelle digitale Kluft bestätigen, wird diese von negativen Altersstereotypen und der Unterstützung durch Vorgesetzte beeinflusst. Studie 2 beleuchtet die Auswirkungen verschiedener Entscheidungsbefugnisse von Homeoffice auf das Wohlbefinden und die Produktivität von Büromitarbeitenden. Auswertungen von 639 Befragten zeigen, dass Mitarbeitende unabhängig ihres Alters erhöhte Erschöpfung und Einsamkeit aufweisen, wenn ihr Vorgesetzter die hauptsächliche Anzahl an Homeoffice bestimmt. Studie 3 untersucht anhand von 1.165 Produktionsmitarbeitenden, ob die Bereitschaft, sich für den digitalen Wandel im Unternehmen einzusetzen, mit steigendem Alter abnimmt. Während ältere Beschäftigte zwar generell weniger Veränderungsbereitschaft aufweisen, wird dies zusätzlich von technologischer Unsicherheit beeinflusst. Studie 4 beschäftigt sich mit intergenerationalem Wissenstransfer und stellt anhand der Auswertungen von 868 Produktionsmitarbeitenden fest, dass ältere Beschäftigte sowohl weniger generelles als auch digitales Wissen teilen und empfangen, während das subjektive Alter dies verstärken oder auch abschwächen kann. Insgesamt liefern die Ergebnisse dieser Dissertation wichtige Erkenntnisse, wie ältere

Beschäftigte verschiedener Berufsgruppen mit den Herausforderungen der veränderten Arbeitswelten umgehen und worauf es ankommt, dass sie auch in Zukunft bereit sein werden, Wandel mitzugehen und zu gestalten.

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1. General Introduction

1.1 Relevance and Research Purpose

The modern workplace is undergoing significant transformation, driven by the convergence of multiple global trends that shape how work is organized, how employees engage with their tasks, and how organizations evolve. At the heart of these changes is the concept of *New Work*, a term originally coined by Bergmann (1990) in the late 20^{th} century. Initially, New Work was defined as a shift toward greater autonomy, flexibility, and self-fulfillment in work, focusing on tasks aligned with personal passions and creativity (Bergmann, 1990). Over time, the concept of New Work has expanded to reflect several contemporary trends that fundamentally change the nature of work (Berend & Brohm-Badry, 2020).

Overall, the ongoing digitalization and digitization of the workplace is radically transforming how work is performed, shifting the emphasis from traditional, manual labor to more knowledge-based and technology-driven tasks (Waschull et al., 2022). In 2023, 59 percent of all businesses across the EU had adopted at least basic digital technologies (Eurostat, 2024). Overall, digitalization encompasses the integration of information and communication technologies (ICTs) into the workplace, enabling automation, enhanced communication, and data-driven decision-making (Colbert et al., 2016; Gradillas & Thomas, 2023). Digitization, on the other hand, stands for the technical process of converting analogue processes into digital artefacts (Gradillas & Thomas, 2023; Legner et al., 2017). These shifts affect a wide range of industries, from those driven by knowledge-based tasks to sectors that rely on manual or operational work. For instance, the Fourth Industrial Revolution, or Industry 4.0, which is primarily associated with manufacturing, refers to "the confluence of new innovative technologies" (Waschull et al., 2022, p. 1) and combines both digitalization and digitization to create more automated and efficient workplaces including smart machines and artificial intelligence (Machado et al., 2019). For organizations among all sectors, it is crucial to ensure employees have the competencies and persistence to adapt to the changes without succumbing to technostress, the strain caused by constantly adapting to and engaging with new technologies (Ragu-Nathan et al., 2008; Schneider & Sting, 2020).

Furthermore, the COVID-19 pandemic acted as a catalyst and forced employees worldwide to abandon the office and perform their work from home or remotely, aided by digitalization and the use of ICTs (Brown & Leite, 2023). What began as a temporary response to a global crisis has now become a more permanent fixture in the modern workplace. In Germany, for instance, around 23.5 percent of the workforce still worked from home in 2023, compared to 12.9 percent before the pandemic in 2019, and 21.0 percent during the first year of the pandemic in 2020 (Statistisches Bundesamt, 2024b). The rise of remote work signifies not only a shift in work location but also a broader transformation towards increased flexibility in work arrangements allowing employees greater autonomy over their schedules and work environment (Nyberg et al., 2021). For organizations, remote work has introduced opportunities such as access to a geographically broader talent pool and cost reductions related to office space (Ferreira et al., 2021). However, this flexibility also brings challenges, particularly in managing employee well-being, maintaining organizational cohesion, and sustaining productivity across a dispersed workforce (Ferreira et al., 2021; Wang et al., 2021).

At the same time, demographic change is reshaping workforces of developed economies around the globe. Due to increased life expectancy and declining birth rates, a smaller proportion of younger employees enters the workforce, while the percentage of older employees rises (Kunze et al., 2011). For example, in Germany, the proportion of employees aged 55 to 64 has almost doubled in the last 20 years and will lead to shortages of skilled workers with the upcoming retirement of the baby boomer cohorts (Koneberg & Jansen, 2022). With such aging workforces, age diversity in teams and organizations also increases, as a broader range of age groups remains in the workplace longer, creating a more diverse age spectrum (Hertel et al., 2013). At the same time, the digital divide hypothesis suggests that digital competencies are unequally distributed among younger generations (the so-called digital natives) and the older generations (the digital immigrants) (Prensky, 2001a). Therefore, organizations need to adapt to these changes and make sure that all age groups are effectively supported and prepared to embrace new digital technologies, upskill and, and collaborate efficiently in a rapid evolving work environment (Zacher, 2015). Also, with a significant portion of the workforce aged 50 or older, organizations face the pressing challenge of knowledge loss as older employees approach retirement (Dietz et al., 2022; Strack et al., 2008).

While these trends are reshaping the nature of work, they do not affect all employees equally. A key distinction of the workforce lies between *white-collar* and *blue-collar workers*, each of whom faces distinct challenges in adapting to these fundamental changes (Waschull et al., 2022). Employees in white-collar occupations are typically employed in professional, managerial, or administrative roles that are primarily knowledge-based and often possess higher levels of education (Lips-Wiersma et al., 2016). In Germany, around 36.7 percent of the workforce is employed in such white-collar roles, primarily in office environments, where they usually engage in information processing, problem-solving, and communication-based tasks that are particularly shaped by digitalization and remote work (Cappelli, 2021; Hammermann & Voigtländer, 2020). In contrast, blue-collar workers are primarily engaged in manual labor or skilled trades, typically in industrial settings such as manufacturing plants, construction sites, or logistics hubs. With lower levels of formal education, their jobs involve hands-on work, operating machinery, and technical expertise, and often require physical presence on-site. However, with the advent of Industry 4.0, blue-collar workers are increasingly impacted by automation and the integration of digitally controlled machinery (Gallie, 1996; Waschull et al., 2022) While measuring the exact proportion of blue-collar workers is challenging due to unclear definitions and blurring boundaries, combined figures show that around 22.1 percent of the German workforce is employed in blue-collar roles with manufacturing or construction tasks (Statistisches Bundesamt, 2024a; Waschull et al., 2022)

This dissertation explores how New Work with its key trends of digital transformation, automation and work flexibilization, is experienced differently by white-collar and blue-collar employees, with a particular focus on the aging workforce. While white-collar employees face growing demands of remote work, digital competencies, and increased flexibility in work arrangements, blue-collar employees are confronted with the profound impact of digitalization and automation on traditionally manual tasks, requiring the acquisition of new technical skills to operate and maintain advanced machinery (Waschull et al., 2022). The aging workforce adds further complexity to the challenges posed by digitalization and Industry 4.0 as older employees, whether in white-collar or blue-collar roles, need to adapt to rapidly evolving work environments and technologies (Colbert et al., 2016).

With this dissertation, I aim to answer the following overarching research question: *How do aging white-collar and blue-collar employees react to the distinct challenges of New Work, and how can organizations support their successful adaptation to a changing work environment?*

In the following, I will review existing research on the aging workforce and its adaptation to an increasingly digitalized work environment, with particular focus on the different implications for employees in white-collar and blue-collar occupations. This review will identify key findings and shortcomings in the existing research. Based on these insights, I will then formulate the four research questions that this dissertation seeks to address.

1.2 Literature Overview and Research Questions

1.2.1 Digital Competencies and Flexible Work Arrangements among Aging White-Collar Workers

The rapid advancement of digital technologies has transformed the nature of work across all sectors, particularly in white-collar professions, where the reliance on digital technologies, data analytics, and artificial intelligence has become integral to daily operations (Colbert et al., 2016). In these roles, employees are increasingly expected to work with ICTs and navigate constantly evolving digital tools and platforms. While adopting and using digital technologies, technostress may appear, which “relates to the phenomenon of stress experienced by end users in organizations as a result of their use of ICTs” (Ragu-Nathan et al., 2008, p. 417f.). Research showed that technostress, with its several different stressors, negatively impacts employees’ well-being and performance (Gerdiken et al., 2021; Nastjuk et al., 2024; Ragu-Nathan et al., 2008; Tarafdar et al., 2015). Closely related to that, digitalization can also lead to a blurring of boundaries between private and professional life and, thus, contribute to increased work family conflicts (Boswell & Olson-Buchanan, 2007; Sonnentag et al., 2010).

To combat such negative consequences, it becomes essential for employees to develop robust digital competencies (Bartra-Rivero et al., 2024). One effective way to assess the digital competencies of white-collar employees is through *digital fluency*, which refers to the capacity to “reliably achieve desired outcomes through the use of technology” (Briggs & Makice, 2012, p. 62). In doing so, digital fluency builds on two subdimensions, digital knowledge (e.g., knowing how and when to accurately use digital technologies) and digital self-efficacy (e.g., having the confidence in their abilities to successfully carry out tasks using digital technologies) (Briggs & Makice, 2012; Wang et al., 2013; Zimmermann, 2022).

Hence, modern white-collar workers rely on digital fluency in the modern workplace, as it positively affects their digital work performance (Zimmermann, 2022). Despite its importance for employees and organizations, the distribution of digital fluency among the aging workforce remains uncertain in existing research. While the digital divide hypothesis suggests a gap in digital competencies between younger and older employees, research did not provide sufficient evidence for this claim (Guo et al., 2008; Prensky, 2001a; Wang et al., 2013). Moreover, existing research has yet to provide a comprehensive understanding of the organizational or social conditions that could exacerbate or mitigate such a digital divide, leaving researchers and practitioners focusing on aging workforces and the distribution of digital fluency with unanswered questions. This leads me to my first research question:

Research Question 1: How is digital fluency distributed among younger and older white-collar workers and what psychological or organizational conditions influence this distribution?

While digital fluency became an important factor in enabling white-collar employees to adapt to increasingly digitalized work environments (Briggs & Makice, 2012), the rise of *remote work* since the COVID-19 pandemic introduced additional complexities (Wang et al., 2021). For employees in white-collar occupations all over the world, remote work became a necessity that was facilitated by advancements in digitalization that allowed employees to collaborate, communicate, and complete tasks from anywhere (Nyberg et al., 2021). Even after the pandemic, remote work remains a prevalent feature of white-collar professions, with 28 percent of paid workdays in the United States being completed remotely by June 2023 (Barrero et al., 2023) and almost 24 percent of the employees working remotely in Germany (Statistisches Bundesamt, 2024b). Employee preferences for remote work remain high, driven by the flexibility it offers in balancing personal and professional responsibilities, as well as the ability to maintain productivity outside traditional office settings (Barrero et al., 2021; Flüter-Hoffmann & Stettes, 2022; Kunze et al., 2020). However, not all organizational leaders share this enthusiasm. Some managers express reservations, citing concerns over reduced team cohesion, decreased oversight, and potential declines in employee performance and engagement (Werner, 2022). These conflicting views highlight a growing tension in the workplace, where the autonomy to choose work location must be balanced with organizational goals and managerial expectations (Nyberg et al., 2021).

Recent studies highlighted the importance of voluntariness in remote work agreements, arguing on behalf of self-determination theory (Ryan & Deci, 2000) that employees should perceive autonomy in their work arrangements to enhance their intrinsic motivation and ensure well-being and individual performance (Dias et al., 2022; Lopes et al., 2023). Yet, the question of who actually controls remote work decisions remains underexplored. Most existing research differentiates between voluntary and involuntary remote work (Dias et al., 2022; Lopes et al., 2023) but recent developments suggest that it's not just a matter of whether remote work is imposed or chosen, but rather who holds the decision-making power (Alexander et al., 2021; Lopes et al., 2023).

Thus, the level at which remote work decisions are made- whether by the individual, team, manager, or organization, may play a crucial role in shaping the outcomes of future remote work arrangements. For organizations, this presents a key strategic challenge: balancing the need for control and oversight with employee autonomy. This is particularly important in light of demographic change, as older workforces may have different preferences and needs for remote work decision-making compared to younger workers (Kanfer & Ackerman, 2004; Ng & Feldman, 2014). Ensuring that employees of all age groups feel empowered in their work decisions can foster a more supportive and productive work environment, while an imbalance of decision-making authority may lead to varied impacts on employee well-being and performance (Chua & Koestner, 2008; Gagné & Deci, 2005). Thus, I propose my second research question:

Research Question 2: What impacts do different levels of decision-making authority (individual, team, managerial, or organizational) over remote work arrangements have on the well-being and performance of aging white-collar employees?

1.2.2 Readiness for Change and Knowledge Sharing among Aging Blue-Collar Workers

Unlike white-collar workers, who have been gradually incorporating digital technologies into their tasks, many employees in blue-collar occupations are still in the early stages of digital adoption. For some, particularly those performing routine manual work, digital technologies have yet to become a regular part of their daily responsibilities. One reason for this delay is that blue-collar workers are often excluded from the early stages of digital transformations, typically led by white-collar employees, which can lead to biases that prevent digital tools from fully addressing the specific needs of blue-collar workers (Quintop, 2023). While digitalization brings potential benefits, it therefore also leads to questions about how quickly blue-collar employees, especially older ones, can adjust to these new demands (Cillo et al., 2019; McClure, 2018; Waschull et al., 2022).

As the incorporation of digital technologies into the blue-collar workplace, for some occupations, is closely related to automation, blue-collar employees often face fears of "technologically induced unemployment" (McClure, 2018, p. 139). Ragu-Nathan et al. (2008) capture these concerns as a specific stressor within their technostress construct, identifying technological insecurity as that which describes the fear of being replaced by machines or rendered obsolete by new technologies (McClure, 2018; Ragu-Nathan et al., 2008). Furthermore, as Waschull et al. (2022) elaborated, the increasing presence of digital technologies in blue-collar roles is shifting the nature of many tasks. This integration requires workers to develop new competencies and interact more frequently with digital systems, demanding continuous adaptation, particularly from older workers who may find it challenging to adjust to evolving technological requirements (Drazic & Schermuly, 2021).

In light of these evolving demands, it is important that both the employer and its employees are ready for the upcoming digital change (Gfrerer et al., 2021; Halpern et al., 2021). Previous literature highlights the critical role of *readiness for change*, which is a multifaceted concept of encompassing the cognitive, emotional, and intentional readiness of employees to engage with upcoming change (Bouckenooghe et al., 2009; Drazic & Schermuly, 2021; Holt & Vardaman, 2013). Given the rapid digitalization of blue-collar work environments, it is crucial to examine the readiness for change among aging blue-collar workers. Despite the growing importance of this workforce in adapting to technological transformations, research remains limited. Existing studies often apply the Technology Acceptance Model (TAM) (Davis, 1989), which prioritizes factors like perceived usefulness and ease of use but, for blue-collar workers, it may be too technology-specific and overlooks critical elements such as technological insecurity and resistance due to automation fears (Davis & Venkatesh, 1996; Morris & Venkatesh, 2000; Ragu-Nathan et al., 2008; Venkatesh et al., 2012). These challenges underscore the need to focus on readiness for change, which involves not only cognitive but also emotional preparedness to adapt to evolving work processes and organizational transformations.

Demographic changes, particularly the aging workforce, have a more pronounced impact on industries reliant on blue-collar labor, such as manufacturing, construction, and logistics, as they typically have an older workforce compared to sectors dominated by white-collar roles (Manufacturing Institute, 2020). Yet, research on blue-collar employees and their readiness for change remains limited, despite the growing importance of these workers in sectors increasingly affected by digital transformation. This lack of attention calls for a deeper understanding of how blue-collar occupations, particularly aging workers, are willing to adapt to upcoming changes in the workplace. Thus, I propose this dissertation's third research question:

Research Question 3: To what extent are aging blue-collar workers ready to commit to digital change at their organizations, and what strategies can organizations implement to support their workforce in adapting to digital transformations?

Furthermore, as demographic change leads to an increasingly aging workforce in blue-collar industries, organizations face the challenge of retaining critical expertise and tacit knowledge before older employees leave the workforce and retire (Burmeister & Deller, 2016; Strack et al., 2008). According to official calculations, approximately 12.9 million people in Germany are expected to reach the legal retirement age, accounting for nearly 30 percent of the current workforce (Statistisches Bundesamt, 2022). Older employees often have decades of hands-on experience and knowledge that is not always formally documented, making effective knowledge transfer essential for maintaining organizational continuity (Fasbender et al., 2021). The urgency of this issue is further compounded by digitalization, which requires employees to not only share general work-related knowledge but also adopt and disseminate digital competencies crucial for operating in a modernized work environment (Madsen et al., 2016; Waschull et al., 2022). As the workforce ages, organizations are increasingly challenged to foster intergenerational knowledge transfer, ensuring that younger workers receive the practical, often tacit knowledge accumulated by their older colleagues (Fasbender et al., 2021; Gerpott et al., 2017).

While previous literature increasingly focused on knowledge sharing in organizations among employees of different age groups, the main focus often lies on white-collar employees with office tasks, failing to extend the scope to blue-collar employees (Muniz Jr et al., 2022; Nakano et al., 2013). Furthermore, while older employees are typically seen as the primary senders of general work-related knowledge due to their extensive experience and generativity-related motives, younger employees may play a key role as senders of digital knowledge, given their advantages in using digital technologies (Gerpott et al., 2017; Prensky, 2001a). This dynamic of knowledge sharing, particularly with regard to the differentiation of general and digital-related knowledge, has not been sufficiently explored in recent literature. Therefore, I propose the fourth and last research question of this dissertation:

Research Question 4: How is general and digital knowledge shared among aging blue-collar workers, and what factors drive effective knowledge exchange within these workforces?

1.3 Dissertation Outline and Paper Structure

This dissertation aims to expand our understanding of how New Work, with its key trends of digitalization, automation, and flexibilization, together with demographic change is affecting employees in different types of work environments, with a particular focus on blue-collar and white-collar occupations. Each of the four research papers examines a distinct aspect of the challenges and opportunities faced by aging employees in adapting to these workplace transformations.

Chapter 2 addresses Research Question 1, focusing on the distribution of digital fluency among white-collar workers. In this study, my co-author, Florian Kunze, and I empirically test the digital divide hypothesis (Prensky, 2001a) and hypothesize that younger workers will exhibit higher levels of digital fluency perceptions than their older colleagues. Furthermore, drawing from stereotype embodiment theory (Levy, 2009), we suggest that potential age differences are contingent upon negative age stereotypes and supervisor support. To test our theoretical considerations, we use a sample of 1,007 white-collar employees with office jobs from a German industrial company.

Chapter 3 explores Research Question 2, which investigates how different levels of decision-making authority regarding remote work arrangements affect the well-being and performance of aging white-collar employees. In this single-authored study, I further explore whether age or leadership styles moderate this relationship and use a self-determination theory (Ryan & Deci, 2000) framework to discuss my findings. To empirically analyze the effects of decision-making authority levels of remote work, I use a sample of 639 white-collar employees which, based on their demographic structure, reflects the German working population.

Chapter 4 addresses Research Question 3, focusing on blue-collar workers and their readiness for digital change. Drawing from socioemotional selectivity theory (Carstensen, 2006), I generally argue in this single-authored study that older blue-collar employees are less ready to commit to the digital change in their organization due to their limited future time perspective, while younger employees may have advantages and pursue different goals. Furthermore, this paper analyzes how technological insecurity and promotion-oriented change communication strategies within organizations can influence such willingness of older blue-collar workers to engage in digital transformations. For the quantitative analysis of this study, I use a sample of 1,165 blue-collar employees who work at several production sites of a German automotive supplier.

Chapter 5 explores Research Question 4, investigating the dynamics of general and digital knowledge sharing among aging blue-collar employees. Incorporating theoretical assumptions from socioemotional selectivity theory (Carstensen, 2006), my co-author Sophie Moser and I examine what factors drive knowledge exchange within young and old workforces. Focusing on both general as well as digital-related knowledge shared among blue-collar workforces, we argue that older employees could tend to share general work-related knowledge, while younger employees may take the lead in sharing digital competencies. Furthermore, we assume that blue-collar employees' subjective age can play a crucial role when engaging in knowledge exchange with colleagues as it may further explain one's future time perspective (Carstensen, 2006). To test our assumptions, we use data on 868 employees in 85 working units of a German automotive manufacturing company.

The introductory chapter establishes the importance of addressing these issues by examining the demographic shifts and technological advancements reshaping both white-collar and blue-collar occupations. In the concluding chapter of this dissertation, the findings of the four research papers are integrated, with a discussion of the broader theoretical implications for organizational behavior research, followed by limitations and suggestions for future research. Finally, practical implications for managing an aging workforce in a rapidly digitalizing world are outlined, providing actionable insights for organizations.

2. The Older, the Less Digitally Fluent? The Role of Age Stereotypes and Supervisor Support

Kilian Hampel and Florian Kunze

ABSTRACT

Over the last decades, digital technologies have progressively made their way into the workplace. Therefore, it becomes increasingly important for employees to have digital competencies, which can be measured through digital fluency, including its two subdimensions digital knowledge and digital self-efficacy. This is particularly the case for older workers, who might be affected by a digital divide that proposes younger and older employees have different prerequisites for digital fluency. Drawing from stereotype embodiment theory, we argue that age is generally negatively related to self-perceptions of digital fluency and particularly impactful when older employees hold negative age stereotypes against older workers and therefore self-stereotype themselves. Furthermore, we argue that developmental support from the direct supervisor has the potential to either amplify or alleviate this negative relation. While a lack of supervisor support may lead to the activation of internalized negative age stereotypes, strong support by the supervisor could strengthen the employees' self-perceptions in several ways. Performing multiple regression analyses on survey data collected from 1,007 white-collar employees, we find support for our three hypotheses. Negative age stereotypes exacerbate the negative relationship between age and digital fluency, whereas the interplay of high individual stereotypes and low supervisor support is the most negative condition for the relation of age on digital fluency. On the other hand, strong supervisor support with low negative stereotypes counteract existing age differences in digital fluency. Therefore, our findings have important theoretical and practical implications.

Keywords: digital fluency; age; digital age divide; negative age stereotypes; stereotype embodiment; developmental supervisor support.

2.1 Introduction

Over the last decades, information and communication technologies (ICTs) have significantly transformed the workplace, fundamentally changing how businesses operate and employees perform their tasks. According to a German Federal Ministry of Labor and Social Affairs study from 2016, 79 percent of the questioned employees started experiencing digital changes in their workplace and equipment (Arnold et al., 2016). To cope with such changes and avoid increased stress due to technology, labeled as technostress (Ragu-Nathan et al., 2008; Tarafdar et al., 2015), or blurring of boundaries between private and professional life (Boswell & Olson-Buchanan, 2007; Sonnentag et al., 2010), employees rely on having digital competencies.

One way of measuring digital competencies of white-collar employees is digital fluency, defined as the ability to "reliably achieve desired outcomes through the use of technology" (Briggs & Makice, 2012, p. 62). Digital fluency builds on two essential components: *digital knowledge* and *digital self-efficacy*. Digital knowledge implies knowing how and when to accurately and effectively use digital technologies to create added value at the workplace (Briggs & Makice, 2012; Wang et al., 2013; Zimmermann, 2022). Digital self-efficacy is based on the social cognitive theory approach by Bandura (1986) and describes a person's "belief in or expectation of his/her ability to successfully perform a certain behavior" (Aesaert & van Braak, 2014, p. 328). Therefore, digital self-efficacy can be seen as the "motivating force behind the successful application of digital knowledge" (Zimmermann, 2020, p. 8). To be digitally fluent, employees need high competencies on both sub-facets.

While research has increasingly focused on digital fluency (Briggs & Makice, 2012; Colbert et al., 2016; Zimmermann, 2022), we know little about how such skills are gained, developed, and distributed among the workforce, particularly in different age groups. A widespread assumption is that digital competencies are unequally distributed among younger generations (the so-called digital natives) and the older generations (the digital immigrants), leading to a digital age divide in competencies (Prensky, 2001b; Wang et al., 2013). Entering a workplace that is more and more characterized by digital tools, digital natives who grew up with ICTs and online applications might know how to use a smartphone or the internet. Through this digital competency advantage, they might outperform digital immigrants who have to acquire digital competencies later in their working life (Prensky, 2001b; Wang et al., 2013).

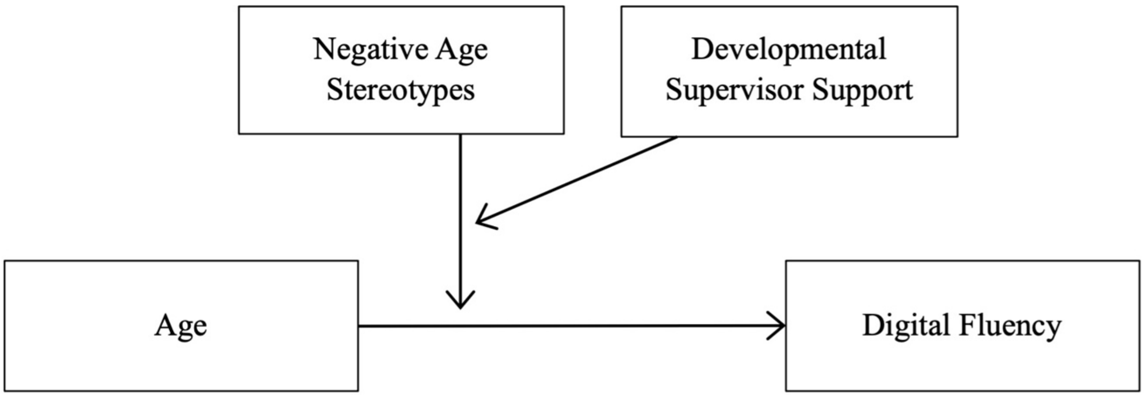
Notwithstanding, it remains unclear to which extent an actual digital divide of competencies between young and old employees exists. Extant empirical research on this relationship is inconsistent and contradictory. Guo and colleagues (2008), for example, do not find age to automatically relate to lower digital competencies, while Li and Ranieri (2010) find such results but only in a Chinese school context not focusing on all age groups. Recently, Hecker and colleagues (2021) found age differences in digital skill screening tests, but their analysis relied on a binary categorization of employees as either younger or older than 50 years in age. Among the extensive body of literature on the Technology Acceptance Model (TAM), Morris & Venkatesh (2005) link increasing age with less technology acceptance but do not focus on digital competencies and digital fluency in particular. Still, research including all age groups in an organizational context is scarce, and it remains unclear if, and under which contextual conditions, older employees perceive high or low levels of digital fluency.

With this article, we therefore aim to fill this research gap and contribute to the existing research on digital competencies at the workplace by shedding light on the role of age, as well as personal and situational context factors, in employees' digital fluency development. Overall, we argue that older employees evaluate their digital knowledge and digital self-efficacy to be lower than younger employees. Entering a workplace that is more and more characterized by digital tools, digital natives who grew up with ICTs and online applications might intuitively perceive themselves as having higher digital skills. Digital immigrants, on the other hand, had to acquire digital competencies later in their working life and, thus, might be disadvantaged in their digital knowledge and digital self-efficacy (Prensky, 2001b).

Furthermore, we assume that individual and social contextual factors are relevant to understand the relation between age and digital fluency. First, drawing from stereotype embodiment theory (Levy, 2009), we propose that endorsing negative age stereotypes is crucial for older employees to develop digital competencies and therefore negatively moderates the age-digital fluency relationship. The internalization of negative stereotypes against one's own age group can lead to psychological and digital disengagement (Lagacé et al., 2016) and amplify existing age differences. Lastly, we assume that supervisors impact the overall relationship between age, digital fluency, and negative age stereotypes in the form of a three-way interaction. Prior research indicates that developmental supervisor support matters for employees' developmental and training activities (Maurer et al., 2002; Noe & Wilk, 1993; van Vianen et al., 2011), employees' self-efficacy (Dvir et al., 2002), as well as their performance (Dvir et al., 2002). Further extending stereotype embodiment theory (Levy, 2009) and integrating it with the concept of stereotype threat (Steele & Aronson, 1995), we expect that the combination of internalized negative age stereotypes and missing developmental supervisor support may affect the relationship between age and digital fluency. Figure 1 illustrates our proposed conceptual model. By explaining differences in digital fluency levels among different age groups, this research contributes to the existing literature on aging workforces and digital competencies in several ways. First, the paper helps to unpack the complexity that underlies the development of digital competencies at the workplace. By inspecting the relationship between age and digital fluency, we find empirical support for the disputed digital divide hypothesis in the workforce (Prensky, 2001b; Wang et al., 2013). Through this proceeding, we integrate the digital divide theory with the conceptual ideas of stereotype embodiment and supervisor support, and highlight that the relationship between age and digital competencies might be affected by complex personal and social factors (Lagacé et al., 2016 & Firzly, 2016; Levy, 2009; van Vianen et al., 2011). Furthermore, this research offers important practical implications for companies and managers to overcome a potential digital divide by supporting aging employees in developing digital competencies.

Figure 1

Conceptual Framework of Study 1



2.2 Theoretical Framework and Hypotheses Development

2.2.1 The Concept of Digital Fluency

In an increasingly digitalized workplace, employees' digital competencies are critical factors. Over the past decades, scholars have increasingly paid attention to these competencies with various labels. Gilster (1997) as well as Eshet (2004), for example, frame technology employee capabilities as *digital literacy*, while Ktoridou and Eteokleous-Grigoriou (2011) use the term *computer literacy*. Other researchers used the term *ICT competency* (Guo et al., 2008) or *digital competency* (Ferrari et al., 2012). For this study, we think that a more sophisticated and holistic conceptualization of digital competencies is necessary, by focusing on the concept of *digital fluency* (Briggs & Makice, 2012; Wang et al., 2013; Zimmermann, 2022; Zimmermann & Kunze, 2019). Even though the different terms are often used interchangeably, digital fluency describes more than just the simple knowledge of how to use digital technologies and being able to "produce things of significance" (Wang et al., 2013, p. 410). Beyond pure digital knowledge, the concept of digital fluency also involves digital self-efficacy, which is based on the social cognitive theory by Bandura (1986) and assumes that the inner belief and self-competence of using digital technology is a core characteristic of digital competencies. Nevertheless, digital fluency does note equal technological affinity: Being digitally fluent also means to evaluate a situation to see whether the adoption of a specific technology is even necessary and to apply another technology or even choose the analog alternative if assessed to be more effective (Briggs & Makice, 2012).

Subsequently, digital fluency focuses on the individual's perception of being digitally knowledgeable and self-confident to use digital technologies at the workplace to attain digital work performance (Zimmermann, 2022). Thus, digital fluency differs from other theoretical models that focus on the use of ICTs, such as the Technology Acceptance Model (TAM) by Davis (1989). TAM implies that the actual usage of technologies is defined by one's behavioral intention to use that technology. This intention towards using is, in turn, determined by the two factors, perceived usefulness and perceived ease of use. Perceived usefulness describes the expectation of technology to enhance individual productivity. Perceived ease of use refers to "the extent to which a person believes that using a technology will be free of effort" (Venkatesh, 2000, p. 344) and determines perceived usefulness. TAM, therefore, focuses on the behavioral process behind individual decisions to use a certain technology but not specifically on individual preconditions and competencies that we want to capture with the digital fluency construct. Nonetheless, the TAM literature provides a relevant framework for our intended contribution and we will discuss the implications for this literature stream in the discussion section.

2.2.2 Employees' Age and Digital Fluency

The digital age divide concept assumes that digital competencies are unequally distributed among the younger generation – digital natives – and the older generations – digital immigrants (Colbert et al., 2016; Prensky, 2001b; Wang et al., 2013). The digital divide can be generally categorized into three categories: (1) digital access divide, (2) digital skill and use divide, and (3) digital outcome divide (Wang et al., 2013). Digital access divide refers to inequality in accessing IT, often because of socioeconomic reasons (Wei et al., 2011 & Tan, 2011). Even though access to digital technologies is necessary to gain digital competencies, it is not sufficient for becoming digitally fluent (Wang et al., 2013). In particular, in the current work and societal setting, where in most Western societies smartphone and internet penetration is close to 90 percent (Statista, 2021; WorldBank, 2021), an access divide was more present then in the 1990s, when the access to digital technologies was restricted by costs or socioeconomic conditions (Wang et al., 2013; Wei et al., 2011). As Fischer (2005) describes, access to digital technologies is necessary but insufficient to gain digital competencies. In consequence, we propose that in the current work context, both the digital skill and use divide (i.e., differences in the utilization and perceived easiness of digital technologies) and the digital outcome divide (i.e., differences in the perceived usefulness and learning and productivity outcomes using digital technologies) trigger the digital divide among age groups.

Results about the digital divide among employee age groups are inconsistent. Tijdens and Steijn (2005), for example, report in a Dutch sample that younger employees rate their adaptability to ICTs better than other age groups, which supports the digital outcome divide component. However, the authors could not show an age effect on the willingness to acquire ICT competencies, and the study was limited by a categorical measurement of age and the exclusion of employees older than 50 years. Wagner, Hassanein, and Head (2010) find age to have a negative relationship with computer use and thus support the component of the digital use divide. Similar to that, Hauk, Hüffmeier, and Krumm (2018) looked at age and TAM in their meta-analysis and found age to be negatively related to (1) perceived ease of use, (2) perceived usefulness, and (3) intention to use a technology (Hauk et al., 2018). More specifically, they found perceived ease of use to mediate both negative relationships between age and perceived usefulness as well as between age and intention to use. Due to less experience in technologies, "older adults find it more difficult to handle technologies and perceive technologies as less easy to use" (Hauk et al., 2018, p. 5) than younger employees, which in turn affects actual usage behavior (Morris & Venkatesh, 2000; Morris et al., 2005).

Regarding the impact of age on digital skills, Guo et al. (2008) do not find age to automatically be connected with lower digital competencies, while Li and Ranieri (2010) find such results. Sunkel and Ullmann (2019) explore the use and appropriation of ICTs in Latin America and also link increased age with decreased odds of using the Internet. Nevertheless, these results must be interpreted with caution in the organizational context. For instance, Li and Ranieri (2010) only studied digital competencies in a Chinese school context and did not include all age groups. Van Deursen and Van Dijk (2011) found age to be a decisive factor when measuring the operational and formal internet skills, which were significantly worse with increasing age. Salajan et al. (2010) examined the perceived usefulness of digital technologies for learning and teaching in a university context and found slight inter-generational differences but no universal applicability.

In sum, some previous research offers initial evidence for the digital divide hypothesis. Still, for the specific case of digital fluency, consisting of digital knowledge and digital self-efficacy, we argue that older employees may have more significant problems with overcoming the digital divide components, such as the digital skill divide and the digital outcome divide, than younger employees. Younger employees might have more experience in using digital technologies as they grew up constantly applying these, while older adults at some point in their lives had to acquire digital competencies (Hauk et al., 2018; Prensky, 2001b; Van Deursen & Van Dijk, 2011; Wang et al., 2013). Thus, the negative effect of age on technology acceptance may lead to an even bigger digital divide. Therefore, we propose that older employees may evaluate their digital knowledge and digital self-efficacy to be lower than younger employees. This effect could even be regardless of the actual digital performance at work, as digital fluency

- with its two components - represents employees' perceptions of their ability and self-confidence in using ICTs (Zimmermann, 2022). In line with the theoretical argumentation, as well as with evidence from previous research, we propose the following hypothesis:

Hypothesis 1: Chronological age is negatively related to the employee's level of digital fluency.

2.2.3 The Moderating Role of Negative Age Stereotypes

We assume that purely inspecting the main relation between age and digital fluency is insufficient and individual and social contextual factors need to be considered to understand this relationship. First, integrating the digital divide concept with the stereotype embodiment theory (Levy, 2009), we assume that one's endorsement of negative age stereotypes can be crucial for the self-perception of digital fluency in older employees. According to Kunze et al. (2013b), "work-related age stereotypes are individual beliefs and expectations about employees that are merely based on their age group membership" (p. 419). Even though such work-related age stereotypes are possible for any age group, stereotypes are predominantly expressed against older individuals (Kunze et al., 2013b; O'Brien & Hummert, 2006; Posthuma & Campion, 2009). Whereas research often focused on negative age stereotypes expressed by younger individuals to separate themselves from older age groups, it became more and more prominent to also focus on the mechanisms that underlie the phenomena of more senior people holding negative age stereotypes (Lagacé et al., 2016; Levy, 1996; O'Brien & Hummert, 2006).

According to the theory of stereotype embodiment (Levy, 2009), negative age stereotypes present in an individual's surroundings can lead to the internalization of these stereotypes by the affected target groups across the life span. In the course of this internalization, the "internalized stereotypes are directed at the self and turn into self-fulfilling prophecies by evoking corresponding cognitive and behavioral responses" (Weiss & Kornadt, 2018, p. 478). Levy (1996) showed that the activation of negative age stereotypes tended to worsen the participants’ memory performance, self-efficacy, and views of aging. Hence, older workers who hold negative age stereotypes run the risk of a potential “self-fulfilling prophecy”; holding negative age stereotypes may result in psychological disengagement (e.g., lower self-confidence and self-esteem in one’s abilities to use ICTs) (Lagacé et al., 2016; Levy, 1996, 2009; Tougas et al., 2008).

Furthermore, Lagacé et al. (2016) argue that psychological disengagement through the internalization of negative age stereotypes also leads to digital disengagement (e.g., investing less time in training and using ICTs): By endorsing negative prejudices against one’s own age group, these employees invest less time in training and involuntarily widen the digital divide (Lagacé et al., 2016). Other researchers found that age-specific self-stereotyping also has negative consequences for employees’ social activities at work, as it is likely to reduce employees’ sense of belonging in the workplace and shape their social emotions and social motivations (Rahn et al., 2021 2021). Furthermore, Weiss and Perry (2020) demonstrated the negative effects of older adults' internalized age stereotypes on personal outcomes like job search self-efficacy. In the context of digital technologies, similar results could also be shown for older individuals, even though not in a workplace setting. In a study among retired seniors in Canada, Lagacé et al. (2015) reported seniors to be less interested in learning about and using digital technologies when they held negative age stereotypes among themselves.

In line with current theorizing and empirical results on self-stereotyping and stereotype internalization, we argue that older adults' internalization of such negative age stereotypes may negatively affect the employees and their self-perception of digital fluency. As presented, the internalization of such negative stereotypes can impair self-esteem and self-confidence and lead to psychological disengagement, resulting in disengagement towards using digital technologies and potential digital training on and off the job (Lagacé et al., 2016). While for younger employees, agreeing to stereotypes about older workers’ difficulties to deal with ICTs might be a cause of age-group dissociation, for older workers this should most likely imply self-stereotyping (Lagacé et al., 2016; Levy, 2009; Steele & Aronson, 1995). Subsequently, through the self-fulfilling prophecy mechanism, these employees are not likely to report having high values on the two components of digital fluency, digital knowledge and digital self-efficacy. While digital disengagement impedes their digital knowledge, their digital self-efficacy may be hampered through the lower self-esteem that comes from the internalization of age stereotypes (Lagacé et al., 2016; Owens & Massey, 2011). Thus, the internalization of negative age stereotypes has significant negative consequences for one's self-perception of digital fluency. In line with these theoretical arguments, we propose the following hypothesis:

Hypothesis 2: Negative age stereotypes moderate the negative relationship between chronological age and digital fluency, such that chronological age is more negatively related to digital fluency for employees that have high levels of negative age stereotypes than for employees that have low levels of negative age stereotypes.

2.2.4 Developmental Supervisor Support as a Decisive Factor

Furthermore, we argue that supervisors play a further contextual role if older employees internalize negative stereotypes, affecting their digital competency perceptions. In general leadership research, supervisory support was shown to positively relate to developmental activities and training attitudes by employees and, thus, impact their self-efficacy and performance (Dvir et al., 2002; Maurer et al., 2002; Noe & Wilk, 1993; van Vianen et al., 2011). Supervisors can show developmental support in multiple ways: For instance, they can encourage their employees to learn new skills, participate in training offered by the organization or reflect on their career development and potential vacant positions within the organization (van Vianen et al., 2011).

Further extending stereotype embodiment theory (Levy, 2009) and integrating it with the concept of stereotype threat (Steele & Aronson, 1995), we expect that the combination of internalized negative age stereotypes and missing developmental supervisor support may may affect the relationship between age and digital fluency. Following van Vianen et al. (2011), we assume that a lack of supervisory support could have enormous consequences for the aging employees' self-efficacy and their self-evaluation regarding their capacity to learn new skills and participate in training. A lack of supervisor support could thus bring about settings conducive to the activation of stereotype threat (Steele & Aronson, 1995). Stereotype threat describes the process in which, when confronted with stereotypes, one's individual performance may decline as the confrontation results in the activation of existing stereotypes. For instance, Weiss and Perry (2020) demonstrated that older adults (in their setting: 60-79 years old) are more likely to be affected by stereotype threat than middle-aged adults (50-59 years old). Most recently, Mariano and colleagues (2021) investigated stereotype threat and technology use among older adults (60-95 years) and found adults who perceived stereotype threat to have lower levels of technology use than those who did not perceive stereotype threat.

As Levy (1996) shows, the likelihood of involuntarily experiencing stereotype threat is higher for employees with high levels of implicit stereotypes against themselves. In this case, a lack of supervisory support could function as a stereotype activator for aging employees in the following way: Older employees might interpret missing supervisor support as an indication of the supervisor's lack of confidence in the employee's ability to gain digital skills, and this may activate the employee's negative age self-stereotypes when they perceive the stereotype threat (Levy, 1996; Steele & Aronson, 1995). The now activated age stereotypes could aggravate the employee's self-efficacy and inhibit their training and development willingness with the possibility of gaining digital knowledge (Bandura, 1986; van Vianen et al., 2011).

Furthermore, the digital divide's various components, such as the digital use divide, digital skill divide, or digital outcome divide, may be enhanced and lead to an even stronger negative effect of age on digital fluency (Mariano et al., 2021). Therefore, Lagacé et al. (2016) also ascribe managers a key role when it comes to communication in the workplace and the counteraction or reinforcement of "negative outcomes of such stereotypes" (Lagacé et al., 2016,

p. 70). Consequently, if employees do not experience supervisor support and helpful suggestions on career and training prospects, and they have high levels of negative age stereotypes against the aging workforce, this may amplify the relation of age and digital fluency.

On the contrary, we argue that high supervisor support also has the chance to preempt existing age stereotypes of older workers and lead to higher levels of perceived digital fluency: By supporting employees in their development and suggesting helpful possibilities to gain new skills, supervisors may increase older workers' self-efficacy and their willingness to participate in further training (Bandura, 1986; van Vianen et al., 2011). In the digital context, strengthening one's digital self-efficacy may lead to a higher level of training, and general confrontation, with digital technologies and could weaken employees' prevailing age stereotypes. Therefore, high levels of developmental supervisor support and low levels of internalized negative age stereotypes might result in favorable consequences for older employees and alleviate the digital divide components such as the digital use divide, digital skill divide, or digital outcome divide, leading to Hypothesis 3:

Hypothesis 3: Developmental supervisor support weakens the existing moderating effect of negative age stereotypes on the negative relationship between chronological age and digital fluency, such that the relationship is no longer significant when employees have low negative age stereotypes and perceive high developmental supervisor support but significant and negative when employees have high negative age stereotypes and perceive low developmental supervisor support.

2.3 Methods

2.3.1 Data Collection and Sample

To test the proposed hypotheses, we collected data in July 2020 from white-collar employees with engineering office tasks in a German industrial company operating in the automotive sector. As part of the cooperation, the company received a benchmarking report on their workforce's digital fluency levels. As the company experienced major changes in their daily work due to the workplace's digital transformation, its environment appears to be the appropriate context to examine different levels of digital fluency and other contextual factors among their employees. In total, 1,007 white-collar employees with office jobs completed the full online survey. Respondents' age ranged from 19 to 65 years old, with an average of 40 for the sample (*SD = 10.10*). This matches the mean age of the German working population (Börsch-Supan & Wilke, 2009). In the sample, 77.8% were males with a job tenure of 12 years (*SD = 9.41*) and a mean of 37.4 weekly working hours (*SD = 6.11)*. The majority of the respondents held a master's degree (66.2%), while 12.9% had received a doctorate, 12.2% a bachelor's degree, 4.8% an apprenticeship, and 3.9% high-school education only. An overall of 21.6% indicated being in a leadership position.

2.3.2 Measures

In order to test the validity of the latent construct variables, separate confirmatory factor analyses (CFA) were performed. Unless otherwise noted, 5-point Likert scales (1 = strongly disagree, 5 = strongly agree) were used for all measures.

Chronological Age. Employees' age was measured by their chronological age in years.

Digital Fluency *(α = 0.88).* To measure employees' level of digital fluency, the digital fluency scale developed by (Zimmermann, 2022) was used, which contains six items from the two subdimensions, digital knowledge and digital self-efficacy. An example item for digital knowledge is "*I know how to use digital technologies without too much effort.*", while a sample item for digital self-efficacy is "*I feel confident that I can reliably achieve the desired work results with the help of digital technologies*". Also, the CFA showed a sufficient model fit to our data (χ^2 = 116.12; df = 8; χ^2/df = 14,52; CFI = 0.97; IFI = 0.97; TLI = 0.95; SRMR = 0.06).

Negative Age Stereotypes (*α = 0.80*). Employees' own negative stereotypes against older workers were captured by a three-item-scale further developed by Kunze et al. (2013b) and based on the age stereotype scale by Chiu, Chan, Snape, and Redman (2001). To measure age stereotypes in a digital work context, the items were slightly adjusted to stereotypes against older workers' adaptability to digital technologies and the speed of the digital change. All item loadings were significant ($p < 0.001$) and above the threshold of 0.5, a threshold often applied in factor analysis to evaluate the fit of the latent constructs to their respective indicators (Hulland, 1999). As opposed to the other constructs, for this variable, the CFA did not allow to report reliable fit indices, as more than three items are required to do so (Hu & Bentler, 1999).

Developmental Supervisor Support (*α = 0.91).* Perceived supervisory support was measured using the scale developed by Greenhaus, Parasuraman, and Wormley (1990). To reduce participant fatigue, we chose five items from the original nine-item scale that most appropriately aimed at developmental supervisor support at the workplace and included support towards acquiring important skills by getting feedback and participating in training. Results from the CFA also revealed acceptable model fit properties (χ^2 = 167.95; df = 5; χ^2/df = 33,59; Comparative Fit Index (CFI) = 0.95; Incremental Fit Index (IFI) = 0.95; Tucker-Lewis-Index (TLI) = 0.91; Standardized Root Mean Square Residuals (SRMR) = 0.03).

Controls. To analyze the hypothesized relations without running the risk of disregarding a potential omitted variable bias, we included several control variables. First, we controlled for organizational tenure in years, as employees with higher levels of tenure may be expected to have more "organization-specific experience and a better understanding of how to assimilate the stress creating effects of ICTs in their work context" (Ragu-Nathan et al., 2008, p. 430) and therefore may feel more comfortable using digital technologies and thus have a positive effect on digital work performance (Tarafdar et al., 2015). Second, it may make a difference for the employees' level of digital fluency whether they work in agile teams or not. As agile teams are often related to digital backgrounds, online collaborations, and software development, employees from agile teams may have stronger prerequisites for developing digital competencies (Booth et al., 2016; Stray et al., 2018). Therefore, we also controlled for whether an employee reported working in an agile team ("*Do you work in an agile team?"; No = 0, Yes = 1*). Third, we included the educational background of the employee as a control variable, as the educational level was shown to make a difference in the development of various internet skills (van Deursen & van Dijk, 2010). Fourth, we included the extent to which employees were used to working remotely: Even though the workplace is already highly digitized, working remotely may stand for higher use of digital technologies to stay connected, communicate, and use online tools to achieve satisfactory work results (Vuori et al., 2019). Therefore, we asked employees how many hours on average per week they usually spend working remotely– except for extraordinary and involuntary situations such as the coronavirus-pandemic. Lastly, we controlled for the number of trainings employees participated in within and outside the company. Whether an employee increasingly participated in many trainings may affect their work performance and, more specifically, their digital fluency, as trainings promote these factors (Konings & Vanormelingen, 2015; Mohammadyari & Singh, 2015). Therefore, the respondents were asked to answer how many trainings – internal and external of the organization – they participated in over the last two years.

2.3.3 Analytical Techniques

To test the measurement structure of our model, we applied structural equation modeling (SEM) techniques using the statistical package AMOS 26. In doing so, SEM allows to analyze structural relationships between the observed variables and enables "a comprehensive, confirmatory assessment of construct validity" (Anderson & Gerbing, 1988, p. 411). We tested the hypotheses by multiple linear regression analyses. For testing the proposed moderation effects of the second and third hypotheses, we complied with the instructions given by Little, Bovaird, and Widaman (2006) and therefore used orthogonalized product terms of the latent constructs. Furthermore, we applied simple slope testing to graphically plot and superiorly interpret the regression results of the interaction effects by following the recommendations of Dawson and Richter (2006) and Liu, West, Levy, and Aiken (2017).

2.4 Results

2.4.1 Descriptive Statistics

First, Table 1 provides detailed information about the means, standard deviations, and intercorrelations for all relevant variables used in this study. As expected, employees' age was negatively related to the level of digital fluency (r = -0.27, $p < 0.01$). Age was also negatively related to negative age stereotypes (r = -0.19, $p < 0.01$) and agility (r = -0.10, $p < 0.01$). Digital fluency was negatively related to negative age stereotypes (r = -0.08, $p < 0.05$), developmental supervisor support (r = -0.15, $p < 0.01$), and tenure (r = -0.29, $p < 0.01$).

Table 1

Means, Standard Deviations and Intercorrelations of Study Variables

Variable	*M*	*SD*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
(1) Age	39.94	10.10									
(2) Negative Age Stereotypes	3.13	0.88	- 0.19**								
(3) Developmental Supervisor Support	3.35	0.97	- 0.04	- 0.07*							
(4) Digital Fluency	4.16	0.67	- 0.27**	- 0.08*	- 0.15**						
(5) Tenure	11.70	9.42	0.79**	- 0.10**	- 0.03	- 0.29**					
(6) Agility	0.48	0.50	- 0.10**	- 0.01	0.02	0.13**	- 0.10**				
(7) Educational Background	8.68	1.24	0.01	- 0.06*	- 0.02	0.12**	- 0.16**	- 0.04			
(8) Remote Work in %	14.09	17.75	0.04	- 0.07*	0.01	0.00	0.00	0.06*	- 0.05		
(9) Training Participation internal	5.41	4.20	- 0.03	- 0.03	0.00	0.03	- 0.01	- 0.01	- 0.04	0.02	
(10) Training Participation external	7.99	4.83	- 0.01	0.07*	0.00	- 0.03	0.02	- 0.06	0.00	0.01	0.12**

Note. N = 1,007. * $p < 0.05$; ** $p < 0.01$

2.4.2 Measurement Model

The measurement model displayed in Table 2 consists of the three latent constructs negative age stereotypes, developmental supervisor support, and digital fluency measured with 14 items overall and, additionally, the manifest single item variable of chronological age. For the evaluation of the model fit, we followed the recommendations by Bentler (2007) as well as Hoyle (1995) and included several fit indices such as the abovementioned CFI, IFI, and TLI, as well as the Root Mean Squared Error of Approximation (RMSEA), which assess the overall model fit (Bentler, 2007; Hoyle, 1995). Commonly applied threshold values for the incremental fit indices CFI, IFI, and TLI who all range from zero to one are values >0.90, while the RMSEA should be <0.08 in order to indicate acceptable model fit (Hu & Bentler, 1999). For the measurement model of this study, sufficient values for all indices were obtained (CFI = 0.95, IFI = 0.95, TLI = 0.94, RMSEA = 0.07). Additionally, we compared the measurement model to three alternative models, displayed in Table 2. In the first alternative model, the negative age stereotypes and digital fluency items loaded on one common factor and had a significantly worse fit than the hypothesized model ($\Delta\chi^2$ = 1,642; Δdf = 4). Similar results could be found for the second alternative model, in which the items of negative age stereotypes, digital fluency, and developmental supervisor support loaded on one common factor ($\Delta\chi^2$ =4,877; Δdf = 6). Lastly, the one-factor model (alternative model 3) with all items loading on one common factor again fitted worse than the previous models ($\Delta\chi^2$ = 7,813; Δdf = 7).

Table 2

Measurement Model Comparison

Model	χ^2	df	χ^2/df	$\Delta\chi^2$	Δdf	CFI	IFI	TLI	RMSEA
Hypothesized Model	502	84	5.98	***		0.95	0.95	0.94	0.07
Alternative Model 1[a]	2,144	88	24.36	1,642 ***	4	0.76	0.76	0.72	0.15
Alternative Model 2[b]	5,379	90	59.77	4,877 ***	6	0.39	0.39	0.29	0.24
Alternative Model 3[c]	8,315	91	91.37	7,813 ***	7	0.05	0.05	-0.01	0.30

Note. N = 1,007. CFI = Comparative Fit Index; IFI = Incremental Fit Index; TLI = Tucker-Lewis-Index; RMSEA = Root Mean Squared Error of Approximation. All measurement models are compared to the hypothesized model.
[a] Negative age stereotypes and digital fluency on one common factor. [b] Negative age stereotypes, digital fluency, and developmental supervisor support on one common factor. [c] Negative age stereotypes, digital fluency, developmental supervisor support, and age on one common factor.

2.4.3 Hypotheses Testing

Table 3 displays the results of the multiple linear regression analyses. Model 1 tested the relation of age on digital fluency (Hypothesis 1). The results show a negative and statistically significant relation of age on digital fluency (β = -0.13, p < 0.001), supporting Hypothesis 1.

In Model 2, we added the interaction term of negative age stereotypes and chronological age and found a negative and significant effect (β = -0.07, p < 0.001). We plotted it in Figure 2 at one standard deviation above and below the mean to better interpret this interaction effect. Furthermore, we deployed simple slope tests to substantiate the regression and the graphical interaction results. The slope for high negative age stereotypes turns out to be steep and statistically significant (β = -0.23, t= -5.85, p < 0.001) with a slope gradient that is almost three times the slope gradient for low negative age stereotypes (β = -0.09, t= -2.32, p < 0.05). These results support Hypothesis 2.

Table 3

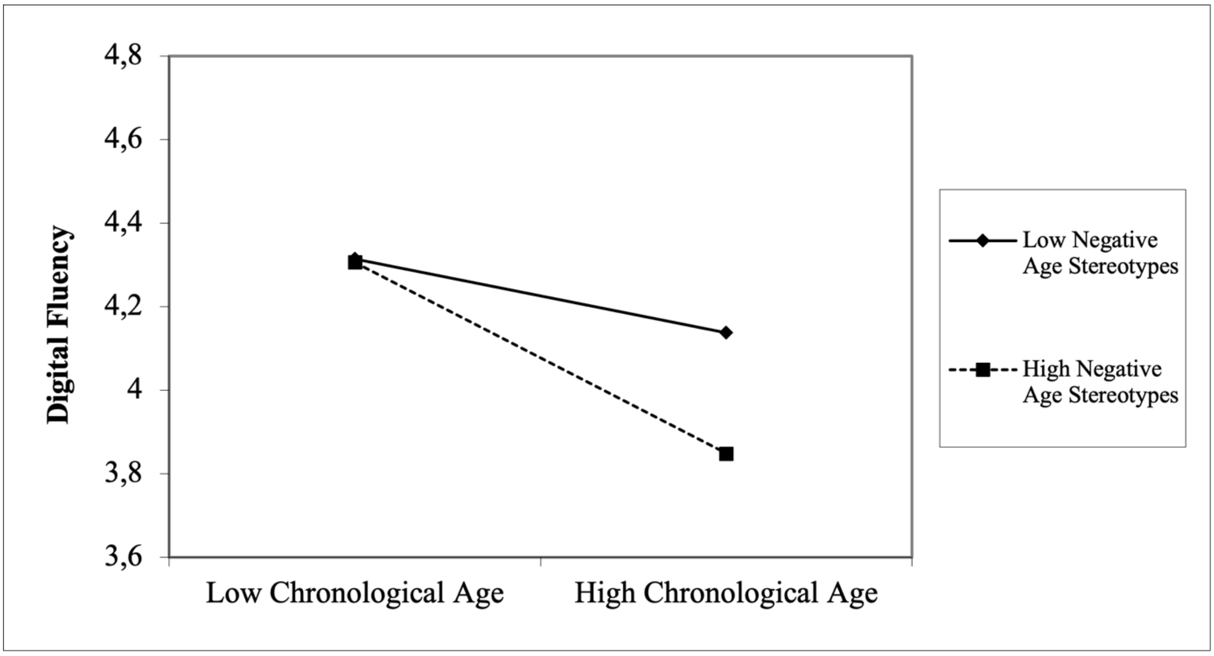
Regression Analysis

	Digital Fluency					
	Model 1		**Model 2**		**Model 3**	
Age (H1)	**-0.13 *****	(0.03)	-0.16 ***	(0.03)	-0.17 ***	(0.03)
Negative Age Stereotypes			-0.07 ***	(0.02)	-0.07 ***	(0.02)
Developmental Supervisor Support					0.08 ***	(0.02)
// Interaction Effects						
Age x Negative Age Stereotypes (H2)			**-0.07 *****	(0.02)		
Age x Negative Age Stereotypes					-0.07 ***	(0.02)
Age x Developmental Supervisor Support					0.01	(0.02)
Negative Age Stereotypes x Developmental Supervisor Support					0.01	(0.02)
Age x Negative Age Stereotypes x Developmental Supervisor Support (H3)					**-0.04 ***	(0.02)
// Controls						
Tenure	-0.08 *	(0.03)	-0.06	(0.03)	-0.06	(0.03)
Agility	0.09 ***	(0.02)	0.07 ***	(0.02)	0.07 ***	(0.02)
Educational Background	0.08 ***	(0.02)	0.08 ***	(0.02)	0.08 ***	(0.02)
Remote Work	0.01	(0.02)	0.01	(0.02)	0.01	(0.02)
Training Participation internal	0.02	(0.02)	0.02	(0.02)	0.02	(0.02)
Training Participation external	0.02	(0.02)	-0.01	(0.02)	-0.01	(0.02)
Constant	4.17 ***	(0.02)	4.15 ***	(0.02)	-4.15 ***	(0.02)
N	1,007		1,003		997	
Adjusted R^2	0.11		0.14		0.15	
ΔR^2			0.03		0.01	

Note. Standard errors in parentheses. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Figure 2

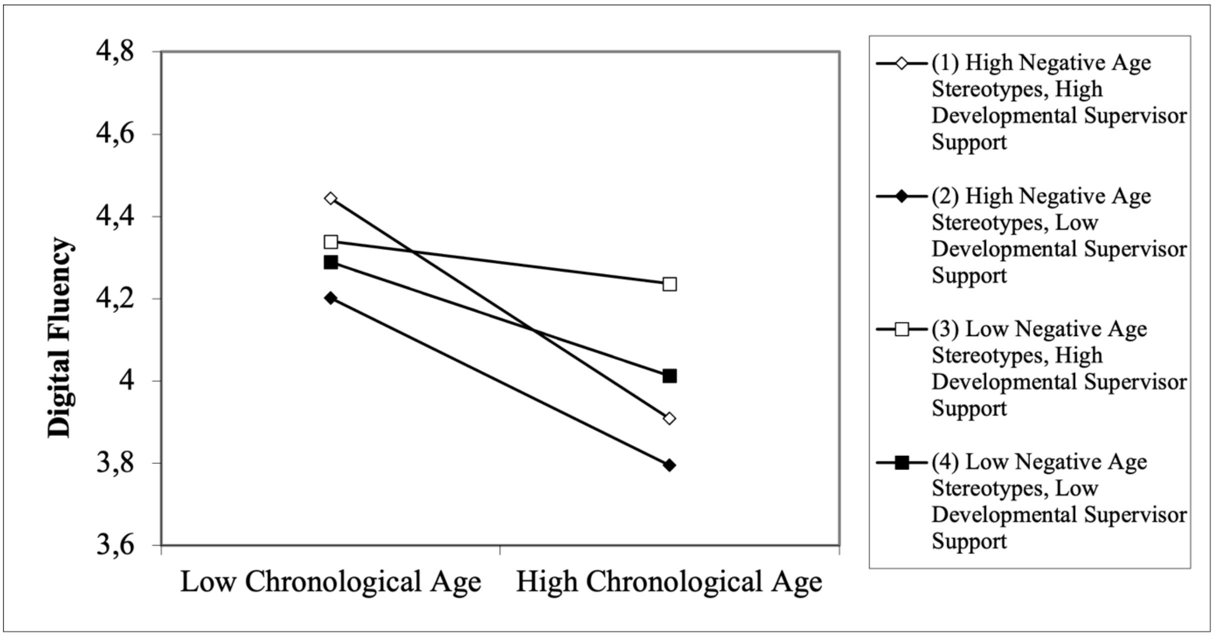
Moderating Effect of Negative Age Stereotypes on the Negative Relationship between Employees' Age and Digital Fluency (Hypothesis 2)



Ultimately, the regression results from Model 3 also support Hypothesis 3 and the assumed three-way-interaction effect of age, negative age stereotypes, and developmental supervisor support on digital fluency (β = -0.04, p < 0.05). In Figure 3, we graphically plotted the moderating effects of negative age stereotypes and developmental supervisor support on the negative relationship between age and digital fluency. In addition, the simple slope tests assist in interpreting the effects (all coefficients and slope difference tests can be found in the Appendix). Slope 2 – illustrating the condition of high negative age stereotypes and low developmental supervisor support – provokes a negative and significant slope (β = -0.20 t= -4.37, p < 0.001). In contrast, slope 3 – illustrating the condition of low negative age stereotypes and high developmental supervisor support – turns out to be non-significant (β = -0.05, t= -1.18, p = n.s). Also, the slope difference test between Slope 2 and Slope 3 is statistically significant (β = -0.15, t= -2.87, p < 0.01). Thus, these results support Hypothesis 3.

Figure 3

Moderating Effects of Negative Age Stereotypes and Developmental Supervisor Support on the Negative Relationship between Age and Digital Fluency (Hypothesis 3)



2.5 Discussion

This study aimed to examine the relationship between employees' age and their level of digital fluency. As argued, there were several reasons to assume that age is generally negatively related to employees' level of digital fluency. Using a sample of 1,007 white-collar employees from a German company, we found empirical support for the negative relationship between age and digital fluency. Thus, age was negatively associated with perceived lower levels of digital fluency. Nevertheless, we argued that this effect is contingent upon personal and situational factors such as negative age stereotypes and developmental supervisor support. First, drawing from stereotype embodiment theory (Levy, 2009), we proposed and found that ageist stereotypes held by employees moderate the age-digital fluency relationship, with older employees with high negative age stereotypes reporting lower levels of digital fluency. Importantly, younger employees' digital fluency levels were not affected by holding such stereotypes. Second, we argued and showed that developmental supervisor support contextualizes this existing moderating effect. In particular, our results indicated that older employees with strong negative age stereotypes and low supervisor support reported the lowest levels of digital fluency. Additionally, age differences in digital fluency perceptions diminished when employees disagreed with such stereotypes and experienced strong supervisor support. This highlights the essential role of leadership in the employees' (digital) development and self-views. Thus, all three hypotheses could be confirmed.

2.5.1 Theoretical Implications

The present study extends our knowledge on aging and digitalization in the workplace in multiple ways. First, we find empirical support for the disputed digital divide hypothesis among the workforce (Prensky, 2001; Wang et al., 2013): While we controlled for important factors like educational background, tenure, or training participation, older employees perceived significantly lower levels of digital fluency than younger employees and therefore exhibited difficulties when adjusting to the more digitalized work environment. By using digital fluency as an outcome variable, we incorporate a new holistic approach and do not only focus on digital knowledge but also on digital self-efficacy, which is necessary for employees to satisfactorily adopt ICTs at work (Briggs & Makice, 2012; Zimmermann, 2022).

Furthermore, we demonstrate that digital fluency perceptions with inclining age depends on important personal and situational factors. So far, to our knowledge, the moderating role of internalized age stereotypes in that context was only shown by Tougas et al. (2008) for retired seniors but not in a workplace context for digital work-related skills. Mariano and colleagues (2021) showed that perceived stereotypes influence the technology acceptance of older adults. They, however, focused on adults' perceptions of whether they are judged by their age when using technologies, but not whether adults generally hold age stereotypes themselves (Mariano et al., 2021). Furthermore, their context was also not work-related but mostly among retired seniors. Thus, our research indicates that when holding negative age stereotypes, older workers - due to psychological disengagement - are on one hand less digitally knowledgeable and, on the other hand less self-confident in their abilities and prospects to perform well using digital technologies.

Most importantly, this research highlights the essential role supervisors play in older employees' digital fluency development. As van Vianen et al. (2011) argued, developmental support by the direct supervisor is essential for employee's self-efficacy and willingness to participate in training and developmental activities. Our results broaden this view and suggest that a lack of developmental supervisor support together with strong negative age stereotypes is most detrimental for employees and creates the biggest age differences in digital fluency levels. In contrast, strong supervisor support together with low negative age stereotypes seem to nullify the effect of age on digital fluency and lead to strong perceptions of digital fluency among all age groups. Therefore, supervisor support has the potential to counteract prevalent age stereotypes and prevent the potential negative consequences of stereotype-threat (Steele & Aronson, 1995).

Nonetheless, besides the mentioned contribution to the literature on age stereotypes, self-stereotyping, and stereotype threat, this research contributes to the digital fluency literature and literature on digital competencies in general (Becker et al., 2012; Briggs & Makice, 2012; Tarafdar et al., 2015; Wang et al., 2013; Zimmermann, 2022). So far, research on digital fluency is still in its infancy as the theoretical approach to combine digital knowledge and digital self-efficacy as core factors of digital competencies is innovative and rather unexplored (Zimmermann, 2022). We integrate the literature on digital fluency, including its subdimension of digital self-efficacy, with the broad literature stream on stereotype embodiment (Lagacé et al., 2016; Levy, 1996, 2009). In doing so, we highlight the crucial role personal beliefs (like age stereotypes) and situational factors (like supervisor support) have in employee's personal development. Both factors make a substantial impact on employees' self-efficacy beliefs and not just their competencies in general.

Lastly, our research can also be put into the context of technology acceptance and the TAM (Davis, 1989). Even though digital fluency conceptually differs from the TAM, both concepts are interconnected. Venkatesh (2000), for instance, expanded TAM by external factors that affect the individual's user behavior, such as computer self-efficacy or computer anxiety. According to this approach, these external factors directly influence perceived ease of use. Similarly, Mohammadyari and Singh (2015) showed digital literacy to predict TAM variables like effort expectancy and performance expectancy, and indirectly enhance performance in an e-learning context at work. Thus, we argue that digital fluency can be seen as a determinant and an outcome of using behavior. Employees who feel self-confident and knowledgeable while using digital technologies are likely to use them in a work context. The final use of technologies, of course, can increase one's performance and thus, one's digital fluency (Mohammadyari & Singh, 2015). Therefore, our research also indirectly contributes to the literature on technology acceptance. While the meta-analysis of Hauk et al. (2018) found age to be negatively related to TAM components among adults, our research indicates a negative relationship between age and digital fluency perception among employees. Thus, if individuals have less intention to use technologies, they also feel less self-confident and knowledgeable about digital technologies. Furthermore, no difference between young and old employees in their digital fluency levels was shown with supervisor support and low levels of negative age stereotypes. Therefore, we expect self-stereotyping and supervisor support to indirectly influence the relationship between age and technology acceptance. The results from Mariano et al. (2021) support this argumentation.

2.5.2 Practical Implications

Furthermore, this research offers important practical implications for companies and managers to overcome the negative consequences of a potential digital divide by motivating the aging workforce to gain digital knowledge and digital self-efficacy. Overall, this research encourages companies to assess the levels of digital fluency among their workforce and to observe and countervail potential age differences. Even though we showed age to be generally negatively related to digital fluency, the two moderators elaborated in this paper impacted this relationship. This research showed the importance of personal and situational factors to compensate for potential digital inequalities between digital natives and digital immigrants. Besides several other insights, the current company setting shows that stereotypes about the adaptability of older employees to the digital work environment are prevalent and should not be underestimated. Therefore, trainings on aging at the workplace could let the employees reflect on their age stereotypes and counteract such psychological tendencies. It is also necessary to promote the development of employees regardless of their age group and offer diversity-friendly HR-policies (see Kunze et al., 2013b; Wegge et al., 2012 for further suggestions on such HR-policies).

Also, as this study shows, supervisor support can, together with low levels of negative age stereotypes, decisively impact the relationship between age and digital fluency. Managers should therefore be empowering and offer support to their followers. Additionally, when encouraging their employees to participate in additional trainings and development programs provided by the organization, they offer their followers appreciation and are likely to “create an environment in which individuals learn to trust their capability to successfully perform tasks with the help of digital technologies” (Zimmermann, 2020, p. 30). Regarding the development of age stereotypes at work, managers should also increasingly focus on employees’ potential self-stereotyping to promote their digital competencies at the workplace.

2.5.3 Limitations and Suggestions for Future Research

Even though this study's approach has several strengths, such as a large sample size and various control variables, it is not free from limitations, which also opens up several possibilities for future research. First, as the methodological approach of this research relies on cross-sectional and self-reported data, this does not allow causal claims about the relationship between age and digital fluency. While we see the self-perception measurement of digital fluency, particularly of digital self-efficacy, as a strength, one could include alternative, objective data sources of digital knowledge. Nevertheless, we also tested alternative models following the procedure described by Shaver (2005) and Antonakis et al. (2010) and did not find endogeneity or multicollinearity to bias our results. Nevertheless, future research could include alternative data sources on the first subdimension of digital fluency, digital knowledge. Potential solutions could be supervisor evaluations, assessments by performance tests or, depending on the work complexity, objective data on job performance, and the use of longitudinal data.

Second, it may also be interesting to include supervisors' actual beliefs about the aging workforce, and its ability to cope with digital changes at the workplace, into the picture. Van Vianen et al. (2011), along with Kunze et al. (2013b) and Posthuma and Campion (2009), found that managers who hold negative age stereotypes can negatively impact both organizational performance and individual employees' willingness to engage in further training and development. In their meta-analysis, Posthuma and Campion (2009) suggest that managers who agree with such stereotypes "tend to favor organizational practices that mirror these stereotypes and, as such, offer less promotion/training opportunities and provide more negative performance feedback to older workers in comparison to younger workers" (Lagacé et al., 2016, p. 69). Therefore, future research could add supervisors' potential age stereotypes to the picture and analyze whether they affect the process of stereotype embodiment of their employees and its impact on these employees' digital fluency levels.

Third, we assume that employees who agree with negative stereotypes about older employees and their digital competencies internalized these stereotypes and self-stereotype themselves with the negative consequences of stereotype embodiment and stereotype threat (Lagacé et al., 2016; Levy, 2009; Steele & Aronson, 1995). As Weiss and Kornadt (2018) discussed in detail, agreeing to such stereotypes could also result in age-group dissociation but not in stereotype internalization (Weiss & Kornadt, 2018). Still, our results clearly indicate that, for older employees, internalization is the case rather than dissociation from the stereotypes. Nonetheless, future research may incorporate both scenarios and compare these processes using experimental approaches to explore negative age stereotypes at the digital workplace. To better understand the exact proceeding and mechanisms underlying the activation of negative age-related stereotypes and their impact on job-related development, future research could also explore the precise origin of such stereotypes as well as possibilities to counteract such stereotypes from the outset.

2.6 Conclusion

In summary, this research attempts to understand the complex relationship between age and digital competencies. In doing so, high developmental supervisor support and low levels of negative age stereotypes seem to counteract existing age differences in digital fluency perceptions among white-collar workforces. Still, the study results reveal the impending consequences resulting from missing supervisor support and strong negative age stereotypes. Towards the mutual development of digital fluency among the workforce, we hope to encourage other scholars and practitioners to explore further potential situations that might impact aging at the workplace.

3. Who Decides Where to Work from? Determinants of Remote Work and Their Effects on Individual Level Outcomes

Kilian Hampel

ABSTRACT

Since the COVID-19 pandemic, remote work has become an integral part of workplace reality. However, a growing number of organizations and CEOs publicly express concerns about remote work and consider forcing their employees to return to the office. While self-determination theory generally argues that employees need autonomy to avoid being stressed and unproductive, recent research has only focused on general involuntariness of remote work but not on the specific actors who can decide where to work from. With this study, I identify four levels of remote work decision-making authority – individual, team, managerial, and organizational. Using a self-determination theory framework, I examine whether these four authority levels have various effects on individual work-related well-being (emotional exhaustion, loneliness) and productivity (performance, engagement) outcomes and, furthermore, explore potential moderating effects of age as well as leadership consideration and initiating structure. Results from multiple regression analyses with 639 white-collar employees indicate that employees whose manager mainly determines the amount of remote work allowed significantly show higher levels of emotional exhaustion and loneliness. In contrast, the impact on productivity-related outcomes such as performance and engagement remains largely unaffected by the hierarchical level of the decision-making authority. Notably, the study finds that the negative effects of managerial decision-making authority on well-being do not depend on either chronological age or leadership styles, though leader consideration shows a marginal moderating effect on performance. These insights are vital for crafting remote work policies as

they highlight the critical role of employee autonomy in remote work arrangements, emphasizing the potential adverse impact of managerial control on well-being.

Keywords*:* remote work; decision-making autonomy; individual outcomes; self-determination theory; age differences; leadership

3.1 Introduction

The COVID-19 pandemic fundamentally changed the way we work. As nations grappled with the need for social distancing and lockdown measures, organizations around the world rushed to adopt remote work as a viable solution to maintain operations while protecting employee health (Brown & Leite, 2023). Workforces with office tasks quickly adapted to virtual meetings, home offices and asynchronous collaboration tools. In Germany, the percentage of employees working from home rose from 12.9% in 2019 to 21.0% in 2020, and by 2023, it remained high at 23.5% (Statistisches Bundesamt, 2024b). What began as a temporary response to a global crisis has since evolved into a fundamental question facing companies today: To what extent should remote work, defined as the possibility to work from anywhere outside the office (Kunze et al., 2021), be integrated into our work culture, and who should have the authority to make this important decision? Decisions about the future of remote workplaces are complex, touching on issues of employee well-being, company productivity, and adapting work practices to society's changing expectations (Nyberg et al., 2021; Wang et al., 2021).

At the heart of this debate is the question of who should be pulling the strings when it comes to determining the extent of remote work for employees whose jobs could theoretically be done from anywhere (Colley et al., 2023). On the one hand, a growing number of organizational decision-makers, for instance Elon Musk, are openly expressing concerns about employee productivity and engagement and have begun to limit or, in the case of Tesla, outright ban any remote work options (Werner, 2022). On the other hand, several studies on employee preferences clearly point to more individual flexibility and decision-making power for employees in the choice of the work location (Barrero et al., 2021; Flüter-Hoffmann & Stettes, 2022; Kunze et al., 2020). In an emerging hybrid work environment, where remote and office work coexist, the challenge should therefore be to proactively find a way to optimize remote work and its decision-making while mitigating potential drawbacks such as reduced collaboration, increased isolation, or difficulty maintaining work-life boundaries (Colley et al., 2023; Grzegorczyk et al., 2021). Thus, it is important to investigate the effects that various determinants of remote work can have on employees.

Overall, four primary stakeholders within organizations have the authority to make decisions about the actual amount of time white-collar employees spend working remotely. As a first dimension, *individual decision-making autonomy* leaves employees with the autonomy to independently decide whether they want to work remotely or at the office (Gagné & Deci, 2005). Second, members of teams can also collaboratively agree on the extent of remote work leading to *team participation in decision-making* (Chen & Kanfer, 2006). Third, leaders of teams may have the authority to determine the amount of remote work for their subordinates resolving in *managerial decision-making* (Raghuram et al., 2001). Fourth, *organizational decision-making* may allow corporate management to set strategic policies about remote work using a classic top-down approach (Fabbri, 2018; Katz & Kahn, 1978).

While recent studies have highlighted the importance of voluntariness in remote work agreements, the specific determinants that shape the decision-making on these arrangements remain underexplored (Dias et al., 2022; Lopes et al., 2023). The purpose of this paper therefore is to examine whether, and to which extent, these four dimensions have different effects on employees. In doing so, I utilize self-determination theory (SDT) (Ryan & Deci, 2000) as the primary theoretical framework to understand how autonomy impacts both well-being and productivity-related work outcomes (Gagné & Deci, 2005). First, I select emotional exhaustion and loneliness as two commonly established well-being outcome variables often used within SDT and autonomy-related research (Chua & Koestner, 2008; Van den Broeck et al., 2010). Second, I rely on self-assessed performance and engagement as two productivity-related outcome variables (Humphrey et al., 2007; Van den Broeck et al., 2008).

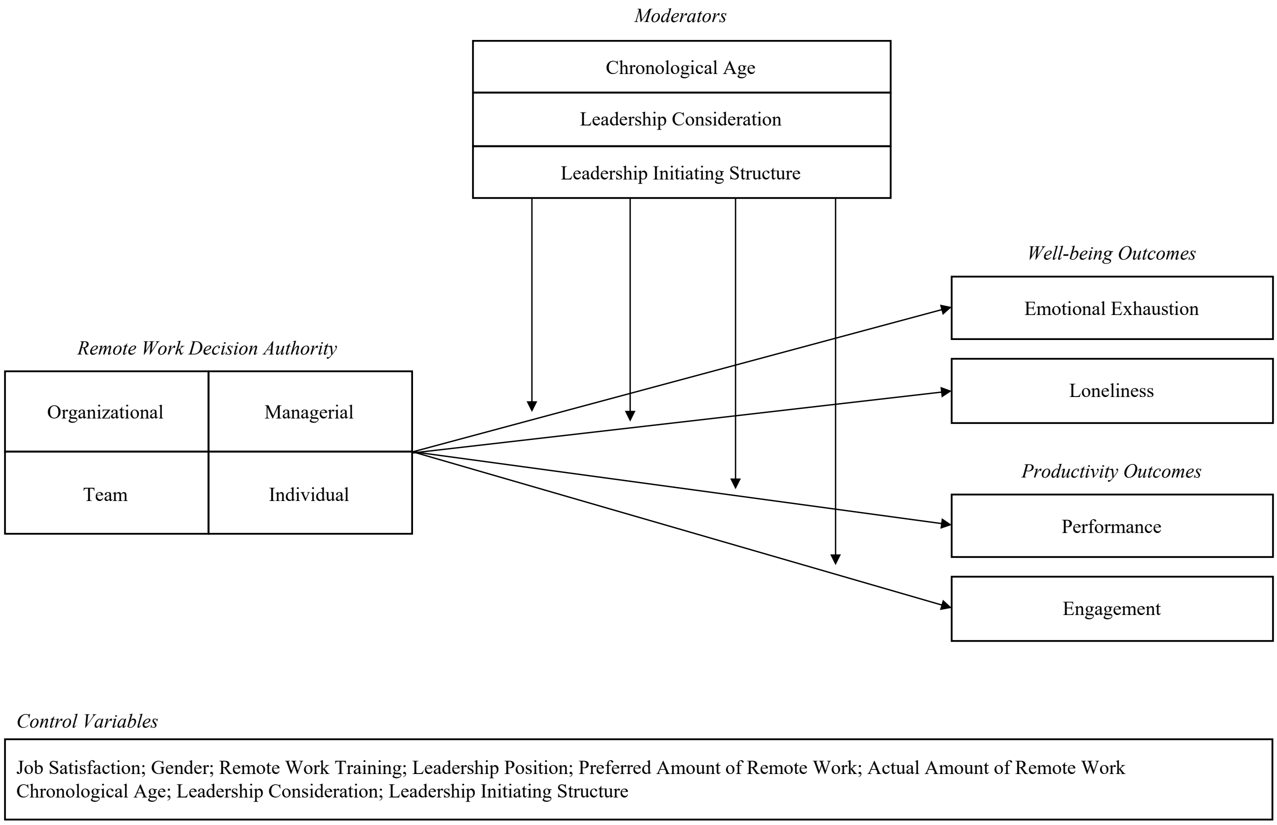
In accordance with existing research, I will introduce several moderators to test whether these determinants of remote work affect individual outcomes differently when interacting with important contextual variables (Ng & Feldman, 2014; Slemp et al., 2018). First, the study incorporates the moderating role of age to assess how different age cohorts may uniquely experience the impact of remote work decision making. The incorporation of age is particularly vital to address the ongoing impact of demographic change on the labor market and to ensure that such policies are equitable and effective across all age groups (Ng & Feldman, 2014). Second, two leadership styles, specifically consideration and initiating structure, are being analyzed as contextual factors. While consideration leadership style is characterized by its empathetic and person-oriented approach, initiating structure leadership style is known for its task-oriented and directive nature (Lambert et al., 2012). By examining these leadership styles as separate moderators, the study aims to uncover nuanced insights into how managerial approaches can enhance employee well-being and performance when working remotely.

To empirically explore these relationships, I use representative data from the German workforce with 639 participants. In doing so, I test multiple linear regression models and control for several important potential confounding variables such as job satisfaction, gender, remote work training, leadership position, preferred amount of remote work, actual amount of remote work, age, as well as leadership consideration and initiating structure. Figure 4 shows all key variables examined in this study.

With this research, I contribute to the growing debate on hybrid future of work (Colley et al., 2023; Grzegorczyk et al., 2021; Ng & Feldman, 2014) and remote work voluntariness (Dias et al., 2022; Lopes et al., 2023) and offer potential solutions to the question often asked: Who should determine the amount of remote work allowed for employees? In doing so, this article holds significant implications for workforce well-being and future work arrangements. By investigating the distinct effects of individual choices, team dynamics, managerial decisions, and organizational top-down approaches, I aim to offer a comprehensive understanding of how each determinant impacts individual employee-related outcomes, while acknowledging potential age- and leadership style-related variations. By showing that managerial decision-making authority in particular has detrimental effects on employee well-being, I contribute to SDT (Ryan & Deci, 2000). In addition, this study also has implications for the growing literature on idiosyncratic deals (i-deals) (Budd et al., 2010; Hornung et al., 2010; Rousseau et al., 2006), highlighting the importance of autonomy and involvement in the decision-making process. The results therefore also have valuable practical implications for organizations, managers, and employees.

Figure 4

Conceptual Framework of Study 2



3.2 Background: Remote Work Decision-Making Authorities

Over the past years, remote work has fundamentally transformed how organizations and employees approach work. It offers flexibility and autonomy, which have been shown to positively impact employee well-being, satisfaction, and productivity (Gajendran & Harrison, 2007). However, there is a growing debate on how future remote work arrangements should be managed (Colley et al., 2023; Kniffin et al., 2021).

Recent literature suggests that involuntariness of remote work, meaning that employees do not have a choice in determining the amount of telework they can engage in, can lead to increased stress levels and decreased engagement levels among employees due to autonomy-motivation related reasons (Dias et al., 2022; Lopes et al., 2023). However, we know little about how the specific determinants of remote work in particular impact employees and their work-related outcomes. Existing literature has predominantly focused on whether remote work is voluntary or imposed (Wang et al., 2021), yet little attention has been given to the authority levels involved in decision-making. Overall, four distinct levels of remote work decision-making authority can be identified:

First, *individual* decision-making gives employees the freedom and flexibility to shape their work arrangements and independently decide how much remote or office work they want to engage in (Spreitzer et al., 2017). This allows individuals to optimize their work environments to suit both their productivity preferences but also private surroundings, helping them avoid work-family conflict and family-work conflicts (Allen et al., 2015; Gajendran & Harrison, 2007).

Second, such decision-making can take place within *teams*: With colleagues as well as leaders expressing their individual needs and preferences for work location and amount of remote work, team participation in decision-making enhances collaboration by fostering engagement and sharing responsibility (Chen & Kanfer, 2006; Cotton et al., 1988; West, 2002).

Third, *managers* of teams may determine how and when employees can engage in remote work or should come to the office (Raghuram et al., 2001). This may offer consistency in structures and accountability, as well as alignment with productivity goals, but may also limit employees' perceived and actual autonomy (Gajendran & Harrison, 2007; Golden & Veiga, 2008).

Fourth, *organizational* decision-making authority over remote work involves centralized policies that apply uniformly across the organization, often through formal agreements or company-wide mandates allowing for consistency and equal treatment of all employees (Fabbri, 2018; Katz & Kahn, 1978).

With this research, I aim to shed light on how the various decision-making authorities influence key well-being and productivity outcomes. While existing literature has extensively explored remote work's benefits and challenges, little attention has been given to how varying levels of decision-making authority impact employee work outcomes (Gajendran & Harrison, 2007; Wang et al., 2021). Most studies focus on whether remote work is voluntary or imposed (Dias et al., 2022; Lopes et al., 2023) without considering these different decision-making authorities. Therefore, I aim to fulfil this research gap by investigating the four distinct decision-making levels and their effects on employees. In doing so, I use SDT (Ryan & Deci, 2000) as the primary theoretical framework when examining how the various autonomy levels in remote work settings impact employee outcomes. SDT posits that satisfying the basic psychological needs of autonomy, competence, and relatedness is essential for experiencing intrinsic motivation work motivation and achieving well-being and productivity outcomes (Gajendran et al., 2014; Ryan & Deci, 2000). SDT has been widely applied in organizational contexts to explain how different work environments, particularly in terms of autonomy, influence personal well-being and performance (Gagné & Deci, 2005; Van den Broeck et al., 2016). In exploring how the four decision-making authorities represent different autonomy levels and hence influence employees, I draw on existing research and focus on two well-being outcomes, emotional exhaustion (Van den Broeck et al., 2010) and loneliness (Chua & Koestner, 2008) as well as on two productivity outcomes, performance (Humphrey et al., 2007) and engagement (Van den Broeck et al., 2008).

In addition, moderators play a crucial role in shaping how different levels of autonomy influence employee outcomes. In accordance with existing research, employee age as well as leadership styles are included. First, age can function as an important factor influencing the relationship between autonomy and individual related outcomes (Ng & Feldman, 2014). Therefore, the goal is to determine whether various age cohorts experience the impact of remote work decision-makers differently. Age is particularly relevant as demographic shifts continue to reshape the workforce, and policies must be designed to ensure they are equitable and effective for employees across different life stages (Ng & Feldman, 2014). Research indicates that older employees may demonstrate stronger resilience to work-related stressors and could be less impacted by shifts in autonomy, thanks to their greater experience and more developed coping mechanisms (Kooij et al., 2010; Ng & Feldman, 2010, 2014). In contrast, younger employees, who are in the early stages of their careers and focused on building skills and gaining independence, may be more sensitive to restrictions on autonomy (Kanfer & Ackerman, 2004). To explore whether the four decision-making authority levels influence individual work-related outcomes, I therefore include chronological age as a first moderator.

Second, I analyze two leadership styles – consideration and initiating structure – as moderators to further examine their contextual influence. Consideration is characterized by empathy and a focus on personal relationships, while initiating structure emphasizes task completion and directive behaviors (Lambert et al., 2012). By investigating these leadership styles separately, I seek to uncover how different managerial approaches can tailor the remote work experience to optimize employee well-being and performance. Within the SDT-framework, existing research emphasized the important role managers have when employees experience different levels of autonomy (Deci et al., 1989; Slemp et al., 2018). Therefore. I decided to explore both leadership consideration and initiating structure as potential moderators for the relationship of the four remote work decision-making authority levels on individual employee work outcomes.

Grounded in SDT (Ryan & Deci, 2000), I seek to explore how varying levels of autonomy in remote work settings impact employee outcomes. Given the emerging nature of this research area and the lack of clear established directions for the various authority levels, this study adopts an exploratory approach rather than a deductive hypothesis-testing model. Instead of testing predefined hypotheses, this study poses an open research question:

How do different levels of decision-making authority in remote work environments influence employee well-being and productivity? And to what extent do chronological age or leadership consideration and initiating structure moderate this relationship?

This exploratory approach is crucial for uncovering novel insights and building foundational knowledge in this under-researched field, which can guide future theoretical and empirical work.

3.3 Methods

3.3.1 Data Collection and Sample Description

I collected data for this study as part of the *Konstanz Homeoffice Study* (Kunze et al., 2020) in March 2023 from 639 white-collar employees. Participants were recruited by a survey company (Bilendi), which allowed for taking into account relevant demographic factors such as age and gender distribution in order to reflect the German working population based on official calculations (Statistisches Bundesamt, 2023). Pre-screening ensured that only participants who had an employment contract and whose job could theoretically be performed remotely were included in the survey. The final sample consisted of 639 employees, 47.1 % of whom were female. Participants' chronological age ranged from 21 to 73 years, with an average of 44.3 years. On average, employees worked 42.1 percent of their weekly working hours remotely, while a share of 21.8 percent did not work remotely at all, and 11.9 percent reported working entirely remotely. Overall, 33.2 percent of the participants had leadership responsibility.

3.3.2 Measures

To test the latent construct variables' validity, I performed separate confirmatory factor analyses (CFA). As the CFA does not allow reliable fit indices to be reported for constructs with three items or less, the analyses are limited to the factor loadings for such constructs (Hu & Bentler, 1999). Unless otherwise noted, 5-point Likert scales (1 = strongly disagree, 5 = strongly agree) were used for the variables' measurement. As the data collection of this study was part of the *Konstanz Homeoffice Study* (Kunze et al., 2020) in a longitudinal setting with comparison of working weeks, most variables were adjusted to week-specific assignments.

Independent Variable: Remote Work Decision-Making Authority. To measure decision-making authority regarding the extent of remote work, participants were asked: "Who primarily determines the amount of remote work in your everyday work?" This question aligns with established measures of decision-making autonomy and control in the organizational behavior literature (Gajendran & Harrison, 2007; Raghuram et al., 2010; Raghuram et al., 2003). As previously elaborated, four main determinants can be identified, which results in four response options: 1) "individual decision-making" (Gagné & Deci, 2005), 2) "team participation in decision-making" (Chen & Kanfer, 2006), 3) "managerial decision-making" (Raghuram et al., 2001), and 4) "organizational decision-making" (Katz & Kahn, 1978).

Dependent Variable: Emotional Exhaustion (*α = 0.92)*. Employees' levels of emotional exhaustion were measured by drawing on the Maslach Burnout Inventory (Maslach & Jackson, 1981). Specifically, three items from a shortened German adaptation by Schermuly and Meyer (2016) were used to minimize potential participant fatigue. Example items were "this week, I felt emotionally drained from my work" and "this week, I felt burnt out from my work". The results of the CFA showed satisfactory results with significant factor loadings and ranging from 0.86 to 0.92.

Dependent Variable: Loneliness (*α = 0.94)*. To measure perceived loneliness, I used the loneliness scale developed by Wright et al. (2006). In developing their scale, the authors define employee loneliness as having two sub-dimensions, emotional deprivation and social companionship. To avoid participant fatigue, I used a shortened version and selected three items per dimension based on the highest factor loadings (Wright et al., 2006). Example items were: "This week, I felt alienated from my co-workers" and "this week, there was no one at work, I could talk about my day to work problems, if I needed to". Overall, the results from the CFA revealed a satisfactory model fit to our data (χ^2= 14.49; df = 812; χ^2/df = 1.21; CFI = 0.99; TLI = 0.99; SRMR = 0.02) as well as significant factor loadings ranging from 0.89 to 0.95.

Dependent Variable: Performance (*α = 0.88).* I measured employees' work performance by using the in-role performance scale formulated by Williams and Anderson (1991). Again, I used a shortened three-item version of the original scale, orientating on Fritz and Sonnentag (2006). Sample items were "this week, I performed tasks that were expected of me" and "this week, I adequately completed assigned duties". Factor loadings ranged from 0.81 to 0.91.

Dependent Variable: Engagement (*α = 0.91).* Work engagement was measured by using the engagement scale from Rich et al. (2010), who subdivide the construct into physical, emotional, and cognitive engagement. Thus, I again used a shortened version by choosing two items per dimension based on the highest factor loadings (Rich et al., 2010). Sample items include "this week, I devoted a lot of my energy to my job", "this week, I felt enthusiastic in my job", and "this week, my mind was focused on my job". The results from the CFA again showed a satisfactory model fit to our data (χ^2= 51.46; df = 8; χ^2/df = 6.43; CFI = 0.98; TLI = 0.97; SRMR = 0.06)

Moderator: Chronological Age. Participants' individual age was measured by their chronological age in years.

Moderator: Leadership Consideration (α = *0.93).* Leader consideration was measured using the original scale developed by Lambert et al. (2012). Respondents were asked to rate their direct supervisor's behavior within a given week from 1 (never) to 5 (always). Example items include "she/he acted friendly and approachable" and "she/he acted supportive when talking to me". Factor loadings ranged in between 0.77 and 0.94.

Moderator: Leadership Initiating Structure (α = *0.90).* Leader initiating structure was also measured by the original scale from Lambert et al. (2012). Example items include "she/he let me know what is expected of me" and "she/he maintained definite performance standards with me". Factor loadings ranged from 0.82 to 0.94.

Controls. When analyzing both individual well-being and performance-related work outcomes, there are several potential confounders that need to be included in the analysis as control variables. First, I controlled for employees' job satisfaction as it may play an important role in explaining individual stress and performance levels at work (Judge et al., 2001; Wright & Cropanzano, 1998). In doing so, job satisfaction was measured with a single item: "How satisfied were you with your job this week?" (Tschopp et al., 2014). Second, I controlled for gender, as work-related outcomes may be experienced, perceived, and responded to differently by men and women (Joshi et al., 2015; Posig & Kickul, 2004; Purvanova & Muros, 2010). Employees therefore reported whether they identified as 1 = male, 2 = female, or 3 = diverse. As only two people identified as non-binary, I decided to include only the binary gender categories of "male" and "female", as no reliable assessments could be made for non-binary people. Third, I included whether the employee's organization offered specific training for remote work. With the majority of the sample working remotely at least part-time, stress and productivity levels may be different for employees who have had the opportunity to learn methods and techniques to perform better when away from the office (Allen et al., 2015). Respondents were therefore asked if they had received any specific training on working remotely from their organization (1 = yes, 2 = no). Fourth, as managers may show different levels of, for instance, stress (Skakon et al., 2011) or engagement (Tims et al., 2011), I controlled for whether the employee held a leadership position or not (1 = yes, 2 = no). Fifth, I included the preferred amount of remote work in number of days as it reflects an individual's desired work environment, which can influence their well-being and outcomes by shaping expectations and satisfaction with their work conditions (Bailey & Kurland, 2002; Golden, 2006). Sixth, I also controlled for the actual amount of remote work measured by the proportion (i.e., percentage) that employees worked remotely within the last working week. Several studies on remote work suggest that it might lead to better work-life balance and the reduction of stress due to perceived autonomy and, thus, impact work-related outcomes (Gajendran & Harrison, 2007). On the other hand, there may be a risk of social isolation and loneliness (Cooper & Kurland, 2002). Therefore, I decided to include the percentage of actual remote work of employees as a control variable. In addition, the three moderator variables of age, leader consideration, and initiating structure were also included as control variables when they did not function as interacting factors. Both age (Kanfer & Ackerman, 2004; Ng & Feldman, 2010) and the two leadership behaviors (Judge et al., 2004; Liang et al., 2023) may directly influence personal well-being and performance-related work outcomes.

3.3.3 Analytical Procedure

To explore the relationships between the determinants of remote work and individual work-related outcomes, I conducted several multiple linear regression analyses, following the recommendations by Cohen et al. (2014). In doing so, all direct and interacting effects are reported without (*Model a*) and with (*Model b*) control variables. As the independent variable determinants of remote work is categorical, the regression results relate to the baseline, individual level decision-making. This allows for comparison of the effects of team participation, managerial, and organizational decision-making against the baseline, facilitating an understanding of how deviations from individual autonomy influence outcomes. With the exception of the main independent categorical variable, all other predictor variables were standardized to facilitate comparison and interpretation of regression coefficients (Aiken & West, 1991).

3.4 Results

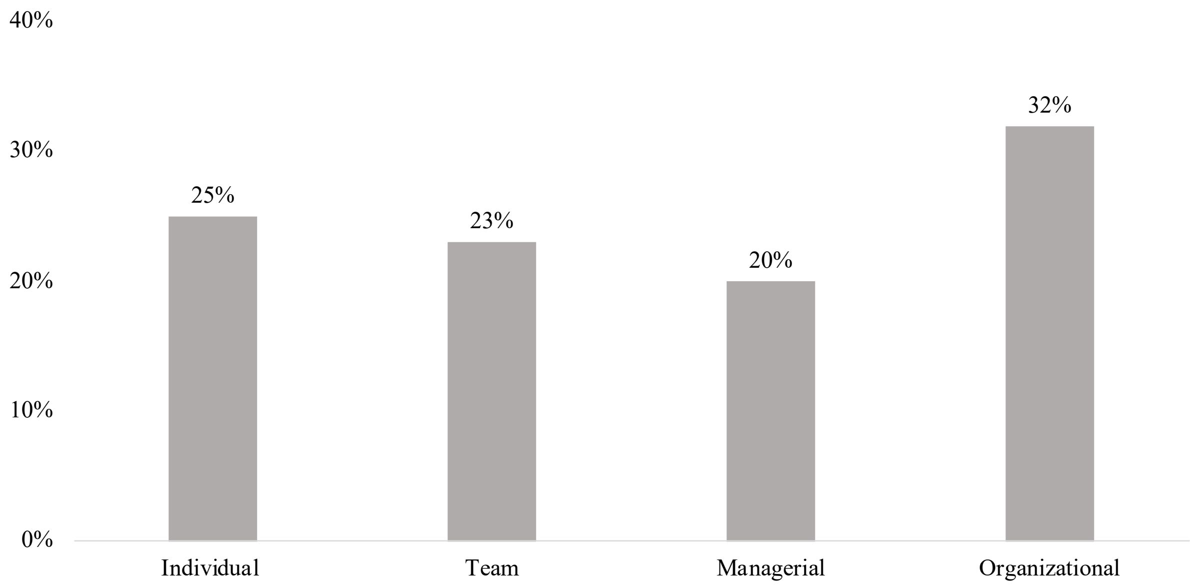
3.4.1 Descriptive Statistics

As the independent variable of this research is categorical, it is not included in the descriptive statistics. Instead, Figure 5 shows the distribution of the four remote work authority levels among the sample. Overall, 25 percent of the sample were able to choose their amount of remote work independently, while 23 percent decided together with their team. For 20 percent of the employees, the teams' leaders decided on the amount of remote work and a total of 32 percent have organizational policies determining the extent of remote work.

For all other relevant factors, Table 4 displays means, standard deviations, and zero-order correlations. Among the four individual work-related outcomes, several significant relationships emerged. Emotional exhaustion was positively correlated with loneliness ($r = 0.46, p < .001$) and negatively correlated with both performance ($r = -0.30, p < .001$) and engagement ($r = -0.28, p < .001$). Loneliness was also negatively correlated with performance ($r = -0.31, p < .001$) and engagement ($r = -0.31, p < .001$). Furthermore, performance and engagement were strongly positively correlated ($r = 0.56, p < .001$). Regarding the moderators, chronological age showed significant negative correlations with emotional exhaustion ($r = -0.23, p < .001$) and loneliness ($r = -0.20, p < .001$), while positively correlating with performance ($r = 0.12, p < .01$) and engagement ($r = 0.14, p < .001$).

Figure 5

Remote Work Decision-Making Authority



Note. "Who Primarily Determines the Amount of Remote Work In Your Everyday Work?" N = 639.

Consideration was negatively correlated with emotional exhaustion (r = -0.33, p < .001) and loneliness (r = -0.29, p < .001), but positively associated with performance (r = 0.29, p < .001) and engagement (r = 0.43, p < .001). Additionally, initiating structure showed a significant negative correlation with emotional exhaustion (r = -0.19, p < .001) and loneliness (r = -0.15, p < .01), and was positively correlated with both performance (r = 0.24, p < .001) and engagement (r = 0.41, p < .001). Both leadership styles showed a strong positive intercorrelation (r = 0.72, p < .001).

High intercorrelations among variables can raise concerns if they lead to multicollinearity. To assess this, I computed the Variance Inflation Factors (VIFs) for all models and predictor variables. The results showed that all VIFs were well below the critical value of 10 (*mean* = 1.57, *SD* = 0.44). These values indicate that multicollinearity is unlikely to be an issue in the analysis (Myers, 1990).

Table 4

Descriptive Statistics of Focal Study Variables

Variables	M	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Emotional Exhaustion	2.55	1.21												
(2) Loneliness	1.83	0.95	0.46***											
(3) Performance	4.44	0.72	-0.30***	-0.31***										
(4) Engagement	4.12	0.76	-0.28***	-0.31***	0.56***									
(5) Chronological Age	44.34	12.36	-0.23***	-0.20***	0.12**	0.14***								
(6) Consideration	3.71	1.02	-0.33***	-0.29***	0.29***	0.43***	-0.02							
(7) Initiating Structure	3.46	1.16	-0.19***	-0.15***	0.24***	0.41***	-0.08*	0.72***						
(8) Job Satisfaction	3.96	0.91	-0.47***	-0.31***	0.45***	0.55***	0.12**	0.43***	0.35***					
(9) Gender	1.47	0.50	0.11**	-0.03	0.03	-0.04	-0.03	-0.06	-0.10*	-0.11**				
(10) Remote Work Training	1.75	0.43	0.06	-0.07	-0.02	-0.12**	0.13**	-0.16***	-0.18***	-0.10*	0.11**			
(11) Leadership Position	1.67	0.47	0.03	-0.03	-0.00	-0.10*	0.01	-0.07	-0.11**	-0.11**	0.24***	0.17***		
(12) Preferred Remote Work	3.92	1.51	0.03	0.03	0.01	-0.02	-0.01	-0.08*	-0.03	-0.06	-0.04	-0.01	0.10*	
(13) Actual Remote Work	42.06	34.93	-0.10*	0.02	0.09*	0.04	0.05	0.06	0.05	0.09*	0.01	-0.11**	0.09*	0.66***

Note. N = 639. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

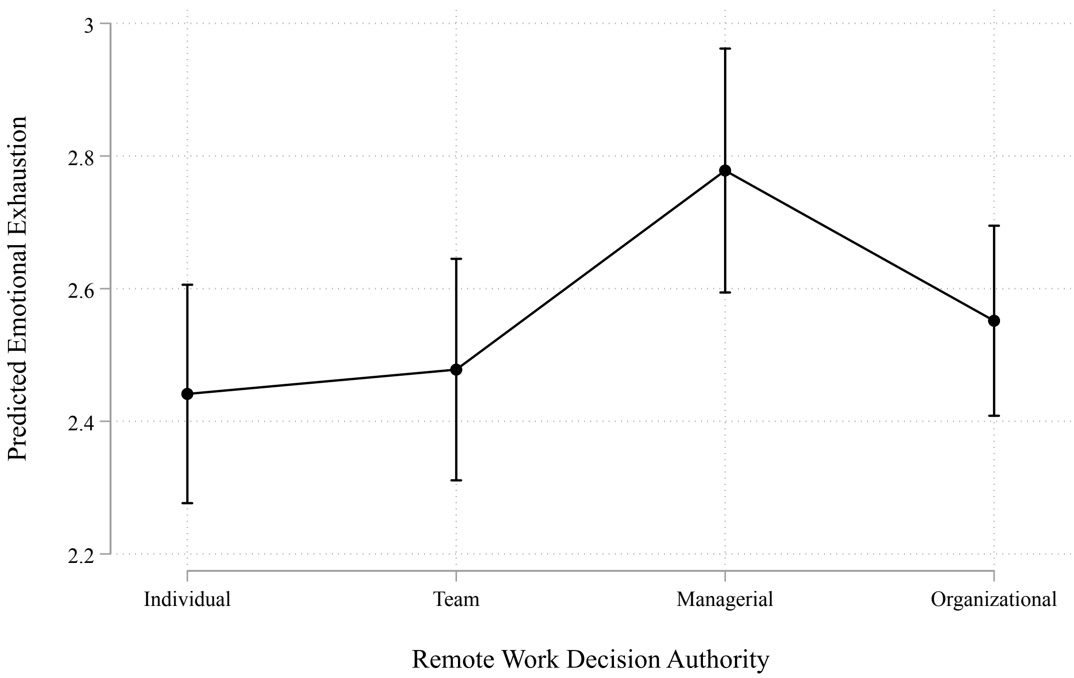
3.4.2 Regression Analyses

3.4.2.1 Dependent Variable: Emotional Exhaustion

Table 5 contains the regression results for the first outcome, emotional exhaustion. For the direct effect of remote work decision-making authority without control variables added, Model 1a indicates that both managerial decision-making authority (β = 0.68, p < 0.001) and organizational decision authority (β = 0.38, p < 0.01) are significantly associated with higher levels of emotional exhaustion compared to the baseline, individual decision-making. Model 1b reveals that after various control variables were added to the analysis, only managerial decision-making authority remained to have a strong significant positive effect on employees' emotional exhaustion (β = 0.34, p < 0.01). In both models, team participative decision-making did not have a statistically relevant impact on emotional exhaustion compared to individual decision-making authority (Model 1b: β = 0.04, p = 0.76). In comparison with Model 1a without control variables (R^2 = 0.04), Model 1b explained a lot more variance (R^2 = 0.27). In order to better understand these differences in emotional exhaustion levels, I plotted them graphically in Figure 6 across the margins. While employees who can individually decide where to work from displayed an average predicted level of emotional exhaustion of 2.44 (95% *CI* [2.28, 2.61]), employees whose managers mainly determine the amount of remote work had an emotional exhaustion level of 2.78 (95% *CI* [2.59, 2.96]). Employees whose organizations determine the amount of remote work for all employees show slightly higher but not statistically significant different levels of emotional exhaustion (margin = 2.55, 95% *CI* [2.41, 2.69]) than employees with individual decision authority.

Figure 6

Predicted Emotional Exhaustion by Remote Work Decision-Making Authority



I tested the interaction effects between remote work decision-making authority and chronological age in Model 2a and Model 2b. Both models do not display significant interactions between authority level and age, indicating that employees of different age groups do not respond differently to various remote work decision authorities.

Furthermore, the two leadership styles, consideration (Models 3a and 3b) and initiating structure (Models 4a and 4b) do not interact with different levels of remote work decision-making authority. Without controls, consideration displays a marginally significant interaction for the organizational level (β = -0.22, p = 0.065), but with controls included, this effect weakens (β = -0.17, p = 0.108). Similar results can be found for initiating structure, which shows a slightly significant interaction effect on the team authority level (β = -0.28, p = 0.058), but not with controls included (β = -0.18, p = 0.115).

Table 5

Regression Analysis for Emotional Exhaustion

	Regression Analysis															
Emotional Exhaustion																
	Model 1a		**Model 1b**		**Model 2a**		**Model 2b**		**Model 3a**		**Model 3b**		**Model 4a**		**Model 4b**	
Remote Work Decision-Making Authority:																
Baseline**: Individual**																
2: Team	**0.11**	(0.14)	**0.04**	(0.12)	**0.07**	(0.13)	**0.04**	(0.12)	**0.09**	(0.13)	**0.05**	(0.12)	**0.13**	(0.13)	**0.04**	(0.12)
3: Managerial	**0.68*****	(0.14)	**0.34****	(0.13)	**0.56*****	(0.14)	**0.34****	(0.13)	**0.56*****	(0.14)	**0.34****	(0.13)	**0.70*****	(0.14)	**0.34****	(0.13)
4: Organizational	**0.38****	(0.13)	**0.11**	(0.11)	**0.30***	(0.12)	**0.11**	(0.11)	**0.31***	(0.12)	**0.13**	(0.11)	**0.41****	(0.12)	**0.12**	(0.11)
Authority Level x Age																
Baseline**: Individual**																
2: Team x Age					**0.01**	(0.13)	**-0.04**	(0.12)								
3: Managerial x Age					**0.13**	(0.14)	**0.08**	(0.13)								
4: Organizational x Age					**0.17**	(0.12)	**0.12**	(0.11)								
Authority Level x Consideration																
Baseline**: Individual**																
2: Team x Consideration									**-0.04**	(0.13)	**-0.07**	(0.12)				
3: Managerial x Consideration									**-0.19**	(0.14)	**-0.17**	(0.12)				
4: Organizational x Consideration									**-0.22**	(0.12)	**-0.17**	(0.11)				
Authority Level x Initiating Structure																
Baseline**: Individual**																
2: Team x Initiating													**0.25**	(0.13)	**0.18**	(0.11)
3: Managerial x Initiating													**-0.04**	(0.14)	**0.05**	(0.13)
4: Organizational x Initiating													**-0.04**	(0.12)	**0.06**	(0.10)
Age			-0.20***	(0.04)	-0.32***	(0.09)	-0.25**	(0.08)			-0.21***	(0.04)			-0.20***	(0.04)
Consideration			-0.25***	(0.06)			-0.24***	(0.06)	-0.25**	(0.09)	-0.14	(0.09)			-0.25***	(0.06)
Initiating Structure			0.09	(0.06)			0.08	(0.06)			0.09	(0.06)	-0.28**	(0.08)	0.03	(0.09)
// Controls																
Job Satisfaction			-0.43***	(0.05)			-0.45***	(0.05)			-0.43***	(0.05)			-0.43***	(0.05)
Gender			0.08	(0.04)			0.08	(0.04)			0.08	(0.04)			0.08	(0.04)
Remote Work Training			0.02	(0.04)			0.02	(0.04)			0.02	(0.04)			0.02	(0.04)
Leadership Position			-0.03	(0.04)			-0.04	(0.04)			-0.03	(0.04)			-0.03	(0.04)
Preferred Remote Work			0.04	(0.06)			0.04	(0.06)			0.04	(0.06)			0.04	(0.06)
Actual Remote Work			-0.08	(0.06)			-0.07	(0.06)			-0.07	(0.06)			-0.08	(0.06)
Constant	2.27	(0.09)	2.44	(0.08)	2.34	(0.09)	2.45	(0.08)	2.31	(0.09)	2.42	(0.08)	2.25	(0.09)	2.42	(0.08)
Adjusted R^2	0.04		0.27		0.08		0.28		0.13		0.28		0.08		0.28	

Note. N = 639. Standard errors in parentheses. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

3.4.2.2 Dependent Variable: Loneliness

Table 6 presents the regression analysis for the second outcome variable loneliness. Similar to before, managerial decision authority is associated with significantly higher levels of loneliness. This holds for both Model 5a without control variables ($\beta = 0.51$, $p < 0.001$) as well as for Model 5b with controls ($\beta = 0.30$, $p < 0.01$). Both organizational and team participative remote work decision-making authority do not lead to different loneliness levels than individual decision-making authority. Again, Figure 7 contains the margins and reveals that people whose manager decides on their remote working arrangements experience the highest levels of predicted loneliness (margin = 2.06, 95% *CI* [1.90, 2.21]), whereas those with individual authority experience the lowest levels of loneliness (margin = 1.76, 95% *CI* [1.62, 1.89]). For the moderating effects of age, consideration, and initiating structure, no indications for significant effects were found.

Figure 7

Predicted Loneliness by Remote Work Decision-Making Authority

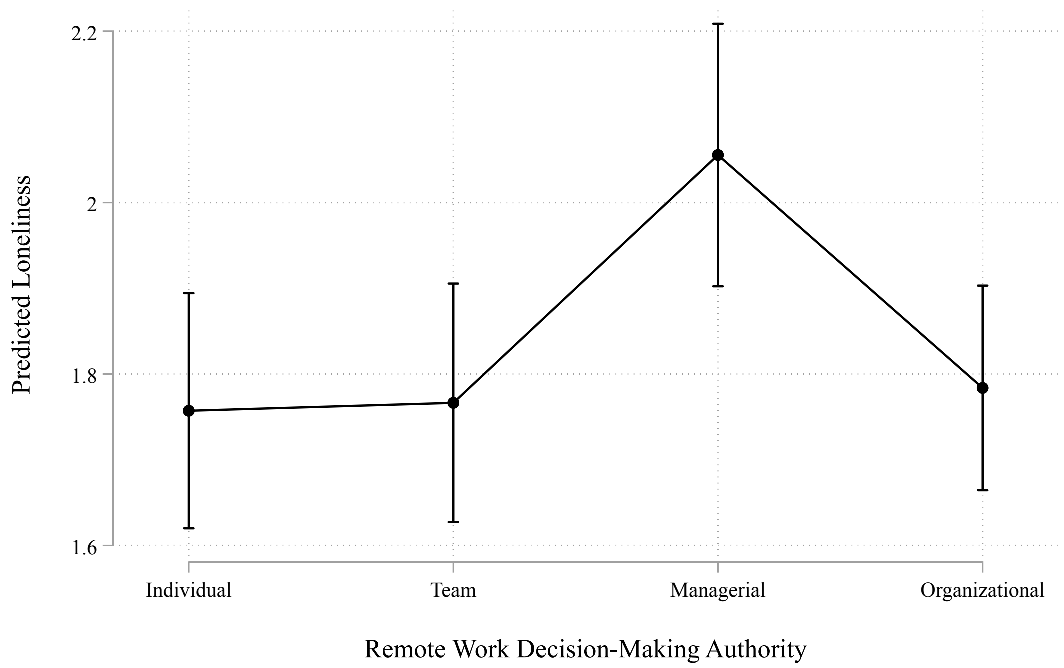


Table 6

Regression Analysis for Loneliness

	Regression Analysis															
Loneliness																
	Model 5a		**Model 5b**		**Model 6a**		**Model 6b**		**Model 7a**		**Model 7b**		**Model 8a**		**Model 8b**	
Remote Work Decision-Making Authority:																
Baseline**: Individual**																
2: Team	**0.04**	(0.11)	**0.01**	(0.10)	**0.00**	(0.11)	**0.00**	(0.10)	**0.01**	(0.10)	**0.01**	(0.10)	**0.04**	(0.11)	**0.01**	(0.10)
3: Managerial	**0.51*** **	(0.11)	**0.30** **	(0.11)	**0.41*** **	(0.11)	**0.27* **	(0.11)	**0.43*** **	(0.11)	**0.30** **	(0.11)	**0.52*** **	(0.11)	**0.30** **	(0.11)
4: Organizational	**0.13**	(0.10)	**0.03**	(0.09)	**0.07**	(0.10)	**0.02**	(0.09)	**0.07**	(0.10)	**0.01**	(0.10)	**0.14**	(0.10)	**0.03**	(0.09)
Authority Level x Age																
Baseline**: Individual**																
2: Team x Age					**0.09**	(0.11)	**0.07**	(0.10)								
3: Managerial x Age					**0.07**	(0.11)	**0.02**	(0.11)								
4: Organizational x Age					**0.17**	(0.10)	**0.14**	(0.09)								
Authority Level x Consideration																
Baseline**: Individual**																
2: Team x Consideration									**0.02**	(0.11)	**0.01**	(0.10)				
3: Managerial x Consideration									**0.05**	(0.11)	**0.04**	(0.10)				
4: Organizational x Consideration									**0.00**	(0.09)	**0.00**	(0.09)				
Authority Level x Initiating Structure																
Baseline**: Individual**																
2: Team x Initiating													**0.06**	(0.10)	**0.02**	(0.10)
3: Managerial x Initiating													**0.06**	(0.11)	**0.08**	(0.11)
4: Organizational x Initiating													**-0.05**	(0.09)	**-0.01**	(0.09)
Age			-0.15***	(0.04)	-0.26***	(0.07)	-0.22**	(0.07)			-0.15***	(0.04)			-0.15***	(0.04)
Consideration			-0.27***	(0.05)			-0.27***	(0.05)	-0.27***	(0.07)	-0.28***	(0.08)			-0.27***	(0.05)
Initiating Structure			0.08	(0.05)			0.08	(0.05)			0.08	(0.05)	-0.15*	(0.07)	0.07	(0.07)
// Controls																
Job Satisfaction			-0.20***	(0.04)			-0.20***	(0.04)			-0.20***	(0.04)			-0.20***	(0.04)
Gender			-0.06	(0.04)			-0.06	(0.04)			-0.06	(0.04)			-0.05	(0.04)
Remote Work Training			-0.07	(0.04)			-0.06	(0.04)			-0.07	(0.04)			-0.07	(0.04)
Leadership Position			-0.03	(0.04)			-0.03	(0.04)			-0.03	(0.04)			-0.03	(0.04)
Preferred Remote Work			-0.06	(0.05)			-0.06	(0.05)			-0.06	(0.05)			-0.06	(0.05)
Actual Remote Work			0.08	(0.05)			0.09	(0.05)			0.08	(0.05)			0.08	(0.05)
Constant	1.68	(0.07)	1.76	(0.07)	1.74	(0.07)	1.77	(0.07)	1.72	(0.07)	1.76	(0.07)	1.68	(0.07)	1.76	(0.07)
Adjusted R^2	0.03		0.18		0.06		0.18		0.10		0.18		0.05		0.18	

Note. N = 639. Standard errors in parentheses. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

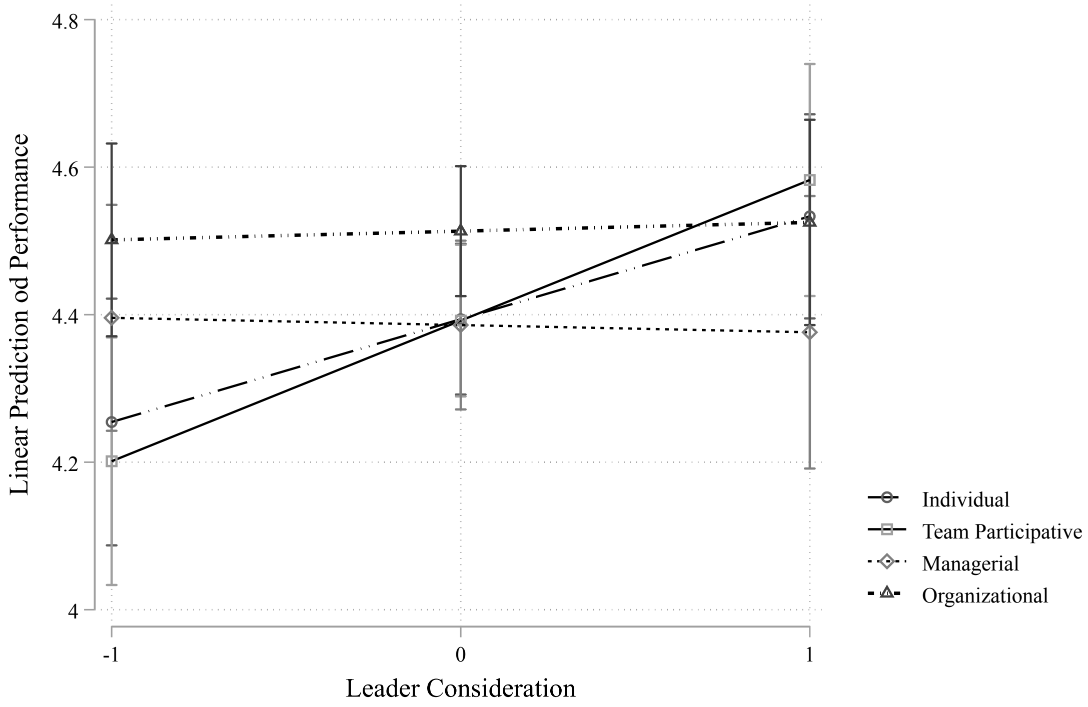
3.4.2.3 Dependent Variable: Performance

For the first of two productivity-related work outcomes, performance, the regression results can be found in Table 7. Contrary to the results from the emotional exhaustion and loneliness analyses, no statistical differences among the various decision-making levels of remote working can be found. This holds for the direct effect with and without controls as well as for the interacting effects of age and leadership initiating structure.

Interestingly, Model 11b, the interaction effect of leadership consideration with control variables added is marginally significant for managerial (β = - 0.15, p = 0.052) and organizational decision-making authority (β = -0.13, p = 0.052). To better understand the dynamics behind these effects, I graphically plotted the margins and simple slopes, as displayed in Figure 8. The slopes highlight a potentially significant influence of leadership consideration on employees' performance, particularly for those with individual or team participative decision-making authority. Specifically, at lower levels of leadership consideration, both individual (β = -0.25, $p < 0.05$) and team participative (β = -0.30, $p < 0.01$) decision-making authorities are associated with significantly reduced employee performance. However, when leadership consideration is strong, these slopes are no longer significant (individual: β = 0.01, p = 0.93; team: β = -0.12, p = 0.08). In contrast, managerial and organizational decision-making authority levels show no significant changes in performance, regardless of the level of leadership consideration.

Figure 8

Simple Slope Analysis for the Moderating Effect of Leader Consideration



3.4.2.4 Dependent Variable: Engagement

Lastly, Table 8 presents the regression results for the second productivity-related work outcome, engagement. Again, the analysis indicates no significant differences in engagement levels across the various remote work decision authority levels (team: β = -0.002, p = 0.98; managerial: β = -0.04, p = 0.57; organizational: β = 0.01, p = 0.89). This pattern persists across Models 13a through 16b. In doing so, the interaction effects involving age, consideration, and initiating structure also do not exhibit significant results.

Table 7

Regression Analysis for Performance

Performance	**Model 9a**		**Model 9b**		**Model 10a**		**Model 10b**		**Model 11a**		**Model 11b**		**Model 12a**		**Model 12b**	
Remote Work Decision-Making Authority:																
Baseline: **Individual**																
2: Team	**-0.02**	(0.08)	**-0.01**	(0.07)	**0.00**	(0.08)	**0.00**	(0.07)	**0.01**	(0.08)	**0.00**	(0.07)	**-0.03**	(0.08)	**-0.01**	(0.07)
3: Managerial	**-0.15**	(0.09)	**-0.01**	(0.08)	**-0.12**	(0.09)	**-0.02**	(0.08)	**-0.09**	(0.08)	**-0.01**	(0.08)	**-0.16**	(0.08)	**0.00**	(0.08)
4: Organizational	**0.01**	(0.08)	**0.11**	(0.07)	**0.04**	(0.08)	**0.11**	(0.07)	**0.06**	(0.07)	**0.12**	(0.07)	**-0.01**	(0.07)	**0.11**	(0.07)
Authority Level x Age																
Baseline: **Individual**																
2: Team x Age					**-0.07**	(0.08)	**-0.04**	(0.07)								
3: Managerial x Age					**-0.10**	(0.09)	**-0.08**	(0.08)								
4: Organizational x Age					**0.02**	(0.08)	**0.04**	(0.07)								
Authority Level x Consideration																
Baseline: **Individual**																
2: Team x Consideration									**0.03**	(0.08)	**0.05**	(0.08)				
3: Managerial x Consideration									**-0.14**	(0.08)	**-0.15**	(0.08)				
4: Organizational x Consideration									**-0.10**	(0.07)	**-0.13**	(0.07)				
Authority Level x Initiating Structure																
Baseline: **Individual**																
2: Team x Initiating													**-0.02**	(0.08)	**0.02**	(0.07)
3: Managerial x Initiating													**-0.07**	(0.09)	**-0.09**	(0.08)
4: Organizational x Initiating													**0.01**	(0.07)	**-0.04**	(0.06)
Age			0.06*	(0.03)	0.11*	(0.06)	0.07	(0.05)			0.06*	(0.03)			0.06*	(0.03)
Consideration			0.07	(0.04)			0.07	(0.04)	0.26***	(0.05)	0.14*	(0.06)			0.08	(0.04)
Initiating Structure			0.03	(0.04)			0.03	(0.04)			0.02	(0.03)	0.18***	(0.05)	0.05	(0.05)
// Controls																
Job Satisfaction			0.29***	(0.03)			0.29***	(0.03)			0.30***	(0.03)			0.29***	(0.03)
Gender			0.05*	(0.03)			0.05*	(0.03)			0.05*	(0.03)			0.05	(0.03)
Remote Work Training			0.01	(0.03)			0.01	(0.03)			0.01	(0.03)			0.01	(0.03)
Leadership Position			0.02	(0.03)			0.02	(0.03)			0.02	(0.03)			0.02	(0.03)
Preferred Remote Work			0.01	(0.03)			0.01	(0.03)			0.00	(0.03)			0.01	(0.03)
Actual Remote Work			0.04	(0.04)			0.04	(0.04)			0.05	(0.04)			0.04	(0.04)
Constant	4.47	(0.06)	4.44	(0.05)	4.45	(0.06)	4.44	(0.05)	4.43	(0.06)	4.39	(0.05)	4.48	(0.06)	4.41	(0.05)
Adjusted R^2	0.00		0.23		0.01		0.23		0.09		0.23		0.05		0.22	

Note. N = 639. Standard errors in parentheses. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 8

Regression Analysis for Engagement

Regression Analysis																
Engagement																
	Model 13a		**Model 13b**		**Model 14a**		**Model 14b**		**Model 15a**		**Model 15b**		**Model 16a**		**Model 16b**	
Remote Work Decision-Making Authority:																
Baseline**: Individual**																
2: Team	**0.00**	(0.09)	**0.00**	(0.07)	**0.03**	(0.09)	**0.01**	(0.07)	**0.03**	(0.08)	**-0.01**	(0.07)	**-0.01**	(0.08)	**0.00**	(0.07)
3: Managerial	**-0.18**	(0.09)	**-0.04**	(0.07)	**-0.13**	(0.09)	**-0.04**	(0.08)	**-0.08**	(0.08)	**-0.04**	(0.08)	**-0.20***	(0.08)	**-0.04**	(0.07)
4: Organizational	**-0.06**	(0.08)	**0.01**	(0.07)	**-0.02**	(0.08)	**0.02**	(0.07)	**0.01**	(0.07)	**0.01**	(0.07)	**-0.10**	(0.07)	**0.01**	(0.07)
Authority Level x Age																
Baseline**: Individual**																
2: Team x Age					**-0.13**	(0.09)	**-0.07**	(0.07)								
3: Managerial x Age					**-0.09**	(0.09)	**-0.07**	(0.07)								
4: Organizational x Age					**-0.04**	(0.08)	**-0.02**	(0.06)								
Authority Level x Consideration																
Baseline**: Individual**																
2: Team x Consideration									**0.00**	(0.08)	**0.03**	(0.07)				
3: Managerial x Consideration									**0.00**	(0.08)	**0.02**	(0.07)				
4: Organizational x Consideration									**0.02**	(0.07)	**0.00**	(0.06)				
Authority Level x Initiating Structure																
Baseline**: Individual**																
2: Team x Initiating													**0.03**	(0.08)	**0.07**	(0.07)
3: Managerial x Initiating													**0.01**	(0.09)	**-0.02**	(0.07)
4: Organizational x Initiating													**0.14**	(0.07)	**0.07**	(0.06)
Age			0.09***	(0.02)	0.16**	(0.06)	0.13**	(0.05)			0.09***	(0.02)			0.09***	(0.03)
Consideration			0.08*	(0.04)			0.08*	(0.04)	0.31**	(0.05)	0.07	(0.06)			0.08*	(0.04)
Initiating Structure			0.14***	(0.04)			0.14***	(0.04)			0.14***	(0.04)	0.26***	(0.05)	0.10*	(0.05)
// Controls																
Job Satisfaction			0.33***	(0.03)			0.33***	(0.03)			0.33***	(0.03)			0.33***	(0.03)
Gender			0.06*	(0.02)			0.06*	(0.03)			0.06*	(0.02)			0.06*	(0.03)
Remote Work Training			-0.04	(0.02)			-0.04	(0.03)			-0.04	(0.03)			-0.04	(0.03)
Leadership Position			-0.03	(0.03)			-0.03	(0.03)			-0.03	(0.03)			-0.02	(0.03)
Preferred Remote Work			0.05	(0.03)			0.05	(0.03)			0.05	(0.03)			0.05	(0.03)
Actual Remote Work			-0.05	(0.03)			-0.05	(0.03)			-0.05	(0.03)			-0.05	(0.03)
Constant	4.18	(0.06)	4.13	(0.05)	4.14	(0.06)	4.12	(0.05)	4.13	(0.06)	4.13	(0.05)	4.20	(0.05)	4.13	(0.05)
Adjusted R^2	0.00		0.37		0.02		0.37		0.18		0.37		0.17		0.37	

Note. N = 639. Standard errors in parentheses. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

3.5 Discussion

The goal of this study was to explore the effects of different levels of remote work decision-making on employees and their work-related outcomes. In doing so, I analyzed two well-being (emotional exhaustion and loneliness) and two productivity-related (performance and engagement) work outcomes. Furthermore, I tested for potential interaction effects via chronological age and the two leadership styles consideration and initiating structure, which may additionally impact the potential effects. By testing these effects with and without the inclusion of various potential confounders, I controlled for important factors that might influence individual work-related outcomes.

First, the findings demonstrate that managerial decision-making authority significantly contributes to employees' emotional exhaustion. Employees whose remote work arrangements are primarily determined by their managers reported higher levels of exhaustion compared to those who could make these decisions themselves. On the other hand, the decision within the team and given by the organization did not show a significant relation on exhaustion after including the controls, even though organizational decision authority appeared to have a significant negative effect on exhaustion when controls were not included. As the inclusion of the control variables in Model 1b resulted in a change of explained variance of 0.23 compared to Model 1a, the effects with control variables included appear to be robust and stable.

Second, loneliness was also found to be higher among employees whose amount of telework was decided upon by a managerial decision-making authority. Employees felt more loneliness when their manager decided how much remote work they were allowed to do, regardless of the preferred and actual amount of remote work the employees performed. While individual, team, and organizational decision-making authority was not associated with statistical differences in employee's perceived loneliness, managerial decision-making seems to lead to greater experienced feelings of isolation.

While the direct effects on emotional exhaustion and loneliness are stable and robust, no significant moderating effects could be found for either chronological age, consideration, or initiating structure. For age, this suggests that different age groups do not emotionally react differently to a gain or loss of autonomy and control depending on the remote work decision authority. For the two leadership styles, it appears that the negative consequences of a manager's top-down decision on remote work arrangements on employees' emotional well-being cannot be buffered or compensated by caring and encouraging leadership.

In contrast, no significant direct effects could be found for the two productivity-related outcomes, performance and engagement. Regardless of whether employees had individual decision-making power or were subject to managerial or organizational oversight, their performance and engagement levels remained constant. The only exception is the marginally significant moderating effect of leader consideration on the relationship between the decision-making authority level and performance, with a p-value of $p = 0.052$. Interestingly, the simple slopes reveal that low levels of leadership consideration significantly reduce performance for employees who either individually or within the team decide how much remote work they want to do. Employees whose managers or organizations determine the amount of remote work are not affected by high or low levels of leader consideration. Thus, the results suggest that the benefits of leader consideration are context dependent and that when employees have more autonomy in their work arrangements, supportive leadership behaviors are crucial to maximizing their performance outcomes. In particular, a lack of leader consideration may be detrimental to employees who make individual or team decisions about where to work from. The other two tested moderators, age and initiating structure, did not reveal any significant relations for neither performance nor engagement as outcome variable.

3.5.1 Theoretical Implications

This study adds to the growing literature on remote work and how its adaption impacts organizations and their employees in many ways (Colley et al., 2023; Gajendran & Harrison, 2007; Grzegorczyk et al., 2021). By examining how different levels of decision authority affect employees' well-being and productivity outcomes, my results highlight the detrimental effects for employee well-being when managers solely decide for employees how much remote work they are allowed to do.

According to SDT (Ryan & Deci, 2000), individuals need to satisfy their autonomy, competence, and relatedness needs to experience work motivation, achieve well-being, and be productive (Gajendran et al., 2014). As recent literature has shown, involuntariness of telework, meaning that employees do not have the autonomy to determine the amount of telework they can engage in, is often associated with heightened levels of emotional exhaustion (Dias et al., 2022; Lopes et al., 2023). The need for voluntariness is crucial to avoid feelings of pressure and loss of control, which may otherwise result in stress and dissatisfaction (Lopes et al., 2023). This applies not only to employees who are forced to come to the office but also to those forced into working remotely, as happened during the COVID-19 pandemic, which resulted in a lack of control and exacerbated stress levels (Wang et al., 2021).

Therefore, this study contributes to SDT (Ryan & Deci, 2000) by highlighting the different impacts of various levels of decision-making authority on well-being outcomes. As shown, managerial decision-making authority, in particular, leads to higher levels of emotional exhaustion and loneliness in employees. Building on this, the concept of *i-deals* might be helpful to further explain why managerial decision-making authority is especially detrimental to emotional well-being; i-deals are personalized work arrangements negotiated between an employee and their employer to cater to the employee's specific needs (Rousseau et al., 2006). When decision-making authority is concentrated at the managerial level, opportunities for employees to negotiate these individualized arrangements are limited, which can lead to feelings of disempowerment and alienation. In contrast, when employees have more say in their work arrangements—whether individually or within a team—they may feel more empowered to negotiate flexible arrangements that fit their personal and professional needs, thereby reducing the risk of emotional exhaustion and loneliness (Hornung et al., 2008). This might even involve organizational top-down decision-making, where standardized policies or collective agreements for all employees also can lead to i-deals and perceptions of control and autonomy for employees (Budd et al., 2010; Hornung et al., 2010). Together with these considerations, my research implies that it is vital for employees to be able to get involved into the decision-making process about how much remote work will be allowed or required. If the manager decides on behalf of a team, feelings of injustice and loss of control can lead to higher levels of stress and loneliness.

Interestingly, I could not find similar relations between the level of remote work decision authority and individual productivity-related outcomes like performance and engagement. Therefore, it appears that the loss of autonomy has stronger negative effects on employees' well-being than on their productivity.

Furthermore, by analyzing potential interaction effects, I aimed to explore the nuances of the relationship between remote work decision-making authority and individual work-related outcomes. First, age was tested to moderate the relationship, as it can shape how employees perceive autonomy and manage work-related stressors. Existing research has shown that older employees may exhibit greater resilience to work stressors and could be less affected by changes in autonomy due to experience and coping strategies (Kooij et al., 2010; Ng & Feldman, 2010). Younger employees could be more affected by autonomy restrictions because of their early career stage, where they are seeking to establish themselves and eager to develop skills and independence (Kanfer & Ackerman, 2004). Still, I could not find chronological age to significantly moderate the relationship between remote work decision authority and work-related outcomes. Thus, the results suggest that age groups may not react differently to loss of autonomy, or that potential effects may balance each other out. Second, the two leadership styles of consideration and initiating structure were introduced as potential moderators. While examining how employees react do various decision-making authorities, empathetic (consideration) as well as task-oriented (initiating structure) leadership may additionally shape employee outcomes (Judge et al., 2004; Ryan & Deci, 2000).

While for initiating structure no significant interaction effects could be found for all four regression analyses' outcomes, consideration was shown to marginally moderate the relationship between decision authority and employee performance. The marginally significant interaction effect found suggests that leader consideration does have an influence on performance, but this effect is context-dependent, particularly relevant when employees possess higher levels of decision-making autonomy over their work arrangements. Specifically, when consideration is absent, it seems to negatively affect performance when the employees have a lot of autonomy over the choice of their working location. This finding aligns with the research on i-deals (Hornung et al., 2008), which emphasizes that personalized work arrangements can only be successful when accompanied by ongoing leader support (Hornung, 2018; Liao et al., 2017). Similar to that, SDT (Ryan & Deci, 2000) also emphasizes that autonomy alone is not enough to foster motivation and performance. Furthermore, employees also need relatedness – feeling connected and supported by their leaders and peers (Ryan & Deci, 2000). Thus, these findings contribute to existing literature on SDT (Ryan & Deci, 2000) and i-deals (Hornung et al., 2008; Hornung et al., 2010; Rousseau et al., 2006).

3.5.2 **Practical Implications**

This research provides important practical insights for organizations, managers, and employees as they design, implement and shape, remote work policies for the future. First, granting employees more autonomy in deciding their remote work arrangements is crucial for their well-being. When managers solely dictate these arrangements, it can directly affect employees and lead to increased levels of emotional exhaustion and loneliness. This aligns with the principles of SDT (Ryan & Deci, 2000) and research on i-deals (Hornung et al., 2008), which highlight the need for autonomy to support well-being and motivation. Therefore, employees should actively be involved in the process of how remote work gets implemented at the company. As my findings show, this does not automatically mean that employees should be given complete control over remote work arrangements on an individual basis. Rather, this process can also take place within the team at a participative level, with all team members and managers jointly expressing their opinions and preferences, or it can involve organizational top-down decision-making with standardized policies or collective agreements being drawn up for all employees. Here, labor unions may also play an active role.

For leaders, it is important to be considerate and supportive. As my findings suggest, this is particularly the case when employees are given the autonomy to decide on their work arrangements. Leadership can mitigate potential negative effects on performance by providing relational support. Additionally, research on i-deals emphasizes the importance of fairness and consistency in managerial decisions around remote work policies, ensuring that all employees perceive these arrangements as equitable (Liao et al., 2017).

3.5.3 **Limitations and Suggestions for Future Research**

Although this research offers a valuable contribution to how remote work arrangements should be managed in the future, there are some limitations that need to be acknowledged when designing future research on this topic. First, the cross-sectional nature of the study limits the ability to infer causal relationships between decision-making authority and the observed outcomes. While the results highlight significant associations for employees' emotional well-being, it remains unclear whether the decision-making authority directly causes these effects or if other factors influence the outcomes. With the inclusion of several control variables, I tried to minimize omitted variable bias (Podsakoff et al., 2003). Still, future research should employ longitudinal designs to examine how the impact of remote work decision-making authority unfolds over time, allowing for a better understanding of the temporal dynamics and causal pathways.

Second, the data used for this study relies on self-reporting, which can be subject to biases such as social desirability and common method variance (Podsakoff et al., 2003). Although established and validated scales were used to measure the constructs, there is still a risk that employees may have reported responses consistent with social norms rather than their actual experiences. Future studies could benefit from incorporating objective performance measures or supervisor ratings to triangulate the self-reported data and provide a more comprehensive view of the results.

Third, the measurement of the independent variable, remote work decision-making authority, may vary based on different roles and perceptions of how decisions are made in organizations. For example, some employees may perceive managerial authority in remote work arrangements, while others rate it as a collective decision within a team. This may depend on the level of collaboration and communication involved in the process. Therefore, future research could incorporate mixed methods approaches to better understand how decisions about remote work arrangements are made.

Finally, the organizational context may play an important role, particularly in branches where remote work is a new practice. For organizations who traditionally did not engage in remote work, this may require time to develop effective processes, routines, and digital infrastructure (Du Plessis, 2022). In contrast, industries that have long embraced remote work may already have the necessary expertise but could face the challenge of implementing stricter regulations to address recent top managers' concerns and preferences (KPMG, 2023). Future research could explore how varying levels of familiarity with remote work affect decision-making authority across sectors.

3.6 Conclusion

In conclusion, this study highlights the critical role of decision-making authority in shaping employee well-being in remote work contexts. Overall, managerial control over remote work decisions significantly exacerbates employees' emotional exhaustion and loneliness, revealing the potential downsides of top-down approaches carried out by managers. In contrast, individual, team participative as well as organizational decision-making significantly differ from managerial control. Thus, this research underscores the value of autonomy and participation as key drivers of well-being. Notably, performance and engagement were not significantly affected by the hierarchical level of the decision-making authority. Leadership consideration showed a marginal moderating effect at the individual and team levels, impairing performance when supportive leadership was absent. All in all, these findings offer actionable guidance for organizations and emphasize the need to prioritize employee autonomy and incorporate participative decision-making in remote work policies. As remote work becomes an enduring feature of the modern white-collar workplace, ensuring employee autonomy will be critical to both well-being and organizational success.

4. Committing to the Digital Change in Organizations: A Study on Aging Blue-Collar Workers

Kilian Hampel

ABSTRACT

Industrial companies and their workforces are currently facing several trends that challenge them in their working environment. First, the ongoing digitalization of the workplace has led to unprecedented career challenges for blue-collar workers and requires them to increasingly incorporate digital technologies at work. Second, demographic change has led to an aging workforce and higher proportions of older employees at work. Therefore, it is becoming continuously important for blue-collar employees of all age groups to be willing to commit to the digital change in their organization and to adapt to their changing working environment. Drawing from socioemotional selectivity theory, I argue that age is generally negatively related to blue-collar employees' readiness for digital change. Furthermore, I assume this relationship to be moderated by technological insecurity and promotion-oriented change communication. Testing multiple regression analyses with survey data on 1,165 blue-collar employees at the production sites of a German automotive supplier, I find partial support for my hypotheses. While age is generally negatively related to readiness for digital change, perceived technological insecurity moderates this effect. While promotion-oriented change communication was not shown to function as a moderator, its direct effect on employee readiness for change regardless of employee age stood out. Therefore, my findings have important theoretical and practical implications.

Keywords*:* readiness for digital change; blue-collar workers; aging; socioemotional selectivity theory; technological insecurity; promotion-oriented change communication

4.1 Introduction

Due to the ongoing digitalization of the workplace, blue-collar employees with manufacturing tasks are facing “unprecedented career challenges” (Chin et al., 2019, p. 397). This technological shift, often referred to as the Fourth Industrial Revolution or Industry 4.0, has fundamentally changed how work is performed in many sectors, leading to higher levels of complexity and requiring employees to increasingly incorporate digital technologies at work (Madsen et al., 2016). Closely related, blue-collar employees, especially with simple routine tasks, often face fears of “technologically induced unemployment” (McClure, 2018, p. 139). Blue-collar workers often face higher levels of job displacement risk due to automation, as many of their tasks are routine and can be easily automated (McClure, 2018). This technological insecurity can be a critical factor influencing their readiness to commit to digital change, especially among older employees who may feel particularly vulnerable to job loss. While actual computations of jobs threatened by automation are ambiguous and highly disputed, many tasks are expected to transform due to the application of digital technologies (Hampel et al., 2021; Hirsch-Kreinsen, 2016; Madsen et al., 2016; Spath et al., 2013). To cope with these challenges, it is important that both the employer and its employees are ready for the upcoming digital change (Gfrerer et al., 2021; Halpern et al., 2021). In general, such readiness for change can be defined as the extent to which employees are “cognitively and emotionally inclined to accept, embrace, and adopt a particular plan to purposefully alter the status quo” (Holt et al., 2007, p. 326). For blue-collar workers, this results in openness toward digitalization as well as in the willingness to interact with digital technologies and devote themselves to potential changes (Bouckenooghe et al., 2009; Drazic & Schermuly, 2021).

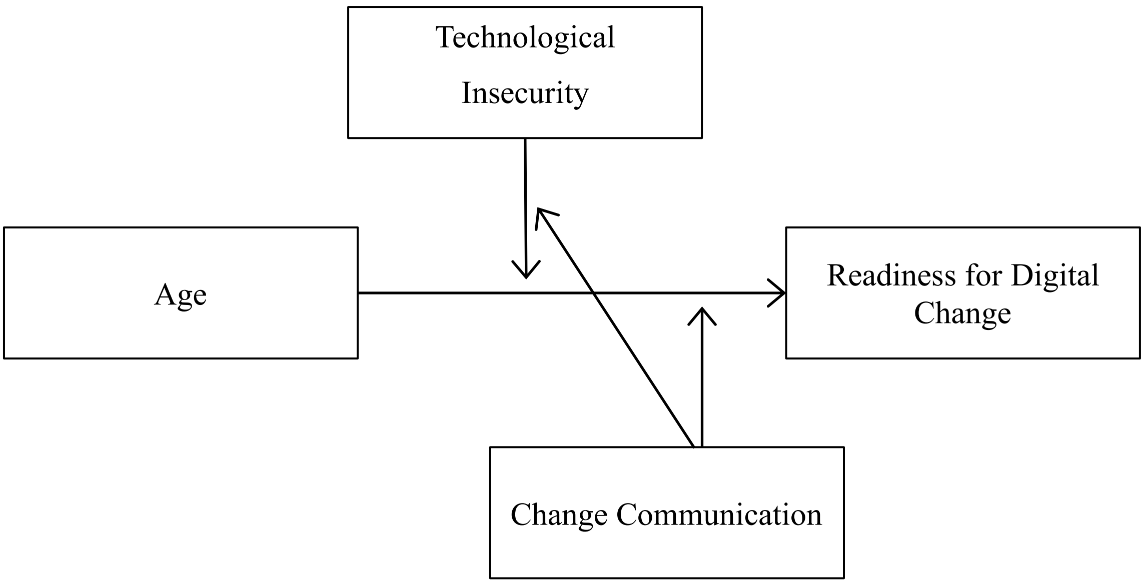
While the digitalization of the workplace leads to changing work tasks and requirements, demographic change simultaneously transforms the labor force. Across many developed countries (including Germany, the context of this study), rising life expectancies and lower birth rates have resulted in older workers constituting a significant part of the labor force (Hertel & Zacher, 2018). Even though demographic change has opened up various broad streams of literature on the aging workforce, including topics like successful aging (e.g., Zacher, 2015) or age diversity (e.g., Kunze et al., 2011; Reinwald & Kunze, 2020), little is known about aging blue-collar workers and their adaptiveness to an increasingly digitalized workplace. In general, Ng and Feldman (2010, 2012), find in their two meta-analyses that age is negatively related to training motivation and motivation to learn, but not to training participation. In the context of information and communication technologies (henceforth ICTs), the relationship between age and specific outcome variables like ICT skills, ICT use, and participation in training about ICT remains inconclusive (Bertschek & Meyer, 2009; De Koning & Gelderblom, 2006; Hauk et al., 2018; Kunze et al., 2013a; Tijdens & Steijn, 2005; Zwick, 2015). Most importantly, and to my knowledge, no research has so far investigated the relationship between age and readiness for digital change in a blue-collar work context. Neither was it shown whether older employees are less willing to commit to the digital change at their company than younger employees, nor whether certain situational work-related factors influence this readiness for change. In particular, the extensive body of research on technology adoption including the Technology Acceptance Model (TAM) by Davis (1989) predominantly focuses on white-collar and knowledge-based workers (Morris & Venkatesh, 2000). In light of the enormous impact that both digital transformation and demographic change have on the workforce with manufacturing tasks, this can clearly be identified as a lack of research.

Therefore, I aim to fill this research gap and focus on blue-collar employees of various age groups dealing with imminent and direct digital change in their organization. In general, I draw on socioemotional selectivity theory (Carstensen, 2006) and argue that with increasing age, blue-collar employees are less willing to commit to digitalization at their workplace due to different goals pursued depending on their perception of future time. While younger employees with unlimited future time follow the goal of knowledge acquisition, older employees rather focus on emotional regulation and maintenance (Carstensen, 2006; Stamov-Roßnagel & Hertel, 2010; Zwick, 2015). Thus, older employees may be less motivated to put effort into adjusting to the digital transformation at their workplace as their future time at work is limited compared to younger employees.

Furthermore, drawing from socioemotional selectivity theory (Carstensen, 2006), I argue that the age-change readiness relationship is contingent upon certain work-related factors: First, the degree to which employees perceive technological insecurity such as the fear of job loss due to ICTs may play a role in terms of whether blue-collar employees of different age groups perceive readiness for digital change (Huang et al., 2021; Ragu-Nathan et al., 2008). Due to their limited future time perspective, older employees with high levels of technological insecurity may be even less motivated to commit to the digital change at their organizations compared to younger employees who, due to unlimited future time, might feel an additional motivation to deal with the technological change at their company (Carstensen, 2006). Second, I expect that the manner in which digitalization is communicated and framed within the organization will have an impact on older employees' intention to commit to these changes. As Stam et al. (2018) recently elaborated, promotion-oriented communication generates a stronger potential for individuals to generate motivation when facing crisis situations. Promotion-oriented change communication focuses on potential positive outcomes and one's pursuit of success in tasks and goals, and it can be expressed by the company's top management as well as by managers on all levels. In consequence, I argue that the perception of a promotion-oriented focus of communication about the digital transformation within the company is important for employees' willingness to face digital change. With such a perception of promotion-oriented change communication, older blue-collar employees might rethink their position and become motivated to commit to digital change in the future. The absence of such a promotion-oriented focus may, on the other hand, may amplify existing doubts about the change and, thus, moderate the negative relationship between age and readiness for change. Lastly, I propose that promotion-oriented change does not only impact the relationship between age and readiness for digital change but also countervails or amplifies the particular effects of technological insecurity on the age-change readiness relationship. With a strong perception of promotion-oriented communication at the company, blue-collar employees may react differently to potential fears about the digital change and see solutions towards a successful future. On the contrary, low promotion-oriented communication might amplify existing technological insecurity and further decrease older blue-collar employees' motivation to commit to digital change at their company. Figure 9 displays my proposed theoretical model.

Figure 9

Conceptual Framework of Study 3



By examining blue-collar employees and their readiness for digitalization within the workplace among different age groups, this research contributes to the existing literature on readiness for change and aging in several ways (Bouckenooghe et al., 2009; Carstensen, 2006; Zacher, 2015). First, the paper sheds light on the age-digital readiness relationship in the blue-collar context and examines if and when older blue-collar employees are willing to commit to digital change in their organization. By adding moderating factors to the picture, I integrate the socioemotional selectivity theory (Carstensen, 2006) with two important (especially for the blue-collar context) and substantial factors, respectively technological insecurity and promotion-oriented change communication. Furthermore, this study offers important practical implications for companies, top management, and leaders on how to handle their aging workforce and motivate them in the digital age.

4.2 Theoretical Framework and Hypotheses Development

4.2.1. Committing to the Digital Change in the Blue-Collar Work Context

As stated, the digital transformation of the workplace is progressively challenging companies and their workforces. Especially for blue-collar employees with manufacturing tasks, digitalization often leads to uncertainty and changes in their work environment, and thus requires employees' willingness to commit to potential changes in their work environment (Chin et al., 2019; Hampel et al., 2021; Hirsch-Kreinsen, 2016). Regarding employees' attitudes towards general organizational change, existing research often refers to constructs like "readiness for change, commitment to change, openness to change, and cynicism about organizational change" (Choi, 2011, p. 480). Work by Choi (2011) and Holt and Vardaman (2013) comprehensively compare and demarcate such constructs. Bouckenooghe et al. (2009) elaborated on the readiness for change concept and took a multidimensional and holistic view of employees' attitudes towards change. In doing so, the authors distinguished between the following three subdimensions: *emotional, cognitive, and intentional readiness for change*. First, emotional readiness for change contains the employees' feelings about the change. Second, the cognitive dimension deals with the general beliefs and thoughts the employees have about the change and, in particular, its outcomes. For example, in the context of blue-collar employees and the digital transformation of the workplace, cognitive readiness for change focuses on whether digitalization will improve future work. Third, the intentional dimension of readiness for change focuses on the "effort and energy organizational members are willing to invest" (Kirrane et al., 2017). Thus, for blue-collar employees in the context of the process of digitalization at their company, this relates to the employees' actual motivation to commit and devote to digital change within their company. With the multifaceted readiness for change construct by Bouckenooghe et al. (2009), the goal is to refer to blue-collar employees' emotions, beliefs, and intentions towards digital change at their company but, purposely, not on one particular exemplary digital change project like the implementation of a certain technology or work method (Drazic & Schermuly, 2021; Paruzel et al., 2020). Focusing on blue-collar employees' general attitude towards digital change allows us to draw broader conclusions and not be limited to a certain technology or occupational specification.

So far, research on blue-collar employees' readiness for change in the context of digitalization and automation is scarce. Especially with respect to demographic change, there is, to my knowledge, no research so far that focuses on the effect employee age has on one's readiness for digital change in a blue-collar-employee setting. In the following sections, I therefore aim to examine if aging blue-collar workers are ready and motivated to commit to digital change in their organization and under which circumstances they might be reluctant.

4.2.2. Age and Readiness for Digital Change

Alongside digitalization, demographic change progressively influences the labor market and leads to an older workforce. By 2060, in Germany, every third person will be 65 years or older (Enste, 2019). With the increasing proportion of older employees, the question arises as to how blue-collar employees feel about digital change and if they are ready to commit to potential changes. When researching age and digital technologies in general, one inevitably encounters the Technology Acceptance Model (TAM) by Davis (1989). TAM deals with one's behavioral intention to actually use certain technologies and entails the concepts of perceived usefulness as well as perceived ease of use of certain technologies. Hauk, Hüffmeier, and Krumm (2018) examined the relationship between age and TAM in their meta-analysis and negatively linked age with (1) perceived ease of use, (2) perceived usefulness, and (3) intention to use technology (Hauk et al., 2018).

In their two meta-analyses, Ng and Feldman (2010, 2012), find negative relations between age and training motivation as well as between age and motivation to learn but not between age and training participation. Drazic and Schermuly (2021) investigated the relationship between age and readiness for change in an agile project management setting. While they did not find chronological age to influence employees' readiness for change, they found subjective age to moderate this relationship, such that with lower subjective age, chronological age had a positive relation with readiness for change. Contrary to their theoretical assumptions, Kunze et al. (2013a) found employee's age to be negatively related to resistance to change. Furthermore, they compared white and blue-collar employees and found this relationship to only affect white-collar employees. In a blue-collar setting, Hampel et al. (2021) focused on the impact certain work characteristics have on employees' attitudes towards new digital technologies, like technology enthusiasm or user resistance to change. While work characteristics were not related to employees' resistance, older blue-collar employees were shown to be more resistant to new digital technologies at work than younger age groups, even though age was only included as a control variable (Hampel et al., 2021).

Drawing from socioemotional selectivity theory (Carstensen, 2006), I argue that chronological age generally determines whether blue-collar employees are motivated to commit to potential upcoming changes due to digitalization. Socioemotional selectivity theory is a life-span theory of motivation that describes patterns that affect employees of various generations differently due to their perception of time (Carstensen, 2006; Stamov-Roßnagel & Hertel, 2010; Zwick, 2015). Thus, as Carstensen (2006) describes, adults follow two main goals in life: knowledge acquisition and emotional regulation. "Knowledge acquisition entails behaviors aimed at learning about new or changing elements in their environment, analyzing that information, and incorporating that knowledge into job performance and career advancement activities" (Ng & Feldman, 2010, p. 685f.). Emotional regulation, in contrast, comprises behaviors that aim to act emotionally fulfilling and rather focus on the present, such as social interactions and emotional well-being. While younger employees, due to their early career stage, perceive their future time to be unlimited, they rather follow the goal of knowledge acquisition, whereas older employees with limited future time prioritize the goal of emotional regulation (Carstensen, 2006). For older blue-collar workers who have a limited future time perspective, the attractiveness of adapting to a changing work environment, perceiving digitalization as something positive, and committing to the digital change is, on the basis of my theoretical considerations, lower than it is for younger employees (Carstensen, 2006; Kanfer & Ackerman, 2004; Stamov-Roßnagel & Hertel, 2010). Therefore, I assume blue-collar employees' emotional, cognitive, and intentional readiness for digital change to decline with increasing age. Therefore, I hypothesize:

Hypothesis 1: Blue-collar employees' chronological age is negatively related to their readiness for digital change.

Furthermore, I argue that, when investigating the main effect of employee age on readiness for digital change, there are certain situational work-related factors that function as moderators of this relationship. Drawing from socioemotional selectivity theory (Carstensen, 2006), I identify technological insecurity as well as promotion-oriented change communication as relevant boundary conditions.

4.2.3. The Moderating Role of Technological Insecurity

Socioemotional selectivity theory (Carstensen, 2006) posits that as individuals age, they prioritize emotional well-being and tend to avoid stress-inducing situations. For older blue-collar employees, technological insecurity acts as a significant stressor as it creates "situations where users feel threatened about losing their jobs, either because of automation from ICTs or to other people who have a better understanding of ICTs" (Ragu-Nathan et al., 2008, p. 427).

Therefore, I argue that the perception of technological insecurity (i.e., job loss fear caused by digitalization and automation) might be especially crucial for aging blue-collar employees and their readiness to commit to the digital change in their organization. According to socioemotional selectivity theory (Carstensen, 2006), the perception of remaining time defines the motivation for employees in several ways. Younger blue-collar employees, due to their unlimited future time and, thus, forthcoming careers, might be more concerned and additionally motivated by the threat of potentially losing their job and should be more interested in acquiring additional knowledge and proactively adapting to the digital change. Older adults, on the contrary, with limited future time, rather focus on maintenance and emotional regulation such as well-being and the avoidance of negative experiences (Carstensen, 2006). As a result, they might lose confidence and optimism to successfully adapt to an increasingly digitalized work environment. As Huang et al. (2021) recently argued for job insecurity in general, older adults thus might not be as committed as younger employees to "further invest personal resources to advance their careers" (Huang et al., 2021, p. 538). While the absence of insecurity feelings might not impede their motivation, the presence thereof could demotivate them. Zainun et al. (2020) also found high levels of technological insecurity to decrease commitment to change, even though they did not include age as a factor in their model. Similarly, Paruzel et al. (2020) found employees with low levels of readiness for change to report strong fears, like a fear of job loss. In line with these arguments, I therefore propose that technological insecurity takes a moderating role in the negative relationship between age and readiness for digital change. Thus, I propose the following second hypothesis:

Hypothesis 2: Technological insecurity moderates the negative relationship between blue-collar employees' chronological age and their readiness for digital change, such that chronological age is negatively related to readiness for digital change when employees perceive high levels of technological insecurity, while it is no longer significant with low levels of technological insecurity.

4.2.4. Promotion-Oriented Change Communication as a Second Moderator

Furthermore, as suggested by socioemotional selectivity theory (Carstensen, 2006), older workers tend to prioritize emotionally meaningful and rewarding activities over goal-driven pursuits, especially when faced with potential disruptions like digital transformation. In such cases, the way these changes are communicated within the organization plays a crucial role in determining whether older employees engage with or resist digitalization efforts (Armenakis & Harris, 2009). Specifically, promotion-oriented change communication is a concept originally descending from regulatory focus theory (Higgins, 1997), which states that individuals get motivated by either promotion-oriented or prevention-oriented framing in communication and leadership styles, depending on their regulatory fit. While prevention-oriented people are motivated by the avoidance of failure, pain, and losses, promotion-oriented people tend to prefer a framing which relies on potential positive outcomes and the pursuit of success in tasks and goals (Bruch et al., 2007; Higgins, 1997; Lockwood et al., 2002). In doing so, promotion-oriented change communication "emphasizes ideals, focuses on growth and achievement, and conveys positive affect" (Stam et al., 2018, p. 2862). This is closely connected with research on charismatic and transformational leadership (Shamir et al., 1993). Furthermore, as Stam et al. (2018) noted, communication with a promotion-oriented focus generates stronger potential for individuals to generate motivation when facing crisis situations.

Promotion-oriented change communication can be induced, organized, and implemented by an organization's top management but, especially for employees at shop floor levels, it often requires that leaders and managers in several departments internalize and distribute the change communication's message (Bouckenooghe et al., 2009; Petrou et al., 2015; Stam et al., 2018; Van den Heuvel et al., 2009). Thus, internal change communication "affects managerial and operational aspects of organizational function" (Zainun et al., 2020, p. 1330) and therefore is highlighted as a method at the organizational level.

In consequence, I argue that the perception of a promotion-oriented focus of communication about the digital transformation within the company is important for older blue-collar employees to be willing to face the digital change. As outlined with socioemotional selectivity theory, the absence of a positive vision of the future due to the missing promotion-oriented framing of digitalization could therefore guide aging blue-collar employees to be less likely to be motivated and to commit to digital change. As they rather focus on emotional regulation but not on the attainment of goals regarding the digital change at their organization, their readiness to change might decrease with age (Carstensen, 2006). With such a perception of promotion-oriented change communication, they potentially might rethink their position and become motivated to commit to digital change in the future. Potential age differences in employees' levels of readiness for change could, according to this argumentation, be reduced with high levels of perceived promotion-oriented change communication. Therefore, I assume that promotion-oriented change communication moderates the relation between age and employee's readiness for digital change and propose the following hypothesis:

Hypothesis 3: Promotion-oriented change communication moderates the negative relationship between blue-collar employees' chronological age and their readiness for digital change, such that chronological age is negatively related to readiness for digital change when employees perceive their organization's change communication to not be promotion-oriented, while it is no longer significant with high levels of promotion-oriented communication.

4.2.5. The Interplay of Age, Technological Insecurity, and Promotion-Oriented Change Communication

Third, I propose that promotion-oriented change communication not only impacts the relationship between age and readiness for digital change but also the impact that technological insecurity has on this relationship. According to socioemotional selectivity theory (Carstensen, 2006), older workers prioritize emotional well-being and stability over future-oriented goals, especially when facing potential disruptions like digital transformation. Having drawn a positive picture including hope and faith about the future with the digital transformation of the workplace, this communication approach likely mitigates the effects of uncertainty and anxiety (Bordia et al., 2004; Miller & Monge, 1985; Schweiger & Denisi, 1991). This is consistent with research showing that effective communication during periods of change reduces perceived threats and helps employees adjust (Ashford et al., 1989; Schweiger & Denisi, 1991). Furthermore, this also aligns with socioemotional selectivity theory (Carstensen, 2006), as promotion-oriented communication offers emotional rewards, helping older workers reframe digital change in a way that is emotionally secure (Stam et al., 2018). Thus, when blue-collar employees perceive promotion-oriented change communication, and a positive picture is drawn by their company, this might weaken employees' potential fears of technological insecurity, such as job loss or a fear of being replaced. With the perception that the company has a substantial, collective, and optimistic estimation of the future, older blue-collar employees might not be further demotivated by technological insecurity. On the contrary, the absence of promotion-oriented change communication might amplify existing doubts about the future and increase the negative consequences for older employees who might then not be willing to commit to the digital change in their organization. Consequently, low levels of perceived promotion-oriented change communication together with high levels of technological job insecurity should have the strongest negative moderating effects on the age-readiness for digital change relationship. This leads to the following fourth hypothesis:

Hypothesis 4: Promotion-oriented change communication weakens the existing moderation effect of technological insecurity on the negative relationship between blue-collar employees' chronological age and their readiness for digital change, such that the relationship is no longer significant when employees perceive high levels of both technological insecurity and promotion-oriented change communication but significant and negative when employees *perceive high levels of technological insecurity and low levels of promotion-oriented change communication.*

4.3 Methods

4.3.1. Data Collection and Sample

I collected data from a German automotive supplier with two distinct production sites in 2022. As part of the cooperation, the company received a benchmarking report on the retrieved results. As the company is currently experiencing major changes in its daily production work due to the workplace's digital transformation, its environment appears to be the appropriate context to examine blue-collar employees' readiness for digital change. To ensure participation from all blue-collar employees, including those without a personal desk or regular computer access at the organization, I provided both paper-and-pencil and online questionnaire options. Overall, 1,165 blue-collar employees completed the survey. Participants were on average 48.34 years old (*SD* = 10.61) and predominantly male (76.05%). A total of 11.01 percent held a leadership position. When asked about their highest educational degree, 40.00 percent of employees reported having completed an apprenticeship, 32.45 percent held a lower secondary school diploma ("*Hauptschulabschluss*"), and 15.36 percent had a secondary school certificate ("*Realschulabschluss*"). Higher education degrees were less common, with only 1.54 percent of employees holding a university degree.

4.3.2. Measures

In order to test the validity of the latent constructs used in this study, I performed separate confirmatory factor analyses (CFA). Unless otherwise noted, five-point Likert-type scales (1 = "strongly disagree" to 5 = "strongly agree") were used. All items were coded in a way that higher item scores indicate higher levels of the respective construct.

Chronological Age. Employees' individual age was measured by their chronological age in years.

Readiness for Digital Change (α = 0.89). Employees' readiness for digital change was captured by using the readiness for change scale by Bouckenooghe et al. (2009), including its three subdimensions emotional, cognitive, and intentional readiness for change. In order to put the items into context, I based my approach on that used by Höyng and Lau (2023), and adapted the items to digital change. To evaluate the model fit, I followed the recommendations by Hoyle (2000). Results from the CFA revealed a satisfactory model fit (χ^2= 21.63; df = 8 χ^2/df = 2.70; CFI = 0.997; TLI = 0.99; SRMR = 0.02) with significant factor loadings ranging from 0.79 to 0.94. Example items were "I have a good feeling about digitalization" (Emotional readiness), "Digitalization will improve work" (Cognitive readiness), and "In general, I would be willing to invest energy in the digitalization process at my organization" (Intentional readiness).

Technological Insecurity (α = 0.75)**.** To measure employees' technological insecurity, I used the five-item scale on techno-insecurity from the original technostress creators concept developed by Ragu-Nathan et al. (2008) and slightly adapted it to the digital change context. Overall, the results from the CFA revealed a moderate model fit (χ^2 = 104.53; df = 5; χ^2/df = 20.91; CFI = 0.92; TLI = 0.85; SRMR = 0.05). Example items are "I feel that new digital technologies constantly threaten my job security" and "I feel threatened by colleagues with better knowledge of digital technologies".

Promotion-Oriented Change Communication (α = 0.75). For promotion-oriented change communication, I adapted a three-item scale originally inspired by the promotion-orientation scale by Lockwood et al. (2002) and put the items into the context of communication by the company towards digital change. As the scale consists of only three items, the CFA did not allow for the reporting of reliable fit indices. Nevertheless, all item loadings were significant and above the often used threshold of 0.5 (Hulland, 1999). The items were "I have the perception that my company mostly focuses its communication on the successes we want to achieve better in the future through digitalization", "I have the perception that my company lets us employees share ideas on how we can be successful through digitalization", and "I have the perception that my company often presents positive things that can happen in the future through digitalization".

Controls. To analyze the hypothesized relations without running the risk of disregarding a potential omitted variable bias, several control variables were included. First, I controlled for supervisor support, as employees with stronger supportive actions by their direct supervisor may be expected to have more chances to participate in developmental training, learn new skills and thus commit to the digital change at their company (Dvir et al., 2002; Höyng & Lau, 2023; Noethen, 2011; van Vianen et al., 2011). Thus, I included five items from the original nine-item scale of supervisor support by Greenhaus et al. (1990). Second, I included organizational tenure in years, as more experienced employees might react differently to upcoming changes caused by digitalization at the organization than employees with less experience at the organization (Eby et al., 2000; Hameed et al., 2013; Morris & Venkatesh, 2000). Third, I controlled for gender as previous research showed men to respond quicker to upcoming organizational changes, as they tend to adopt new technologies more quickly, while women may require more social support and exhibit a more cautious approach (Oreg & Berson, 2011; Venkatesh et al., 2000). I measured gender as follows: 1 = male, 2 = female, 3 = non-binary ("diverse"). With only 11 people identifying as non-binary, I decided to include only the binary gender categories of "male" and "female", as no reliable assessments could be made for non-binary people.

4.3.3. Analytical Techniques

I tested the four hypotheses with multiple linear regression analyses. For testing the proposed moderation effects of the second, third, and fourth hypotheses, I complied with the instructions given by Little et al. (2006). Furthermore, I applied simple slope testing to graphically plot and interpret potential significant regression results of the interaction effects following the recommendations of Dawson and Richter (2006) as well as Liu et al. (2017). All independent variables in my models were z-standardized (Frazier et al., 2004).

4.4 Results

4.4.1. Descriptive Statistics

Table 9 shows the means, standard deviations, and intercorrelations for all relevant variables used in this study. As expected, employees' chronological age was negatively related to readiness for digital change (r = -0.15, $p < 0.001$), indicating that older employees may feel less ready to engage with digital transformation. Chronological age was also positively related to technological insecurity (r = 0.11, $p < 0.01$). Similarly, technological insecurity was negatively related to readiness for digital change (r = -0.26, $p < 0.001$)-Promotion-oriented communication showed a positive relationship with readiness for digital change (r = 0.36, $p < 0.001$) and with supervisor support (r = 0.44, $p < 0.001$), indicating that employees who perceive more promotion-oriented communication and support from their supervisors feel more ready for digital transformation.

4.4.2. Hypotheses Testing

Table 10 displays the regression results. Model 1 tests the relation of age with employees' readiness for digital change. The results indicate a statistically significant negative relation of employees' age on their motivation to commit to the digital change ($\beta = -0.07$, $p < 0.05$), which supports Hypothesis 1.

Table 9

Descriptive Statistics and Correlations of Study Variables

Variables	M	SD	*1*	*2*	*3*	*4*	*5*	*6*
(1) Readiness for Digital Change	3.55	0.72						
(2) Chronological Age	48.34	10.61	-0.15***					
(3) Technological Insecurity	2.76	0.77	-0.26***	0.11**				
(4) Promotion-Oriented Communication	3.30	0.75	0.36***	0.04	-0.15***			
(5) Supervisor Support	2.95	1.02	0.28***	0.01	-0.17***	0.44***		
(6) Tenure	25.28	10.02	-0.14***	0.80***	0.07	0.2	0.02	
(7) Gender	1.24	0.43	-0.11**	0.00	-0.02	-0.02	-0.05	0.03

Note. N = 1,165. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 10

Regression Analysis

	Readiness for Digital Change							
	Model 1		Model 2		Model 3		Model 4	
Age (H1)	**-0.07 ***	(0.03)	-0.04	(0.03)	-0.08 **	(0.03)	-0.09*	(0.04)
Technological Insecurity (TI)			-0.15 ***	(0.02)			-0.18 ***	(0.03)
Promotion-Oriented Communication (PMC)					0.21 ***	(0.02)	0.27 ***	(0.03)
Age x TI (H2)			**0.04 ***	(0.02)			0.04	(0.03)
Age x PMC (H3)					**0.00**	(0.02)	0.02	(0.03)
TI x PMC							0.05 *	(0.02)
Age x TI x PMC (H4)							**-0.03**	(0.02)
Supervisor Support	0.20 ***	(0.02)	0.18 ***	(0.02)	0.11 ***	(0.02)	0.12 ***	(0.03)
Tenure	-0.06	(0.03)	-0.06	(0.03)	-0.05	(0.03)	-0.07	(0.04)
Gender	-0.08 ***	(0.02)	-0.09 ***	(0.02)	-0.08 ***	(0.02)	-0.11 ***	(0.03)
Constant	3.53 ***	(0.02)	3.53 ***	(0.02)	3.53 ***	(0.02)	0.03	(0.03)
N	1,165		1,165		1,165		1,165	
Adjusted R^2	0.11		0.15		0.18		0.22	
ΔR^2			0.04		0.03		0.04	

Note. Standard errors in parentheses. * p < 0.05; ** p < 0.01; *** p < 0.001.

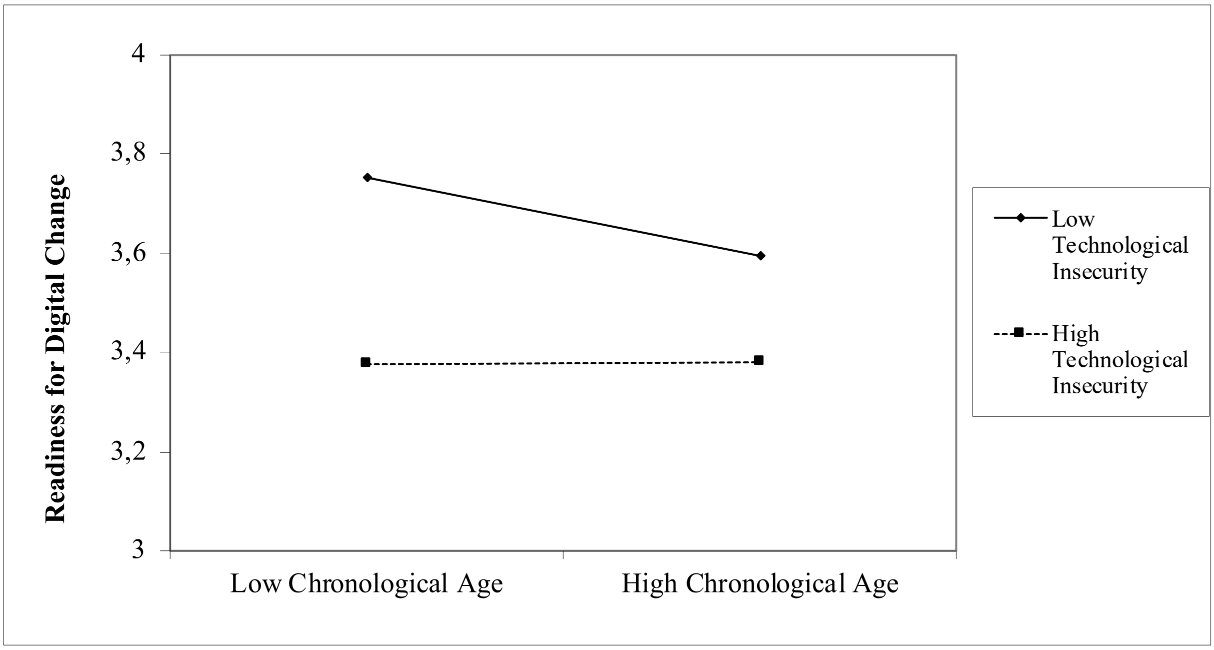
Second, Model 2 investigates the moderating role of technological insecurity on the relation between age and readiness for digital change. As the results from Model 2 show, the interaction term of age and technological insecurity is statistically significant (β = 0.04, p < 0.05). To better understand and interpret this interaction effect, I graphically plotted it in Figure 2 for one standard deviation below and above the mean and deployed simple slope tests. As Figure 10 shows, the slope for low levels of technological insecurity turns out to be statistically significant (β = -0.08, p < 0.05), meaning that younger employees with low levels of perceived technological insecurity are more willing to commit to the digital change at their organization than older employees. Surprisingly, high levels of technological insecurity do not lead to a significant slope (β = 0.00, p = 0.98) indicating that for this condition, there is no age difference in readiness for digital change. Therefore, Hypothesis 2 is not fully supported.

Model 3 focuses on the moderating effect of promotion-oriented change communication. Contrary to my expectations, the interaction effect between age and promotion-oriented communication is not significant (β = 0.00, p = 0.93), which leads to the rejection of Hypothesis 3.

Ultimately, Model 4 examines the three-way interaction effect of technological insecurity and promotion-oriented communication on the relationship between age and digital readiness for change. Different than expected, the three-way interaction is not statistically significant (β = -0.03, p = 0.17), which does not support Hypothesis 4.

Figure 10

Moderating Effect of Technological Insecurity on the Negative Relationship Between Age and Readiness for Digital Change (Hypothesis 2)



4.4.3. Robustness Checks

To ensure the robustness of the regression results, I conducted supplementary analyses. First, I ran all models with and without the inclusion of control variables to rule out that theoretically relevant third variables do not impact my results. While for Model 1, the direct effect of age on readiness for digital change is even stronger when control variables are excluded (β = -0.11, $p < 0.001$) than when included (β = -0.07, $p < 0.05$), the model without variables only contains explained variance of Adjusted R^2 = 0.02. For the other models, the regression results without control variables do not differ from the Models displayed in Table 10. Interestingly, the direct effects of technological insecurity (β = -0.03, p = 0.17) and promotion-oriented change communication (β = 0.27, $p < 0.001$) are both strong and significant, suggesting that these moderators independently affect employees' readiness for digital transformation more than the interaction effects. Also, I calculated the Variance Inflation

Factors (VIFs) for all explanatory variables to rule out multicollinearity issues due to high and significant correlations. All VIFs fell far below the threshold of 10 (*mean* = 1.63; *SD* = 0.76), suggesting that multicollinearity was not a problem in the analyses (Myers, 1990).

4.5 Discussion

The present study aimed to examine whether blue-collar employees of various age groups feel open and ready to commit to potential changes that will occur due to digital transformation at the workplace. As argued on behalf of socioemotional selectivity theory (Carstensen, 2006), there were several reasons to assume that older blue-collar employees feel less ready for digital change than younger employees do. Furthermore, I argued that the effect of age on digital change readiness is contingent upon work-related factors like technological insecurity feelings and perceived promotion-oriented change communication.

I tested the hypothesized relationships using a sample of 1,165 blue-collar employees from a German automotive supplier company while controlling for several factors like supervisor support, tenure, and gender. First, I found blue collar employees' chronological age to be negatively related to their emotional, cognitive, and intentional readiness for digital change at their organization, supporting Hypothesis 1. Second, I argued that technological insecurity feelings such as fears of job loss due to technologies and automation may impact this relationship. My results only partially supported Hypothesis 2. While technological insecurity negatively influenced readiness for digital change, it also significantly moderated the relationship between age and readiness. The interaction suggests that younger blue-collar employees with low levels of technological insecurity are more willing to commit to digital change than older employees. However, at high levels of technological insecurity, the age differences in readiness for change become non-significant. Third, I did not find promotion-oriented change communication to moderate the relationship between age and readiness for change. Lastly, Hypothesis 4, which predicted a three-way interaction between age, technological insecurity, and promotion-oriented change communication, was also not supported by the data. Furthermore, I found strong direct effects of both technological insecurity and promotion-oriented change communication on readiness for digital change. Technological insecurity was negatively associated with readiness for change, while promotion-oriented change communication had a strong positive effect.

4.5.1. Theoretical Implications

This study makes several important contributions to the literature on blue-collar workers in the digital workplace (Hampel et al., 2021; Hirsch-Kreinsen, 2016). First, my results extend the application of socioemotional selectivity theory (Carstensen, 2006) to a blue-collar workforce in the context of digital transformation. While the majority of recent literature has focused on white-collar workers with office jobs, this study reveals that, in a blue-collar work context, older employees differ from younger ones because to their limited future time. Thus, readiness for change declines with increasing employee age. As explained, younger employees are more motivated to adapt to the changing digitized work environment than older employees due to their unlimited future time perspective, while older employees have a limited future time perspective (Carstensen, 2006). The age-related decline in readiness for digital change confirms the theory's emphasis on the importance of emotional stability in later life and suggests that interventions must address these emotional priorities to successfully engage older workers during digital transformation. Thus, readiness for change declines with increasing employee age.

Second, the moderating effect of technological insecurity underlines the importance of considering emotional and job security concerns when examining resistance to digital change.

Specifically, when technological insecurity is low, younger blue-collar employees demonstrate higher readiness for digital change compared to their older counterparts Yet, when technological insecurity is high, age-related differences in readiness diminish, implying that technological fears exert a similar influence on both younger and older blue-collar workers. Even though this effect is different than hypothesized, this highlights that technological insecurity can exacerbate or diminish the age-related differences in readiness for change. Additionally, the statistically strong direct and negative effect of technological insecurity highlights that in the blue-collar work context, the fear of being replaced by automated solutions or by employees with better ICT skills leads to a general decline in the readiness to commit to the digital change in the future (Ashford et al., 1989; van Hootegem et al., 2019).

Third, the direct effect of promotion-oriented communication emphasizes its critical role in fostering readiness for digital change, regardless of age. While the direct effect of promotion-oriented change communication was strong and significant, its role as a moderator was not confirmed. This suggests that promotion-oriented communication may be more universally beneficial, positively influencing readiness across all age groups. This finding is consistent with the regulatory focus theory. Thus, framing digital transformation in a manner that emphasizes growth, opportunity, and success can increase employees' willingness to engage with digital change, even among blue-collar workers who may otherwise be resistant. This aligns with the literature on regulatory focus theory (Higgins, 1998),which posits that individuals are more likely to engage with change when it is framed in a way that aligns with their promotion focus – emphasizing growth, opportunity, and success. By adopting a promotion-focused approach, organizations can increase employees' willingness to engage with digital change, even among blue-collar workers who may otherwise be resistant. Similar to the results on technological insecurity, promotion-oriented change communication seems to affect all age groups and leads to increased readiness for change of all blue-collar employees (Petrou et al., 2018).

4.5.2. Practical Implications

Finally, my findings have important practical implications for company executives in times of digitalization and automation. With regard to the immense impact digitalization, but also demographic change, will have on work tasks, work characteristics, and labor market composition, industrial companies should invest resources to assess the levels of readiness for digital change among their blue-collar workers. When facing digital change, it is important that especially blue-collar employees are committed and motivated to successfully adapting to a changing work environment (Gfrerer et al., 2021; Halpern et al., 2021).

As the results from my analyses show, the readiness for digital change among blue-collar employees generally declines with increasing age. Therefore, organizations should recognize that older workers may require additional support and motivation to successfully navigate digital transformations. To ensure productivity and employability across all age groups, sustainable and successful training methods are required and should be adjusted to the specific needs of older employees (Zwick, 2015).

Furthermore, organizations and managers should incorporate strategies to reduce technological insecurity among their workforces. As shown, blue-collar employees who have fears about job displacement and technological obsolescence are less motivated to commit to the digital change at their organization. Training programs should be designed to enhance employees' digital competencies, making them feel more confident and capable of working in technology-driven environments. Additionally, managers should provide transparent communication regarding the long-term role of technology within the organization to reduce uncertainty and minimize anxiety over job loss. As my results show, this is important for all age groups.

Also, this research showed how important it is that employees perceive their company as painting a positive, optimistic, and goal-directed picture of the digitalized future at the company. Without such promotion-oriented change communication, blue-collar employees are significantly less committed to the digital change. Also, as the strong significant and negative intercorrelation between change communication and technological insecurity suggests, communication about upcoming changes due to digitalization should try to address feelings of technological insecurity that employees may have by discussing future perspectives, solutions, and the intended role for blue-collar workers at the organization.

4.5.3. Limitations and Suggestions for Future Research

Besides strengths and contributions to the literature, there are also a few limitations to this research that merit mentioning and may open up possibilities for future research. First, the methodological approach of this research relies on cross-sectional data and therefore does not allow causal claims to be made. Even though I included a large sample of blue-collar employees, future research may want to incorporate longitudinal data on blue-collar employees' willingness to adapt to digital change. This may be especially helpful with regard to the implementation of direct changes in the working environment, such as the implementation of certain technologies.

Second, I use self-reported survey-data to assess the variables of interest. Even though I controlled for factors like supervisor support, tenure, and gender, an objective measure could further avoid common method bias. While for technological insecurity and readiness for change the self-perception measure can be seen as a strength, one may want to include alternative data sources of promotion-oriented change communication. For instance, one could perform systematic analyses of company communication material to see how it affects employees and whether it is rather promotion- or prevention-oriented. Other potential solutions here could be top management questionnaires or supervisor evaluations (Podsakoff et al., 2003).

Third, the direct effects of both technological insecurity and promotion-oriented change communication on readiness for digital change highlight areas for future research. While these direct effects are meaningful, their strength raises a potential methodological concern, as it may be possible that the direct effects overshadowed the hypothesized moderating effects, making it difficult to detect interactions. Even though I tested for multicollinearity and found Variance Inflation Factors to be below the conventional threshold, direct effects can obscure interaction terms in the model. Future research should test for further multicollinearity and consider using alternative statistical techniques to ensure sufficient power to detect moderation effects (Aiken & West, 1991). Additionally, future research should explore the role of other possible moderators, such as job autonomy or organizational support, that may provide additional insights into how different factors interact to influence blue-collar workers' readiness for digital change.

4.6 Conclusion

To summarize, this study explored how age, technological insecurity, and promotion-oriented change communication influence blue-collar employees' readiness for digital transformation. The findings show that readiness for digital change generally declines with increasing age. While technological insecurity negatively impacted readiness for digital change, it also moderated the relationship between age and readiness, with high levels of insecurity diminishing age differences. However, promotion-oriented communication did not moderate the relationship between age and readiness, but had a strong direct positive effect on readiness for digital change. These findings highlight the importance of addressing technological insecurity and fostering positive communication to ensure that employees of all age groups are motivated and ready for digital transformation.

5. Feeling Younger, Exchanging Knowledge: Understanding Blue-Collar Workers' Knowledge Transfer Behavior

Kilian Hampel and Sophie Moser

ABSTRACT

This article investigates the relationship between employees' chronological age and their knowledge sharing behavior in the manufacturing context and how this relationship is influenced by employees' subjective age. Drawing from socioemotional selectivity theory, we expect older employees to be senders, and younger employees to be recipients, of general work knowledge. Regarding specific knowledge on digital technologies, however, we assume that younger employees engage in the sending and receiving of knowledge, while older employees disengage from knowledge transfer. We furthermore expect that decreasing engagement in knowledge exchange of aging employees is buffered if individuals have a low subjective age. Using data from 868 blue-collar employees in 85 distinct work units, we show that the older employees get, the less active they are in knowledge exchange both as knowledge senders and as knowledge recipients. For employees who subjectively feel younger, age differences in knowledge exchange entirely diminish. We discuss theoretical implications for the knowledge transfer and aging literatures, and emphasize practical implications for manufacturing companies that are confronted with demographic shifts and workplace digitalization.

Keywords*:* aging; blue-collar workers; knowledge exchange; relative subjective age

5.1 Introduction

The process of knowledge sharing between employees has increasingly moved to the focus of organizational researchers in recent years (Burmeister et al., 2018; Dietz et al., 2022). Organizations are compelled to retain expertise and foster knowledge transfer among their workforce for several reasons: First, demographic change in many countries leads to an aging workforce whose work-specific knowledge needs to be retained (Strack et al., 2008; Wilke, 2020). Second, the digital transformation of the workplace in line with Industry 4.0 requires employees to constantly update their knowledge to incorporate digital technologies at work (Madsen et al., 2016; Zangiacomi et al., 2020).

In general, knowledge transfer describes the disclosure of "information from one source to another" (Schmidt & Muehlfeld, 2017, p. 381f.) and contributes to individual and collective learning in organizations. Thus, when analyzing processes and mechanisms behind knowledge transfer, research often differs between *knowledge receiving* and *knowledge sending* (Fasbender et al., 2021). With research on knowledge sharing among employees intensifying, the main focus often lies on white-collar employees with office tasks, failing to extent the scope to another major group in the labor force: blue-collar employees, especially with manufacturing tasks (Muniz Jr et al., 2022; Nakano et al., 2013). While digital technologies are becoming increasingly embedded in office environments, many blue-collar industries, particularly in manufacturing, continue to navigate significant digital transitions (Madsen et al., 2016; Waschull et al., 2022). Historically focused on manual, task-oriented work, these sectors are experiencing a growing integration of digital tools—transforming routine processes that previously required little technological expertise (Boehm et al., 2016; Schenk & Schumann, 2015; Waschull et al., 2022). Zangiacomi et al. (2020) highlight the growing need for blue-collar workers to acquire and exchange digital knowledge, particularly in the context of manufacturing. The shift toward digital technologies requires rapid adaptation across the workforce, introducing challenges in skills development that are not exclusive to any particular age group (Gerpott et al., 2017; Hampel & Kunze, 2023). Therefore, knowledge on digital technologies at work is not yet universally adopted as many manufacturing tasks have not yet fully (or at all) adopted technological and digital developments driven by Industry 4.0 (Waschull et al., 2022). Thus, one might differ between *general knowledge* about daily work processes and general information and *digital knowledge* focusing on knowledge about the specific use of digital technologies such as the use of tablets and software to digitally control machines. Even though research has increasingly focused on knowledge sharing behavior of age-diverse white-collar employees, there is only little insight into blue-collar workers' knowledge sending and receiving (Gerpott et al., 2017; Muniz Jr et al., 2022; Nakano et al., 2013). In particular, it remains unclear whether age has an impact on the transfer of general work-related but also specific digital-related knowledge at the workplace. Furthermore, the role of subjective age – how old employees feel compared to their actual age – has mostly been overlooked in research on knowledge exchange among blue-collar workers (Fasbender et al., 2021; Lazazzara & Za, 2020).

With this paper, we therefore want to empirically investigate the relationship between employees' chronological age and their knowledge sharing behavior in the manufacturing context. Drawing on socioemotional selectivity theory (Carstensen, 2006), we assume older blue-collar workers to be senders of knowledge about general work information, while younger employees should be recipients of such knowledge. While general knowledge transfer is often seen as unidirectional, recent research suggests that knowledge sharing is more of a mutual exchange, with both older and younger employees sharing and receiving knowledge from one another (Burmeister et al., 2018; Gerpott et al., 2017). For specific knowledge on digital technologies, we, therefore, assume different relations. With more expertise and confidence in using digital technologies, we expect younger employees to share more knowledge with their coworkers, while older blue-collar workers with less future time might, opposite to white-collar circumstances, rather disengage from digital technology-related knowledge transfer (Carstensen, 2006; Hampel & Kunze, 2023). Thus, we argue that chronological age is also negatively related to digital knowledge receiving. Most importantly, chronological age might not tell the entire story within the process of knowledge sharing among blue-collar employees. Specifically, we propose that relative subjective age conceptualized as the difference between the blue-collar workers' "perceived subjective age and their chronological age" (Kunze et al., 2015, p. 1512) moderates the relationship between chronological age and the various knowledge sharing outcomes. Drawing from socioemotional selectivity theory (Carstensen, 2006), we assume that when older employees feel younger than they are (implying lower levels of relative subjective age), they are more willing to actively participate in knowledge sharing behavior and therefore share and receive both more general work-related as well as digital-specific knowledge (Lazazzara & Za, 2020). Figure 11 contains our conceptual model including the directions of the proposed hypotheses. We test our hypotheses using data on 868 employees in 85 working units at two distinct production sites of a German automotive manufacturing company.

By examining knowledge sharing behavior among blue-collar employees of various ages, our study makes several important contributions to the literature on organizational behavior and knowledge exchange. First, our research challenges existing assumptions in the literature on intergenerational knowledge exchange (Dietz et al., 2022; Doerwald et al., 2021; Fasbender et al., 2021), which often suggest that older employees are more likely to act as knowledge senders due to their expertise and generativity motives. Contrary to these assumptions, we find that older blue-collar employees disengage from both general and digital knowledge sharing, particularly in the manufacturing context.

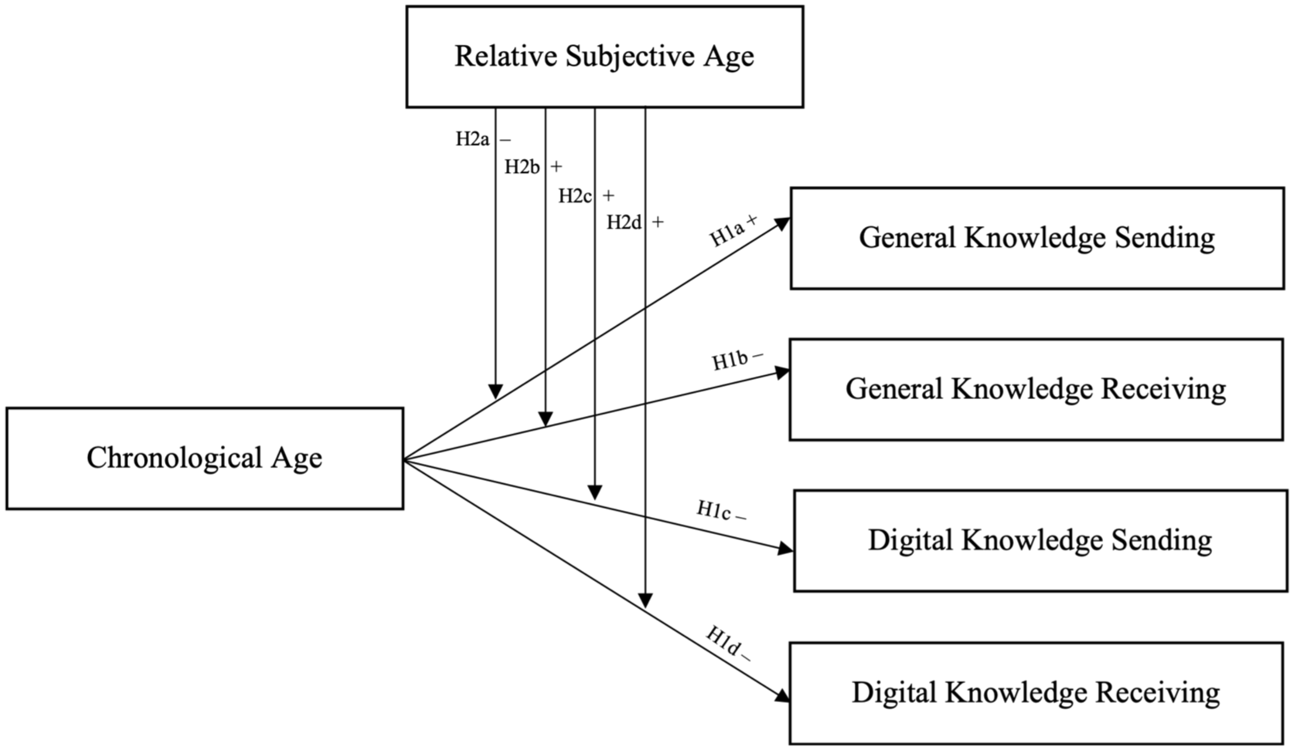
Second, by differentiating between general and digital knowledge shared and received, we respond to calls in the literature to further explore the types of knowledge exchanged in modern workplaces (Fasbender et al., 2021; Gao & Nee, 2018). This distinction is particularly relevant as Industry 4.0 introduces new forms of digital expertise into traditionally manual work processes, where younger employees may have advantages due to digital competencies expertise (Hampel & Kunze, 2023; Prensky, 2001a).

Third, by incorporating blue-collar workers' subjective age into our model, we contribute to a better understanding of aging in the workplace and how subjective age moderates the relationship between chronological age and knowledge exchange. Our findings highlight the crucial role of subjective age for buffering disengagement associated with chronological age, as well as align with and extending socioemotional selectivity theory (Carstensen, 2006), thereby contributing to subjective age research on organizational outcomes (Kunze et al., 2021; Kunze et al., 2015; Lazazzara & Za, 2020).

Moreover, our research offers practical implications for companies in the manufacturing sector. In times of demographic change and digital transformation, understanding how subjective and chronological age interact to influence knowledge sharing is key to maintaining organizational knowledge and ensuring successful digital integration.

Figure 11

Conceptual Framework of Study 4



5.2 Theory and Hypotheses Development

5.2.1. Employees' Chronological Age and Knowledge Exchange

When investigating knowledge exchange among blue-collar employees, it is important to consider both elements of the knowledge transfer process: knowledge sharing on the one hand and knowledge receiving on the other. In general, knowledge sharing refers to the "act of making knowledge available to others within the organization" (Ipe, 2003, p. 431), while knowledge receiving requires obtaining, decoding, and conserving the transmitted information (Fasbender et al., 2021). Putting these two elements in the context of an age-diverse working environment, existing research often relates to intergenerational knowledge transfer (Bjursell, 2015; Gerpott et al., 2017; Schmidt & Muehlfeld, 2017). While the concepts of generational differences are disputed (Rudolph et al., 2021), recent research often uses the terms age-diverse and intergenerational interchangeably, although the focus is on the age of employees rather than their birth cohorts.

In their review, Dietz et al. (2022) argue that employees' abilities, motivations, and opportunities can be antecedents to either share or receive knowledge (Appelbaum et al., 2000; Blumberg & Pringle, 1982). Here, besides one's cognitive abilities to possess certain knowledge and the opportunities to exchange it with others, the motivational reasons for sharing and receiving knowledge are particularly important: According to socioemotional selectivity theory (Carstensen, 2006), employees of various age groups follow certain goals and, here, are differently affected due to their perception of time. Thus, older employees should, because of their perceived limited future time, generally tend to follow generativity goals, which belong to socioemotional goals and "in general are present-oriented and emphasize the employee's prompt emotional gratification" (Dietz et al., 2022, p. 265). Relatedly, research found older employees to perceive themselves as knowledge senders (Burmeister et al., 2018), while in their meta-analysis on generativity at work, Doerwald et al. (2021) also found older employees as stereotypical knowledge senders. Younger employees, on the contrary, who perceive their future time to be unlimited, rather tend to follow developmental goals such as knowledge acquisition and, therefore are stereotypically perceived as knowledge recipients (Burmeister et al., 2018).This argumentation on knowledge sharing motivation is in line with the classical source-recipient model which states that intergenerational knowledge transfer occurs with older employees as knowledge senders, as they possess more expertise, whereas younger employees are seen as recipients due to their little experience (Dietz et al., 2022; Fasbender et al., 2021; Wikström et al., 2018).

Nevertheless, an entirely unidirectional view has often been challenged in previous literature and might not consider all facets of knowledge sharing at the workplace (e.g., Burmeister et al., 2018; Gerpott et al., 2017). Therefore, the mutual exchange model takes a bidirectional viewpoint and argues that both older and younger employees share and receive knowledge with and from each other (Fasbender et al., 2021; Harvey, 2012). In their research, Fasbender et al. (2021) find both generativity striving and development striving to play a role in knowledge sharing and receiving behaviors of young and old colleagues. More precisely, they showed that "employees' generativity striving was related to their knowledge sharing, which in turn predicted their colleagues' reception of knowledge (Dietz et al., 2022, p. 266). Furthermore, development striving predicted younger colleagues' knowledge receiving (Fasbender et al., 2021).

Nevertheless, these results neither focus on what type of knowledge is both shared and received by an age group, nor do they incorporate the specific context of blue-collar employees with manufacturing tasks. With regard to such a blue-collar working environment, the qualitative study by Gerpott et al. (2017) provides insight regarding the knowledge sharing of both young and old age groups. Conducting a case study on a 3-year intergenerational learning program, the authors showed that both younger and older blue-collar workers developed a sense for various knowledge sharing. While older coworkers tended to share their knowledge (e.g., on organizational procedures), younger employees in some cases helped their older coworkers to incorporate new technologies at work (Gerpott et al., 2017). However, these findings were drawn from a specific, structured intergenerational learning program, which may not reflect the dynamics of everyday blue-collar work environments where such formal opportunities for knowledge exchange are absent. Other research among blue-collar-specific knowledge exchange focused on general antecedents of knowledge sharing such as shared language, openness, and trust but did not specifically differ between various age groups as senders/recipients (Muniz Jr et al., 2022; Nakano et al., 2013). Thus, we aim to contribute to the closure of this research gap by identifying intergenerational knowledge sharing behavior among blue-collar workers with manufacturing tasks.

Drawing on socioemotional selectivity theory (Carstensen, 2006), we propose that, for aging blue-collar employees, engagement in knowledge transfer depends on the type of knowledge exchanged. Here, we differ between general knowledge, which focuses on daily work processes and general expertise on the job and digital knowledge referring to knowledge on the specific use of digital technologies such as the use of tablets or digital software to control machines. In the manufacturing context, we hereby assume that Industry 4.0 is on the verge of being universally adopted in assembly lines but is not yet fully adopted by organizations and their workforce (Waschull et al., 2022). Therefore, we expect general knowledge to be mostly non-digital, while digital knowledge explicitly refers to the use of digital technologies at work. As older employees perceive limited future time, they should prioritize sharing general knowledge (work processes) over acquiring digital knowledge, which is less emotionally relevant (Carstensen, 2006; Dietz et al., 2022). With limited future time perceived, older employees should be motivated by generativity to pass on their expertise to younger generations, while they should rather not be interested in acquiring additional knowledge towards the end of their professional career (Doerwald et al., 2021). Conversely, younger employees should seek developmental striving and knowledge acquisition goals due to their unlimited future time and, thus, function as recipients of general work-related knowledge (Fasbender et al., 2021). Therefore, we propose:

Hypothesis 1a: Chronological age is positively related to general knowledge sending.

Hypothesis 1b: Chronological age is negatively related to general knowledge receiving.

For the exchange of knowledge about digital technologies, we assume different effects of age on knowledge sharing behavior. In general, knowledge transfer on digital work elements might work differently among blue-collar employees with manufacturing tasks. Compared to a white-collar context in which digital work elements have already progressed in the past decades, blue-collar working settings, particularly in assembly lines, have not yet fully adopted digital technologies. Nevertheless, as Waschull et al. (2022) describes, such transformation due to Industry 4.0 is imminent. Therefore, due to their experience, abilities, and motivation towards the usage of digital technologies, we expect younger employees to be the main participants of such knowledge exchange. With more experience in using digital technologies, young employees are often considered digital natives with advantages in the digital world, while older employees are said to have disadvantages in using digital tools (Gerpott et al., 2017; Hampel & Kunze, 2023; Prensky, 2001a). With unlimited future time, this ability advantage should also transform into a motivational advantage, as the incorporation of digital technologies at the workplace is inevitable and will shape future work in assembly lines (Waschull et al., 2022). Older blue-collar employees, on the contrary, might see their limited future time, together with less experience, as hindering factors for actively engaging in knowledge exchange on digital-related expertise. Even though the multidirectional viewpoint of knowledge sharing among the workforce could assume that younger employees share their digital knowledge with both young and old colleagues, we assume on behalf of socioemotional selectivity theory (Carstensen, 2006) that older blue-collar employees might disengage from such knowledge, as they might not see the necessity nor motivation to incorporate it. Therefore, we expect younger employees to be both knowledge senders and recipients of digital knowledge in blue-collar settings. This leads to the following hypotheses:

Hypothesis 1c: Chronological age is negatively related to digital knowledge sending.

Hypothesis 1d: Chronological age is negatively related to digital knowledge receiving.

5.2.2. Feeling Younger: The Moderating Role of Subjective Age

While chronological age plays a significant role in shaping knowledge-sharing behaviors, it may not fully explain knowledge sharing's underlying dynamics. According to socioemotional selectivity theory (Carstensen, 2006), individuals' perceptions of future time become crucial as they age, shifting their focus toward emotionally meaningful goals, such as sharing knowledge rather than acquiring new skills. However, one's subjective age – how old or young an individual feels – may further shape these motivations. As recent research proposed, employees' subjective age can be an important predictor for personal but also work-related and organizational outcomes (Kotter-Grühn et al., 2016; Kunze et al., 2015; Montepare, 2009). In doing so, an employee's relative subjective age is conceptualized as the difference between the perceived subjective age of an individual and the chronological age (Kunze et al., 2015). Thus, a high relative subjective age indicates that the employee feels older than their real age would indicate.

For instance, Goecke and Kunze (2018) found that older employees who felt younger than they were, were more absent from work. In their analyses, the authors included both white-collar and blue-collar employees but only found these effects in white-collar work settings. However, Anser et al. (2020) collected survey data in three waves on employees working in the service and manufacturing sector and found employees to be significantly more satisfied with their job when they felt younger. Furthermore, they found these effects to be more pronounced for employees who were 44 years old or older, than for younger employees. In a recent study on employees' readiness for change toward new working methods (e.g., Scrum), Drazic and Schermuly (2021) found subjective age to moderate the relationship between actual age and readiness for change such that older employees that felt younger were more likely to be open-minded toward the proposed change.

For knowledge exchange, we also assume subjective age to play an important role. So far, existing research on that interplay is, especially with regard to blue-collar employees, scarce. In a public sector context, Lazazzara and Za (2020) found that employees who felt older than they were shared less knowledge with their coworkers. The study's findings align with socioemotional selectivity theory (Carstensen, 2006), suggesting that employees who feel older prioritize emotional stability and conservation over development, leading to disengagement from future-oriented behaviors like knowledge sharing. On the other hand, with a lower relative subjective age (meaning that employees feel younger than they actually are), older employees should have a more open future time perspective than older employees who feel older than they are (Carstensen, 2006; Goecke & Kunze, 2018). Thus, they might be more interested in knowledge acquisition but also in knowledge sharing, while with strongly limited future time, emotional acquisition might be the driving force. Hence, we expect older employees to actively engage and disengage from knowledge exchange within their teams, depending on whether they feel younger or older. Both knowledge sharing and receiving behaviors should be higher for employees who feel younger than for employees who feel older, regardless of the type of knowledge exchanged. Furthermore, we assume that feeling younger or older is only of significance for older employees, while for younger employees with an already unlimited future time, changes in their subjective age do not make a difference in their knowledge sharing and receiving behavior (Anser et al., 2020). For instance, a relative subjective age of +8 (indicating that a person feels 8 years older than his/ her chronological age) might have different implications for employees of various age groups. While for a 25 year old occupational newcomer such a subjective age of 33 years might not have detrimental effects, for a 60 year old employee such a subjective age of 68 years might even indicate “low levels of mental and physical energy” (Anser et al., 2020, p. 2) and could imply less job satisfaction and career prospects (Anser et al., 2020; Bergland et al., 2014). This theoretical argumentation leads to the following four hypotheses:

First, blue-collar employees who feel younger may have a more expansive view of their future, motivating them to share their general work knowledge. On the other hand, older-feeling employees might be less inclined to share, as they prioritize emotional goals rather than workplace contributions.

Hypothesis 2a: Relative subjective age moderates the positive relationship between chronological age and general knowledge sending such that the relationship is stronger when employees feel younger than they are and no longer significant when employees feel older than they are.

Second, blue-collar employees who feel older are expected to be less receptive to receiving general knowledge, focusing more on emotional stability. On the other hand, those who feel younger are likely to be more open to learning and development.

Hypothesis 2b: Relative subjective age moderates the negative relationship between chronological age and general knowledge receiving such that the relationship is stronger when employees feel older than they are and no longer significant when employees feel younger than they are.

Third, we suggest that younger-feeling employees are also more willing to share digital knowledge due to their perceived future time. Conversely, older-feeling employees are likely to disengage from digital knowledge-sharing due to reduced future time perspective and relevance.

> ***Hypothesis 2c:*** Relative subjective age moderates the negative relationship between chronological age and digital knowledge sending such that the relationship is stronger when employees feel older than they are and no longer significant when employees feel younger than they are.

Finally, employees who feel older may be less motivated to acquire digital knowledge, seeing it as irrelevant for their future career prospects. In contrast, younger-feeling employees, with their developmental focus, are expected to stay receptive to learning new digital skills.

> ***Hypothesis 2d:*** Relative subjective age moderates the negative relationship between chronological age and digital knowledge receiving such that the relationship is stronger when employees feel older than they are and no longer significant when employees feel younger than they are.

5.3 Methods

5.3.1. Data Collection and Sample Description

To test this study's hypotheses, we surveyed employees of two distinct production sites of a German automotive supplier. To ensure that all blue-collar employees, including those who do not necessarily have access to a computer in their daily working life, were able to participate in the study, we offered both paper-pencil as well as online questionnaires. Initially, 1,351 blue-collar employees participated in the survey. Since for 305 respondents, information on focal study variables was missing and a further 178 individuals were identified as having responded unrealistically – defined as answers in the relative subjective age measure that deviated more than two standard deviations from the mean value (Bühner & Ziegler, 2017) – we arrived at a final sample size of 868 individuals who were part of 85 distinct work units at two production sites. Participants in this final sample were on average 48.13 years old (*SD* = 10.72) and felt on average 3.55 years younger (*SD* = 7.16). Overall, 11.85 percent of the respondents in our final sample size had leadership responsibility. The majority was male (77.44%) and spoke German as their mother tongue (92.71%).

5.3.2. Measures

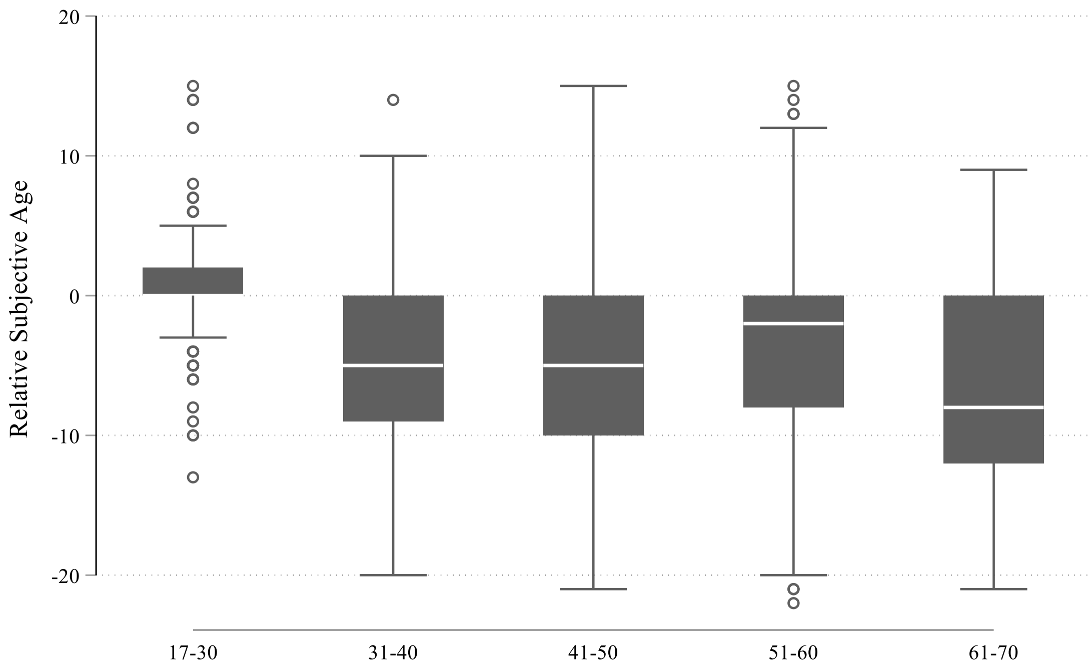
Chronological Age. We assessed our focal predictor variable chronological age by asking participants to indicate their age in years. Responses ranged from 20 to 66 (*mean* = 48.13; *SD* =10.71).

Knowledge Exchange. We measured blue-collar workers' knowledge sharing and receiving behavior via four distinct variables. As our hypotheses implied, we asked participants to rate their involvement in knowledge transfer of general work processes and information, but also their involvement in knowledge transfer of digital expertise and know-how. For both domains, participants had to indicate how frequently they received information from colleagues and how frequently they sent information to colleagues within the past three months on a five-point Likert-type scale (1 = "strongly disagree" to 5 = "strongly agree"). In doing so, we followed the logic applied by Ellwart et al. (2013) in capturing individual's engagement in knowledge exchange with colleagues. Precisely, we arrived at four distinct dependent variables and respective measures: *general knowledge (GK) sending* ("In the past three months I have shared a lot of knowledge about my daily work with my colleagues. (e.g., work processes, general information)."; *mean* = 3.45; *SD* = 0.98), *general knowledge (GK) receiving* ("In the past three months I have received a lot of knowledge about my daily work from my colleagues. (e.g., work processes, general information).”; *mean* = 2.91; *SD* =1.08), dig*ital knowledge (DK) sending* (“In the past three months, I have shared a lot of knowledge about digital technologies with my colleagues. (e.g., use of software & apps, digital control of machines).”, *mean* = 2.40; *SD* =1.01), and *digital knowledge (DK) receiving* (“In the past three months, I have received a lot of knowledge about digital technologies from my colleagues. (e.g., use of software & apps, digital control of machines).”; *mean* = 2.58; *SD* =1.08).

Relative Subjective Age. In addition to the chronological age, we asked participants to indicate their subjective age by providing an answer to the question “How old do you feel, regardless of your chronological age?”. To ultimately arrive at a measure of an individual's relative subjective age, we followed the procedure by Kunze et al. (2015) and subtracted the respondent’s chronological age from their self-indicated perceived age. Positive values thus indicate that individuals feel older than they are, while negative values imply that individuals feel younger than they are. The resulting scores ranged from -33 to 55 (*mean* = -3.18, *SD* = 9.90). Since it is very likely that the extreme values in this variable are a result of respondents’ fake reporting, we decided to follow the recommendations by Bühner and Ziegler (2017) and removed those individuals whose relative subjective age deviated more than two standard deviations from the sample mean (*n* = 178). The final relative subjective age scores thus ranged from -22 to 15 (*mean* = -3.55; *SD* = 7.16). The distribution of relative subjective age over chronological age groups is illustrated in Figure 12. It reveals that among individuals under 30 years, the deviation of the subjective age from their chronological age is smallest. For all other age groups, the misfit between subjective and relative age is bigger meaning that older individuals more strongly disassociate their perceived age from their actual age. On average, respondents under 30 tended to feel slightly older than they were, whereas respondents over 30 rather felt younger than they were. For instance, 50 percent of the respondents under 30 years had a relative subjective age score between 0 and 2 while 50 percent of the 41- to 50-year-old employees had a relative subjective age score between -10 and 0.

Figure 12

Distribution of Relative Subjective Age over Chronological Age Groups



Note. White horizontal lines represent median values. Grey boxes represent 25^{th} to 75^{th} percentiles. Black lines represent upper and lower adjacent values. Black circles represent outside values.

Controls. In our analyses, we controlled for the demographic variable *gender* (male was coded as 1, female as 2), because the level of (digital) knowledge that employees hold and the intensity to which they engage in exchanging it with others might depend on their gender – be it because of actual differences in traits and interests between men and women, or because of internalized gender stereotypes (Abukhait et al., 2019). Following Trivellas et al. (2015), we also controlled for each respondent's *educational level*, which impacts the degree of knowledge a person already possesses and thus has a direct impact on the amount of knowledge someone can share, or needs to receive. Moreover, we included the information whether a person was in a *leadership position* as a binary control variable. As opposed to standard follower positions, leadership positions already come with the internal function to transfer knowledge to subordinates, and the central position of leaders makes them more likely to engage in knowledge transfer (van Wijk et al., 2008). The number of hours worked was also included in our statistical models, since this very likely shapes an individual's involvement in interpersonal interactions such as knowledge sending and receiving. The probability to teach a colleague or learn something from a coworker is likely higher for employees who work full time than for employees with less working hours. Lastly, we included a binary variable *location* that entailed the information on which of the two production sites an employee worked to ensure that our findings are not biased by organizational differences between the two locations.

5.3.3. Analytical Procedure

To test our study hypotheses, we conducted ordinary-least square regressions at the individual level. Put precisely, for each outcome variable, we first ran a model with the dependent variable chronological age only and, afterwards, included the moderator relative subjective age as well as the interaction term. For all models, we reported results with and without control variables. As previously mentioned, the individuals in our data set were nested in 85 distinct work units. As this nesting, however, can be considered a nuisance that is not of central theoretical interest in our study hypotheses, we followed Reinwald et al. (2021) and used clustered standard errors which account for interdependence between observations from the same work unit. As such, no additional assumptions about the appropriate specification of random effects at the work unit level are necessary (McNeish et al., 2017). Following recommendations by Dawson (2014), all predictor variables were z-standardized prior to hypothesis testing to ensure greater comparability of effect sizes. As illustrated in detail in the robustness checks section, we also tested all hypotheses relying on general linear random-effects models, also known as hierarchical linear models (Snijders & Bosker, 2011) as an alternative approach to account for the nested data structure. All data analysis steps were performed using Stata 17.

5.4 Results

5.4.1. Descriptive Statistics

Table 11 presents the means, standard deviations, and bivariate correlations for all study variables. As theoretically expected, chronological age was negatively correlated with general knowledge receiving (r = -0.17, p < 0.001) and with digital knowledge sending (r = -0.14, p < 0.001). Not aligning with theoretical expectations, age was furthermore also negatively correlated with general knowledge sending (r = -0.11, p < 0.01). With digital knowledge receiving, age displayed no significant correlation (r = -0.03, p > 0.1). The moderator variable relative subjective age was only significantly and negatively correlated with digital knowledge sending (r = -0.10, p < 0.05). The four distinct facets of knowledge transfer (digital/ general knowledge receiving/ sending) showed high intercorrelations. As they do not appear together in a joint statistical model during the data analysis, this should not be a cause for concern. Among the explanatory variables, very few high and significant correlations occur. The only significant bivariate correlations exceeding 0.2 and thus to be considered as high, lie between chronological age and education (r = -0.22, p < 0.01). Since such high intercorrelations are only problematic if they produce multicollinearity, we calculated the Variance Inflation Factors (VIFs) for all explanatory variables. All VIFs fell far below the critical threshold of 10 (*mean* = 1.06; *SD* = 0.02), which speaks against the existence of multicollinearity (Myers, 1990).

Additionally, since our results also hold in models without any control variables, multicollinearity concerns are ruled out.

5.4.2. Hypothesis Testing

Hypotheses 1a-d made claims about the impact of age on different aspects of knowledge transfer. Mirroring these four hypotheses, in Models 1a-d, the effect of age on the four distinct outcome variables is tested. Results are depicted in Table 12. The coefficient of chronological age in Model 1a revealed that there is a significant negative effect of age on general knowledge sending. The older the respondents, the less general knowledge they send (β = -0.12, $p < 0.05$) – which contradicts Hypothesis 1a. Moreover, in Model 1b we find that there is a significant negative effect of age on general knowledge receiving: the older the respondents, the less general knowledge they receive (β = -0.22, $p < 0.01$) – which supports Hypothesis 1b. Model 1c reveals that age has a significantly negative effect on digital knowledge sending (β = -0.16, $p < 0.01$). Hypothesis 1c is thus supported. Finally, Model 1d suggests that chronological age does not significantly affect how much digital knowledge a person receives (β = -0.06, $p > 0.1$), which is why Hypothesis 1d is not supported. As illustrated in the no controls models in Table 12, these results all also hold in models without any control variables.

Table 11

Descriptive Statistics of Focal Study Variables

Variables	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Gender	1.24	0.44	--										
(2) Leadership	0.12	0.32	-0.10**	--									
(3) Working Hours	33.43	3.84	-0.19***	0.03	--								
(4) Education	4.25	2.00	-0.08*	-0.01	0.03	--							
(5) Location	1.83	0.37	-0.05	-0.09**	-0.11**	-0.07*	--						
(6) Chronological Age	48.13	10.71	0.01	0.09*	0.01	-0.22***	-0.03	--					
(7) Relative Subjective Age	-3.55	7.16	0.02	-0.11**	-0.05	0.04	0.05	-0.15***	--				
(8) General Knowledge Sending	3.45	0.98	-0.01	0.09**	0.02	0.03	0.01	-0.11**	-0.06	--			
(9) General Knowledge Receiving	2.91	1.08	0.04	0.01	-0.07*	-0.08*	0.06	-0.17***	0.02	0.44***	--		
(10) Digital Knowledge Sending	2.40	1.01	-0.12***	0.08*	0.04	0.04	-0.02	-0.14***	-0.10*	0.50***	0.28***	--	
(11) Digital Knowledge Receiving	2.58	1.08	-0.02	0.08*	-0.03	-0.10**	0.01	-0.03	-0.06	0.36***	0.56***	0.60***	--

Note. N = 868. * p < 0.05; ** p < 0.01; *** p < 0.001

Table 12

Age Predicting Different Facets of Knowledge Transfer

	Knowledge Transfer:							
	GK sending		**GK receiving**		**DK sending**		**DK receiving**	
Model	**no controls**	**1a**	**no controls**	**1b**	**no controls**	**1c**	**no controls**	**1d**
Constant	3.47*** (0.04)	3.46*** (0.04)	2.89*** (0.03)	2.88*** (0.03)	2.62*** (0.04)	2.62*** (0.04)	2.41*** (0.03)	2.41*** (0.04)
Gender		0.01 (0.04)		0.04 (0.03)		-0.12** (0.06)		-0.02 (0.04)
Leadership		0.10*** (0.03)		0.04 (0.03)		0.10** (0.04)		0.09** (0.04)
Working hours		0.03 (0.04)		-0.06 (0.04)		0.03 (0.04)		-0.02 (0.03)
Education		0.01 (0.03)		-0.12*** (0.03)		0.00 (0.03)		-0.11*** (0.03)
Location		0.02 (0.04)		0.03 (0.04)		-0.02 (0.05)		-0.00 (0.04)
Chronological Age	-0.10** (0.04)	-0.12** (0.04)	-0.18*** (0.06)	-0.22*** (0.05)	-0.15*** (0.05)	-0.16*** (0.04)	-0.03 (0.06)	-0.06 (0.05)
Observations	868	829	870	831	866	827	867	828
R^2	0.01	0.02	0.03	0.05	0.02	0.04	0.00	0.02
F Statistic	5.35	4.98	9.99	10.18	10.67	4.96	0.31	3.62

Note: * p < 0.05; ** p < 0.01; *** p < 0.001.
(GK = General Knowledge, DK = Digital Knowledge)
Standard errors (shown in brackets) account for the clustering of individuals within 85 work units.

Hypotheses 2a-d made claims about the moderating impact of relative subjective age on the relationship between age and the different facets of knowledge transfer. Mirroring these four hypotheses, in Models 2a-c, the interaction term of chronological age with relative subjective age was included. As depicted in Table 13, when explaining general knowledge receiving (Model 2b), digital knowledge sending (Model 2c) and digital knowledge receiving (Model 2d), the interaction terms are negative and significant. Only in Model 2a, which aims to predict general knowledge sending, is the interaction term not significant. This finding contradicts Hypothesis 2a which stated that, with increasing age, general knowledge sending increases when employees feel younger than they are, and that increasing age has no impact on general knowledge sending when employees feel older than they are. What we find is that, with increasing age, general knowledge sending significantly declines, and this decline is not buffered by a low subjective age. Relative subjective age, however, seems to significantly alter the effect that age has on the three other facets of knowledge transfer. To facilitate interpretation and test whether the nature of these interactions was in line with our theoretically assumed mechanisms, we calculated simple slopes for low (*mean – 1 SD*) and high (*mean + 1 SD*) levels of relative subjective age for each of the four models. To additionally identify the ranges of chronological age in which relative subjective has a significant impact, we calculated Johnson-Neyman regions of significance (Johnson & Fay, 1950).

Table 13

The Interaction of Age and Relative Subjective Age in Predicting Different Facets of Knowledge Transfer

	Knowledge Transfer:							
	GK sending		**GK receiving**		**DK sending**		**DK receiving**	
Model	**no controls**	**2a**	**no controls**	**2b**	**no controls**	**2c**	**no controls**	**2d**
Constant	3.46*** (0.04)	3.45*** (0.04)	2.87*** (0.03)	2.86*** (0.03)	2.60*** (0.04)	2.59*** (0.04)	2.39*** (0.03)	2.39*** (0.03)
Gender		0.01 (0.03)		0.04 (0.03)		-0.12** (0.06)		-0.02 (0.04)
Leadership		0.09*** (0.03)		0.04 (0.03)		0.09** (0.04)		0.08** (0.04)
Working hours		0.03 (0.03)		-0.06 (0.04)		0.03 (0.04)		-0.02 (0.03)
Education		0.01 (0.03)		-0.11*** (0.03)		0.01 (0.03)		-0.10*** (0.04)
Location		0.02 (0.04)		0.04 (0.04)		-0.01 (0.04)		0.01 (0.04)
Chronological Age	-0.09* (0.05)	-0.11* (0.05)	-0.13* (0.07)	-0.17** (0.06)	-0.12*** (0.04)	-0.13*** (0.04)	0.01 (0.06)	-0.01 (0.05)
Relative Subjective Age	-0.07* (0.04)	-0.06* (0.04)	0.02 (0.04)	0.02 (0.04)	-0.11*** (0.04)	-0.09** (0.04)	-0.05 (0.03)	-0.03 (0.03)
Chronological Age x Relative Subjective Age	-0.07 (0.04)	-0.06 (0.04)	-0.17*** (0.04)	-0.15*** (0.04)	-0.16*** (0.03)	-0.15*** (0.03)	-0.17*** (0.03)	-0.17*** (0.03)
Observations	868	829	870	831	866	827	867	828
R^2	0.02	0.03	0.05	0.07	0.05	0.07	0.03	0.04
F Statistic	7.53	5.65	13.27	10.22	20.84	17.05	11.59	10.93

Note: * p < 0.05; ** p < 0.01; *** p < 0.001.
(GK = General Knowledge, DK = Digital Knowledge)
Standard errors (shown in brackets) account for the clustering of individuals within 85 work units.

As illustrated in Figure 13, if the relative subjective age is high (i.e., if people have the tendency to feel older than they are), the degree of general knowledge receiving significantly diminishes with increasing chronological age (β = -0.03, p < 0.01). If the relative subjective age, however, is low (i.e., if people have the tendency to feel younger than they are), the negative impact of chronological age on the degree of general knowledge sending disappears (β = -0.00, p= 0.89). The Johnson-Neyman region of significance starts at a chronological age of 56 years, meaning that the buffering effect of a low subjective age applies to employees who are 56 years old and older. This finding supports Hypothesis 2b and emphasizes the notion that older people tend to receive less general knowledge, but that this is not true for old people who subjectively feel younger.

Figure 13

The Effect of Chronological Age on General Knowledge Receiving Conditional on Relative Subjective Age (Model 2b)

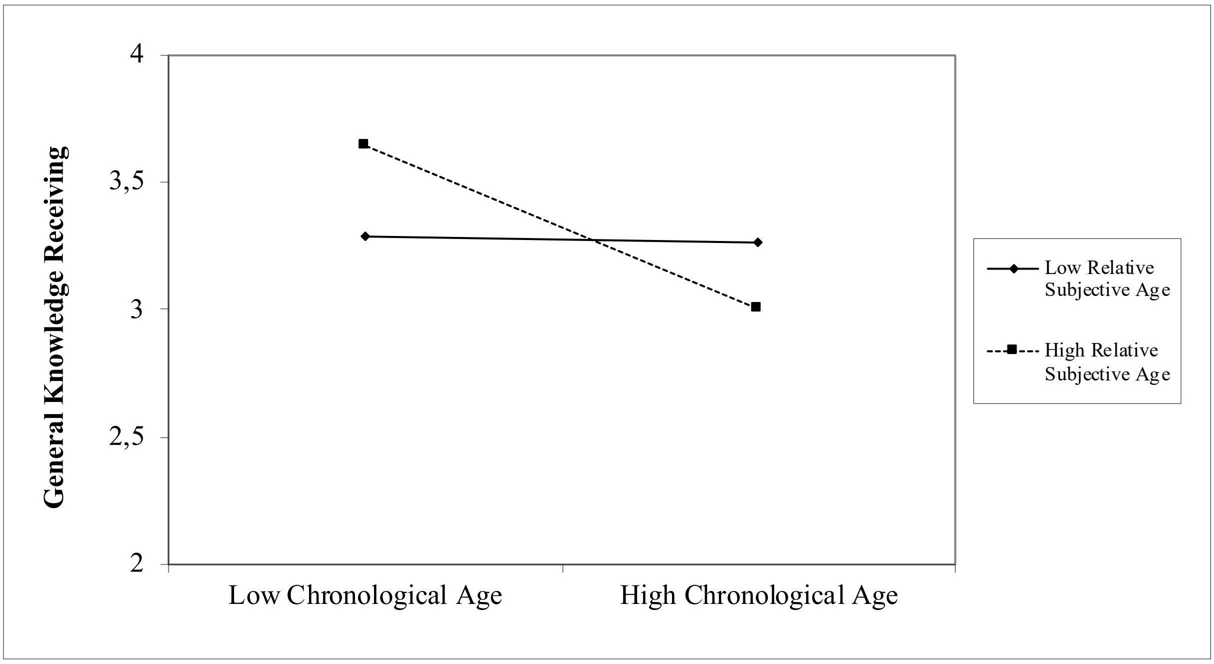
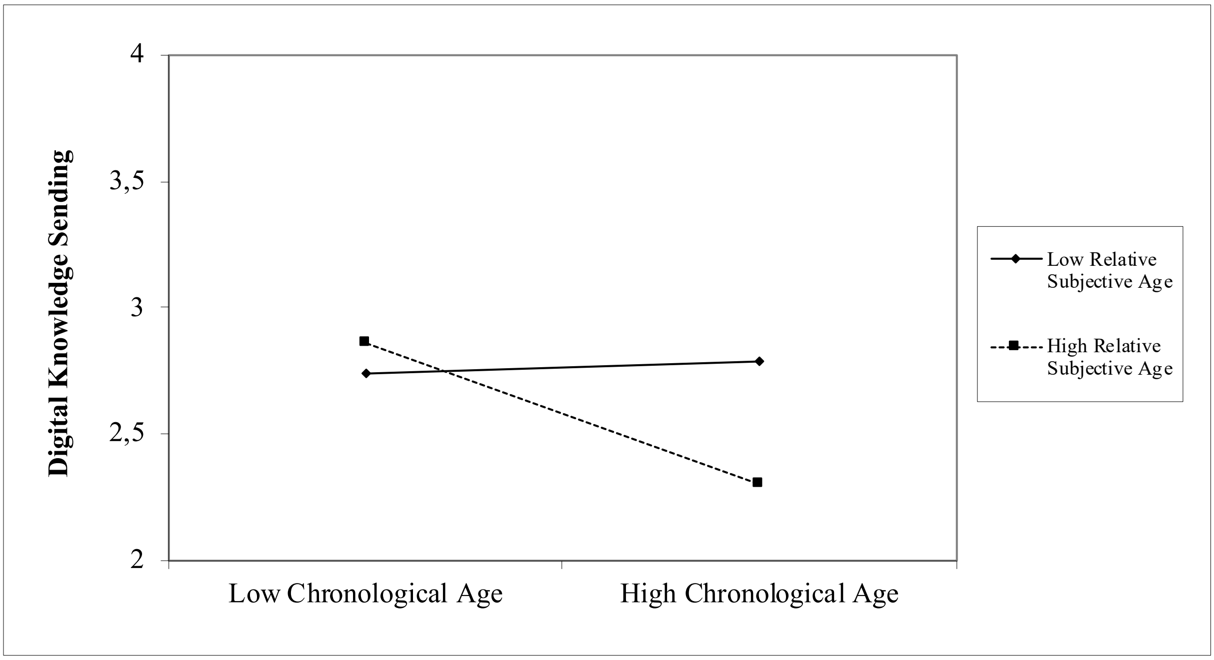


Figure 14 reveals that, if the relative subjective age is high, the degree of digital knowledge sending indeed significantly diminishes with increasing chronological age (β = -0.03, p < 0.01). If the relative subjective age, however, is low, the negative impact of chronological age on the degree of digital knowledge sending disappears (β = -0.00, p= 0.60). The Johnson-Neyman region of significance starts at a chronological age of 47.5 years, meaning that the buffering effect of a low subjectively age applies to employees who are 47.5 years old and older. This finding supports Hypothesis 2c and emphasizes the notion that older people tend to send less digital knowledge, but that this is not true for old people who subjectively feel younger than they are.

Figure 14

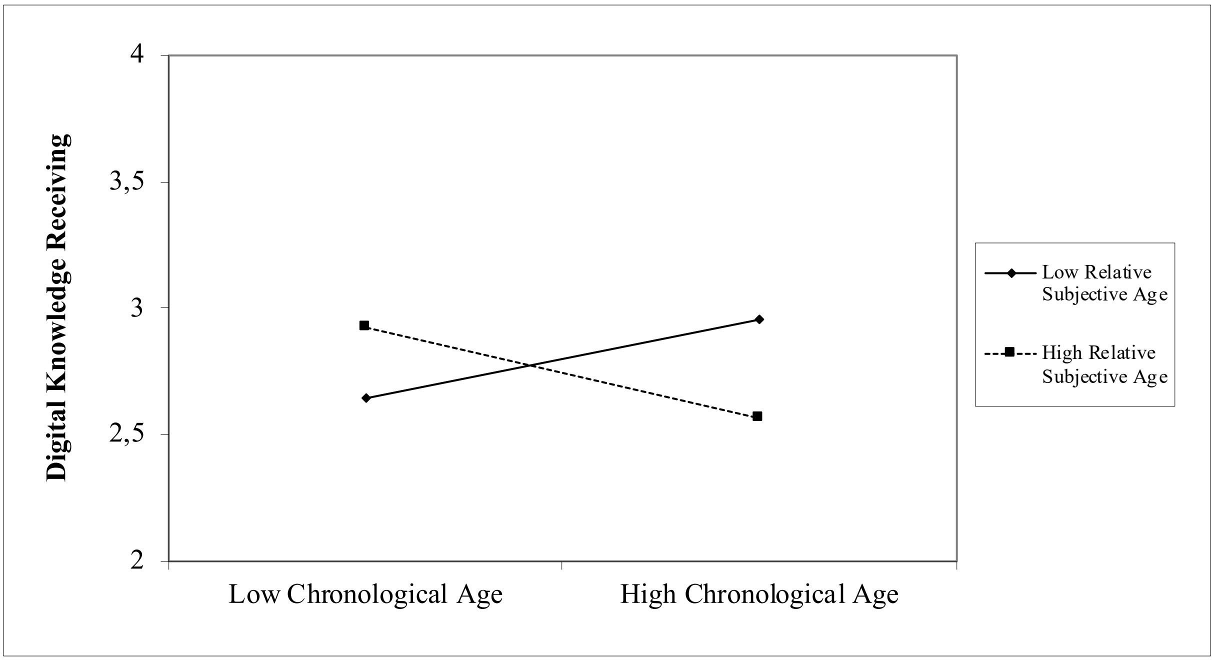
The Effect of Chronological Age on Digital Knowledge Sending Conditional on Relative Subjective Age (Model 2c)



Lastly, a glance at Figure 15 allows for testing Hypothesis 2d. It reveals that if the relative subjective age is high, the degree of digital knowledge receiving significantly diminishes with increasing chronological age (β = -0.02, $p < 0.05$). If the relative subjective age is low (, the negative effect of chronological age does not occur anymore. Rather, it reverses and becomes positive: The older the respondents, the more digital knowledge they receive (β =0.01, $p < 0.05$). The Johnson-Neyman region of significance starts at a chronological age of 50 years, meaning that the reversing effect of a low subjectively age applies to employees who are 50 years and older. This finding supports Hypothesis 2d.

Figure 15

The Effect of Chronological Age on Digital Knowledge Receiving Conditional on Relative Subjective Age (Model 2d)



5.4.3. Robustness Checks

To verify the results' robustness, we conducted the following set of supplementary analyses. First and foremost, as depicted in Tables 12 and 13, we ran all models with and without control variables to ensure that our results do not depend on the inclusion of certain third variables. All results remained the same in terms of direction and significance of effect sizes.

Additionally, as previously mentioned, we applied an alternative to the single-level OLS model with clustered standard errors that considers the nested data structure in a different way. To account for the nesting of individuals I work units, we followed Moser et al. (2022) and applied general linear random-effects model, also known as hierarchical linear model (Snijders & Bosker, 2011) for our model testing. We adopted a stepwise model building procedure to increase the model complexity from step to step by adding random effect predictors (Aguinis et al., 2013). This procedure allowed the testing of the study hypotheses and the evaluation of multilevel model fit. Put precisely, for each outcome variable, we started by performing a so-called null-model, and in a stepwise manner included random intercepts before finally inserting the predictor variables as well as the interaction terms. To contrast the fit of the models, we compared the -2 log-likelihood values in a likelihood-ratio test and the Akaike information criterion, where smaller values indicated better relative model fits (Singer & Willett, 2003). Instead of z-standardization commonly applied in single-level research, we followed Aguinis et al. (2013), and applied the standard centering procedures for multilevel research. Predictors at the individual level were group-mean centered, while predictors at the team level were grand-mean centered.

Moreover, as some work units consisted of a very high number of employees, we reran all models without individuals that were part of a work unit that, in terms of size, deviated more than one standard deviations from the mean work unit size ($n = 288$). In that way, we could exclude bias due to the wide range in work unit size (Bühner & Ziegler, 2017). Patterns of results remained almost exactly the same; the slightly increased p-values very likely are a mere issue of weaker statistical power originating from the strongly reduced sample size (Bates et al., 1992). Similarly, we reran all analyses without those individuals that were part of a single-person work unit, since knowledge transfer processes might differ in work settings were individuals work entirely alone. As a last robustness check, we also included the study participants that previously were classified as extreme outliers in the relative subjective age measure and replicated our findings. All supplementary analyses thus spoke in favor of the robustness of our initial results. A detailed illustration of all supplementary analyses' results is available upon request.

5.5 Discussion

Our aim with this study was to analyze, first, whether the chronological age of blue-collar employees influences their level of engagement in *general* and *digital* knowledge exchanging among coworkers and, second, how this impact of chronological age gets buffered or reinforced by individuals' subjective age. Drawing on socioemotional selectivity theory (Carstensen, 2006), we argued that, with regard to *general knowledge*, chronological age is positively related to knowledge sending but negatively related to knowledge receiving. With regard to *digital knowledge*, however, we argued that chronological age is negatively related to both knowledge sending and receiving. Our analyses partly met these theoretical expectations. Chronological age was found to decrease general knowledge sending, general knowledge receiving, and digital knowledge sending and to be unrelated to digital knowledge receiving. These findings suggest that the older blue-collar employees get, the less active they are in knowledge exchange both as knowledge senders and as knowledge recipients. Only the receiving of digital knowledge does not decrease with age – eventually because certain needs from various age groups could balance out: While younger employees might already possess high levels of digital knowledge, older employees might feel the necessity to acquire such knowledge for the future (Hampel & Kunze, 2023).

Furthermore, we expected the impact of chronological age on knowledge exchange to be altered by individuals' relative subjective age (Carstensen, 2006). For all four facets of knowledge exchange, we found that for employees who subjectively feel older, a negative effect of chronological age on knowledge exchange occurs. For three of the four facets of knowledge transfer, however, such age differences in knowledge exchange entirely diminish for employees who subjectively feel younger. In the case of digital knowledge receiving only, the negative effect even reverses and becomes positive for employees who subjectively feel younger. Summarizing, it can be said that increasing chronological age reduces many facets of knowledge exchange among blue-collar workers. A low subjective age, however, prevents employees with increasing age from reducing their engagement in knowledge transfer. In the case of digital knowledge, it even makes them learn more from their colleagues the older they get.

5.5.1. Theoretical Implications

By analyzing knowledge sharing and receiving behavior among blue-collar workers of all age groups, we contribute to existing literature in several ways. Overall, this work helps to shed light on knowledge exchange in an under researched group, blue-collar workers with manufacturing tasks (Gerpott et al., 2017; Muniz Jr et al., 2022; Nakano et al., 2013). With demographic change as well as challenges due to Industry 4.0 further shaping their work, blue-collar employees with manufacturing tasks face "unprecedented career challenges" (Chin et al., 2019, p. 397). By differentiating between different types of knowledge shared and received, we contribute to the growing literature on knowledge exchange and incorporate suggestions made by several authors (Fasbender et al., 2021; Gao & Nee, 2018)

In doing so, we use socioemotional selectivity theory (Carstensen, 2006) to explain the dynamics behind knowledge sharing for blue-collar workers. While we expected older blue-collar employees to disengage as both senders and receivers of digital knowledge due to their prioritization of emotionally meaningful activities and perceived limited future time, our results confirm and further expand this perspective (Gerpott et al., 2017). Furthermore, we do not find support for the classical generativity argument that older workers tend to share their knowledge and expertise with younger colleagues, but instead reveal that older employees also tend to disengage from general knowledge transfer, contrary to common assumptions in the literature that older workers typically act as primary knowledge senders due to their expertise and experience (Dietz et al., 2022; Doerwald et al., 2021). Thus, our results challenge existing research on intergenerational knowledge exchange and suggest that, in assembly lines, sharing and receiving behavior does not take place as often as assumed.

Moreover, our findings align with existing literature identifying younger employees as the primary holders and sharers of digital expertise (Gerpott et al., 2017; Hampel & Kunze, 2023; Prensky, 2001a). Even though Gerpott et al. (2017) indicated similar patterns for knowledge on computers and new technologies, we quantitively linked younger employees' experience with digital technologies with their knowledge sharing on using them (Hampel & Kunze, 2023). Younger workers are more engaged in digital knowledge exchange, driven by a greater comfort with technology and motivation to acquire future-oriented skills (Carstensen, 2006; Fasbender et al., 2021; Prensky, 2001a). As digital tools become more prevalent in blue-collar settings, younger employees lead this exchange and readily integrate these technologies into their work (Waschull et al., 2022).

Building on this, our study reveals that subjective age plays a significant moderating role in the relationship between chronological age and knowledge exchange, further aligning with socioemotional selectivity theory (Carstensen, 2006). All significantly negative paths from chronological age to knowledge exchanging behavior turn out to be non-significant for employees who feel younger than their chronological age indicates. By maintaining a younger subjective age, older workers effectively counter the disengagement typically associated with aging, particularly for those who feel closer to the end of their career trajectory (Lazazzara &

Za, 2020). Thus, we extend existing research on subjective age on organizational outcomes in general (Kunze et al., 2021; Kunze et al., 2015) but also specifically on its importance for intergenerational knowledge exchange trajectories (Lazazzara & Za, 2020).

5.5.2. Practical Implications

For several reasons, it should be in the interest of manufacturing companies to support high levels of knowledge exchange among employees of various age groups. Our study provides fruitful insights on how this can be achieved. If, especially during current times of demographic change, knowledge transfer between employees is ensured, organizations are well-placed to withstand the threat of big demographic shifts without losing valuable knowledge when employees leave the company or retire. For a successful digital transformation of the workplace, it is necessary for all employees to constantly update and share their knowledge to incorporate such new technologies at work. Therefore, our study offers important practical implications.

First, we offer timely and relevant insights on how to prevent a decreasing willingness to participate in knowledge exchanging behavior of aging blue-collar workers. Our results emphasize that old employees do not disengage from knowledge exchange as long as they are of low relative subjective age. Managers in the manufacturing sector could see this as an opportunity considering that, while the chronological age is fixed, the subjective age can be influenced (Weiss & Weiss, 2019). Our results revealed that the chronological age range where a low subjective age can operate as a buffer begins between 47.5 and 56 years – depending on knowledge transfer type. Supporting employees of these age groups in staying subjectively young should therefore be a main goal of organizations. Concrete measures that stimulate the workforce to feel younger could, for instance, be the designing of stimulating tasks with a high level of autonomy. In the blue-collar sector, this could be achieved by job enlargement (e.g., adding responsibilities to a job) and job enrichment (e.g., making tasks less repetitive) (Kunze et al., 2015). Moreover, establishing HR-management practices with the goal to encourage a positive climate and attitude on aging could contribute to decreasing subjective age among employees (Wegge et al., 2012). With our study, we follow the call by Boehm et al. (2014) to offer these HR-management practices in an age-inclusive and diversity-friendly way.

While implementing these suggestions is a rather long-term measure for companies that might only unfold its effect over time, we furthermore suggest a more immediate organizational intervention that could prevent the acute shortage of critical knowledge in the manufacturing sector during demographic change. As our results revealed, the transfer of knowledge that is possessed by older employees to younger colleagues (and vice versa) is not guaranteed, since older employees generally tend to engage in knowledge exchanging behavior than their younger counterparts. In order to possess and retain the highest possible amount of knowledge, work teams should thus not exclusively consist of individuals of the same age group, since those could then simply lack the knowledge typically possessed by representatives of other age groups. We thus encourage managers in the manufacturing sector to allocate age-diverse work teams and recruit new candidates from all age groups. Moreover, especially with regard to the imminent incorporation of digital technologies to the workplace, approaches like reverse mentoring could help to foster existing knowledge within the organization on the usage of such technologies.

5.5.3. Limitations and Suggestions for Future Research

Besides several strengths, such as a large sample of nested data in a manufacturing work setting, our study suffers from some limitations. First and foremost, the detection of causal conclusions is limited by the cross-sectional nature of our data, which also comes with the risk of common method biases (Podsakoff et al., 2003). While chronological age as an objective demographic information might be less affected, our measures of relative subjective age and knowledge exchange are at risk for common method variance. To prevent overestimated effect sizes, future research could split the surveys and gather data on the predictors prior to the outcomes (Ohly et al., 2010). Alternatively, replacing the self-assessed knowledge exchange measures with more objective evaluations from coworkers or supervisors (2018) or even measure the degree of knowledge transfer via objective markers at the team level (Ellwart et al., 2013) would contribute to a more valid and unbiased measure.

Linking directly to this, our operationalization of knowledge transfer contains room for improvement. Our distinction in the dimensions *general* and *digital* knowledge is not yet established in prior work, and it can be disputed whether digital knowledge indeed is completely distinct from general knowledge, rather than a component thereof. However, we would like to emphasize that the distinction arose from detailed consultation with practitioners from the company at hand: In the manufacturing context, where employees work on assembly lines, our distinction applies: General knowledge about daily work processes and general expertise on the job has been and is essential up until today. Digital knowledge is different to that in a way that it (a) contains know-how on the specific use of technologies such as the use of tablets or digital software to control machines, and (b) its adoption in assembly lines is on the verge but not yet fully executed (Waschull et al., 2022). Nevertheless, as recommended by Reinholt et al. (2011), our general and digital knowledge-exchange measures would benefit from a dyadic measurement approach that unifies the sender with the receiver perspective of knowledge exchange (by averaging the sender and the receiver assessments, Burmeister et al., 2018) and uses multiple-item rather than single-item scales. Factor analyses could then also test the applicability of the dimensions *general* and *digital* knowledge introduced by us.

In a similar vein, one might discuss the selection and measurement of our moderator variable relative subjective age. Critics of the construct argue that it does not provide insights above those of other constructs such as chronological age or locus of control (e.g., Rudolph & Zacher, 2020). With our empirical finding that subjective age only has an impact on chronologically old employees but does not affect chronologically young employees, we join Drazic and Schermuly (2021) in arguing that the critique might only apply to certain age groups. For other age groups, however, subjective age is decisive for a whole set of important work-related outcomes (Akkermans et al., 2016; Kunze et al., 2015; Nagy et al., 2019). Furthermore, with our operationalization of relative subjective age as the discrepancy between the chronological and the subjective age we followed Kunze et al. (2015). Recent research, however, is starting to introduce multi-item scales to capture the possible multi-faceted nature of the construct subjective age (e.g., Kunze et al., 2021; Rudolph et al., 2019).

5.6 Conclusion

Based on the two current mega trends demographic change and workplace digitalization, our study analyzed the role of chronological as well as subjective age of blue-collar employees in shaping intra-organizational knowledge transfer processes. Results revealed that increasing age reduces many facets of knowledge exchange among blue-collar workers. A low subjective age, however, prevents older employees from reducing their engagement in the exchange of general as well as digital know-how. With this result, we contribute to the literature by emphasizing that the assumed mechanisms of knowledge transfer might not apply to the manufacturing sector. Our results furthermore offer direct practical implications for manufacturing companies to implement measures that support employees in staying subjectively young and for managers of blue-collar teams to allocate age-diverse work units. With that in mind, organizations should be well-equipped to successfully handle the digital transformation during times of demographic change without losing organizational knowledge.

General Discussion

5.7 Summary and Integration

This dissertation set out to examine how aging employees, both in white-collar and blue-collar occupations, navigate the complex challenges posed by New Work – challenges that are primarily driven by the intertwined forces of digitalization and demographic change. As organizations increasingly embrace digital technologies, comprehending the factors that enable or hinder successful adaptation by workforces of different age groups has become critical. To better understand how aging employees in white- and blue-collar occupations react to these challenges, and how organizations can offer support, I conducted four studies that concentrated on key aspects influencing how employees engage with the changing work environment. In doing so, Study 1 and 2 took a white-collar perspective, while Study 3 and 4 centered on blue-collar employees.

With Study 1, my co-author Florian Kunze and I aimed to answer this dissertation's first research question, which inquired about the distribution of digital fluency among white-collar employees of various age groups. Overall, we generally assumed age to be negatively related to employees' level of digital fluency. Using a sample of 1,007 employees with engineering office tasks from a German industrial company operating in the automotive sector, we found support for the digital hypothesis (Prensky, 2001a), as older employees significantly perceived lower levels of digital fluency than younger employees. Furthermore, based on stereotype embodiment theory (Levy, 2009), we suggested that negative age stereotypes and developmental supervisor support act as moderators of the negative relationship between age and digital fluency. Our results confirmed these assumptions, as older employees who internalized negative age stereotypes reported significantly lower levels of digital fluency, while younger employees' digital fluency levels remained unaffected by holding such stereotypes. Moreover, developmental supervisor support also played a critical role in shaping the outcomes. Older employees with high negative age stereotypes and low developmental supervisor support exhibited the lowest levels of digital fluency. However, when older employees received strong supervisor support and did not agree to such ageist stereotypes, the age differences in digital fluency perceptions diminished. This study extends our understanding of aging and digitalization in the workplace in several ways. First, it provides empirical support for the digital divide hypothesis, showing that older employees report lower levels of digital fluency, even after controlling for factors like education and tenure. Additionally, it highlights the moderating role of negative age stereotypes and the crucial impact of developmental supervisor support on older employees' digital fluency. This research contributes to both the literature on digital competencies and ageist stereotypes (Lagacé et al., 2016; Oberländer et al., 2020; Rahn et al., 2021; van Vianen et al., 2011), demonstrating how personal beliefs and workplace support shape employees' confidence and ability to use digital technologies effectively.

In Study 2, I explored how decision-making autonomy in remote work arrangements impacts aging white collar employees' well-being and performance. Using representative data from the German workforce with 639 white-collar employees, the results showed that employees whose managers predominantly dictated the remote work arrangement reported significantly higher levels of emotional exhaustion and loneliness. However, this managerial control did not substantially affect productivity-related outcomes such as performance or engagement. Furthermore, individual, team-level, as well as organizational decision-making of remote work did not lead to differences in employees' well-being or performance. Interestingly, while leadership consideration showed a marginal moderating effect on performance, age did not influence the relationship between decision-making authority and well-being or productivity outcomes meaning that different age groups are not affected differently by decision-making authority levels. These findings emphasize the importance of self-determination and autonomy in maintaining employee well-being in remote work environments and underscore the potential negative effects of managerial control without incorporating employees' perspectives in this context (Lopes et al., 2023; Ryan & Deci, 2000).

With Study 3, I aimed to explore whether blue-collar employees of different age groups are ready to embrace digital changes in the workplace, particularly in the context of the ongoing digital transformation in organizations. Drawing on socioemotional selectivity theory (Carstensen, 2006), I hypothesized that older blue-collar employees would feel less prepared for digital change compared to their younger colleagues due to perceived future time perspectives and lower career prospects in times of digitalization and automation. Additionally, I examined whether this relationship between age and readiness for digital change would be influenced by work-related factors such as technological insecurity and promotion-oriented change communication. Using a sample of 1,165 blue-collar employees from a German automotive supplier company, I found that chronological age was negatively associated with emotional, cognitive, and intentional readiness for digital change. Furthermore, technological insecurity played a partial moderating role in this relationship. Employees with low levels of technological insecurity, especially younger workers, were more willing to commit to digital change. However, when technological insecurity was high, age differences in readiness for change became insignificant. Contrary to my expectations, promotion-oriented change communication did not moderate the relationship between age and readiness for digital change, nor was the predicted three-way interaction between age, technological insecurity, and promotion-oriented communication supported by the data. However, both technological insecurity and promotion-oriented communication had strong direct effects on readiness for change – technological insecurity negatively impacted readiness, while promotion-oriented communication had a positive influence. Thus, Study 3 extends socioemotional selectivity theory (Carstensen, 2006) to blue-collar workers, showing age-related declines in readiness for digital change due to limited future time perspectives. Technological insecurity moderates this effect, with insecurity reducing age differences in readiness (Huang et al., 2021). Lastly, promotion-oriented communication boosts readiness across all age groups, reinforcing the importance of framing digital transformation as an opportunity for growth (Stam et al., 2018).

Lastly, with Study 4, my co-author Sophie Moser and I aimed to investigate how the chronological age of blue-collar employees affects their engagement in both general and digital knowledge exchange, and whether this relationship is influenced by subjective age. Drawing on socioemotional selectivity theory (Carstensen, 2006), we hypothesized that chronological age would be positively related to general knowledge sending but negatively related to general knowledge receiving. In contrast, we expected that chronological age would be negatively related to both the sending and receiving of digital knowledge, as older employees tend to prioritize emotionally meaningful activities and may feel less motivated to engage with future-oriented digital skills. Additionally, we examined whether subjective age – how old employees feel compared to their actual age – moderates these relationships. Using a sample of 1,165 blue-collar employees from a German automotive manufacturing company, we found chronological age to be negatively associated with both general knowledge sending and receiving, as well as digital knowledge sending, and had no significant relationship with digital knowledge receiving. These findings suggest that older blue-collar employees are, compared to their younger colleagues, less likely to engage in knowledge exchange overall. However, subjective age played a key moderating role in these relationships. For employees who subjectively felt younger than their chronological age, the negative effects of age on knowledge exchange diminished or even reversed. Specifically, for digital knowledge receiving, feeling younger led to a positive effect of age, indicating that older workers with a younger subjective age were more engaged in learning digital skills. Thus, Study 4 sheds light on intergenerational knowledge exchange in blue-collar settings, revealing that older employees are less active in sharing both general and digital knowledge, but subjective age can buffer this decline. This extends socioemotional selectivity theory to blue-collar workers, showing that subjective age plays a crucial role in maintaining knowledge exchange behaviors, particularly in the context of digital knowledge (Carstensen, 2006; Kunze et al., 2021; Lazazzara & Za, 2020).

Across the four studies, several overarching themes emerged that provide deeper insights into how aging employees in white-collar and blue-collar occupations engage with the challenges posed by New Work, primarily driven by digitalization and demographic change. First, a consistent finding across Studies 1, 3, and 4 is the negative relationship between age and digital engagement. In Study 1, older white-collar employees reported lower levels of digital fluency, while in Study 3, older blue-collar employees demonstrated reduced readiness for digital change. Similarly, in Study 4, chronological age was negatively associated with both general and digital knowledge sharing. These results align with socioemotional selectivity theory (Carstensen, 2006), suggesting that as employees age, their priorities shift towards emotionally meaningful activities, making them less likely to engage with future-oriented tasks such as digital adaptation.

However, the findings across the studies also reveal that age is not a fixed barrier to the engagement with digital technologies or knowledge sharing. Various moderating factors significantly shape these relationships. In Study 1, negative age stereotypes and developmental supervisor support moderated the age-digital fluency relationship. Integrating insights from stereotype embodiment theory (Levy, 2009), we found that older employees who internalized negative age stereotypes had lower levels of digital fluency, but strong developmental support from supervisors significantly mitigated this effect. Similarly, in Study 3, technological insecurity moderated the relationship between age and readiness for digital change. While younger employees with lower technological insecurity were more receptive to digital change, higher insecurity levels diminished age-related differences in readiness, highlighting the importance of emotional and job security during organizational transformations (Huang et al., 2021).

Furthermore, subjective age emerged as a crucial moderating factor in Study 4, illustrating that employees' perceptions of their own age can significantly influence their engagement in knowledge sharing. While chronological age was generally found to be negatively related to knowledge sharing behaviors, the results showed that when older employees felt younger than their actual age, they were more likely to engage in both general and digital knowledge exchange. In fact, for digital knowledge receiving, feeling younger even reversed the negative impact of chronological age, making older workers more willing to learn new digital skills. This highlights the role of subjective age in mitigating the disengagement typically associated with aging and aligns with socioemotional selectivity theory (Carstensen, 2006), which emphasizes the psychological dimensions of aging. These findings suggest that subjective age can serve as a buffer against the decline in knowledge sharing and digital adaptation often seen in older employees, offering new insights into how organizations can leverage subjective age to enhance engagement across all age groups (Goecke & Kunze, 2020; Kunze et al., 2021).

5.8 Practical Implications

The findings of my dissertation offer several actionable insights for organizations navigating the challenges of digital transformation, evolving work environments, and demographic change. By addressing these insights, decision-makers in organizations can provide better support for aging white-collar and blue-collar workers in adapting to the future of work.

First, this dissertation highlights the unique challenges that both white-collar and blue-collar employees face when adapting to the digital transformation in their organization, with older white-collar workers reporting lower levels of digital fluency and older blue-collar workers demonstrating reduced readiness for digital change. The findings underscore the importance of creating work environments that actively support successful aging in the workplace (Zacher, 2015). Overall, negative ageist stereotypes about the limited capacity of older workers' adaptiveness to digital transformations can lead to internalization and self-stereotyping, further hindering their confidence and willingness to learn digital competencies. To counter such stereotypes, organizations should foster a culture that values continuous learning and development for all employes regardless their chronological age (Zacher & Yang, 2016). To create such culture, "organizational leaders as the main carriers of culture could act as positive role models and help to create a work environment that facilitates successful aging" (Zacher & Yang, 2016, p. 9). Supervisors also play a pivotal role in this process, as they offer developmental support and guidance that can enhance older employees' confidence in their abilities to adapt to changing work environments, and can mitigate existing age stereotypes and their effects (Dvir et al., 2002; Maurer et al., 2002; Noe & Wilk, 1993; van Vianen et al., 2011).

Closely related to that, employees' perspectives on aging and their perceived future time can be expressed through subjective age. This dissertation shows that older employees who feel younger than their chronological age are more engaged in knowledge sharing, particularly in receiving digital knowledge. Organizations should therefore consider regularly assessing employees' perceptions of their age to identify areas where large variations in subjective age may be emerging as patterns (Kunze et al., 2021). Further, interventions aimed at aligning employees' subjective age with their work goals, such as offering meaningful and challenging tasks, can help to promote a more youthful self-perception, encouraging older employees to feel capable and motivated to engage in learning new competencies (Kunze et al., 2015).

Furthermore, the findings from Study 2 are particularly relevant for organizational leaders and decision-makers responsible for shaping remote work policies. The results demonstrate that when decisions about remote work arrangements are primarily made by employees' direct managers, this leads to higher levels of emotional exhaustion and loneliness for employees, regardless of age. To counter this, organizations should implement participatory decision-making structures that involve employees in shaping their remote work schedules to increase autonomy and foster individual well-being. This is particularly important in light of public concerns expressed by organizational leaders about the lack of employee productivity and engagement when working remotely (Werner, 2022), although such claims are not based on existing scientific evidence (Bloom et al., 2015; Gajendran & Harrison, 2007). My findings suggest that organizational frameworks and policies on remote work arrangements do not have a significantly different impact on well-being and productivity compared to individual and team-based decisions. Therefore, organizations should create opportunities for collaborative input at the individual, team, and organizational levels and also ensure flexibility through regular feedback mechanisms that allow remote work agreements to be adjusted as needed. By fostering a culture of autonomy, participation, and adaptability, organizations can ensure employee well-being and prevent feelings of injustice.

Moreover, employees in blue-collar occupations face specific challenges when adapting to the evolving work environment due to digitalization and automation (Cillo et al., 2019; Waschull et al., 2022). While I suggested in Study 3 that technological insecurity exacerbates age differences in employees' readiness for digital change, the results indicated that technological insecurity affects blue-collar employees across all age groups equally. For organizations, this highlights the need to address concerns on technological insecurity across all age groups in the blue-collar workforce. Beyond providing ongoing training to develop digital competencies, organizations should implement promotion-oriented change communication strategies, which were also shown to significantly influence employees' readiness for digital change. By framing digital transformation as an opportunity for growth and improvement, this type of communication can help alleviate concerns and foster a more positive outlook toward new technologies (Stam et al., 2018). Clear and consistent change communication could ensure that employees of all ages understand the benefits of the digital transformation and develop readiness for change.

Finally, as the workforce continues to age and a large number of older employees approach retirement, the findings from Study 4 underscore the importance of effective knowledge sharing within organizations, particularly in light of ongoing digital transformation. My results show that older blue-collar employees are less likely to engage in both general and digital knowledge exchange, which poses risks of knowledge loss as they near retirement. To mitigate this, organizations should foster a culture of intergenerational knowledge transfer, ensuring that older workers feel valued and motivated to share their expertise with younger colleagues but also are open to receive knowledge. Overall, recognizing that older and younger employees may differ in their motivations and tendencies when it comes to sharing and receiving knowledge, organizations should foster an age-inclusive climate to counter these barriers (Dietz et al., 2022). Also, implementing reverse mentoring, where younger employees mentor older colleagues, can prevent a widening digital divide by enhancing older workers' digital fluency, while younger employees benefit from the experience of their senior counterparts, fostering a two-way exchange of knowledge and stronger intergenerational collaboration (Dietz et al., 2022; Kaše et al., 2019).

5.9 Overall Limitations and Avenues for Future Research

In addition to the specific limitations of each study (see Chapter 2.5.3, Chapter 3.5.3, and Chapter 4.5.3), this dissertation also faces overarching limitations that cut across the entire research effort and merit further consideration. The first key limitation of this dissertation lies in the challenge of establishing strong causal relationships. Although the relationships observed between chronological age, digital fluency, decision-making authority of remote work, employee outcomes, readiness for change, and knowledge exchange behaviors offer significant contributions to understanding aging workforce adaption in digitalized environments, all four studies rely on cross-sectional data, limiting the ability to capture the temporal dynamics of these relationships. Although I use large samples that provide a solid foundation for identifying patterns across different age groups and work contexts, it remains unclear how these variables evolve over time, particularly as the rapid advancements in digitalization, automation, and flexibilization of the workplace continue to reshape organizational structures and demands for both white-collar and blue-collar employees. Thus, future research would benefit from employing longitudinal approaches and investigate how these trends impact the long-term development and adaptation of aging employees.

Another related limitation lies in the inability to randomize the independent variables in the field settings of the studies presented in this dissertation. Randomization is a key element in establishing causal relationships, as it ensures the exogenous manipulation of predictor variables (Morgan & Winship, 2012). Without randomization, the interpretation of causal effects may be compromised by potential endogeneity issues, such as omitted variable bias, simultaneity, or reverse causality (Antonakis et al., 2010). Although several efforts were made across all studies to minimize such biases, future research could explore experimental or quasi-experimental designs to further strengthen the causal interpretation of the findings (Shadish et al., 2002).

Furthermore, the empirical focus of all four studies is on the German labor market, which may limit the overall generalizability of the findings. Even though the German work context is affected by the trends of digitalization, automation, and demographic change in a similar way to other developed economies such as the United States, the United Kingdom, or Japan, differences in the precise demographic transitions, labor market regulations, or in their specific education systems may lead to different responses and possibilities for adaption (Bührer & Hagist, 2017). Therefore, future studies could broaden the scope by including international comparisons and investigate whether the proposed relationships are context-specific or hold universally.

Additionally, another limitation stems from the reliance on self-reported data, which can introduce common method bias (Podsakoff et al., 2003). Self-reported measures may result in biases such as social desirability, particularly in capturing constructs like digital fluency and readiness for change. Still, these constructs are reflective of personal attitudes, perceptions, and individual experiences, making self-reports particularly valuable for capturing how individuals engage with digital transformation. Also, the inclusion of chronological age as an objective measure that remains stable provides a reliable basis for comparison. Despite these efforts, future research could benefit from adopting multi-source or observational data collection methods to further minimize potential biases and provide a more holistic understanding of workforce adaptation in digitalized environments.

Closely related to that, the primary focus of this dissertation is on individual-level factors, offering valuable insights into how personal characteristics shape adaptation to digital transformation for younger and older employees in both white-collar and blue-collar occupations. While I also incorporate factors into the models that typically operate at other levels, such supervisory support or change communication promoted by the organization, they were still measured at the individual level, based on the employees' perceptions. Thus, future research could benefit from assessing these variables at multiple levels, allowing for a more comprehensive analysis of how colleagues, supervisors, and organizations jointly shape aging employees' perceptions of digital transformations at organizations.

Also, while this dissertation focuses on white-collar and blue-collar employees and offers important insights how these work groups uniquely experience work transformations, its scope is, to a certain degree, limited: As all studies except Study 2 on remote work decision-making were conducted within the industrial sector, other industries, such as the service or creative sectors, are not represented. For example, employees with pink-collar jobs typically have roles in the health care sector and might face unique challenges in adapting to digitalization, given the high degree of interpersonal interaction and emotional labor involved in their work (Lips-Wiersma et al., 2016). Closely related to that, the differentiation between white-collar and blue-collar work is not always clear-cut, as roles and responsibilities often overlap or blur in modern work environments (Waschull et al., 2022). Future studies could therefore broaden the scope and follow an integrative approach among employees from all different sectors and industries.

Beyond the limitations, the findings of this dissertation also open up several avenues for future research. One critical area for further exploration lies in the deeper understanding of how, when, and why aging employees adapt to evolving work environments. Specifically, the psychological mechanisms that influence older employees, such as self-stereotyping and subjective age, offer rich potential for further investigation. As this dissertation has shown, negative age stereotypes can, when internalized, may exacerbate potential age differences in digital fluency levels. Therefore, future research should focus on examining the particular conditions under which self-stereotyping is most pronounced (Levy, 2009). Lagacé et al. (2016) highlighted the role of ageism in fostering psychological and digital disengagement among older workers. Future studies should further explore how ageist stereotypes are developed, disseminated and internalized, and how exactly they lead to digital disengagement for both white-collar and blue-collar workers. Closely related to that, subjective age was shown to play a crucial role in determining how older blue-collar employees engage in digital knowledge sharing. While Kunze et al. (2015) elaborated on antecedents and consequences of subjective age, future research should focus on how subjective age is shaped and influenced by digital technologies and, on the other hand, how it shapes technology adoption. Understanding that relationship could provide deeper insights into the mechanisms that promote or hinder older employees' engagement with digital tools at work and contribute to socioemotional selectivity theory (Carstensen, 2006). To further explore how psychological mechanisms like negative age stereotypes or the subjective age affect employees, longitudinal studies might be particularly necessary, as they can track how these mechanisms evolve and develop over time.

With remote work becoming a permanent feature of modern white-collar workplaces, my findings open room for future research on the participatory decision-making structures and their particular impact on employees. Specifically, I found older employees whose managers mainly determine their share of remote work to report higher levels of exhaustion and loneliness, while individual, team, and organizational decision-making did not lead to different outcomes. According to SDT (Ryan & Deci, 2000), employees need to perceive autonomy to be motivated and productive. Future research might want to investigate how the interplay of decision-making authority levels like, for instance, managers who follow organizational recommendations but consider individual preferences allow employees to perceive feelings of autonomy. Also, it would be valuable to further explore contextual factors that might moderate this interplay. Also, as remote work primarily applies to white-collar employees, this leaves open questions regarding the experience of blue-collar workers, who may lack similar opportunities for autonomy and flexibility. Remote work inequalities, as shown in studies like Ewers and Kangmennaang (2023), highlight how disparities in access to autonomy and control can affect worker well-being and productivity. Combined with the continuing blurring of white-collar and blue-collar tasks (Waschull et al., 2022), future research should explore how organizations in the future can support employees of all occupations to experience autonomy in times of increasing workplace flexibility.

Another important avenue for future research lies in understanding how blue-collar employees adapt to digitalization, automation and workplace transformation. Blue-collar roles, traditionally centered around manual labor, have increasingly begun to incorporate digital tools, automation, and advanced technologies (Waschull et al., 2022). As demonstrated in Study 3, older blue-collar employees are generally less ready to commit to digital change in their organization than younger colleagues. However, my results also point towards the crucial roles of technological insecurity feelings and promotion-oriented change communication. Future research should therefore explore the underlying mechanisms through which technological insecurity impacts blue-collar workers adaptiveness to the digital change, particularly focusing on the use of new digital technologies at work and extending the scope of TAM for blue-collar employees (Höyng & Lau, 2023). The rise of artificial intelligence should also open up new challenges and perspectives for blue-collar workers that call for future research (Meisinger, 2023). Further, examining how promotion-oriented change communication can be leveraged to reduce insecurity feelings and foster a positive perception of digital transformation across all age groups is crucial (Stam et al., 2018; Van den Heuvel et al., 2009).

Finally, as a large number of older employees approach retirement in the context of ongoing demographic change, knowledge exchange becomes increasingly critical for organizations and researchers in the field of organizational behavior. With changing work environments and the increased use of digital technologies, future research should further explore how intergenerational knowledge transfer evolves over time and how career prospects such as future time perspective (Carstensen et al., 2003) may influence knowledge receiving and sharing behaviors. With increased age diversity in teams due to the demographic change (Hertel et al., 2013), it becomes crucial to understand how different age groups interact and share knowledge, and how barriers due to ingroup-outgroup associations can be reduced (Van Knippenberg & Schippers, 2007). In particular, factors that encourage older employees to engage in knowledge exchange will be important to explore, as we found that older blue-collar employees share and receive significantly less knowledge than younger colleagues. Closely related to that, the digital transformation also directly affects the knowledge shared in organizations. While in our study, we differentiated between general and digital-related knowledge, the growing integration of digital technologies at work necessitates further investigation into the specific types of knowledge being shared across different roles and work contexts. Future research could therefore also focus on how digital fluency and readiness for change, together with industry-specific expertise, shape the nature of knowledge transfer among aging workforces.

6. Overall Conclusion

Today's workplace is being reshaped by the profound trends of digitalization and demographic change, which are affecting various industries and altering the way we work. This dissertation contributes to the understanding of how aging employees, in both white-collar and blue-collar occupations, are responding to these shifts. By exploring the key factors that influence employees' adaptation to new work environments, the findings provide important insights for supporting aging employees in effectively managing these transitions. Through this dissertation, I aim to promote a deeper understanding of how aging workforces develop digital competencies and general readiness for digital change, adapt to changing work environments such as remote work, and engage in knowledge sharing practices that are critical for maintaining organizational effectiveness in an era of rapid change.

Declaration of Authorship

I hereby declare that chapter 2 (Study 1) with the title “The Older, the Less Digitally Fluent? The Role of Age Stereotypes and Supervisor Support” is based on joint work with Prof. Dr. Florian Kunze, Chair for Organizational Behavior at the University of Konstanz. As lead author of this joint paper, I collected the data, developed the research question, wrote the manuscript and conducted the empirical analysis. Over multiple rounds of revisions, Florian Kunze supported me in framing and re-writing parts of the paper. Chapter 2 is published as a Research Report in The Journal of “Work, Aging, and Retirement”.

Chapter 5 (Study 4) with the title “Feeling Younger, Exchanging Knowledge: Understanding Blue-Collar Workers’ Knowledge Transfer Behavior” is a joint paper with Sophie Moser, doctoral candidate at the Chair for Organizational Behavior, University of Konstanz. While my co-author supported me in the comprehensive empirical analysis with nested data structure, I am the lead author of the project, collected the data, developed the research question, and wrote the manuscript.

In sum, I declare that I am the sole author of chapter 1, chapter 3, chapter 4, and chapter 6 as well as the supplement materials, and the lead author of chapter 2 and 5.

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Appendix

Slope coefficients, t-values, and *p*-values of the four slopes of Figure 3

Slope 1: High Negative Age Stereotypes & High Developmental Supervisor Support ($\beta = -0.27$, $t = -5.10$, $p = 0.000$)

Slope 2: High Negative Age Stereotypes & Low Developmental Supervisor Support ($\beta = -0.20$, $t = -4.37$, $p = 0.000$)

Slope 3: Low Negative Age Stereotypes & High Developmental Supervisor Support ($\beta = -0.05$, $t = -1.18$, $p = 0.240$)

Slope 4: Low Negative Age Stereotypes & Low Developmental Supervisor Support ($\beta = -0.14$, $t = -2.70$, $p = 0.007$)

Slope difference tests for Figure 3

Slope (1) and (2): ($\beta = -0.06$, $t = -1.08$, $p = 0.278$);

Slope (1) and (3): ($\beta = -0.22$, $t = -4.08$, $p = 0.000$)

Slope (1) and (4): ($\beta = -0.13$, $t = -2.09$, $p = 0.037$)

Slope (2) and (3): ($\beta = -0.15$, $t = -2.87$, $p = 0.004$)

Slope (2) and (4): ($\beta = -0.07$, $t = -1.18$, $p = 0.239$)

Slope (3) and (4): ($\beta = -0.09$, $t = 1.58$, $p = 0.114$)