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Getting Ready for the Future, Is It Worth It? A Dual Pathway Model of Age and Technology Acceptance at Work

Ulrike Fasbender[1,*], Fabiola H. Gerpott[2], and Laura Rinker[1]

[1]Business and Organizational Psychology, University of Hohenheim, Stuttgart, Germany
[2]Leadership, WHU – Otto Beisheim School of Management, Düsseldorf, Germany

[*]Correspondence concerning this article should be addressed to Ulrike Fasbender, University of Hohenheim, Business and Organizational Psychology, Wollgrasweg 49, 70599 Stuttgart, Germany. E-mail: Ulrike.Fasbender@uni-hohenheim.de

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Abstract

Rapid technological advancements and global workforce aging shape the future of work. Drawing on the technology acceptance model, our study aims to connect the literature on aging with the research on technology use in organizations. At its heart, the technology acceptance model suggests that the two core components, perceived usefulness and perceived ease of use, predict the attitude toward a new technology. We connect these components with two age-related processes: first, we suggest a motivational pathway via future time perspective, including one's perceived future opportunities and remaining time at work. Second, we propose a capability pathway via cognitive constraints, including one's perceived struggle to process new information (i.e., perceived processing speed difficulties) and the perceived struggle to organize one's work (i.e., perceived organization difficulties). Moreover, we explore digital leadership as a potential buffer to the detrimental relations between age and technology acceptance. We preregistered our hypotheses and tested them using three-wave data from 643 employees. Our findings support our hypotheses for the motivational pathway, showing that age is negatively linked to attitude toward new technology via future time perspective and subsequent perceived usefulness as well as perceived ease of use. Digital leadership buffered the negative indirect relations between age and attitude toward new technology. For the capability pathway, the results were the opposite of what we expected. Together, our findings put the link between age and technology acceptance into a more positive light than previous research and suggest that motivational and capability-related forces are interwoven in predicting attitude toward new technology.

Keywords: age, occupational future time perspective, cognitive constraints, technology acceptance model, digital leadership

Two major trends shape the future of work in the twenty-first century. First, the global workforce is getting older and more age-diverse (Truxillo et al., 2015). Second, technological advancements such as digitalization and artificial intelligence continuously change the way we work (Landers & Marin, 2021). With regard to the use of technology, acquired knowledge expires every 2 to 3 years (i.e., half-life of knowledge; Helmrich & Leppelmeier, 2020). The duration of a working life, however, is close to 40 years and constantly rising (Eurostat, 2020b), which requires us to update our technology-related knowledge and continue learning and using new technologies over the lifespan.

To date, we know too little about how employees' age is shaping technology use at work (Alcover et al., 2021; Drazic & Schermuly, 2021; Sheng et al., 2022). Some scholars have investigated age as a moderator to technology acceptance (Morris & Venkatesh, 2000; Venkatesh et al., 2003, 2012). For example, Venkatesh et al. (2003) found that age can buffer the relation between performance expectancy (perceived usefulness) and intention to use new technology, arguably due to a stronger focus on instrumentality among younger versus older employees. A meta-analysis revealed that age is negatively related to employees' perceived ease of use, perceived usefulness, and intention to use a technology (Hauk et al., 2018). While these findings seem to support stereotypical views that technology is less popular with increasing age (e.g., Mariano et al., 2020; see also Posthuma & Campion, 2009), the processes behind these findings remain unknown. From the aging literature, we know that there are substantial differences within the group of younger and older employees depending on how employees experience their aging (Fasbender et al., 2019, 2022; Kunze et al., 2015; Nagy et al., 2019). For example, research from Drazic and Schermuly (2021) found that age is not per se related to readiness for change but depends on employees' subjective experience of age. These findings underpin the importance of understanding people's subjective experiences of getting older as core determinants of technology use at work.

The aim of the current study is to connect the literature on aging with research on technology use in organizations. One influential model with regard to technology use is the technology acceptance model (TAM) (Davis, 1985, 1989) and its numerous extensions (e.g., Chen & Chan, 2014; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). At its core, the TAM consists of two components: (1) perceived usefulness and (2) perceived ease of use (Davis et al., 1989). Together, these two core components shape employees' attitudes toward technology, which has been established as a central predictor of intention and actual technology use (Bhattacherjee et al., 2012; King & He, 2006). We aim to connect these two components with two age-related processes, namely (1) future time perspective and (2) cognitive constraints.

We propose that employees' age is linked to attitude toward using new technology through aging-related and technology-related processes. Based on the aging literature, we argue that with increasing age, people's (occupational) future time perspective shrinks (Rudolph et al., 2018), and they experience more cognitive constraints (Salthouse, 2012). Integrating these arguments with the core components of the TAM, we further propose that these aging-related experiences inform perceived usefulness and perceived ease of use. First, we argue that technology is perceived as more useful when employees have an expanded future time perspective because they perceive to have plenty of time and opportunities left to apply the new technology. Because age negatively links to future time perspective (Rudolph et al., 2018), age should have a negative indirect relation with technology use via future time perspective and perceived usefulness. Second, we argue that technology is perceived as more easy to use when employees experience less cognitive constraints, as it will be easier for them to derive, decode, and integrate new information when learning new technology (cf. Fasbender et al., 2021; Grand et al., 2016). Because age has been argued to go hand in hand with increasing cognitive constraints (Salthouse, 2012), age should have a negative indirect relation with technology use via cognitive constraints and perceived ease of use.

While employees' attitude toward new technology is certainly determined by different person factors, including their aging experience and technology motivation, we argue that employees' work environment also matters. Based on previous research on digital transformation (Cortellazzo et al., 2019; Trenerry et al., 2021), we propose that employees' supervisors have an important role in shaping how employees' age is linked to attitude toward new technology. Specifically, we focus on digital leadership, which refers to favorable supervisor behavior and attitudes toward digitalization, including up-to-date digital knowledge and enthusiasm about the digital transformation at work (Zeike et al., 2019). Relying on the notion that supervisors high in digital leadership motivate and develop technology-related capabilities in their employees (Larson & DeChurch, 2020), we explore digital leadership as a potential buffer of the negative indirect relation between age and attitude toward new technology.

We intend to make three contributions to the literature. First, we connect the literatures on aging and technology acceptance. While previous research has found that age is negatively related to technology acceptance (Hauk et al., 2018), we contribute to explaining why this may be the case. Specifically, we develop a dual pathway model that contains a motivational (via future time perspective and perceived usefulness) and a capability (via cognitive constraints and perceived ease of use) pathway to connect age to attitude toward new technology. Second and related, we unpack two aging-related mechanisms each on the motivational and on the capability side. On the motivational pathway, we differentiate the links of two dimensions of (occupational) future time perspective, that of perceived (1) future opportunities and (2) remaining time left until employees retire (Rudolph et al., 2018; Zacher & Frese, 2009). On the capability pathway, we differentiate two dimensions of cognitive constraints, that of perceived (1) processing speed difficulties and (2) organization difficulties (Cheung et al., 2019; Fasbender, 2021). This more fine-grained perspective on the different aging experiences allows us to contribute to the wider aging and gerontology literature. Third, we add to the research on successful aging at work by exploring the moderating role of digital leadership. If digital leadership can indeed buffer the detrimental impact of employees' age on technology use, then we can draw relevant practical implications on enabling continuous learning and using new technology over the lifespan and therewith maintaining competitive advantages for organizations.

From the TAM to a Dual Pathway Model of Age and Technology Acceptance

Our conceptual model is based on the TAM (Davis, 1985, 1989)—an extension of the theory of reasoned action (Ajzen & Fishbein, 1973)—and states that the two components, perceived usefulness (i.e., the expectation that using a technology improves one's productivity) and perceived ease of use (i.e., the perception that using a technology is simple), determine employees' attitude toward new technology (i.e., the positive or negative evaluation of a technology that has been newly introduced to an employee; Davis et al., 1989). We focus specifically on perceived usefulness and perceived ease of use as proximal predictors of attitude toward new technology for two reasons. First, these two components are core to the TAM and all of its extensions (including the TAM2, Venkatesh & Davis, 2000; TAM3, Venkatesh & Bala, 2008; senior TAM, Chen & Chan, 2014; the unified theory of acceptance and technology use, UTUAT, Venkatesh et al., 2003; UTUAT2, Venkatesh et al., 2012). Second, because these two components are helpful in linking age to technology acceptance through a motivational (want to) and a capability (can do) pathway.

Research on technology acceptance has already begun to study the role of age (e.g., Morris & Venkatesh, 2000; Venkatesh et al., 2003, 2012). In this regard, Morris and Venkatesh (2000) have discussed socio-cognitive changes with increasing age, including changes in cognitive abilities, job needs, and preferences. Specifically, the authors have argued that as they get older, employees are less focused on job-related outcomes, task accomplishments, and extrinsic awards, which should reduce their attitude toward new technology. Indeed, their results showed that age was negatively related to technology use through attitude toward new technology, this relation was further moderated by age. Building on Morris and Venkatesh' (2000) research, Venkatesh et al. (2003) further investigated age as a moderator. Specifically, they have argued that there is a stronger focus on instrumentality among younger versus older employees and that processing complex stimuli is more difficult for older versus younger employees. Indeed, Venkatesh et al. (2003) found that age buffered the relation between performance expectancy (perceived usefulness) and intention to use new technology; focus on instrumentality or processing difficulties was, however, not directly measured or tested.

In a similar vein, Venkatesh et al. (2012) have studied whether individual differences, including age among others jointly moderate the components of technology acceptance. In their extension of the TAM, the authors have discussed the role of habits and argued that with increasing age, people rely more on automatic information processing by developing habits that prevent them from learning new technology, and also that it was difficult for older people to override their habits, adapt to, and use new technology. Venkatesh et al. (2012) have found different three-way and four-way interactions, including age as a moderator. Because the authors have focused on the joint moderation effects of different individual differences, it was not fully clear what the unique role of age is. While certainly interesting, these studies (i.e., Morris & Venkatesh, 2000; Venkatesh et al., 2003, 2012) do not capture the underlying mechanisms that explain the role of age. In fact, most of the arguments behind these studies use age as a proxy for other aging-related mechanisms (a problem that does not alone exist in the technology acceptance literature but also in other domains in the study of aging; cf. Bohlmann et al., 2018). Furthermore, the meta-analysis by Blut et al. (2022) found overall inconsistent findings (apart from findings related to personal innovativeness) regarding the role of age, which suggests that there could be countervailing mechanisms involved. To uncover relevant aging-related mechanisms, we take a more fine-grained perspective.

Specifically, to untangle the complex relation between employee age and attitude toward new technology, we develop a dual pathway model consisting of a motivational and a capability pathway. In a nutshell, the motivational pathway captures perceived usefulness as the motivational force, while the capability pathway captures perceived ease of use as the capability-related force driving the attitude toward a new technology. We further derive aging-related mechanisms that match the motivational and the capability-related forces. On the motivational side, we consider the two dimensions of future time perspective, namely perceived future opportunities and remaining time that inform perceived usefulness. On the capability side, we consider two cognitive constraints, namely perceived processing speed difficulties and organization difficulties that inform perceived ease of use. Furthermore, we extend the model by considering digital leadership as a potential moderator of the relations between employee age with future time perspective and cognitive constraints, and its subsequent indirect links with attitude toward new technology. Figure 1 shows our conceptual model.

A motivational pathway via future time perspective and perceived usefulness

The motivational pathway describes the driving forces that determine whether an employee *wants to* engage in the activation, persistence, and intensity of a behavior such as using new technology at work (Robbins & Judge, 2019). To understand why employees are motivated to behave in future-oriented ways at work (e.g., engaging in activities such as learning something new), the aging literature has emphasized the importance of occupational future time perspective (cf. Rudolph et al., 2018), defined as the perceptions of the remaining opportunities and remaining time on the job (Zacher & Frese, 2009). This construct is rooted in the lifespan developmental literature on general future time perspective, which argues that people's beliefs about how much time they have left in the future decreases with age. This decrease goes hand in hand with changing priorities in social goals (Carstensen, 2006; Carstensen et al., 1999). Specifically, when the remaining time becomes more limited, people tend to focus more on meaningful activities and goals in the present rather than setting long-term goals and planning activities for the future (Fasbender et al., 2020).

Ever since Zacher and Frese (2009) adapted the idea of future time perspective to the employment context, research repeatedly found that the two related sub-dimensions of occupational future time perspective—namely perceived future opportunities (i.e., an individual's perceptions of new work-related goals, possibilities, and opportunities that are to be expected in the future) and perceived remaining time (i.e., the amount of future time an individual expects to spend in employment; Zacher & Frese, 2009)—are negatively associated with age (for an overview see Rudolph et al., 2018). With increasing age, employees tend to perceive less possibilities in their remaining career and more substantial investments to lose when trying out new opportunities (Pak et al., 2019). It is much more difficult and unlikely to change one's career at, for example, age 60 compared to the age of 20 (Carless & Arnup, 2011; Healy et al., 1995; Parrado et al., 2007). Furthermore, due to mandatory, forced, or voluntary retirement, institutional pressures result in employees having less time left in their job with increasing age (Rudolph et al., 2018; Zacher & Frese, 2009). To summarize, we hypothesize:

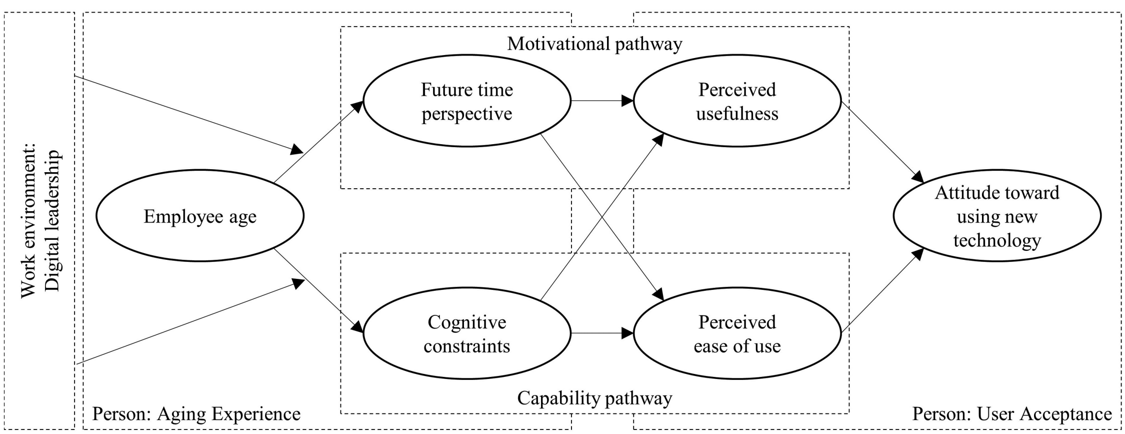

Figure 1. A dual pathway model of age and technology acceptance.

> ***Hypothesis 1.*** Employee age is negatively related to perceived (a) future opportunities and (b) remaining time.

We next argue that an employee's future time perspective as a part of their aging experience determines the perceived usefulness of new technology (i.e., the degree to which a person perceives a technology as enhancing their job-related functioning; Davis, 1989), which constitutes a core component of the TAM (Davis, 1985, 1989). To illustrate, imagine that your employer implements a new customer relationship management software that should replace your manual file cards, which you have used successfully for years. Your employer asks you to learn the new software, which takes some time but eventually should improve the customer handling of all employees. As you are planning to retire in the next year, you probably perceive the usefulness of the new customer relationship software as rather limited because you are aware that in your career, there are not many remaining possibilities for the software to speed up your working routine. Instead, you would probably be slowed down in the next weeks by having to spend additional time learning the new software. As a result, you would probably perceive your well-practiced manual file card approach as much more useful than the new customer relationship software for your remaining year at work. This example illustrates that one's future time perspective can translate to perceived usefulness of new technology.

Conceptually, this line of argumentation can be explained by people's focus on goals in the present rather than goals in the future that comes with a shorter future time perspective (Carstensen, 2006). Based on this notion, we propose that when employees perceive their future opportunities and remaining time at work as limited, they should not find it very useful to invest effort and attention in learning a new technology that slows them down in the present but at the same time will not pay off for them personally in their future career. In contrast, when employees expect to experience many future opportunities in their job, they should perceive it as useful to adopt a new technology that can potentially help leverage these opportunities. Similarly, when employees foresee a long remaining time in their job, then investing in learning a new technology can be useful because, even though it may require effort and slow them down in the present, there remains a lot of time to give a good return. In line with this notion, research demonstrated that personal outcome expectations are crucially tied to the perceived usefulness of continuing to work with a new technology (Ifinedo, 2017). When people know that they will leave their job, they are less motivated to learn new things as it does not seem useful to them (Kuruppuge & Gregar, 2018). Furthermore, preliminary evidence from interviews with 20 employees, who were introduced to a new technology, indicated that time until retirement played a role in experiencing that technology as useful (Ouadahi, 2008). To conclude, we hypothesize:

> ***Hypothesis 2.*** Perceived (a) future opportunities and (b) remaining time are positively related to perceived usefulness of new technology.

Combining our arguments from above, we propose that the negative link identified in previous meta-analytic research (Hauk et al., 2018) between age, perceived usefulness, and technology acceptance can be explained by a motivational pathway related to employees' perceptions of their future opportunities and remaining time at work. Stated formally, we hypothesize:

> ***Hypothesis 3.*** Employee age has a negative indirect relation with attitude toward using new technology via perceived (a) future opportunities and (b) remaining time, and perceived usefulness of new technology.

A capability pathway via cognitive constraints and perceived ease of use

The capability pathway describes processes related to the cognitive possibilities or constraints that impact the degree to which an employee *can* handle the activation, persistence, and intensity of a behavior such as using new technology at work. That is, in contrast to the motivational pathway that focuses on "want to," this path sheds light on the aspect of "being able to." The aging literature has established that with increasing age, the cognitive capabilities responsible for the fast processing and organization of new information decreases (Salthouse, 2012; Verhaeghen, 2013). Of note, this non-pathological loss in cognitive function does not necessarily go hand in hand with a productivity reduction at work (Guzzo et al., 2022; Ng & Feldman, 2008) or lower everyday functioning, because with increasing age, people also become better at utilizing crystallized intelligence that allows to make valuable cross-connections of knowledge (Horn & Cattell, 1967; Salthouse, 2012).

Nevertheless, based on previous research, we do expect that with increasing age, employees notice that both cognitive processes related to speed (i.e., perceived processing speed difficulties, employees' perceptions about how difficult it is for them to process, organize, and learn new information at work; Fasbender, 2021) and related to organization (i.e., organization difficulties, employees' perceptions about how difficult it is for them to organize, plan, and get started with tasks at their daily work; Sullivan et al., 2002) become more constrained. We focus on perceived processing speed difficulties and organization difficulties because previous research has shown how important these components are for successful aging at work (Cheung et al., 2019; Fisher et al., 2017; Parker et al., 2021).[1] For example, scholars have emphasized the challenges that reduced processing speed raises for older workers due to accelerating changes and information processing demands in the technology-driven work environment (Charness & Czaja, 2019), which may be related to its crucial role in cognitive functioning (Verhaeghen, 2013). In terms of organization difficulties, these represent a more general area of cognitive abilities that is particularly important for dealing with technological change, in addition to normal working life due to the influx of technology-related demands (e.g., Karr-Wisniewski & Lu, 2010).

In terms of empirical support for our reasoning, extant research has repeatedly demonstrated that processing speed decreases when people get older (e.g., Caplan & Waters, 2005; Finkel et al., 2007; Salthouse, 1996; Sliwinski &

[1]We have also considered further cognitive processes, including cognitive skills, attention/concentration difficulties, and retrospective memory loss. To reduce the complexity of the overall model, we decided to focus on processing speed difficulties and organization difficulties as most relevant cognitive constraints.

Buschke, 1999). Moreover, scholars found a greater reliance on crystallized abilities (i.e., accumulated knowledge as well as recurring thoughts and behaviors over a lifetime) in older adulthood compared to fluid abilities (i.e., cognitive-control processes used for goal-directed and flexible processing of stimuli) in young adulthood (Spreng & Turner, 2019). Although higher crystallized abilities may improve older employees' cognitive processes responsible for organizing, planning, and making decisions about work tasks for themselves and in coordination with others in routine work situations with increasing experience (Avolio et al., 1990), this cognitive shift suggests that novel situations outside of well-established schemas may be associated with higher difficulties. Similarly, research on expertise suggests that certain experience- and age-related cognitive gains may entail a flip side (i.e., typically older individuals with larger knowledge networks have a harder time absorbing new knowledge depending on the instructional context; Kalyuga et al., 2003). On a neurological level, older people (as compared to younger people) are affected by changes in their frontal lobe structures that are vital for frontally based functions such as executive control, which become apparent from the age of 60 onwards (Fisher et al., 2014; Pfefferbaum et al., 2005). Executive control is linked to "goal selection, planning, monitoring, sequencing, and other supervisory processes" (Foster et al., 1997, p. 117) that "enable a person to engage successfully in independent, purposive, self-serving behavior" (Lezak et al., 2004, p. 35). Although it becomes easier to access higher-order rules for exercising executive control (i.e., rules relating to abstract representations of an event vs. lower-order rules relating to its specific details) with increasing age due to a greater familiarity with situations, scholars argue that these rules are relatively inflexible (Zelazo et al., 2004). Thus, we propose that, as employees age, their organization difficulties become more prominent to them due to an increasing difficulty of deviating from context-bound, preformed rules in light of today's rapidly changing technological work environments. As cognitive difficulties tend to increase in older samples, for example, through lower adaptation in strategic learning (Zhu et al., 2012) or increased display of organization difficulties in the form of procrastination (Stolcis & McCown, 2018)—this cognitive decline may become more relevant for the future workforce, as the current demographic trend suggests a prolongation of employees' working lives (Eurostat, 2020a).

In general, research has established the impact aging and age-related self-perceptions may have on cognitive functioning and vice versa (Seidler & Wolff, 2017). This rationale is also echoed by psychosocial approaches in the aging literature (Levy, 2009), according to which awareness of age-related change and negative age stereotypes applied to the self can translate to cognitive decline (Diehl et al., 2021; Levy et al., 2012). Therefore, we conceptualize the cognitive constraints as perceived difficulties (vs. an objective decline) based on the premise that actual cognitive functioning and perceptions of one's relative cognitive difficulties inform each other. We argue that the connection between the perceptions of one's own aging and cognitive decline causes older employees to perceive more difficulties in processing speed and organization ability as one ages. To conclude, we hypothesize:

> ***Hypothesis 4.*** Employee age is positively related to perceived (a) processing speed difficulties and (b) organization difficulties.

We next argue that employees' perceived cognitive constraints as a part of their aging experience determine the perceived ease of using a new technology (i.e., the degree to which a person believes that using a particular technology is free from effort; Davis, 1989), which constitutes a core component of the TAM (Davis, 1985, 1989). To illustrate our argument, let us come back to the example from above concerning a new customer relationship software that is introduced at your company. In the described scenario, you may have noticed that over the years, it has become more difficult for you to quickly grasp new information at work. While your younger coworkers often seem to adapt very quickly to new challenges or processes, you require a bit longer to modify your behavior. Accordingly, you do not perceive it as easy or straightforward as it may have been the case when you were younger to learn a new technology. As this example illustrates, cognitive constraints linked to age may play a role in explaining employees' perceived ease when it comes to new technology at work.

Empirically, this line of argumentation is supported by research showing that people suffering from cognitive constraints are more likely to feel overwhelmed when seeking new information (i.e., experience cognitive overload; Savolainen, 2015), which hampers their experience of using new technology. Scholars have highlighted the crucial role cognitive abilities play in technology use (Czaja & Sharit, 1998; Ziefle & Bay, 2006) and the necessity to account for age-related cognitive decline in program design to improve their perceived ease of using new technology (Pan & Jordan-Marsh, 2010; Schieber, 2003). In sum, the empirical evidence suggests that cognitive difficulties may cause users to perceive technology as more difficult to use. Thus, we hypothesize:

> ***Hypothesis 5.*** Perceived (a) processing speed difficulties and (b) organization difficulties are negatively related to perceived ease of use of new technology.

Combining our arguments from above, we propose that the negative link identified in previous meta-analytic research (Hauk et al., 2018) between age, perceived ease of use, and technology acceptance can be explained by a capability pathway related to employees' perceptions of their processing speed difficulties and organization difficulties. Stated formally, we hypothesize:

> ***Hypothesis 6.*** Employee age has a negative indirect relation with attitude toward using new technology via perceived (a) processing speed difficulties and (b) organization difficulties, and perceived ease of use of new technology.

The moderating role of digital leadership

Extensions of the initial TAM pointed to the importance of how employees perceive their leaders as a factor that can facilitate positive attitudes toward a new technology (Venkatesh et al., 2016). This is because supervisors play an important role for employees due to their disciplinary guidance as well as their role-modeling function. Research so far has considered general positive leadership behaviors such as acting transformational or transactional (Schepers et al., 2005; Venkatesh et al., 2016), engaging in authentic leadership (Aziz et al., 2020) or leading in a charismatic way (Neufeld et al., 2007) as predictors of technology acceptance. Contributing to a debate in the leadership literature that questions the validity of such broad leadership styles (van Knippenberg & Sitkin, 2013), we focus here on a leadership aspect that is more closely tied to technology and digitalization. Specifically, we explore the role of digital leadership, which refers to favorable supervisor behavior and attitudes toward digitalization, including up-to-date digital knowledge and enthusiasm about the digital transformation at work (Zeike et al., 2019). Leaders who can make others excited about the digital transformation and serve as a role model in terms of digital abilities offer a specific set of skills to employees that is different from broader leadership styles such as transformational leadership. This is also empirically reflected in the perception of employees. For example, Matsunaga (2022) reported low correlations between employees' assessment of their leaders' transformational leadership and their digital leadership skills. However, although specific digital leadership skills have been proposed as a crucial area for investigation against the backdrop of the digital transformation (Larson & DeChurch, 2020), research so far is in its infancy, particularly in the context of aging effects. We therefore decided to explore this area as a research question because although a buffering role of this leadership style is plausible, alternative arguments can be made.

First, considering the link between age and employees' future time perspective, we expect that digital leadership can inspire employees to view the technological advancements as a means to boost their professional skills, thereby setting them up for the future of work. Supervisors, who are positive about the digital transformation and make others feel enthusiastic about it (Zeike et al., 2019), may signal to employees more occupational perspectives in the future, which is particularly relevant with increasing age (Rudolph et al., 2018). For example, digital-oriented leaders, who offer examples about how technology creates new jobs and frame this as an exciting opportunity, can positively stimulate employees' thinking about their job opportunities in the future. In line with this notion, research proposed that people are more motivated to search for and acquire new skills if they perceive the introduction of new technology as an opportunity rather than a threat (Rodriguez-Bustelo et al., 2020). However, although the buffering role of digital leadership in influencing the negative link between age and employees' future time perspective seems reasonable, it is also possible that supervisors, who talk very positively about the digital future and who are digital experts themselves, may threaten older employees because they cannot identify with this leadership vision. In this regard, digital leadership could make older employees even more of aware of the fact that their knowledge and skills are outdated and that there is no place for them in the future of work because, for example, the language that these managers use may implicitly transfer the image that only a younger workforce can sufficiently acquire the required skills (Vickerstaff & Van der Horst, 2021). In sum, although the arguments for a buffering role of digital leadership are more convincing in our view, there is also a theoretical plausible alternative explanation assuming that older employees may report even less opportunities in the future if they perceive their supervisor as scoring high on digital leadership.

Second, in terms of the impact of digital leadership on the proposed negative link between age and employees' cognitive constraints, we expect that supervisors who are perceived by their employees as scoring high on digital leadership challenge older employees' perceptions of cognitive constraints with increasing age by providing clear guidance to employees. Supervisors, who score high on digital leadership, have a concrete idea of the structures and processes that are needed for the digital transformation (Zeike et al., 2019). This clear guidance can enable older employees to compensate for their perceived processing speed difficulties and organization difficulties at work. For example, if leaders can make knowledge about digital support systems easily accessible, then employees may benefit from a better understanding and more elaborated digital implementation ideas that in turn enable them to countervail potential perceived processing speed difficulties and organization difficulties relevant to technology acceptance at work (Wolfson et al., 2014). To the contrary, and similar to the argument outlined above, an alternative view could be that older employees, who perceive their supervisor as scoring high on digital leadership, become particularly aware of their cognitive constrains because the leader may, for example, serve as a role model for thinking and adapting very quickly to new technology, which makes it salient to older employees that these abilities are declining for them. In sum, although we consider a buffering role of digital leadership perceptions as more plausible for the first paths in our model, the lack of extant research and the possible alternative explanations led us to pose the following research question:

> ***Research Question 1.*** Can employees' perceptions of digital leadership buffer the detrimental relations between age with perceived future time perspective and cognitive constraints, and potentially also the indirect relations between age and attitude toward new technology?

Method

Sample and procedure

We pre-registered our hypotheses at the Open Science Framework (https://osf.io/z2vjd). During October and November 2021, we collected three-wave data in Germany. To minimize common-method-bias, we separated the measurement of variables by a 2-week time lag between the waves. We commissioned an ISO 26362-certified research company that manages a large research-only business panel to collect the data for this study. Participants received 1.50€ for taking part in the study. Following the recommendations of A. Newman et al., (2021) on collecting data online, we included attention checks (e.g., "Please select 'strongly disagree' here if you pay attention") to ensure data quality. If participants failed these, they were automatically screened out. Furthermore, the inclusion criteria were that participants are employed, regularly use a computer (at least 50% of their work time) and have been experiencing the introduction of a new information and communication technology or any new technology at work. Participants were automatically screened out if they did not fulfill these criteria. In addition, we also asked participants with open questions to provide details about the new technology that was introduced to them. Specifically, participants reported at Time 1 the name of the new technology (which we used to individualize the further questions with the respective technology mentioned), the situation in which the technology was introduced, the type of technology, and what participants liked or disliked about it. This information helped us to tailor the survey to the individual participant and also to ease participants' retrieval of relevant information for what the survey was about. We manually excluded 14 participants because they did not provide enough data in the open text response, or they provided data that did not make sense to us. These participants were also not invited to the follow-up surveys at Time 2 and Time 3.

Overall, 643 participants completed our survey at Time 1. Of those, 559 participated at Time 2 (dropout to Time 1 = 13.1%), and 470 participated at Time 3 (dropout to Time 2 = 15.9%). In line with recommendations on running longitudinal data analysis (Newman, 2014; Wang et al., 2017b), we used all data available to retain statistical power (i.e., the listwise deletion command was turned off in Mplus[2]). Participants' ages ranged from 19 to 66 years (M = 44.87, SD = 11.38). Of the participants, 59.9% were male, and 47.9% held a university degree. On average, participants worked 37.97 hours per week (SD = 7.55)[3] in a variety of industries; the most represented industries were the public sector (18.2%), professional services, such as consulting (17.6%), industrial production, such as automotive (10.3%), finance and insurance (10.1%), as well as technology, media, and communication (7.6%). Participants reported different types of technologies that were newly introduced at their workplace. The most represented type by far was communication technology (67.3%), followed by database management (4.8%), development platforms (3.9%), data analysis software (3.7%), and customer relations software (2.8%). Participants found out about the new technology through various channels, including their supervisor (33.9%), colleagues (28.0%), training/workshop (15.9%), company newsletter (8.2%), or other channels (14.0%).

Measures

Employees' age and their perceptions of future time perspective, cognitive constraints, and digital leadership were assessed at Time 1, perceived usefulness and perceived ease of use at Time 2, and attitude toward using a new technology at Time 3. The full set of items can be found in the Appendix. We followed typical translation-back-translation procedures to translate items from English to German, if no German-language version was available.

[2]We conducted a sensitivity analysis to investigate whether the findings differ when using all available data (N = 643) as compared to using listwise deletion (N = 470). We found that the estimated coefficients remained stable and significant in the same direction even if we used listwise deletion, which supports the robustness of our findings.

[3]We planned the study with employees who work at least 20 hr per week. Of the participants, 14 indicated that they worked less than 20 hr. We decided to keep them in the sample to use all data possible and controlled for working hours instead.

Employee age

We rescaled the chronological age by factor 10 to facilitate the interpretation of the unstandardized results (cf. Fasbender et al., 2020; Peng et al., 2021).

Future time perspective

We used the 6-item two-dimensional scale by Zacher and Frese (2009) to capture occupational future time perspective. Example items were "My occupational future is filled with possibilities" (***perceived future opportunities***, α = .93) and "Most of my occupational life lies ahead of me" (***perceived remaining time***, α = .81).

Cognitive constraints

We used the 5-item scale from Fasbender (2021) to measure ***perceived processing speed difficulties***; an example item was "As I get older, I experience that learning new information takes me more time" (α = .95). For ***perceived organization difficulties***, we used the 5-item scale from Sullivan et al. (2002); an example item was "I have trouble getting things organized" (α = .95).

Perceived usefulness of new technology

We measured this variable with the 6-item scale by Davis (1989). We adapted the scale by using a placeholder that contained the new technology mentioned by each participant. An example item was "I find this [technology placeholder] useful in my job." (α = .95).

Perceived ease of use of new technology

We captured this variable with the 6-item scale by Davis (1989). Again, we adapted the scale by using a placeholder that contained the new technology mentioned by each participant. An example item was "I find this [technology placeholder] easy to use." (α = .94).

Attitude toward using new technology

We measured this variable using the 4-item scale by Venkatesh et al. (2003). Here too, we adapted the scale by using a placeholder that contained the new technology mentioned by each participant. An example item was "Using this [technology placeholder] is a good idea." (α = .92).

Digital leadership

We measured this variable using the 6-item scale from Zeike et al. (2019). We adapted the scale to be assessed from the perspective of the employee by adding "My leader…" to each item. An example item was "My leader can make others enthusiastic about the digital transformation" (α = .93).

Control variables

First, we controlled for education (0 = *no university degree* and 1 = *university degree*) as it is plausible that people with higher education hold a more favorable attitude toward using new technology due to generally higher mental abilities (Strenze, 2007) and achievement motivation (Hustinx et al., 2009). Second, we controlled for weekly working hours. Employees who work long hours may be more drained (Wong et al., 2019) and have less cognitive and motivational resources to engage with new technology, which could hamper their attitude toward it.

Table 1. Confirmatory factor analysis fit indices for measurement model.

Model	χ^2	*df*	$\Delta\chi^2$ (Δdf)	*p*-Value $\Delta\chi^2$ (Δdf)	*CFI*	*RMSEA*	*SRMR*
Eight-factor model	1,832.49	637	–	–	0.94	0.05	0.05
Seven-factor model[a]	2,215.49	644	383.00 (7)	<.001	0.92	0.06	0.06
Seven-factor model[b]	3,344.45	644	1,511.96 (7)	<.001	0.86	0.08	0.09
Six-factor model[c]	4,497.61	650	2,665.12 (13)	<.001	0.79	0.10	0.08

Note. *N* = 643. Difference of chi-square values ($\Delta\chi^2$) was estimated to compare to the eight-factor model. *CFI* = confirmatory fit index, *RMSEA* = root mean square error of approximation, *SRMR* = standardized root mean square residual.
[a]Future opportunities and remaining time on one factor.
[b]Processing speed difficulties and organization difficulties on one factor.
[c]Perceived usefulness, perceived ease of use, and attitude toward using new technology on one factor.

Analytical strategy

We tested the preregistered hypotheses between employee age and attitude toward using new technology in Mplus 8.4 applying structural equation modeling (Muthén & Muthén, 2019). We used the XWITH command to test the interaction effects between age and digital leadership. Since bootstrapping is not available when using the XWITH command in conjunction with MLR estimation in Mplus, we applied Monte Carlo-simulation of confidence intervals (CIs) for the indirect and conditional indirect paths in R (R Core Team, 2017; see also Preacher & Selig, 2012). We controlled for the direct relations between employee age and first stage mediators (occupational future time perspective and cognitive constraints) on the endogenous variables to ensure that the indirect relations are not inflated (Preacher & Hayes, 2008). In addition, we controlled for the non-hypothesized cross-over relations between future time perspective and perceived ease of use, and cognitive constraints and perceived usefulness to provide a more rigorous examination of the hypothesized model as neglecting these may result in an overestimation of the hypothesized relations.[4] Moreover, we regressed the control variables (education and working hours) on the endogenous variables. We ran the analyses with and without control variables. Since no meaningful differences occurred, we report the results without control variables in line with Spector and Brannick's (2011) recommendation.

Results

Preliminary findings

We conducted confirmatory factor analyses to assess the construct validity of our latent variables, including future opportunities, remaining time, processing speed difficulties, organization difficulties, digital leadership, perceived usefulness, perceived ease of use, and attitude toward using new technology. The proposed 8-factor structure showed a good model fit (χ^2 (637) = 1832.49, *p* < .001, *confirmatory fit index* = 0.94, *root mean square error of approximation* = 0.05, *standardized root mean square residual* = 0.05) with standardized factor loadings of all items being significant and larger than .55. The model fit of our proposed model was also superior to other, alternative models as can be seen in Table 1. Together, these findings support the construct validity of the eight latent measures used.

In Table 2, we present the means, standard deviations, and correlations of the study variables. Attitude toward new technology was significantly and positively correlated to digital leadership, future opportunities, remaining time, perceived usefulness, and perceived ease of use. Moreover, attitude toward new technology was significantly and negatively correlated to organization difficulties. Perceived usefulness of new technology was significantly and positively correlated to digital leadership, future opportunities, remaining time, and perceived ease of use, while it was significantly and negatively correlated to organization difficulties. Perceived ease of use of new technology was significantly and positively correlated to digital leadership, future opportunities, and remaining time, while it was significantly and negatively correlated to age, processing speed difficulties, and organization difficulties.

Future opportunities were significantly and positively correlated to education, working hours, digital leadership, and to remaining time. Furthermore, future opportunities were significantly and negatively correlated to age and organization difficulties. Remaining time was significantly and positively correlated to digital leadership, and organization difficulties, while it was significantly and negatively correlated to age. Processing speed difficulties were significantly and positively correlated to organization difficulties, while they were significantly and negatively correlated to education. Finally, organization difficulties were significantly and negatively correlated to age, working hours, and digital leadership.

Testing the hypotheses

Table 3 shows the direct effects and Table 4 shows the indirect effects of the structural equation modeling. Hypotheses 1–3 concerned the motivational pathway that links age to attitude toward new technology via occupational future time perspective (consisting of the two sub-dimensions future opportunities and remaining time) and perceived usefulness of new technology. The structural coefficients showed that age had negative relations with future opportunities (γ = −.28, *SE* = .03, *p* < .001) and remaining time (γ = −.65, *SE* = .03, *p* < .001), supporting Hypotheses 1a and 1b. We further found that future opportunities had a positive relation with perceived usefulness (γ = .37, *SE* = .07, *p* < .001), supporting Hypothesis 2a. However, the effect of remaining time on perceived usefulness was not significant (γ = .11, *SE* = .13, *p* = .411), thereby not supporting Hypothesis 2b. With regard

[4]To test the robustness of our findings, we ran the analyses with and without including the cross-over relations. The results show that all effects that were significant with cross-over relations being included in the model are also significant without the inclusion of cross-over relations.

to the indirect relations, we found that age had a significant negative relation with attitude toward new technology via future opportunities and perceived usefulness (*indirect effect* = –.032, 95% CI [–.051 to –.018]), supporting Hypothesis 3a. The indirect relation of age with attitude toward new technology via remaining time and perceived usefulness was, however, not significant (*indirect effect* = –.022, 95% CI [–.076 to .028]). Hypothesis 3b was therefore rejected. Although not explicitly hypothesized, we also tested the indirect relations via perceived ease of use and found that age had significant negative relations with attitude toward new technology via future opportunities and perceived ease of use (*indirect effect* = –.015, 95% CI [–.027 to –.005]) as well as via remaining time and perceived ease of use (*indirect effect* = –.072, 95% CI [–.125 to –.027]).

Hypotheses 4–6 concerned the capability pathway that links age to attitude toward new technology via cognitive constraints (consisting of the two sub-dimensions processing speed and organization difficulties) and perceived ease of using new technology. The relation of age with processing speed difficulties was not significant (γ = .06, *SE* = .03, p = .068), thus not supporting Hypothesis 4a. There was a significant relation of age with organization difficulties (γ = –.22, *SE* = .03, p < .001). However, age predicted organization difficulties in the opposite direction of what we hypothesized (i.e., negatively instead of positively). Hypothesis 4b was therefore rejected. Furthermore,

Table 2. Means, standard deviations, and correlations of study variables.

Variable	*M*	*SD*	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. Age	44.87	11.38	–										
2. Education	0.48	0.50	–.05	–									
3. Working hours	37.97	7.55	.01	.14**	–								
4. Digital leadership	3.23	1.01	–.01	–.003	.06	(.93)							
5. Future opportunities	3.33	1.08	–.31**	.13**	.16**	.38**	(.93)						
6. Remaining time	2.80	1.08	–.73**	.07	.06	.15**	.54**	(.81)					
7. Processing speed difficulties	2.99	0.89	.07	–.10*	–.01	.05	–.05	.06	(.95)				
8. Organization difficulties	2.17	0.88	–.28**	–.03	–.08*	–.08*	–.08*	.21**	.32**	(.95)			
9. Perceived usefulness	3.45	1.06	.01	.06	.04	.28**	.38**	.16**	.05	–.13**	(.95)		
10. Perceived ease of use	3.85	0.83	–.10*	–.05	.05	.19**	.37**	.25**	–.13**	–.22**	.55**	(.94)	
11.Attitude toward new technology	3.65	0.96	.02	.01	.04	.23**	.40**	.16**	–.02	–.22**	.69**	.63**	(.92)

Note. N = 643 at Time 1, N = 559 at Time 2, N = 470 at Time 3. Reliabilities (Cronbach's alpha) are shown in parentheses on the diagonal.
*p < .05, **p < .01.

Table 3. Results of structural equation modeling (direct effects).

	Future opportunities			Remaining time			Processing speed difficulties			Organization difficulties		
	Coeff	*SE*	*p*-Value	Coeff	*SE*	*p*-Value	Coeff	*SE*	*p*-Value	Coeff	*SE*	*p*-Value
Employee age (A)	**–.28****	.03	<.001	**–.65****	.03	<.001	.06	.03	.068	**–.22****	.03	<.001
Digital leadership (B)	**.39****	.04	<.001	**.16****	.03	<.001	.06	.04	.144	–.07	.04	.054
Interaction A × B	**.13****	.03	<.001	**.06***	.02	.011	–.02	.04	.547	–.01	.03	.769
R^2 (standardized)	**.33****	.05	<.001	**.47****	.05	<.001	.01	.01	.423	**.08****	.02	<.001

	Perceived usefulness of new technology			Perceived ease of use of new technology			Attitude toward new technology		
	Coeff	*SE*	*p*-Value	Coeff	*SE*	*p*-Value	Coeff	*SE*	*p*-Value
Employee age	.14	.08	.086	**.13***	.06	.023	.02	.05	.654
Digital leadership	**.13***	.05	.011	.03	.04	.360	.03	.04	.953
Future opportunities	**.37****	.07	<.001	**.14****	.05	.006	.07	.04	.114
Remaining time	.11	.13	.411	**.29****	.09	.001	–.02	.07	.792
Processing speed difficulties	**.16****	.05	.004	–.05	.04	.167	.02	.03	.611
Organization difficulties	**–.16****	.06	.009	**–.19****	.04	<.001	–.07	.04	.053
Perceived usefulness							**.31****	.04	<.001
Perceived ease of use							**.38****	.06	<.001
R^2 (standardized)	**.22****	.04	<.001	**.16****	.05	.003	**.64****	.05	<.001

Note. N = 643. Coeff = unstandardized coefficient, *SE* = standard error of unstandardized coefficient. Significant coefficients are highlighted in bold.
*p < .05; **p <.01

Table 4. Indirect effects of employee age on attitude toward new technology.

	Test of serial mediation		
	Coeff	CI LL	CI UL
Hypothesized indirect relations (H3a/b and H6a/b)			
H3a: Age → future opportunities → perceived usefulness → attitude toward new technology	**–.032**	–.051	–.018
H3b: Age → remaining time → perceived usefulness → attitude toward new technology	–.022	–.076	.028
H6a: Age → processing speed difficulties → perceived ease of use → attitude toward new technology	–.001	–.004	.001
H6b: Age → organization difficulties → perceived ease of use → attitude toward new technology	**.018**	.008	.026
Not hypothesized indirect relations (cross-over relations)			
Age → future opportunities → perceived ease of use → attitude toward new technology	**–.015**	–.027	–.005
Age → remaining time → perceived ease of use → attitude toward new technology	**–.072**	–.125	–.027
Age → processing speed difficulties → perceived usefulness → attitude toward new technology	.003	–.00002	.008
Age → organization difficulties → perceived usefulness → attitude toward new technology	**.011**	.003	.021

Note. N = 643. Coeff = unstandardized coefficient, CI LL = lower level of bias-corrected 95% confidence interval, CI UL = upper level of bias-corrected 95% confidence interval. Significant coefficients are highlighted in bold.

the relation of processing speed difficulties with perceived ease of use was not significant ($\gamma = -.05$, $SE = .04$, $p = .167$), rejecting Hypothesis 5a. In line with Hypothesis 5b, we found that organization difficulties had a negative relation with perceived ease of use ($\gamma = -.19$, $SE = .04$, $p < .001$), supporting Hypothesis 5b. With regard to the indirect relations, we found that the relation between employee age with attitude toward new technology via processing speed difficulties and perceived ease of use was not significant (*indirect effect* = –.001, 95% CI [–.004 to .001]). Hypothesis 6a was therefore rejected. Moreover, we found that age had a significant positive relation with attitude toward new technology via organization difficulties and perceived ease of use (*indirect effect* = .018, 95% CI [.008 to .026]). This indirect relation is in the opposite direction of what we hypothesized, Hypothesis 6b was therefore rejected. Although not explicitly hypothesized, we also tested the indirect relations via perceived usefulness. The indirect relation between age and attitude toward new technology via processing speed difficulties and perceived usefulness was not significant (*indirect effect* = .003, 95% CI [–.00002 to .008]). However, age had a significant positive relation with attitude toward new technology via organization difficulties and perceived usefulness (*indirect effect* = .011, 95% CI [.003 to .021]).

Exploring the research question

Research Question 1 addressed the moderating role of digital leadership displayed by the supervisor in the relation between employee age and occupational future time perspective as well as cognitive constraints and its indirect relation to attitude toward technology use. The estimated coefficients showed that digital leadership weakened the negative relation between employee age with future opportunities ($\gamma = .13$, $SE = .03$, $p < .001$) and remaining time ($\gamma = .06$, $SE = .02$, $p = .011$). However, digital leadership did not significantly moderate the relations between employee age with processing speed difficulties ($\gamma = -.02$, $SE = .04$, $p = .547$) and organization difficulties ($\gamma = -.01$, $SE = .03$, $p = .769$).

We plotted the significant moderating effects of digital leadership in Figure 2. We conducted simple slope difference tests to further decipher the relations between employee age with future opportunities and remaining time contingent upon digital leadership. We found that the relation between employee age and future opportunities was significantly weaker for employees with a supervisor displaying higher (+1*SD*) digital leadership (*simple slope* = –.15, $SE = .04$, $p = .001$) as compared to employees whose supervisor showed lower (–1*SD*) digital leadership (*simple slope* = –.40, $SE = .05$, $p < .001$, *slope difference* = .25, $SE = .07$, $p < .001$). Similarly, we found that the relation between employee age and remaining time was significantly lower for employees who perceived their supervisor as engaging in higher (+1*SD*) digital leadership (*simple slope* = –.59, $SE = .04$, $p < .001$) as compared to employees whose supervisor showed lower (–1*SD*) digital leadership (*simple slope* = –.71, $SE = .04$, $p < .001$, *slope difference* =.12, $SE = .05$, $p = .011$).

As can be seen in Table 5, we also tested whether digital leadership moderated the indirect relations between age and attitude toward technology. First, the indirect relation via future opportunities and perceived usefulness was significantly weaker at higher levels of digital leadership (*indirect effect* = –.018, 95% CI [–.031 to –.007]) as compared to lower levels of digital leadership (*indirect effect* = –.046, 95% CI [–.065 to –.028]; *difference* = .029, 95% CI [.013 to .046]). The moderated mediation index was also significant (*compound effect* = .015, 95% CI [.007 to .024]). Second, the indirect relation via future opportunities and perceived ease of use was significantly weaker at higher levels of digital leadership (*indirect effect* = –.008, 95% CI [–.017 to –.002]) as compared to lower levels of digital leadership (*indirect effect* = –.022, 95% CI [–.040, –.006]; *difference* = .013, 95% CI [.003 to .028]). The moderated mediation index was also significant (*compound effect* = .007, 95% CI [.002 to .015]). Third, the indirect relation via remaining time and perceived usefulness was not conditional upon digital leadership as the moderated mediation index was not significant (*compound effect* = .004, 95% CI [–.006 to .016]). Finally, the indirect relation via remaining time and perceived ease of use was significantly weaker at higher levels of digital leadership (*indirect effect* = –.058, 95% CI [–.102 to –.021]) as compared to lower levels of digital leadership (*indirect effect* = –.085, 95% CI [–.151 to –.031]; *difference* = .027, 95% CI [.008 to

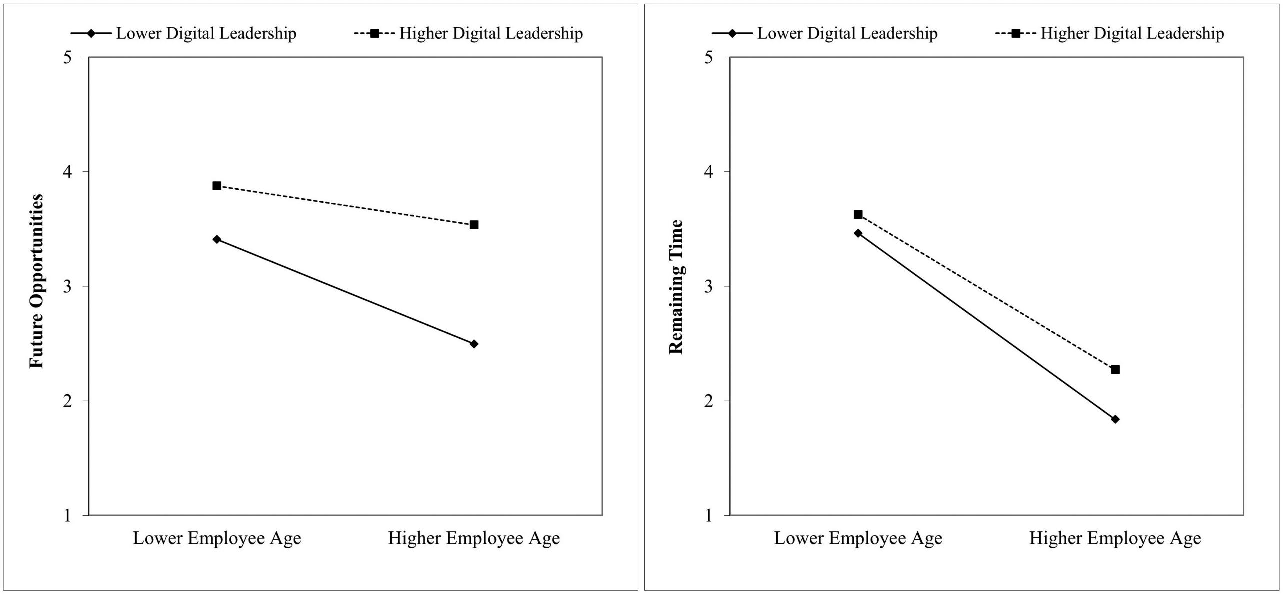

Figure 2. Digital leaderships moderates the relations between employee age with future opportunities and remaining time.

.055]). The moderated mediation index was also significant (*compound effect* = .014, 95% CI [.004 to .029]).

Discussion

The aim of our research was to connect the literature on aging with research on technology use in organizations. Our findings first support a motivational pathway via employees' future time perspective and perceived usefulness of the new technology. In line with previous research (cf. meta-analysis by Rudolph et al., 2018), we found that age is negatively related to perceived future opportunities and remaining time. Perceived future opportunities, but not remaining time, predicted perceived usefulness, which in turn predicted attitude toward new technology. The fact that perceived future opportunities showed significant relations, but remaining time did not, also corresponds with previous research, for example with regard to task performance (Rudolph et al., 2018) or vitality (Oliveira, 2021). We may conclude that employees' motivation to engage in certain behaviors, such as technology use, may be more driven by perceived future opportunity than by remaining time.

Second, with regard to the capability pathway, our results are unexpected because we did not find a relation between age and perceived processing speed difficulties. Moreover, and contrary to our hypotheses, age was negatively related to employees' perceived organization difficulties. In turn, organization difficulties were indirectly linked to attitude toward new technology via perceived ease of use. These findings show that there is a capability pathway between employee age and attitude toward new technology that is, however, in the opposite direction of what we assumed (i.e., it is positive rather than negative). The fact that younger employees reported more difficulties to organize themselves than older employees implies a potential gap between research using objective cognitive ability measures (e.g., Salthouse, 1996) and the cognitive ability perceptions used in our research. Whether organization difficulties represent a type of cognitive ability, such as executive control or function (see Salthouse, 2010) is however debatable and requires further research. In terms of potential explanations, it is on the one hand interesting to note that concerns about lower abilities to pay attention and concentrate have been raised in the public debate, which some have linked to excessive social media consumption in the upcoming generation (e.g., Digital Information World, 2018; Egan, 2016; Firth et al., 2019; Small & Vorgan, 2008). On the other hand, research demonstrated that older employees are better than younger workers at accumulating meta-cognitive knowledge (i.e., knowledge about how to learn or how to structure oneself; Gerpott et al., 2017). Furthermore, comprehensive evidence indicates that older people are better than younger ones at exhibiting self-control (Butterworth et al., 2022), which is tied to the ability to organize oneself. Our results are in line with research according to which a decline in cognitive abilities does not translate into performance deficits (cf. Hedge & Borman, 2012). Possible explanations for this disconnect are offered by the selection, optimization, and compensation model (Baltes & Baltes, 1990) or the role of accumulated knowledge and expertise (i.e., crystallized abilities). Overall, our findings thus point to the importance of considering perceptions of compensatory cognitive processes that may increase with age to fully understand how age relates to technology use.

While not explicitly hypothesized, we also tested and found cross-over relations showing that both perceived future opportunities and remaining time are linked to attitude toward new technology via perceived ease of use. Furthermore, we found that employees' perceived organization difficulties are linked to attitude toward new technology via perceived usefulness. Together, these findings suggest that motivational and capability-related forces are interwoven in predicting attitude toward new technology. Last but not least, we found that employees' perception of their supervisors' digital leadership skills moderated the relations between employee age with perceived future opportunities and remaining time, such that the negative

Table 5. Conditional indirect effects of employee age on attitude toward new technology upon digital leadership.

	Test of serial mediation		
	Coeff	CI LL	CI UL
Age → future opportunities → perceived usefulness → attitude toward new technology			
At higher (+1*SD*)levels of digital leadership	**−.018**	−.031	−.007
At lower (−1*SD*) levels of digital leadership	**−.046**	−.065	−.028
Difference between higher and lower levels of digital leadership	**.029**	.013	.046
Index of moderated mediation	**.015**	.007	.024
Age → future opportunities → perceived ease of use → attitude toward new technology			
At higher (+1*SD*)levels of digital leadership	**−.008**	−.017	−.002
At lower (−1*SD*) levels of digital leadership	**−.022**	−.040	−.006
Difference between higher and lower levels of digital leadership	**.013**	.003	.028
Index of moderated mediation	**.007**	.002	.015
Age → remaining time → perceived usefulness → attitude toward new technology			
At higher (+1*SD*) levels of digital leadership	−.018	−.060	.023
At lower (−1*SD*) levels of digital leadership	−.026	−.089	.034
Difference between higher and lower levels of digital leadership	.001	−.011	.032
Index of moderated mediation	.004	−.006	.016
Age → remaining time → perceived ease of use → attitude toward new technology			
At higher (+1*SD*) levels of digital leadership	**−.058**	−.102	−.021
At lower (−1*SD*) levels of digital leadership	**−.085**	−.151	−.031
Difference between higher and lower levels of digital leadership	**.027**	.008	.055
Index of moderated mediation	**.014**	.004	.029

Note. *N* = 643. Coeff = unstandardized coefficient, CI LL = lower level of bias-corrected 95% confidence interval, CI UL = upper level of bias-corrected 95% confidence interval. Significant coefficients are highlighted in bold.

relations were less pronounced when digital leadership was higher (vs. lower). In terms of the downstream consequences, we further found that digital leadership buffered all three negative indirect relations between age and attitude toward new technology.

Theoretical implications

First, by connecting the literatures on aging and technology acceptance with a dual pathway model, we expand the TAM and its extensions in several ways. On the one hand, in terms of the motivational pathway and its link to perceived usefulness, we contribute an overlooked temporal perspective that identifies future opportunities in one's job as an antecedent of perceived usefulness. So far, extensions of the TAM have suggested that factors related to social influence (i.e., subjective norm, voluntariness, image) and instrumental aspects (i.e., job relevance, output quality, results demonstrability) can help explain the degree to which people perceive a technology as useful (Venkatesh & Davis, 2000), and that age moderates some of these relations (Morris & Venkatesh, 2000; Venkatesh et al., 2003, 2012). Other research has also suggested hedonic perceptions (i.e., perceived enjoyment, Wang & Li, 2019) and system integration (i.e., the connectivity with existing technology at work, Saeed & Abdinnour-Helm, 2008) as predictors of perceived usefulness. However, these extant perspectives overlook an important part of the motivational puzzle: Even if a new technology is generally relevant for the job is well integrated with other technological systems, results in great output quality that can also be demonstrated, and is fun to use once it is learned, an employee may still not develop a positive attitude toward the new technology because the lack of perceived future opportunities in their job decreases their perceived usefulness.

On the other hand, in terms of the capability pathway and its link to perceived ease of use, a widely cited extension of the TAM (Venkatesh & Davis, 1996), suggested objective usability and technology-related self-efficacy as antecedents of perceived ease of use. Using perceived organization difficulties and processing speed, our research complements this picture by considering age-related perceptions of one's cognitive capabilities. While both technology-related self-efficacy and our perceived cognitive constraints are tied to a person's perceived capabilities, the former does not consider potential age-related mechanisms involved in using new technology at work. To illustrate, a person may believe that they possess the general skills and knowledge necessary to learn a new technology (i.e., high technology-related self-efficacy)—but they may nevertheless find it difficult to use because they cannot organize themselves to find the time to adopt it. Our results indicated that such perceived organization difficulties are more problematic than the perceived processing speed difficulties when it comes to the perceived ease of using new technology. This highlights that future research on the TAM could benefit from considering the broader age-related resources that are available to employees to fully understand why they may find it easy to use a technology (or not). In this regard, Park et al. (2011 have differentiated between individual and organizational facilitating conditions to support technology acceptance. Individual facilitating conditions capture individual skills and knowledge related to the technology at hand; whereas organizational facilitating conditions include the organizational means required for the technology use, such as the relevant infrastructure to use the technology as well as the availability of instruction, guidance, and assistance in case of difficulties. As organizational facilitating conditions play a major role in technology use (Park et al., 2011), it would be worth understanding whether different age groups need additional or different support, so they can transform their capabilities into more effective acceptance and use of technology.

Finally, by considering the role of employees' supervisor and their perceived digital leadership skills as a moderator in our dual pathway model, we expand preliminary evidence that has explored general leadership styles (i.e., transformational and transactional leadership, Schepers et al., 2005, authentic leadership, Aziz et al., 2020, or leading in a charismatic way, Neufeld et al., 2007) as predictors of technology acceptance. While evidence on this specific leadership style so far has been lacking and alternative explanations for the directionality of the relation can be developed, our data show clear evidence for a buffering role. Emphasizing the role of digital leadership not only fits well within the nomological net of the TAM, but also makes a contribution to the aging literature that has not yet explored the role of leadership in employees' future time perspective (Rudolph et al., 2018).

Practical implications

Our work offers several practical implications that may help organizations to cultivate employees' attitude toward a new technology. First, in terms of the motivational pathway, our results highlight the need for organizations to support employees' future opportunities because the perception of such opportunities is positively related to employees' attitude toward a new technology. Considering that employees tend to perceive fewer future opportunities with increasing age (cf. Rudolph et al., 2018), organizations should foster the perception of future opportunities among older employees using human resource (HR) systems and adjusting work design. For instance, HR systems targeted at facilitating knowledge, skills and abilities, motivation, as well as opportunities, can expand employees' future time perspective (Korff et al., 2017). For instance, organizations could implement mentoring programs using age-specific points of leverage to achieve this. Mentoring programs may represent a new development role for older employees in the advanced work life stage, which can fulfill their increasing need for high-quality relationships and the transfer of their accumulated wealth of knowledge in line with age-related motivational lifespan trajectories (Fasbender et al., 2021). Others have argued that HR practices are particularly convincing when they are explicitly designed to be age-inclusive (Rudolph & Zacher, 2021). In terms of work design, Rudolph et al. (2018) emphasize job autonomy as a relevant antecedent of employees' future time perspective. Organizations may therefore design jobs such that employees can effectively decide upon the methods and scheduling and allow them to use their personal initiative to carry out work.

Second, in terms of the capability pathway, our findings indicate that organization difficulties negatively impact employees' perceived ease of use of new technology. To alleviate this issue, organizations could consider supporting employees in their organization capabilities. On the one hand, this can be done through interventions targeting these specific aspects of self-organization. For example, initial research suggests that self-reflective interventions with positive thinking can positively influence self-organization (Wang et al., 2017a). On the other hand, employees with high organization skills may also provide assistance and offer advice to colleagues, who struggle to organize themselves and their work tasks (Fasbender et al., 2021; Gerpott et al., 2017).

Third, the results of this study are promising as they open a new perspective on supporting an aging workforce in using new technology by introducing and facilitating digital leadership at work. Scholars have emphasized both the challenges of age-related differences in dealing with technology (Yücebalkan, 2018) as well as the potential positive impact of leadership in successfully navigating organizations' digital transformation (Trenerry et al., 2021). To evaluate and promote digital leadership, organizations could, for example, make use of the competency model developed by Dörr et al. (2012) that describes five competencies (e.g., personal influence of leaders as in leading by example) applicable to digital leadership. In doing so, organizations could help supervisors to bridge the gap between more conventional leadership behaviors and the competencies required for digital leadership (Larson & DeChurch, 2020).

Limitations and future research directions

Although our research offers important insights for theory and practice, it comes with limitations that should be acknowledged to contextualize our findings. First, we used a self-report survey approach to collect the data, potentially raising concerns of common-method-bias (Podsakoff et al., 2012) or that participants may be subject to positive illusions when asked to report on undesirable developments such as cognitive constraints (Gerpott et al., 2020). However, we still consider our measurement approach suitable for several reasons. For instance, to reduce the risk of common-method-bias, we distributed the data collection across multiple time points. In addition, self-report measures are a common form of assessing cognitive decline (Wion et al., 2021), with empirical evidence supporting their relation to objective measures of cognitive functioning (Burmester et al., 2016). Moreover, individuals' perceptions about their cognitive functioning may even be more important than objective measures in shaping the perceived ease of use due to age meta-stereotypes (i.e., beliefs about what stereotypes other age groups hold about one's age group; Finkelstein et al., 2013). For example, even if a younger employee would not be objectively less organized than their older colleague, they may have internalized the perception that younger people are more disorganized (i.e., self-stereotype; Finkelstein et al., 2020; see also Thomas & Finkelstein, 2023), which in turn could affect their attitude toward a new technology at work. Nonetheless, future research should consider objective behavioral measures to capture variables such as cognitive constraints (e.g., cognitive functioning assessment tests; Haas et al., 2021). In this regard, future research may also consider the new directions for measurement in the field of work, aging, and retirement (Fasbender et al., 2023).

Second, although we utilized a time-lagged design, more fine-grained and long-term temporal relations between employee age and attitude toward new technology remain unclear. Replicating this study using different time frames may be worthwhile to further probe the dynamics of the identified relations. In such a replication study, it would also be worthwhile to explore potential overlaps between digital leadership and other more general leadership styles. Although preliminary evidence (Matsunaga, 2022) indicates that digital leadership does not highly overlap with constructs such as transformational leadership, it may be worth exploring whether this leadership style can also be reliably differentiated from more general supportive leadership styles.

Going beyond the focus of this study, there are many versions of the TAM that offer interesting research approaches (for a review see Venkatesh et al., 2016). In that vein, there are several predictors that future research could address to clarify what factors influence employees' attitude toward a new technology. For instance, Venkatesh et al. (2003) showed that social influence (i.e., one's perception whether relevant others think one should use a new technology) has a particularly strong impact on attitude to use new technology for older employees, which is interesting in light of research supporting the notion that susceptibility to social influence decreases with increasing age (Oyibo et al., 2017). Future research could therefore examine this divergence more closely and discover how the impact of social influence may be leveraged to positively shape older employees' attitudes toward technology at work. Furthermore, it would be worth explaining the age-related mechanisms that connect age to hedonic motivation, price value and habits as predictors of technology use. For example, previous research has found a negative relation between age and hedonic motivation (Venkatesh et al., 2012), which could be explained by a changing future time perspective. In addition, further extensions to the TAM are compatibility, education, personal innovativeness, and costs (Blut et al., 2022). In this regard, it would be interesting to assess how age is linked to personal innovativeness and whether future time perspective and cognitive constraints could explain this link.

Last but not least, and in line with the wider scope of this special issue, future research could look beyond the context of work. Although we confined our age-specific lens to attitudes toward technology in a sample of people who regularly use computers at work, our model combining a future time perspective-driven motivational pathway and a cognitive constraints-driven capability pathway could probably be translated to other contexts (e.g., health care, Holden & Karsh, 2010; education, Granić & Marangunić, 2019). Owing to the pervasiveness of technology in all facets of life, it seems reasonable for future research to examine the applicability of our model in different contexts, thereby also considering that people with less experience with technology may expect more effort and less outcome of using it.

Conclusion

Our work seeks to inspire scholars and practitioners when thinking about how to get ready for the future against the backdrop of ever-changing technological advancements and an aging workforce. On the one hand, our findings suggest that organizations are well advised to expand employees' future time perspective (e.g., by promoting digital leadership) to increase the likelihood that these employees perceive new technology as useful, which, in turn, will make them more likely to be positively attuned toward using it. On the other hand, we also found some surprising evidence, such that with age, employees' perceive less organization difficulties, resulting in the practical implication that older employees could serve as mentors to improve organization skills to their younger colleagues. Overall, our work contributes to a more nuanced and positive view of age and technology acceptance.

Supplementary Material

Supplementary material can be found at *Work, Aging and Retirement* online.

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