ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA

DOTTORATO DI RICERCA IN

PSYCHOLOGY

Ciclo 38

Settore Concorsuale: 11/E3 - PSICOLOGIA SOCIALE , DEL LAVORO E DELLE ORGANIZZAZIONI

Settore Scientifico Disciplinare: M-PSI/06 - PSICOLOGIA DEL LAVORO E DELLE ORGANIZZAZIONI

FROM TECHNOLOGY TO ARTIFICIAL INTELLIGENCE: CRAFTING INDIVIDUAL ADOPTION AND USE

Presentata da: Luca Fazi

Coordinatore Dottorato

Mariagrazia Benassi

Supervisore

Sara Zaniboni

Co-supervisore

Samanta Gubellini

Esame finale anno 2026

Contents

PREFACE

In 2022, a combination of fortunate circumstances, the support of brilliant people around me, and maybe a bit of unconscious courage, led me to begin my doctoral journey. I was convinced that this was the right way for me to contribute to the world. I have always believed that science, and the scientific method, is the most reliable way to generate knowledge that can guide human behavior. Then, when the opportunity to pursue a PhD became real, it did not feel like a decision as much as a natural next step. The first question I had to answer was: contribute to what? To address this question, which I believe is fundamental not only for a doctoral project but for any meaningful path in life, I started from what has always fascinated me. I have long been interested in both technology and human behavior, so I chose to focus my efforts on their intersection: the interaction between humans and technology. This choice immediately made sense to me, not only because it aligned with my interests, but also because of its relevance (this has always been my second test: does it matter to others?). Technology had already shown, in the years before, its power to shape individual decisions, social dynamics, and entire sectors of society. I began building my knowledge in this area, formulating questions, reading, studying, doing everything a good doctoral student is supposed to do, when, at the end of that same year, OpenAI released a new tool called ChatGPT. From the very beginning, it was clear that "technology" had just changed meaning. The way humans interacted with this new system was fundamentally different from previous forms of human–technology interaction. Suddenly, I had the opportunity to observe a phenomenon in real time, to study it closely, and to develop my own perspective on it. I hope that the work presented in this thesis contributes to advancing our understanding of humans-technology interaction in this changing context. What I can say with certainty is that now, after three years and countless hours of work, I still believe in science and in the possibility of a better world. Given the speed at which everything around us is changing, and given what many political and institutional decision-makers have shown in the meantime, maintaining that belief already feels like an achievement.

Acknowledgements

This dissertation is dedicated to Life, and to the time it holds.

To my supervisor, Prof. Sara Zaniboni, for guiding me through this amazing journey and continually inspiring me to give my best

To my host supervisor, Prof. Mo Wang, from whom I have learned so much

To Anna Lisa Balestra and Samanta Gubellini, whose vision and mentorship set me on this path and made it profoundly valuable

To my father and my sister, for cheering me on every step of my life

To my mother, for everything else

To Mariangela, who completes me and makes me feel at home anywhere in the world

To all my friends, who help me take life less seriously

To music, which cares for all my dreams and emotions

Finally, to myself, for holding on when quitting made the most sense, and for the quiet discipline of small steps, day after day

Abstract

This PhD dissertation examines the adoption and use of technology in organizational settings, with particular attention to the individual characteristics and behaviors that can lead to positive or negative outcomes. Across three interconnected studies, it traces a path from traditional workplace technologies to artificial intelligence, and from adoption to actual use, seeking to better understand the value that technology generates through human choices. The first study investigates the role of individual characteristic, such that age, in the adoption of technology at work. Through a systematic literature review, 51 papers were identified and analyzed. The findings were organized into five dimensions that emerged as relevant for addressing technology adoption from an age-sensitive perspective. The study concludes by outlining implications for both theory and practice. Building on this, the second study shifts the focus from adoption to use. It examines the different forms of technology use behavior that have been studied in organizational contexts. Using a Bibliographic Systematic Literature Review approach, 122 articles were identified and clustered. A critical analysis of these clusters revealed gaps in the existing literature, and on this basis an integrative model was proposed to guide individual responsibility for the ethical use of technology in the workplace. Grounded in the insights of the first two studies, the third study integrates job crafting theory with the augmentation potential of new AI tools. It introduces the concept of AI Augmented Crafting, defined as workers' enhancement of their own capabilities through the proactive and goal-directed use of AI tools to alter the work. The construct, along with its corresponding measurement, was developed and validated through five different field studies, following established guidelines for the development and validation of formative constructs.

Taken together, these three studies deepen our understanding of technology adoption and technology use in the workplace, understood as two critical stages in which human choices shape the value created by human–technology interaction. Although this dissertation has limitations, which are discussed in the dedicated section and offer avenues for future research, it aims to support both theory and practice in approaching human–technology interaction in a more informed, human-centered way, and to provide a foundation for managing this interaction responsibly.

Keywords: Artificial Intelligence; Human behavior; AI Augmented Crafting; Adoption; Ethical Use

CHAPTER I | General introduction

This doctoral dissertation is rooted in a central, ambitious question: how can humans create positive impacts through technology in the workplace? To approach this question, research and practice have examined human–AI interaction in the workplace from multiple angles and across disciplines (Floridi et al., 2018; Handa et al., 2025; Hughes et al., 2017; Shao et al., 2025). For example, technology designers increasingly adopt a socio-technical perspective, one that treats technology and human activity as mutually constitutive, to orient design toward positive outcomes (Hughes et al., 2017). Differently, from an ethical-normative standpoint, governments and organizations are emphasizing regulation (e.g., the AI Act), seeking to guide the development and use of AI to promote beneficial impacts. Although these efforts are necessary to steer society's ongoing digital transformation in a virtuous direction, they are not sufficient to ensure positive impacts from AI in organizational context, for three main reasons. First, design and regulatory approaches tend to focus on the AI systems that organizations develop or officially adopt, while overlooking the widespread availability of free, off-the-shelf tools. This include the use of shadow IT (Silic et al., 2017), a phenomenon within organizations that can lead to unexpected outcomes. For example, rigorously assessing the risks of an in-house recruitment system may help deliver an inclusive, bias-aware tool, yet it does not prevent employees, for example, from independently using a free AI service to summarize and rank candidates' résumés. Second, AI tools are now so widespread, inexpensive and continuously growing, that it is unrealistic to regulate them all. According to the Artificial Intelligence Index Report 2025 (Maslej et al., 2025), there were 122,511 AI-related patents in 2023, a 29.6% increase over the previous year. Given the vast number of AI solutions and their rapid growth, it is difficult to imagine any system capable of promptly addressing all potential misuses and risks. Third, the pool of potential users is constantly expanding (Economic, 2024), and individual differences, such as age, are becoming more pronounced. The United Nations' World Population Prospects 2024 (Economic, 2024) projects that the global population will approach 10 billion by the mid-2080s, with a steadily increasing share of people aged 65 and over. Such differences can significantly influence how technology is adopted and used (Blut et al., 2022; Morris et al., 2005; Venkatesh et al., 2003), while at the same time making it impossible to fully tailor tools and regulations to every needs. For these reasons, this doctoral research seeks to contribute to both theory and practice by focusing on individual agency and the choices people make when adopting and using technology, as key determinants of AI positive impacts in the workplace. This work first analyzes antecedents of workplace technology adoption, paying close attention to increasingly salient individual differences, such as age. It then investigates individual choices and behaviors in the use of technology at work, with particular emphasis on AI. What follows is organized into the following sections.

Chapter I begins with an exploration of research on workplace technology adoption and use, drawing out key implications from organizational behavior for human–AI interaction. In this section, I provide working definitions of technology, AI, adoption, use, and I discuss why social change matters for this topic, particularly for new technologies such as AI. It concludes with the dissertation's guiding viewpoint, which frames the studies that follows.

Chapter II presents the research aims and questions that guide the investigations, along with the theoretical frameworks used, such that Unified Theory of Acceptance and Use of Technology (UTAUT)(Venkatesh et al., 2003), Lifespan theories (i.e., Socioemotional Selectivity Theory and Selective, Optimization with Compensation Theory)(Baltes & Baltes, 1990; Carstensen et al., 1999), Ethical Behavior theories (Treviño et al., 2014) and Job Crafting theory (Bruning & Campion, 2018).

Chapter III, IV and V presents the studies conducted. In the first study, I examined the antecedents of workplace technology adoption, with particular attention to workers' age. The second study investigates how workers use technology after its adoption, delving into specific usage behaviors and their ethical implications. The third study focuses on proactive use of AI at work, conceptualizing this behavior as a form of job crafting enabled by new AI tools.

In Chapter VI, I discuss the principal findings, articulate the theoretical contributions, propose directions for future inquiry, and delineate practical implications for technology adoption and use, with particular emphasis on emerging AI tools in the workplace.

Technology adoption and use in the workplace

Talking about technology, I refer to tools that allow humans to interact, reprogram, edit digital artifacts (Kallinikos et al., 2013) to generate outputs (e.g., database) and reach goals (e.g., communicate with others). To realize the added value of technology, humans must first adopt it (Venkatesh et al., 2003) and then use it in ways that support goal attainment. Here, I distinguish adoption from use. By adoption, I mean the decision to accept and begin using a particular technological tool (Salahshour Rad et al., 2018). Adoption is conceptually and practically prior to the variety of use behaviors that may follow. By use, I refer to the specific ways the technology is employed after it has been accepted, that is, the post-adoption patterns of behavior enabled by the tool. Within organizational settings, technology adoption has interested both scholars and practitioners since the early 1980s (Blut et al., 2022; Salahshour Rad et al., 2018; Venkatesh et al., 2003), when, the debates over the performance gains from technology investments has been linked to the individual unwillingness to use new systems (Davis et al., 1989). To examine this domain, scholars have applied theories of consciously intended behavior to technology adoption. For example, the Theory of Reasoned Action (TRA) (Ajzen, 1980; Fishbein & Ajzen, 1977) has been used to study adoption decisions (e.g., Shareef et al., 2009). TRA posits that behavior is driven by behavioral intention, which in turn is a function of an individual's attitude toward the behavior and subjective norms (i.e., perceived social pressure) regarding that behavior. Building on this foundation, theories specifically developed to explain individuals' intention to use technology have been advanced (Davis et al., 1989; Venkatesh et al., 2003). In particular, Davis et al. (1989) introduced the Technology Acceptance Model (TAM), which posits that behavioral intention to use a system is a function of attitude toward using it, where attitude is determined by perceived usefulness and perceived ease of use; moreover, perceived usefulness may exert a direct effect on intention. A more recent development in theories of individual technology acceptance is the Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. (2003). UTAUT synthesizes prior models and identifies four core determinants: performance expectancy, effort expectancy, social influence, and facilitating conditions. In the original formulation, performance expectancy, effort expectancy, and social influence predict behavioral intention, whereas facilitating conditions, together with intention, predict actual use; these relationships are moderated by age, gender, experience, and voluntariness of use. UTAUT has been widely applied and refined; together with related models, it has provided the theoretical framework for a substantial literature on technology adoption over the past decades (Blut et al., 2022; Maretto et al., 2023). This emphasis on adoption has been shaped by the characteristics of earlier (pre-AI) workplace systems, which were predominantly single-purpose technologies (Bresnahan & Trajtenberg, 1995) designed for a specific function, with limited flexibility and prescribed user pathways. For example, a CRM system is designed to manage customer information and typically requires users to enter defined data fields when engaging a new client. Similarly, an e-learning platform delivers training through predefined modules and sequences, constraining both the order of activities and the range of permissible user actions. In this context, it is intuitive that the advantage of technology hinges primarily on adoption, as post-adoption usage tends to be constrained by the system's limited degrees of freedom. The actual use behaviors became more interesting when deviating from the expected path. For example, using internet at work for personal purposes (i.e., cyberloafing) is well-investigated in the literature (please see CHAPTER IV), because its relevance for performance gain of technology in the workplace. With the diffusion of new AI tools, this dynamic has shifted. Although end-user adoption of AI within organizations remains a central concern (Kelly et al., 2023; Venkatesh, 2022), increasing attention is directed to patterns of use, not only with respect to potential risks (Baabdullah, 2024; Floridi et al., 2018) but also regarding diverse usage behaviors and their consequences (Klonek & Parker, 2025; Man Tang et al., 2022; Shao et al., 2024; Tang et al., 2023).

The old-new Artificial Intelligence in a changing human world

Artificial intelligence (AI) has a history spanning more than six decades, with its roots in the mid-1950s. In their seminal proposal, McCarthy et al. (1955) described AI as enabling a machine "to behave in ways that would be called intelligent if a human were so behaving." The definition has continued to evolve, especially as AI integrates with emerging technologies such as the Internet of Things (Venkatesh, 2022). Basically, AI relies on algorithms and data, and its rapid diffusion in recent years reflects advances in both (Raisch & Fomina, 2025). Greater computational power, unprecedented data availability, and new learning techniques have scaled AI across domains. Broadly, AI has progressed along two complementary paradigms: predictive AI, which learns from historical data to forecast or classify future outcomes (e.g., weather forecasting), and generative AI, which learns patterns to produce novel outputs (e.g., image generation) (Raisch & Fomina, 2025). In this work, we consider both paradigms, with a primary focus on generative AI (GenAI), defined as the use of machine-learning models to generate new content (e.g., text, audio, video, images, software code, and simulations) from large training datasets (Budhwar et al., 2023).

The diffusion of these tools is unfolding within a human context that is itself undergoing demographic change (Aksoy et al., 2019; Economic, 2024), bringing an ever more diverse set of users into contact with them. Over recent decades, we have witnessed declines in both death and birth rates (Figure 1). These shifts have contributed, and will continue to contribute, to population growth alongside a redistribution toward older age cohorts, particularly those aged 25 and above (Figures 2 and 3) (Economic, 2024).

Figure 1

Graphical representation of projected crude birth and death rates from 1950 to 2100.

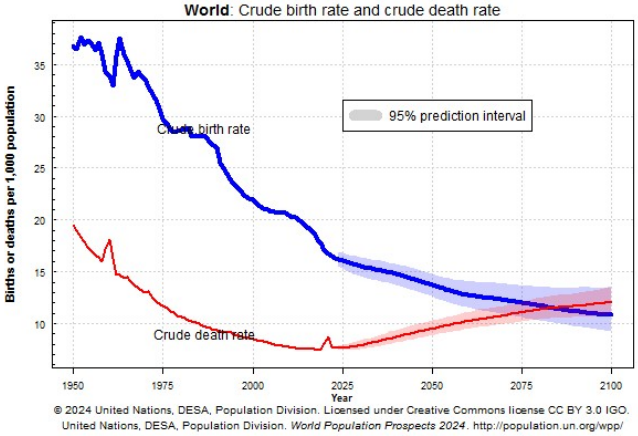


Figure 2

Graphical representation of projected total world population from 1950 to 2100.

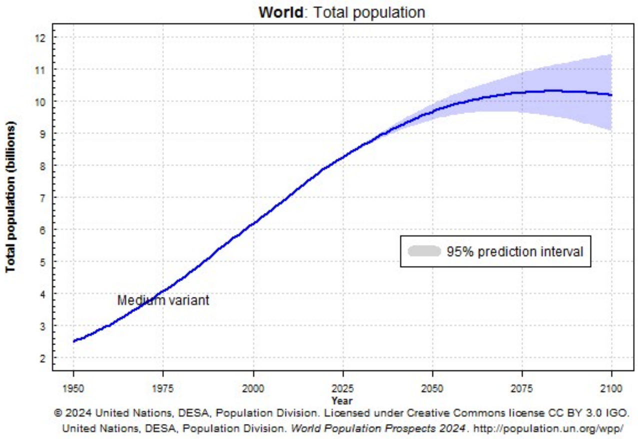
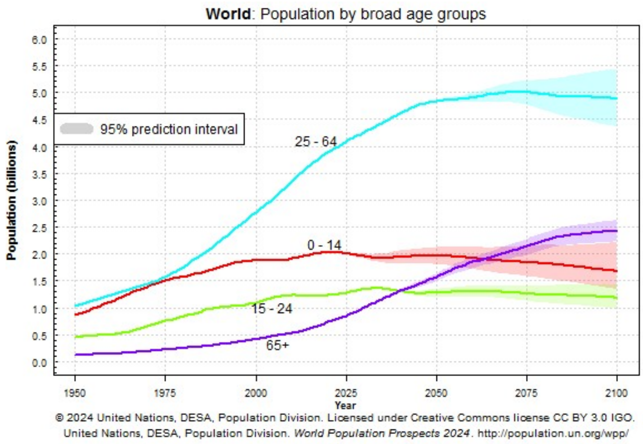


Figure 3

Graphical representation of projected total world population by age groups from 1950 to 2100.



This trend is reflected in an increasingly age-diverse workforce within organizations (Acemoglu et al., 2022). Acemoglu et al. (2022) highlights that the share of workers aged over 50 has risen from one in five to one in three, with workforce participation extending up to age 74. The growing presence of older employees indicates a progressively age-diverse workforce that interacts daily with workplace technologies. Literature showed age-related differences in both the adoption and use of traditional technologies (Morris et al., 2005; Venkatesh et al., 2023). For instance, research shows that younger workers tend to adopt new technologies more readily than older colleagues (P. Brown et al., 2019; S. A. Brown et al., 2010; Nord et al., 2020). However, younger workers have also been found to engage in less ethical or riskier uses of technology (Everton et al., 2005). Human–AI interaction complicates this picture. Depending on how AI is adopted and used, it can either foster integration in age-diverse workforces or exacerbate polarization. Extending findings from traditional technologies to AI, older workers may be less inclined to use these tools than younger colleagues, potentially widening the digital divide. At the same time, younger workers may employ AI in ways perceived as unethical, increasing the gap between their behavior and organizational expectations and creating unpredictable consequences for themselves, coworkers, and the organization. This concern is not limited to unethical use, a core theme in the AI discourse (Floridi et al., 2018), but also encompasses differences in types of use within ethical bounds. For example, GenAI may be used to retrieve information about organization. However, due to its generative nature, GenAI may encourage younger workers to rely on erroneous or misleading outputs. This reliance could reduce opportunities for social interaction and knowledge exchange, in contrast to traditional ICTs, which have been shown to facilitate workplace socialization (Flanagin & Waldeck, 2004). In this sense, individual differences, such as age, may play a critical role in shaping the impacts of human–technology interactions and, more specifically, human–AI interactions, given their potential influence on adoption decisions and patterns of use behavior.

The value generated by human-technology interaction: a distributed responsibility

The rapid spread of generative AI (e.g., ChatGPT) in recent years has brought these tools to a mass audience, making human interactions with them increasingly prominent. The high accessibility lets billions of people use GenAI with a tap, even for work, making the technology potentially highly beneficial or highly risky. Three features drive this power (for better or worse). First, GenAI produces outputs based on user prompts and / or available data, which can yield unpredictable results. Second, it is capable of performing a wide variety of tasks, which makes this technology adaptable for multiple purposes (e.g., evaluating solutions, generating new ideas, acquiring information). Third, GenAI communicates in a human-like manner, often making it hard to distinguish machine-generated content from those human-generated. These three characteristics place human agency at the center of how tool use translates into impact. They enable machines to interact with people with a meaningful degree of autonomy, while allowing users to decide which purposes to pursue with the technology and how much to rely on it. For instance, a person might generate a report and send it to colleagues with minimal oversight, or choose to consult GenAI, rather than coworkers, for feedback or information (Logg et al., 2019). Such choices shift the balance between human–human and human–machine interaction, with downstream consequences for individuals (e.g., stress; Klonek & Parker, 2025; or knowledge acquisition; Jo & Park, 2024) as well as for teams and organizations (Gong et al., 2009). In this sense, it is within human–AI interaction that the potential for positive workplace impact is ultimately realized (Shao et al., 2025), and now more than ever, these impacts depend on human action and judgment.

Research on workplace human–AI dynamics largely spans two streams: human–AI collaboration, which examines joint decision making with AI, and algorithmic management, which studies workers' interactions with AI systems that enact managerial control (Hillebrand et al., 2025). I refer readers to Hillebrand et al. (2025) for comprehensive reviews of these domains and focus here on the role of humans agency within these interactions.

The centrality of human agency within organizations has long been recognized across multiple disciplines as a key determinant of both individual and organizational success (Griffin et al., 2007; Kouchaki & Smith, 2024; Ocampo et al., 2018; Tims et al., 2022). Research on moral decision-making, for instance, highlights employees as moral agents whose choices shape organizational outcomes, for better or worse (de Pedro, 2024; Kouchaki & Smith, 2024). Scholars have also examined specific forms of discretionary behavior such as Organizational Citizenship Behavior (i.e., innovative, spontaneous actions that go beyond formal role requirements to foster cooperation) which are consistently linked to performance (Ocampo et al., 2018). Because uncertainty is a defining feature of organizational life (Katz & Kahn, 1978; Trist, 1981), rapid adaptability is essential for sustaining high performance (Griffin et al., 2007), and the human agency is more relevant than ever. In fact, organizations often adapt more slowly than their environments due to structural inertia in resource investment patterns and routines (Gilbert, 2005). In periods of large, rapid shifts, such as technological disruptions, individuals therefore become pivotal in overcoming organizational rigidity. This is especially salient with contemporary AI tools. The AI landscape is changing at an unprecedented pace (Tang et al., 2020), amplifying the risks of organizational lag, while simultaneously placing powerful capabilities directly in employees' hands, capabilities that can accelerate adaptation (Li et al., 2024) but can also undermine performance if misused (Vaccaro et al., 2024). Consequently, responsibility for steering adaptation toward positive impact is more distributed than ever, resting with each individual inside the organization. A salient form of individual agency that promotes adaptability is job crafting (Tims et al., 2022). Conceptually, job crafting refers to individually initiated job (re)design grounded in role- and resource-based perspectives (Bruning & Campion, 2018). It is also closely connected to technology use. For instance, Bruning and Campion (2018) introduce the Adoption dimension to capture "the active and goal-directed use of technology and other sources of knowledge to alter the job and enhance a work process" highlighting how employees leverage tools to reshape tasks and improve workflows. These proactive individual behaviors may evolve through interaction with AI (Handa et al., 2025; Shao et al., 2025), and could represent one of the most powerful mechanisms for generating positive outcomes from human–AI collaboration within organizations.

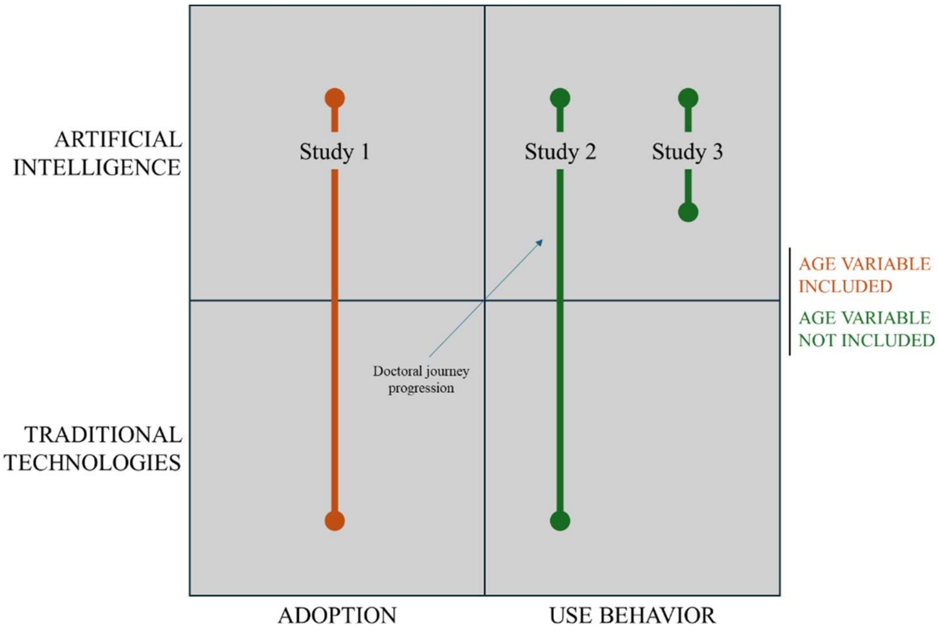
CHAPTER II | This doctoral work

Research aim and questions

As discussed in the previous chapter, the value generated by technology depends first on workers' decisions to adopt it and then, especially for AI, on how they use it. Accordingly, the three studies in this dissertation progress from adoption to use behavior, and from traditional technologies to AI, incorporating demographic change when the literature was sufficiently mature. This design reflects the evolution of the research questions throughout the doctoral journey, grounded in the evidence identified in the literature, and enables a comprehensive contribution across successive stages of the human–technology impact pathway. Figure 4 illustrates the progressively refined research focus that structure the dissertation, developed throughout the doctoral journey.

Figure 4

Graphical representation of the doctoral research trajectory, illustrating the evolution from traditional technologies to artificial intelligence, and from technology adoption to usage behavior.



The first prerequisite for realizing technology's impact is its adoption. Research on technology adoption is extensive and spans multiple perspectives on why users, both inside and outside organizations, choose to adopt new technologies (Blut et al., 2022). However, the specific role of age remains less clearly understood, particularly when the focus is on adoption within the workplace. Then, the first study in this dissertation examines the factors that drive technology adoption in the workplace, considering the role of workers' age. We consider a wide range of technologies to highlight potential differences between traditional technologies and emerging AI tools. The study therefore asks:

Q1.1: What factors influence technology adoption in the workplace?

Q1.2: What is the influence of age on the adoption of technology at work?

After answering this first question, we moved from the adoption to the use of technologies. Building on the first study, we observed that while technology adoption is a well-defined research stream, the literature is less consistent regarding patterns of technology use at work. In particular, there is limited agreement on how to define and evaluate use behaviors as positive or negative (i.e., ethical or unethical), despite their substantial impact. Given the centrality of use behavior in shaping technology's impacts, we analyzed the different type of technology use behaviors investigated in the literature. Accordingly, the second study maps the spectrum of technology use behaviors identified in prior research and proposes a model to guide individual choices toward ethical use, underscoring the central role of individual responsibility. The study therefore asks:

Q2.1: What worker behaviors related to the ethical use of technology have been considered in the literature?

Q2.2: Why are these behaviors classified as unethical, ethical or extraordinary ethical?

Answering the second research question provides evidence of systematic differences between the use of traditional technologies and the use of new AI tools, differences that move beyond human–traditional technology interaction and toward a human-augmented paradigm (Shao et al., 2025). Emerging work on employees' use of AI documents distinct use behaviors and their potential consequences (Klonek & Parker, 2025; Lazar et al., 2025; Shao et al., 2024; Tang et al., 2023). For example, Klonek and Parker (2025) suggest that team members engage with AI for three core purposes, transition, action, and interpersonal, paralleling traditional team dynamics. Despite this growing literature and the role of human agency in shaping human–AI outcomes (see Chapter

I), we still lack evidence on how workers use AI to proactively craft their work. To address this gap, the third study introduces the construct of AI-Augmented Crafting, defined as workers' enhancement of their own capabilities through the proactive and goal-directed use of AI tools to alter the work. The study's objective is to develop and validate a measurement scale for this construct.

Q3.1: How do workers use AI to proactively craft their work?

Q3.2: How can this proactive use of AI be measured?

Theoretical framework

Technology adoption theories: from Unified Theory of Acceptance and Use of Technology to AI-Acceptance Avoidance Model

Adoption of technology has been studied for many years, and multiple theoretical frameworks have been proposed to explain it (Davis, 1986; Davis et al., 1989; Venkatesh et al., 2003). Two of the most widely used are the Technology Acceptance Model (TAM) (Davis, 1986) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). Building on the Theory of Reasoned Action (TRA), which explains the determinants of intentional behavior, Davis et al. (1986) adapted TRA to model user acceptance of information systems. As described earlier in this chapter, TAM proposes that behavioral intention to use a system is primarily driven by three constructs: perceived usefulness, perceived ease of use, and attitude toward using the system. Even after the introduction of UTAUT in 2003, TAM has continued to be widely applied to research on technology adoption across a range of domains (Al-Gahtani, 2008; Fasbender et al., 2023). However, UTAUT extends TAM by incorporating additional determinants that reflect social and contextual influences on adoption decisions. Specifically, alongside performance expectancy (conceptually similar to perceived usefulness) and effort expectancy (similar to perceived ease of use), UTAUT introduces social influence (the perceived expectations of important others) and facilitating conditions (such as the availability of IT support or relevant knowledge). In 2012, UTAUT was further extended to address consumer technology adoption beyond organizational settings (Venkatesh et al., 2012). Since then, UTAUT has been validated both within and outside organizations and has been continuously enriched with additional antecedents, including factors related to the specific type of technology under investigation (Blut et al., 2022). With the rapid evolution of technology and the emergence of new AI tools, researchers have applied UTAUT to understand the adoption of these tools. This has taken two main forms: examining AI adoption directly through the lens of UTAUT (Venkatesh, 2022) and extending UTAUT with factors that are specifically relevant to AI adoption (Cao et al., 2021). In this direction, Cao et al. (2021) developed and tested the AI Acceptance–Avoidance Model (IAAAM), which incorporates three groups of constructs. The first group concerns technology acceptance and includes facilitating conditions, peer influence, performance expectancy, effort expectancy, attitude, and intention to use, coherently with UTAUT. The second group concerns technology threat avoidance and captures perceived threat, defined in terms of perceived severity and perceived susceptibility. The third group addresses concerns related to personal development and well-being. Cao et al. (2021) examined how ten antecedents across these three groups of constructs shape the adoption of AI systems for decision support in the workplace. Table 1 presents the ten antecedents identified in the AI Acceptance–Avoidance Model (IAAAM), along with their corresponding definitions.

Table 1

AI acceptance-avoidance model dimensions and definitions.

Dimensions	Definitions
Performance Expectancy	The degree to which an individual believes that using AI will help him or her to attain gains in job performance
Effort Expectancy	The degree of ease associated with the use of AI
Facilitating Conditions	The degree to which an individual believes that an organizational and technical infrastructure exists to support the use of AI
Social influence	The degree to which an individual perceives that important others believe he or she should use AI
Attitude Toward Using AI	An individual's positive or negative feelings about using AI for organizational decision-making
Perceived Susceptibility	An individual's belief regarding the likelihood that using AI will make bad decisions

Perceived Severity	An individual's belief regarding the degree of the negative consequences of using AI to make bad decisions
Perceived Threat	The extent to which an individual believes that using AI to make decisions is dangerous or harmful
Personal Development Concerns	An individual's concerns regardingthe degree of preventing personal learning from own experience by the use of AI
Personal Wellbeing Concerns	An individual's concerns regarding the degree of personal anxiety and stress caused by the use of AI

Note. Adapted from Cao et al. (2021).

For this dissertation, and particularly for Study 1, the Unified Theory of Acceptance and Use of Technology (UTAUT) was adopted because it incorporates factors relevant to workers' technology adoption that are not fully addressed in the Technology Acceptance Model (TAM) or other adoption theories, such as facilitating conditions and social influence. These factors are especially pertinent for workers across different age groups, a key variable examined in Study 1. In Studies 2 and 3, the UTAUT framework was no longer applied, as it is primarily suited to explaining technology adoption rather than variations in technology use behavior. Specifically, UTAUT does not account for the distinct ways in which technologies are used after adoption, focusing instead on the determinants leading users to adopt a technological system. Consequently, Studies 2 and 3 move beyond the UTAUT perspective to investigate different forms of technology use behavior, both in relation to technology in general and to artificial intelligence in particular.

Life-span theories and technology adoption

Life-span development theories examine how individuals adapt successfully to aging across different domains of life. Two major perspectives dominate this literature. The first, Socioemotional Selectivity Theory (SST; Carstensen et al., 1999) is a life-span theory that explains how people's social goals shift with age as a function of how much time they believe they have left in life. The theory distinguishes between two broad classes of goals: emotion-regulation goals and knowledge-acquisition goals. Emotion-regulation goals involve seeking emotionally meaningful, satisfying experiences, for example, investing in close, familiar relationships that provide comfort, support, and a sense of emotional gratification. In contrast, knowledge-acquisition goals involve pursuing new information, skills, and opportunities, which often requires engaging in unfamiliar social interactions, tolerating uncertainty, and taking on new challenges. According to the theory, age differences in goal selection emerge from differences in perceived time horizons. Older adults tend to view their future time as limited and therefore prioritize present-oriented, emotionally meaningful pursuits, such as deepening existing close relationships. Younger adults tend to view their future time as expansive and therefore prioritize future-oriented pursuits, such as exploring new relationships, seeking novel experiences, and expanding their knowledge and networks (Carstensen et al., 1999).

Second, Selective Optimization with Compensation Theory (SOC; Baltes & Baltes, 1990), proposes that people use three adaptive strategies to cope with age-related losses in resources. Selection refers to choosing which goals to pursue. As people age and certain resources become more limited, they may adjust their priorities and focus on goals that are better aligned with their current capabilities and the demands of their environment. Optimization involves investing effort and resources in order to attain those selected goals as effectively as possible. Compensation refers to the use of alternative strategies or supports (for example, seeking help from others or using assistive tools) to maintain an acceptable level of performance when abilities no longer match task demands. Together, these strategies describe how individuals manage changes in their abilities over time while striving to preserve functioning and goal achievement.

These life-span theories provide a valuable lens through which to examine the role of age in technology adoption, and they have already been applied to explain age-related differences in how individuals engage with technologies (Fasbender et al., 2023; Joshi et al., 2020). For instance, Fasbender et al. (2023) integrated Socioemotional Selectivity Theory with the core dimensions of the Technology Acceptance Model (TAM; Davis et al., 1989), namely, perceived usefulness, defined as the degree to which a person believes that using a particular system would enhance their job performance, and perceived ease of use, defined as the degree to which a person believes that using a particular system would be free of effort. The authors argued that these two TAM dimensions operate through distinct mechanisms: perceived usefulness reflects a motivational pathway, a "want-to" process, while perceived ease of use reflects a capability pathway, a "can-do" process. Based on this distinction, they proposed that future time perspective, a central concept in Socioemotional Selectivity Theory, influences the motivational pathway through perceived usefulness, whereas cognitive constraints associated with aging influence the capability pathway through perceived ease of use. In discussing their results, the authors drew on Selective Optimization with Compensation Theory to explain the absence of significant age effects within the capability pathway. They suggested that older adults may employ compensatory strategies that help them maintain sufficient capability to adopt new technologies, thereby mitigating age-related differences in perceived ease of use.

Ethical technology use behavior

Human behavior is often described as the product of two cognitive systems: a deliberate, effortful, and analytical system (System 2), and an intuitive, fast, and heuristic-driven system (System 1) (Kahneman, 2011; Kahneman & Tversky, 1979). This dual-process perspective also characterizes the debate in the organizational ethics literature (Treviño et al., 2014). Early work on ethical behavior in organizations emphasized rational and deliberative mechanisms, focusing on how individuals evaluate moral issues and intentionally choose their actions (Trevino, 1986; Jones, 1991). More recent work highlights the importance of intuitive and less consciously rational processes in shaping ethical behavior (Sonenshein, 2007). When examining the mechanisms underlying ethical behavior, the literature on the ethical use of technology varies depending on the specific behavior under analysis and the focus of the research. For example, some authors address ethical technology use in general terms (Roberts & Wasieleski, 2012), adopting a rationalist perspective. However, many studies focus on specific forms of technology-related behavior within particular domains, such as cyberloafing, knowledge sharing, and digital citizenship, adopting different theoretical perspectives depending on the aims and context of the research.

Job crafting theory and technology use behavior

Job crafting is defined as the process by which employees proactively alter the boundaries and conditions of their job tasks, relationships, and the meaning they ascribe to their work (Wrzesniewski & Dutton, 2001). This phenomenon, rooted in the job design literature, captures a bottom-up process driven by workers themselves, in contrast to the top-down process through which organizations formally design jobs (Tims & Bakker, 2010). Wrzesniewski and Dutton (2001) originally conceptualized three main forms of job crafting. The first is task crafting, which involves changing the amount, scope, and/or nature of one's job tasks. The second is relational crafting, which involves altering the quality and/or quantity of one's social interactions at work. The third is cognitive crafting, which refers to changing the way one perceives or interprets the job. Later, scholars integrated job crafting with the Job Demands–Resources (JD-R) model (Demerouti et al., 2001; Tims & Bakker, 2010), identifying four types of crafting behaviors: increasing structural job resources (e.g., seeking greater autonomy or opportunities for development); increasing social job resources (e.g., seeking feedback or support from colleagues); increasing challenging job demands (e.g., taking on additional tasks or responsibilities); decreasing hindering job demands (e.g., reducing emotionally draining or cognitively taxing aspects of the job). More recent developments in job crafting theory attempt to integrate these perspectives, suggesting that job crafting can be organized into higher-order categories reflecting approach and avoidance orientations (Bruning & Campion, 2018; Zhang & Parker, 2019). In this sense, Bruning and Campion (2018) combine the role-based perspective (Wrzesniewski & Dutton, 2001) with the resource-based perspective (Tims & Bakker, 2010), proposing a role–resource / approach–avoidance framework. Their model includes four broad categories of crafting: approach role crafting, approach resource crafting, avoidance role crafting, and avoidance resource crafting, each of which contains multiple specific dimensions. Within this view, technology is explicitly recognized as a means through which employees can craft their work. In particular, Bruning and Campion (2018) describe Adoption as a subdimension of approach resource crafting, defined as the active and goal-directed use of technology and other sources of knowledge to alter the job and enhance a work process. Although this conceptualization is valuable for capturing the role of technology in job crafting, it predates the emergence of new generative AI (GenAI) tools, which have introduced new paradigm within human–AI interaction (Atzenbeck et al., 2021; Rotolo, 2024), bringing potential implications for how employees engage in crafting behaviors.

Overview of the studies

Study 1. The study *Age differences in the adoption of technology at work: a review and recommendations for managerial practice*, examines three potential roles of age in workplace technology adoption: age-related differences in antecedents of adoption, the moderating role of age in the relationships between those antecedents and intention to use, and age effects on intention to use and actual use behavior. The article offers a comprehensive review of research that treats age as a potential influencing variable in technology adoption. Following a synthesis of findings, the authors discuss practical implications, limitations, and directions for future research. Methodologically, this is a PRISMA-guided systematic review. The final sample comprised 51 empirical studies, which are critically analyzed and summarized in the article.

Study 2. *Navigating ethical boundaries in workers' use of technology: a review and integrative model* examines the spectrum of technology use behaviors investigated across diverse literatures. Rather than offering an exhaustive review, the article identifies recurring patterns of technology use behavior and advances an integrative model to guide ethical choices in human–technology interactions. Methodologically, the study employs a Bibliographic Systematic Literature Review (BSLR) that combines pattern discovery within the corpus with the authors' critical synthesis. A total of 122 articles were included and analyzed using VOSviewer software. The resulting model links stakeholder impact to core ethical principles, providing a practical framework that emphasizes individual responsibility in technology use.

Study 3. The study *Craft your work through Artificial Intelligence: An investigation of workers' AI Augmented Crafting behavior*, focused on proactive worker behavior in AI use, this study, grounded in job crafting theory, introduces the construct of AI-Augmented Crafting, a new form of proactive use behavior enabled by contemporary AI tools. The study develops and validates a measurement scale for this formative construct through five field studies, encompassing construct and item development, as well as assessments of content, discriminant, convergent, and predictive validity. In the study, different analytical techniques were employed, such as confirmatory factor analysis and path analysis, performed using RStudio software.

CHAPTER III | STUDY 1. Age differences in the adoption of technology at work: a review and recommendations for managerial practice[1]

Abstract

Purpose. The adoption of technology is a key question for nowadays' organizations. The present literature review analyzes the role of workers' age in the adoption of technology at work.

Methodology. A comprehensive literature review based on PRISMA resulted in 51 papers which highlighted age-related differences in technology adoption inside organizational context. Findings. Findings were grouped considering age-related differences in five technology adoption antecedents (i.e., performance expectancy, effort expectancy, social influence, facilitating conditions, attitude toward using technology), affecting behavior intention to use technology, and use behavior. Overall, the literature revealed age-related differences in the adoption's antecedents affecting workers' behavior intention to use technology and use behavior.

Originality. This study presents a comprehensive summary of evidence and practical recommendations for organizations navigating technology implementation in an increasingly age-diverse workforce environment. Additionally, it outlines several future research directions to address the limitations of current studies in this area.

Keywords: Technology adoption; Age; Sustainable innovation; Systematic review, Managerial practice

[1] Fazi, L., Zaniboni, S., & Wang, M. (2025). Age differences in the adoption of technology at work: a review and recommendations for managerial practice. Journal of Organizational Change Management, 38(8), 138-175. doi: 10.1108/JOCM-12-2024-0767

Introduction

Organizations are facing profound demographic changes in their workforce. For the first time in history, four generations are working together inside organizations (Del Campo et al., 2017). This trend is leading to higher attention to age-related differences in the adoption of working technology, which represents a strategic asset for today's organizations (Jeffrey & Dafoe, 2021; Verma & Garg, 2022). The impact of technology can only materialize if workers use technology (Venkatesh & Zhang, 2010; Verma & Garg, 2022), and individual differences, such as age, may contribute substantially (Venkatesh et al., 2003). In fact, research highlighted differences in technology adoption based on workers' age (Adams et al., 2021; Brown et al., 2019; Tam et al., 2014; Venkatesh & Zhang, 2010). For example, Venkatesh and Zhang (2010) in their longitudinal cross-cultural study, showed that technology usage behavior declines with age in both U.S. and Chinese worker sample. Therefore clarifying the role of age in technology adoption is important for today organizations to successfully implement technologies. Despite the growing research evidence on this topic (Becker et al., 2020; Grünloh, et al., 2022; Knight et al., 2022; Park et al., 2021), research is still fragmented, showing an array of different and contrasting findings. Hence, our objective is to address the following research question: Do antecedents of workplace technology adoption (i.e., performance expectancy, effort expectancy, social influence, facilitating conditions, attitude toward using technology) affecting intention to use technology and actual use behavior differently considering workers' age? To answer this question, we first identify the key antecedents of technology adoption that have been linked to age-related differences, examining the most influential theories on technology adoption. Then, we analyzed age-related differences identified in the literature, taking into account additional contextual factors such as the Country in which the study was conducted, the type of technology examined, and the industry sector. By synthesizing scientific evidence, our goal is to provide insights into the limitations of current research, propose directions for future studies, and offer theoretical and practical recommendations for managing technology adoption in the workplace, fostering greater use among workers of all ages.

Materials and Methods

Consistent with the Bibliometric-Systematic Literature Reviews (B-SLRS) approach (Marzi et al., 2024), our first step was an initial informal literature screening on technology adoption and aging, using the keywords (“technology” AND “adoption” OR “use” AND “age*” OR “older*” OR “younger*” AND “work*”). This preliminary exploration informed the development of our research question and the establishment of specific inclusion and exclusion criteria. Our inclusion and exclusion criteria were set as follows. Studies focusing on workplace technology adoption and addressing age-related differences were included. In contrast, studies examining technology adoption among aging individuals outside organizational settings (e.g., elderly technology adoption) and those not on age-related differences in technology adoption were excluded. Only empirical studies employing both quantitative and qualitative data collection methods were included. No restrictions were imposed regarding the publication year, Country, or type of technology examined. Table 1 provides a summary of the inclusion and exclusion criteria, structured according to the PICO search framework.

Table 1

Summary of inclusion and exclusion criteria based on PICO method

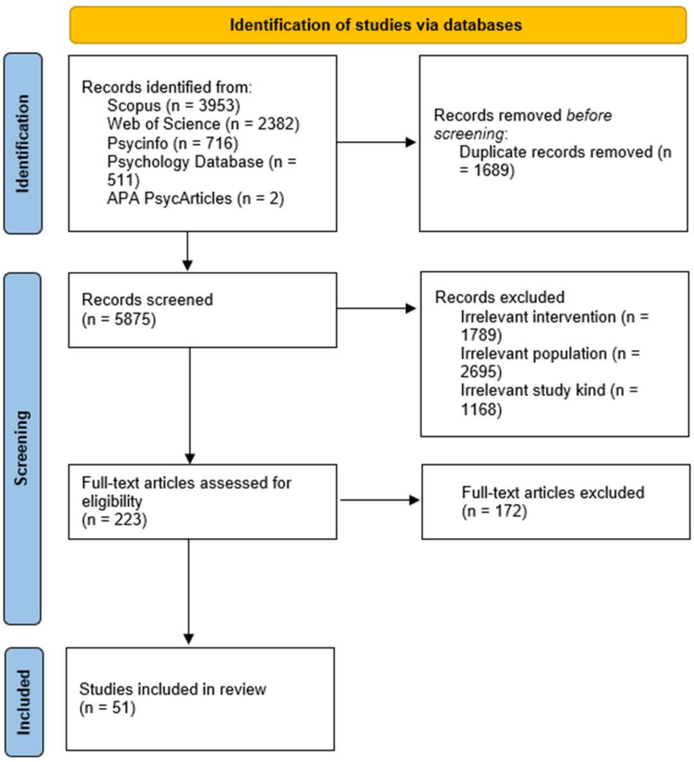
	Inclusion	**Exclusion**
Population	Workers	All the others (e.g., customers, users)
Intervention	Quantitative and qualitative empirical studies	Theoretical and conceptual contribution
Comparison	Test of age-related differences	Papers which no considered age-related differences
Outcome	Antecedents of adoption of working technology and adoption	Consequences of adoption of working technology

Next, we formulated our search string as follows: (“age” OR “young*” OR “middle-age*” OR “old*” OR “elderly” OR “age-related” OR “age comparison” OR “age-based” OR “age differen*”) AND (“technolog*” OR “ict” OR “digit*” OR “information system” OR “computer”) AND (“use” OR “adoption” OR “acceptance”) AND (“workplace” OR “employee*” OR “worker*”

OR "work environment"). To create and validate the set of keywords we involved experts in age-related differences and technology adoption in the workplace (Marzi et al., 2024). Third step was the database selection. We conducted our search across multiple databases, of management, organizational and social psychology studies, specifically, Web of Science (i.e., Clarivate), Scopus (i.e., Elsevier), PsycINFO and APA PsycArticles (i.e., EBSCO), and Psychology Database (i.e., ProQuest). A total of *n* = 7564 articles were found, published from 1933 to 2025. In the fourth step, we screened the data, selecting only peer-reviewed articles published in English while excluding dissertations, conference proceedings, and book chapters. Two researchers independently conducted the analysis and cross-validated the data. The screening processes have been conducted using Rayyan online software (Ouzzani et al., 2016), which align with the PRISMA guidelines (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). After removing the duplicates, abstracts and full texts were screened. Finally, *n* = 51 empirical articles were identified and retained (the flow chart is shown in Figure 1).

Figure 1

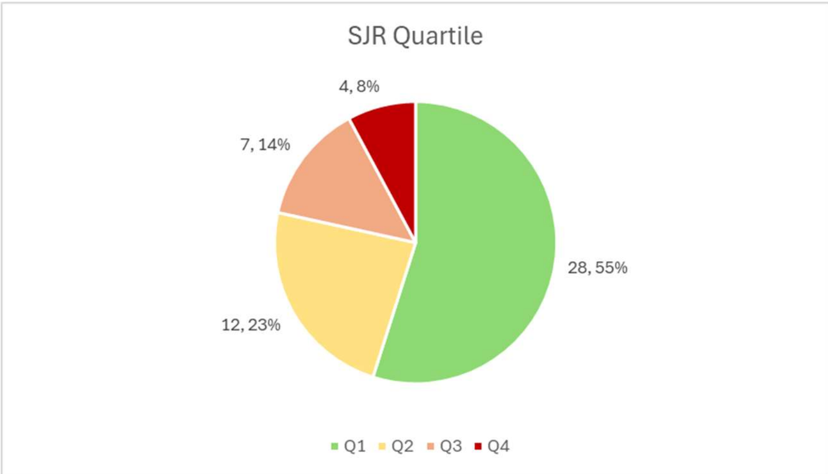
Flowchart of the study selection for the systematic review



The excluded articles fell into one or more of the following categories: those focusing on a not pertinent population (e.g., non-working individuals), an unsuitable study type (e.g., non-empirical research), or unrelated content (e.g., studies not addressing technology adoption or age-related differences). We assessed the quality of the sources using the Scimago Quartiles (Marzi et al., 2023). The 22% of the sources were ranked in Q3 and Q4 according to the Scimago Quartiles (Figure 2).

Figure 2

Sources Journal Ranking based on Scimago Quartiles



However, we chose to include all sources to ensure a comprehensive representation of various sectors (e.g., Tourism, Museums, Utilities) and countries (e.g., Africa, India, Pakistan, Turkey, Saudi Arabia) that would have been excluded if we had considered only Q1 and Q2 journals. For the analysis and cluster identification, we conducted a full-text review to identify paper characteristics aligned with our theoretical approach.

Table 2 (Appendix A) summarizes the main aspects (i.e., title, author(s), type of technology, sector, country, data type, and key results) for each paper retained for the review.

Theoretical Framework of the Literature Review

Technology adoption and age

In developing our model, we identified critical antecedents of workplace technology adoption and use that may differ considering the age of the workers. Davis (1987) introduced the

Technology Acceptance Model (TAM) to explain the influence of perceived usefulness, perceived ease of use, and attitude toward technology on behavioral intention and actual use. TAM have been previously linked to the aging literature (Fasbender et al., 2023). Moreover, additional factors influencing technology adoption have been identified, which may also vary with age. Venkatesh et al. (2003) systematically reviewed existing theoretical models of technology adoption and conducted a longitudinal study to examine the factors affecting workers' adoption and use of technology (summarized in Table 3).

Table 3

UTAUT systematization of theories and dimensions of technology adoption and use

Theories before UTAUT	Dimensions before UTAUT	UTAUT systematization
Theory of Reasoned Action (TRA)	Attitude toward using technology	Not included
	Subjective norm	Social influence
Technology acceptance model (TAM) - Technology acceptance model 2 (TAM2)	Perceived usefulness	Performance expectancy
	Perceived ease of use	Effort expectancy
	Subjective norm	Social influence
Motivational Model (MM)	Intrinsic motivation	Not included
	Extrinsic motivation	Performance expectancy
Theory of planned behavior (TPB)	Attitude toward using technology	Not included
	Subjective norm Perceived behavioral control	Social influence Facilitating conditions
Combined TAM and TPB	Perceived usefulness	Performance expectancy
	Attitude toward using technology	Not included
	Subjective norm	Social influence
Model of PC utilization (MPCU)	Job-fit	Performance expectancy
	Complexity	Effort expectancy
	Long-term consequences	Not included
	Affect toward use	Not included
	Social factors	Social influence
	Facilitating conditions	Facilitating conditions
Innovation Diffusion Theory (IDT)	Relative advantage	Performance expectancy
	Ease of use	Effort expectancy
	Result demostrability	Not included
	Trialability	Not included
	Visibility	Not included
	Image	Social influence
	Compatibility	Facilitating conditions
	Voluntariness	Not included
Socio-Cognitive Theory (SCT)	Outcome expectations	Performance expectancy
	Self-efficacy	Not included

	Affect	Not included
	Anxiety	Not included

Note. Not included: dimensions that do not increase the variance explained by the individual acceptance of technology.

Their systematic approach integrated key dimensions from prior models (e.g., TAM) into four overarching constructs influencing technology adoption: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. Beyond dimensions already considered in TAM (i.e., Perceive Usefulness, Perceived Ease of Use, Attitude Toward Using Technology), Social Influence and Facilitating Conditions are included in Unified Theory of Acceptance and Use of Technology (UTAUT), which may vary with age (Morris & Venkatesh, 2000; Morris et al., 2005). For instance, Morris and Venkatesh (2000) proposed that differences in the need to please (Carstensen et al., 1999) may alter the role of Social Influence in technology adoption, leading to higher relevance of Social Influence for older workers. Additionally, they suggested that age-related declines in cognitive abilities (Baltes & Baltes, 1990; Savolainen, 2015) might influence individuals' perceived difficulty in using technology, thereby affecting Perceived Behavioral Control (i.e., Facilitating Conditions) in determining adoption. Therefore, in addition to the TAM dimensions, Social Influence and Facilitating Conditions, as conceptualized in the UTAUT model, have to be considered from an aging perspective. Our analysis of the reviewed literature supports these considerations, identifing 51 studies on age-related differences in workplace technology adoption, the results are summarized in Table 4.

Table 4

Dimensions considered in the literature about age-related differences in technology adoption.

Dimension	Number of papers using the dimension
Performance expectancy or Perceive usefulness	22
Effort expectancy or Perceive ease of use	17
Social influence or Subjective norms	14
Facilitating conditions, Perceived behavioral control, Confidence in use, IT support or IT knowledge	19
Attitude toward using technology	9
Behavior intention to use technology or use behavior	22

Consequently, our review considers five antecedents of technology adoption (i.e., Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Attitude Toward Using Technology), as well as Behavioral Intention and Use Behavior. A summary of these dimensions and their definitions is provided in Table 5.

Table 5

UTAUT overarching constructs and Attitude toward using technology.

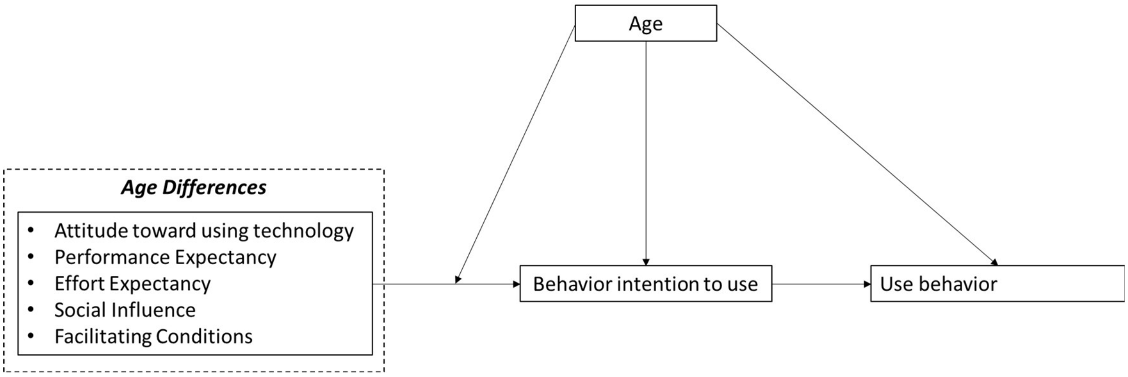
Construct	Definition based on Venkatesh, Morris, Davis and Davis (2003)
Performance expectancy	The degree to which an individual believes that using the system will help him or her to attain gains in job performance
Effort expectancy	The degree of ease associated with the use of the system
Social influence	The degree to which an individual perceives that important others believe he or she should use the new system
Facilitating conditions	The degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system
Attitude toward using technology	The degree to which a person has a favorable or unfavorable evaluation or appraisal of the behavior in question

Note. Other aspects included in UTAUT's extension (i.e., UTAUT-2, Venkatesh, Thong, & Xu, 2012) have not been considered because they are not relevant for organizational context.

After identifying the dimensions, we analyzed the role of age in the relationship between technology adoption antecedents and use behavior. On one hand, the literature on technology adoption considers the interaction effect between age and technology adoption antecedents in shaping behavioral intention and actual usage behavior, thereby treating age as a moderator (Venkatesh et al., 2003). On the other hand, age can directly influence the perception of technology adoption antecedents (Fasbender et al., 2023), as well as behavioral intention and actual technology use (Brown, Daigneault, & Dawson, 2019; Fasbender et al., 2023). The literature review model is illustrated in Figure 3, and the results section is structured in alignment with our proposed literature review model.

Figure 3

Model of the literature review

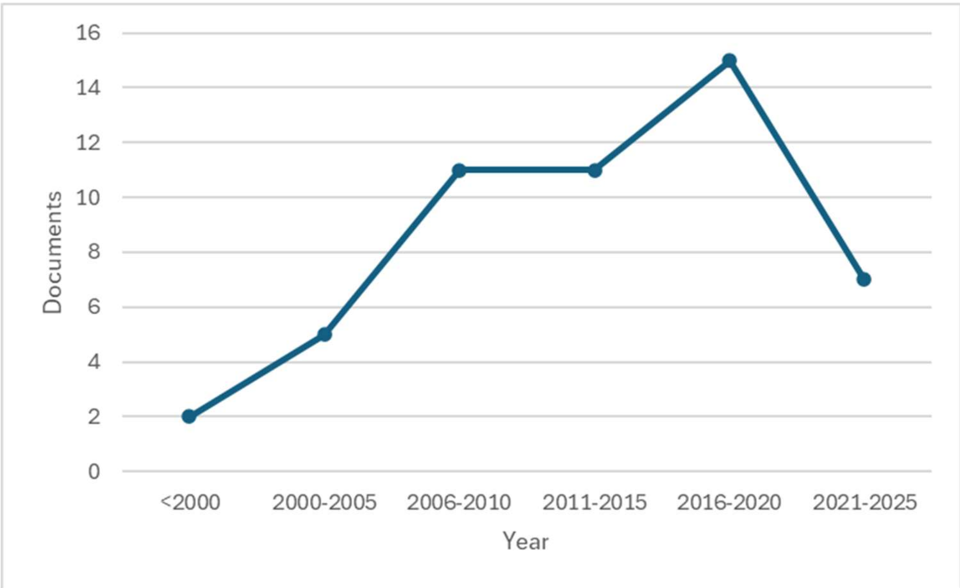


Literature analysis: General trends

Over the past 25 years, the number of studies examining age-related differences in technology adoption in the workplace has increased significantly. Notably, only two articles on this topic were identified as published before the year 2000 (Figure 4).

Figure 4

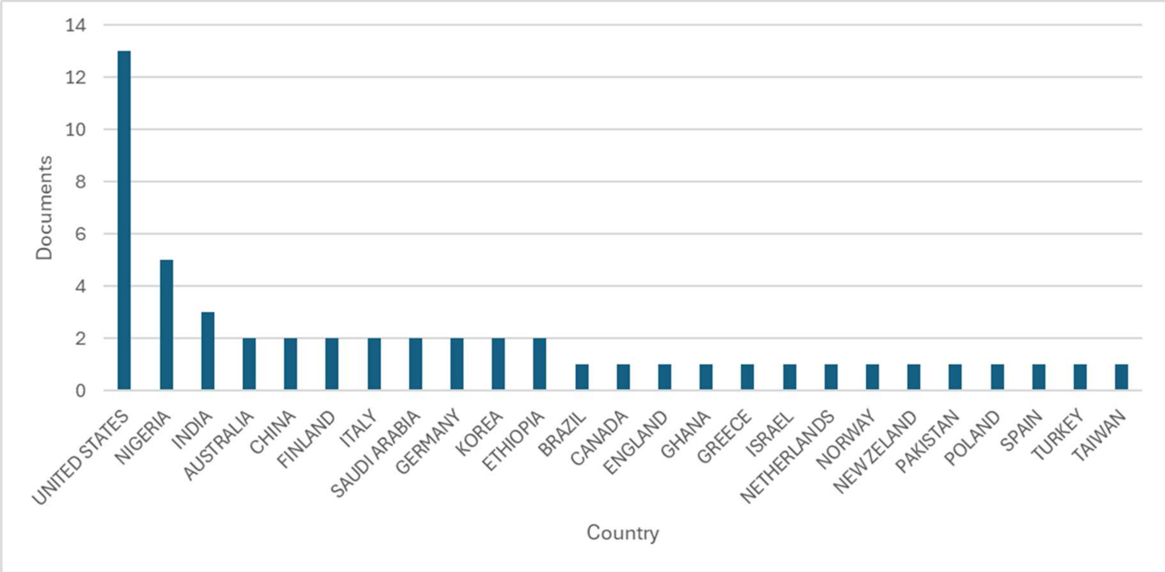
Publication trend



This trend aligns with the growing integration of technology within organizations and the rapid aging of the workforce. More than half of the studies (51%) were conducted in the USA and Europe, the remaining in Asia (20%) and Africa (16%) (Figure 5).

Figure 5

Publication by Country



Among the studies reviewed, eleven (25%) utilized convenience samples or examined multiple sectors. Ten studies (22%) focused on healthcare settings, while seven (14%) were conducted in the agricultural sector (Figure 6). This sectoral distribution is also reflected in the types of technology investigated (Figure 7). Specifically, agricultural studies primarily explored age-related differences in the adoption of productivity-enhancing technologies (4 out of 6 studies; 67%). In contrast, other studies predominantly examined information and communication technology (16 out of 51 studies; 31%), computers and software (7 out of 51 studies; 14%). There is comparatively less research focusing on management technologies (e.g., customer relationship management systems) (4 out of 51 studies; 8%), training technologies (e.g., e-learning platforms) (5 out of 51 studies; 10%), or welfare technologies (e.g., rehabilitation technology) (3 out of 51 studies; 6%).

Figure 6

Publication by Sectors

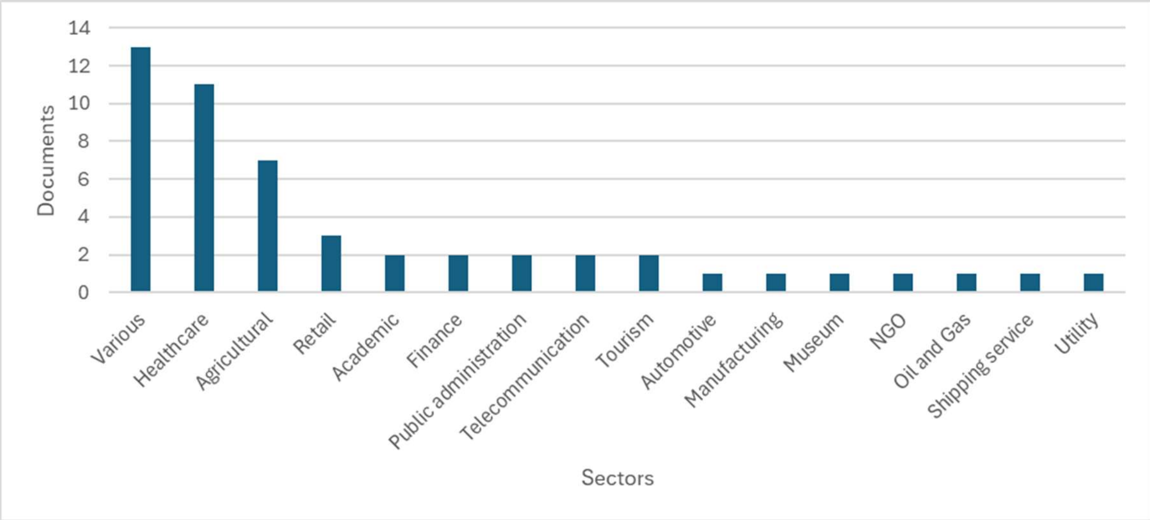
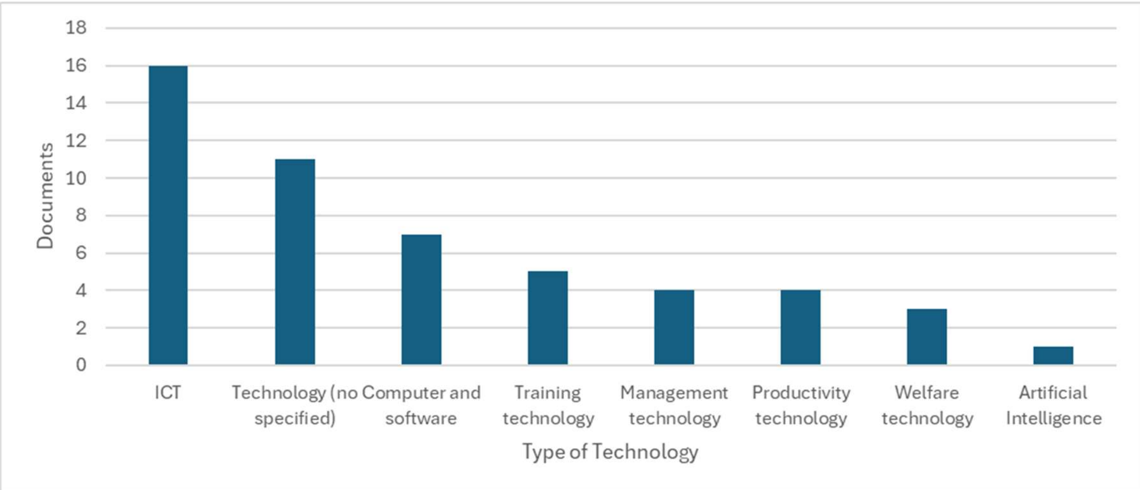


Figure 7

Publication by Type of Technology

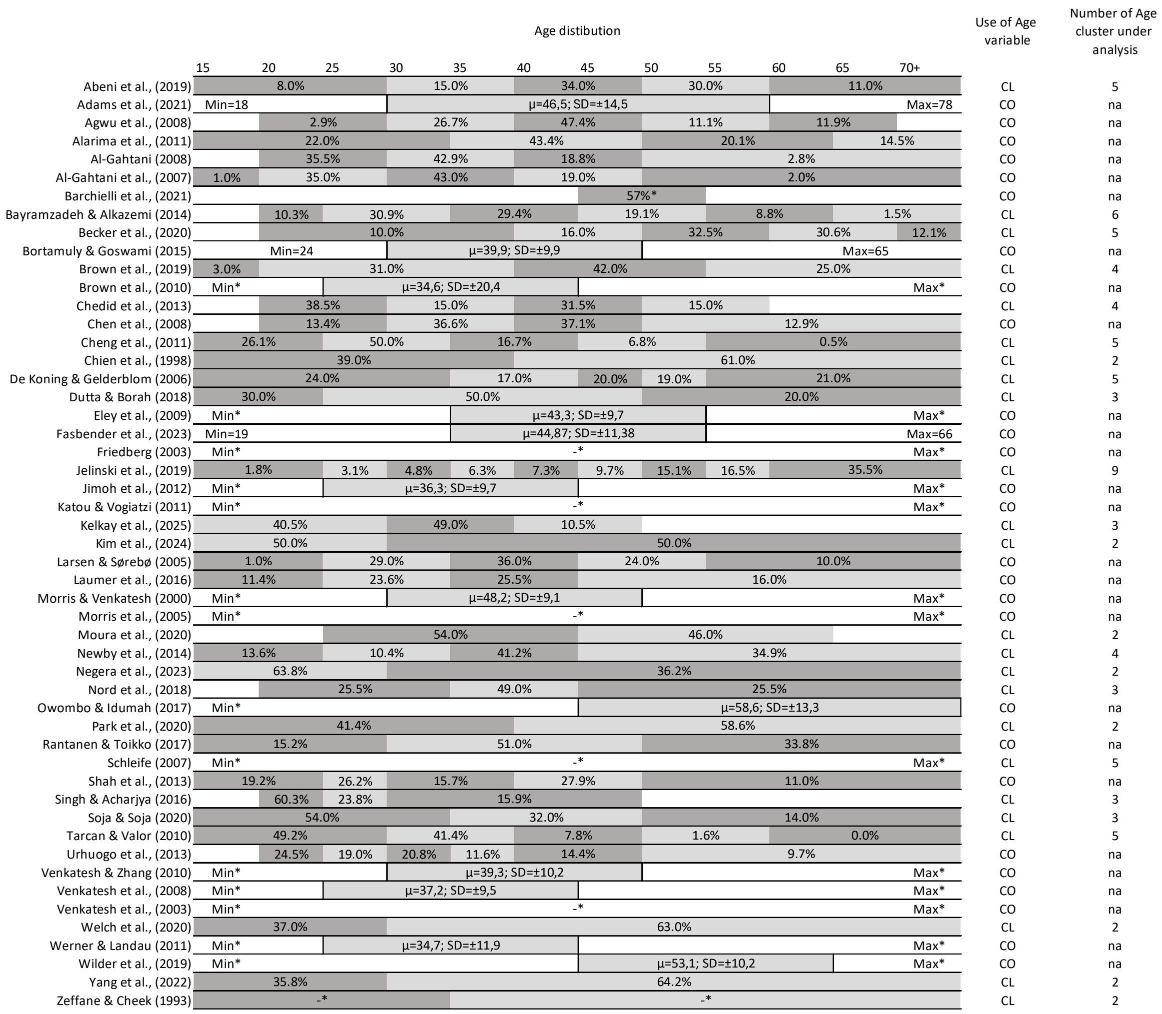


Our review showed heterogeneous approaches regarding the theoretical framework utilized. In fact, among the 51 articles included in this review, 12 (23%) used the UTAUT as a theoretical foundation. The remaining articles used other theories (i.e., 10 papers used the Technology Acceptance Model, 3 papers used the Theory of Planned Behavior) or none (i.e., 25 papers were based on previous empirical evidence).

The age variable has been explored under different roles (Table 2). More specifically, 35 papers analyzed the effect of age across the technology adoption dimensions (e.g., levels of behavioral intention to use technology across ages). Sixteen papers analyzed age as a moderator in the relationship between different technology adoption dimensions (e.g., the impact of age on the relationship between performance expectancy and behavioral intention to use technology). Age, from a methodological perspective, has been operationalized in different ways. 27 out of 51 studies (53%) used age as a continuous variable. The other 24 studies (47%) used age in categorical intervals. A summary of age distribution and use is presented in Figure 8.

Figure 8

Age distribution and use for each study



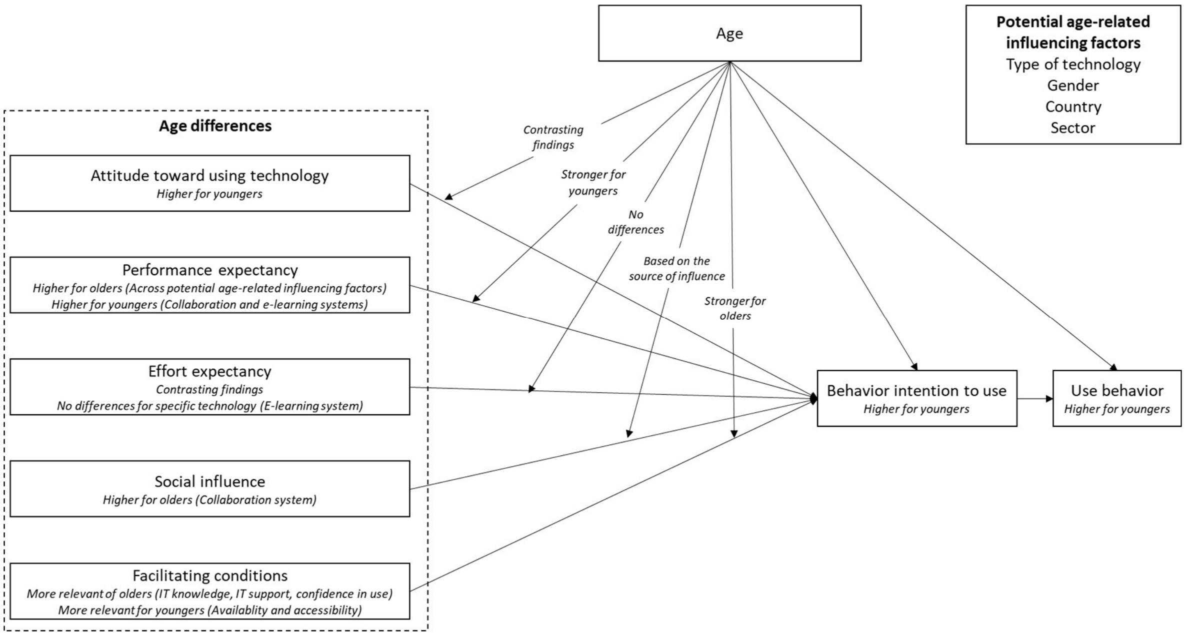
Note. For each study is reported clusters range and distribution (%), or the Mean, SD, Min and Max of participants Age. Use of age variable refers to the use of age as continuous variable or in cluster. CO: Continuous. CL: Cluster. For the use of age in cluster, is reported the number of clusters considered. Na: Not applicable. *Data not available.

Literature analysis: Evidence about age differences on technology adoption antecedents, behavior intention and use behavior

A graphical synthesis of the evidence is provided in Figure 9.

Figure 9

Graphical representations of main findings



Attitudes Toward Using Technology at Work and Age

Evidence summary #1. Younger workers tend to have more positive attitudes toward technology, and attitude plays a role in predicting technology adoption for both older and younger workers.

Age Differences in Attitude Toward Using Technology.

We identified four studies that examined the relationship between age and attitudes toward technology use. When technology is designed for employees' use, younger workers tend to have more positive attitudes toward it (Bayramzadeh & Alkazemi, 2014; Morris & Venkatesh, 2000). For instance, Morris and Venkatesh (2000) showed that the pleasure to use a system was higher for younger than their older counterpart. Similarly, Bayramzadeh and Alkazemi (2014) reported comparable findings. However, when technology is implemented by an organization for client use (e.g., patients), age does not appear to be correlated with attitudes toward work-related technology

(Rantanen & Toikko, 2017; Werner & Landau, 2011). This aligns with the idea that age-related differences in attitudes are more likely to emerge when technology is intended for personal use rather than external purposes.

Age as a Moderator on the Relation between Attitude Toward Using Technology and Behavior Intention.

Research on age as a moderating factor in the relationship between attitudes toward technology and behavioral intention or actual technology use in the workplace has yielded mixed findings (Dutta & Borah, 2018; Morris & Venkatesh, 2000; Morris et al., 2005; Venkatesh et al., 2003). Morris and Venkatesh (2000) found that younger employees exhibited a stronger link between positive attitudes toward technology (e.g., enjoyment of use) and behavioral intention to adopt it. In contrast, Morris et al. (2005) reported the opposite effect: across five organizations implementing new technology, older workers demonstrated a stronger attitude-intention relationship. Two other studies found no significant moderating effect of age on this relationship (Dutta & Borah, 2018; Venkatesh et al., 2003). These conflicting results suggest that contextual factors, such as industry type and implementation strategies, may influence how age moderates technology adoption, highlighting the need for further investigation.

Performance Expectancy about Technology Use at Work and Age

Evidence summary #2. Older workers tend to perceive technology as more useful, except when it is used for networking or knowledge acquisition (e.g., collaboration and e-learning tools). Performance expectancy plays a more significant role in predicting technology adoption for younger workers.

Age Differences in Performance Expectancy.

We identified eight studies examining the relationship between age and performance expectancy. Four of these studies suggest that older workers perceive technology as more useful (Dutta & Borah, 2018; Laumer et al., 2016; Singh & Acharjya, 2016; Tarcan & Varol, 2010). Evidence from diverse professional settings—including postal workers, nurses, employees in hotels, and automotive firms—indicates that older workers tend to recognize greater utility in technology compared to their younger counterparts. This finding aligns with the cognitive characteristics of older (i.e., crystallized intelligence; Beier et al., 2022), which enhances their ability for integrative thinking and applying past experiences to new technological contexts (Horn & Raymond, 1967).

Conversely, the literature suggests that younger workers tend to perceive collaboration and e-learning technologies as more useful (Brown et al., 2010; Shah et al., 2013), probably driven by a stronger need for social networking and continuous skill development (Carstensen, Isaacowitz, & Charles, 1999).

Age as a Moderator on the Relation between Performance Expectancy and Behavior Intention.

Our review identified thirteen studies examining the impact of age on the relationship between performance expectancy and behavioral intention to use technology. Six studies suggest that performance expectancy plays a more significant role in predicting technology adoption among younger employees (Al-Gahtani, 2008; Barchielli et al., 2021; Park et al., 2020; Venkatesh et al., 2003; Venkatesh & Zhang, 2010; Welch et al., 2020). This pattern holds across specific sectors such as healthcare and cultural services. For instance, Barchielli et al. (2021) found that performance expectancy was a stronger predictor of behavioral intention to use technology among younger nurses. Similar findings were reported in health center employees (Park et al., 2020) and science museum workers (Welch et al., 2020). However, when considering different industries and cultural contexts, performance expectancy appears to be more intertwined with gender, reducing the effect of age alone. For example, Venkatesh et al. (2003) and Venkatesh & Zhang (2010), considering different organizations and Countries (i.e., USA and China), found that age was a significant factor in technology adoption only when considered alongside gender.

In contrast, in specialized sectors such as ocean freight shipping, performance expectancy appears to be more influential for older workers (Yang et al., 2022). This suggests that sector-specific demands may shape how age interacts with technology adoption, making the relationship more nuanced.

Meanwhile, six studies found no significant relationship between age, performance expectancy, and behavioral intention to use technology (Al-Gahtani et al., 2007; Brown et al., 2010; Cheng et al., 2011; Kelkay, et al., 2025; Kim et al., 2024; Moura et al., 2020), indicating that additional moderating factors may influence this relationship.

Effort Expectancy about Technology Use at Work and Age

Evidence summary #3. The perception of ease of use is similar for older and younger workers when considering specific technology such as e-learning system, and this perception affects technology adoption similarly across workers of all ages.

Age Differences in Effort Expectancy.

We found seven studies examining the relationship between age and effort expectancy, revealing contrasting findings. Two studies suggest that older workers may perceive technology as easier to use (Laumer et al., 2016; Jimoh et al., 2012). In contrast, Brown et al. (2010) and Dutta & Borah (2018) reported that younger workers exhibited higher effort expectancy. Meanwhile, studies focusing on e-learning systems found no significant age-related differences in effort expectancy (Chen et al., 2008; Shah et al., 2013).

Age as a Moderator on the Relation between Effort Expectancy and Behavior Intention.

Our review identified eleven studies examining the role of age in the relationship between effort expectancy and behavioral intention to use technology. The majority of these studies, encompassing data from various countries, sectors, and technologies, found no significant effect of age on this relationship (Al-Gahtani, 2008; Al-Gahtani et al., 2007; Brown et al., 2010; Kelkay, et al., 2025; Moura et al., 2020; Park et al., 2020).

Among the studies that did report significant findings, the results were contradictory, some found a stronger relationship between effort expectancy and behavioral intention among younger workers (Barchielli et al., 2021; Kim et al., 2024), while others found this relationship to be stronger among older workers (Welch et al., 2020). Moreover, studies by Venkatesh et al. (2003) and Venkatesh & Zhang (2010) indicate that age was only a significant factor when considered alongside gender, highlighting the importance of intersectionality in understanding technology adoption patterns.

Social Influence about Technology Use at Work and Age

Evidence summary #4. The perception of social influence may be higher for older workers in the case of collaboration technologies, and the impact of age on social influence – technology adoption relationship potentially depending on the source of that influence (e.g., peers, leaders).

Age Differences in Social Influence.

Two papers focused on the relationship between age and social influence (Brown et al., 2010; Rantanen & Toikko, 2017). Brown et al. (2010) found that perceptions of social influence to use collaboration technology in Fortune 500 tech companies in Finland were higher for older than for younger workers. Differently, Rantanen and Toikko (2017) highlighted no age-related differences in the perceptions of subjective norms (i.e., the belief of how closely people value the desirability of a particular behavior) to use welfare technology among Finnish home care workers.

Age as a Moderator on the Relation between Social Influence and Behavior Intention.

We identified thirteen studies examining the effect of age on the relationship between social influence and behavioral intention to use technology. Seven studies found no significant effect (Brown et al., 2010; Dutta & Borah, 2018; Kelkay, et al., 2025; Kim et al., 2024; Moura et al., 2020; Park et al., 2020; Venkatesh & Zhang, 2010), suggesting that age has a weak influence on the role of social influence in technology adoption. This finding is further supported by evidence that age alone does not have a meaningful impact unless considered alongside intersectional factors such as gender and experience.

However, some studies highlight significant effects. Specifically, three studies found that peer or senior staff influence played a stronger role in technology adoption among younger workers

(Barchielli et al., 2021; Welch et al., 2020), an effect that was also evident in high power distance cultural contexts (Al-Gahtani et al., 2007).

Conversely, two studies reported opposite findings when measuring general social influence (i.e., people who influence my behavior / who are important to me) suggesting that the source of influence (e.g., peers, leaders) may affect younger and older workers differently.

Facilitating Conditions about Technology Use at Work and Age

Evidence summary #5. Environmental conditions (e.g., the number of computers) are more relevant for younger workers, while IT knowledge and support are more relevant for older workers. Facilitating conditions potentially increases the adoption of technology especially for older workers.

Age Differences in Facilitating Conditions.

We identified nine studies that examined age-related differences in the perception of facilitating conditions (Becker et al., 2020; Brown et al., 2010; Chedid et al., 2013; Dutta & Borah, 2018; Eley et al., 2009; Newby et al., 2014; Rantanen & Toikko, 2017; Soja & Soja, 2020; Urhuogo et al., 2013). These studies consistently indicate that older workers are more concerned about facilitating conditions (Dutta & Borah, 2018), feeling less confident using technology (Becker et al., 2020; Chedid et al., 2013; Eley et al., 2009; Rantanen & Toikko, 2017; Urhuogo et al., 2013). This pattern appears to hold across different countries (i.e., Australia, Finland, the United States), sectors (i.e., academia, healthcare, NGOs, utilities), and types of technology studied (i.e., ICT, welfare technology). Furthermore, research suggests that different facilitating conditions hold varying degrees of relevance depending on age group. According to Eley et al. (2009), for younger workers environmental conditions, such as the location or the availability of technology, were perceived as significant barriers to technology use. In contrast, older workers considered supportive facilitating conditions, such as IT knowledge or technical support, more critical barriers to use (Eley et al., 2009; Soja & Soja, 2020), possibly as a compensatory mechanism for their lower confidence in using technology (Baltes & Baltes, 1990).

Age as a Moderator on the Relation between Facilitating Conditions and Use Behavior.

Our review identified ten studies examining the role of age in the relationship between facilitating conditions and use behavior (Al-Gahtani et al., 2007; Barchielli et al., 2021; Brown et al., 2010; Kelkay, et al., 2025; Kim et al., 2024; Morris & Venkatesh, 2000; Morris et al., 2005; Moura et al., 2020; Venkatesh et al., 2003; Venkatesh et al., 2008). Findings suggest that facilitating conditions play a more significant role in predicting use behavior among older workers compared to younger ones (Brown et al., 2010; Morris & Venkatesh, 2000; Venkatesh et al., 2003; Venkatesh et al., 2008). Additionally, research indicates that this relationship remains stronger for older workers in both short- and long-term technology use (Morris & Venkatesh, 2000). Moreover, other individual characteristic, such as gender, have been found to intersect with age, influencing this relationship (Venkatesh et al., 2008). Two studies suggest that age negatively moderates the relationship between facilitating conditions and use behavior, meaning that facilitating conditions were more relevant for younger workers, although the observed effects were weak (Al-Gahtani et al., 2007; Barchielli et al., 2021). Finally, four studies found no significant differences (Kelkay, et al., 2025; Kim et al., 2024; Morris et al., 2005; Moura et al., 2020).

Behavior Intention, Use Behavior of Technology at Work and Age

Evidence summary #6. Younger workers adopt technology more than older workers.

Age Differences in Behavior Intention and Use Behavior.

Twenty scientific papers emerged from the literature search suggesting that younger workers have a higher intention to use technologies (Abeni et al., 2019; Brown et al., 2010; Rantanen & Toikko, 2017; Wilder, et al., 2019) and they use technologies more than older workers (Adams et al., 2021; Agwu et al., 2008; Alarima, et al., 2011; Bortamuly & Goswami, 2015; Brown et al., 2019; Brown et al., 2010; Chien et al., 1998; De Koning & Gelderblom, 2006; Friedberg, 2003; Jelinsky et al., 2019; Katou & Vogiatzi, 2011; Larsen & Sørebø, 2005; Nord et al., 2020; Owombo & Idumah, 2017; Schleife, 2006; Urhuogo et al., 2013; Zeffane & Cheek, 1993). Only one study reported that younger individuals use technology less frequently (Negera et al., 2023). However, this study categorized 'younger' as those under 30 years old and 'older' as anyone above 30. The authors themselves acknowledge that healthcare workers under 30 may be too young to have sufficient experience with the information system under investigation, highlighting the limitation of this finding.

Discussion

The aim of our research was to understand how different antecedents affecting workplace technology adoption vary across ages. Our literature review suggests that younger workers tend to exhibit more favorable attitudes toward technology, perceiving it as particularly useful for acquiring knowledge and building professional networks, such as through collaboration and e-learning systems. They also emphasize the need for easily accessible and readily available technologies. Beyond these perceptions, their positive attitudes and focus regarding a system's usefulness appear to be the primary drivers of technology adoption. These findings can be explained by differences in life experiences and motivational orientations between younger and older workers. On the one hand, younger individuals, having been more exposed to technology during their formative years, tend to develop heightened expectations regarding its benefits (Morris & Venkatesh, 2000). Consequently, greater exposure to technology, particularly in early life, may foster more positive perceptions of its role in job performance. Additionally, due to a stronger inclination toward knowledge acquisition (Carstensen et al., 1999), younger workers may perceive knowledge-oriented technologies, such as e-learning systems, as particularly valuable in achieving their professional goals. Differently, older workers often exhibit lower confidence in using technology and experience greater pressure to adopt specific tools, such as collaboration systems, which reflect the demands of an increasingly connected work environment. While they generally recognize the usefulness of workplace technologies, they also express a stronger need for support in order to effectively adopt and utilize these systems. These findings align with age-related cognitive changes and the increasing reliance on compensatory mechanisms over time. Older workers, benefiting from greater integrative thinking abilities and extensive prior experience (Horn & Raymond, 1967), may identify more opportunities for leveraging technology to enhance work performance. At the same time, they are more likely to assess and utilize compensation mechanisms that help mitigate resource limitations and optimize their interaction with technology (Baltes & Baltes, 1990). Overall, the literature agrees that younger workers adopt technology more readily than their older counterparts. However, the underlying causes of these differences remain unclear, highlighting the need for further investigation.

Theoretical Implications

By reviewing the literature on the relationship between aging and technology adoption, we highlighted that integrating the antecedents of both the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) provides a comprehensive perspective on this phenomenon in the workplace. In this context, five key antecedents of technology adoption emerged as particularly relevant when considering age-related differences: Attitude Toward Using Technology (TAM), Perceived Usefulness and Perceived Ease of Use (TAM and UTAUT), Social Influence (UTAUT), and Facilitating Conditions (UTAUT). Our findings suggest that these antecedents play different roles depending on workers' age. This underscores the need for future research to account for all relevant antecedents rather than focusing exclusively on one theoretical framework.

#Implication 1. Five antecedents (i.e., performance expectancy, effort expectancy, social influence, facilitating conditions, attitude toward using technology), integrating elements from both TAM and UTAUT, are relevant for understanding the influence of age on technology adoption in the workplace.

We also found that the type of technology itself is a crucial factor in understanding age-related differences in adoption patterns (Evidence 2 and 3). Older and younger workers may respond differently to various technologies based on their motivations and prior experiences. For instance, younger workers may perceive collaborative systems as more useful due to their knowledge-based motivation (Carstensen et al., 1999), whereas older workers may experience greater pressure to use such systems due to heightened susceptibility to age-related stereotypes (Tams & Dulipovici, 2019). These findings highlight the importance of considering specific technologies when studying age-related differences in technology adoption, or at a minimum, including technology type as a control variable in research.

#Implication 2. Focusing on specific characteristics of technology, and how these align with age-related motivations, is crucial for understanding how age influences technology adoption in the workplace.

Moreover, the intersectionality between age and gender appears to influence certain Technology adoption antecedent (i.e., effort expectancy) more than age alone (Evidence 3). Prior research has demonstrated that intersectionality between age and gender influences various workplace dynamics, including work-life balance (Thrasher et al., 2022) and discrimination (Holman & Walker, 2021), and similar interaction is relevant in the context of technology adoption. This highlights the importance of adopting an intersectional perspective, particularly when examining specific antecedents of technology adoption, such as effort expectancy.

#Implication 3. Age and gender together provide a better explanation of how certain antecedents influence technology adoption.

Finally, the country in which a study is conducted is a crucial factor when examining age-related differences. There is significant variability across countries in the age distribution of the working population (International Labour Organization, 2025), which may be reflected in the age of participants in these studies. For instance, research conducted in Africa often includes samples where the majority of participants are under 40 years old (Kelkay et al., 2025) or even under 30 years old (Negera et al., 2023). This demographic variation can substantially influence the observed effects of age on technology adoption, underscoring the need for more cross-country studies to better understand these dynamics.

#Implication 4. Cross-Country differences are important when examining the impact of age on technology adoption in the workplace.

Practical Recommendations

Research indicates that younger employees generally have more positive attitudes toward technology and use it more frequently than their older colleagues (Evidence 1 and 6). Organizations can leverage this dynamic to foster a more technology-friendly culture through social learning mechanisms (Bandura, 1977). Encouraging intergenerational interactions in technology use can facilitate the transfer of positive attitudes from younger to older workers (Hatfield et al., 1993), while also creating opportunities for peer-to-peer learning and knowledge sharing. This also aligns with the greater need for IT support among older workers (Evidence 5). In this context, increased intergenerational interaction during technology use can provide opportunities for peer-to-peer IT support. This form of assistance may be particularly valuable for older workers, as it allows them to receive guidance in a more informal and accessible manner. Moreover, this interaction can also benefit younger workers by exposing them to different perspectives on the usefulness of a system which older workers tend to perceive as higher (Evidence 2). This exchange can enhance younger employees' understanding of technology’s practical value and encourage a more well-rounded approach to its adoption.

Recommendation #1. Create conditions that enable the positive technological outlook and higher usage rates of younger workers to inspire older colleagues, while allowing the higher perceived usefulness among older workers to influence younger employees.

Moreover, research suggests that performance expectancy plays a crucial role in technology adoption, particularly among younger employees (Evidence 2), aligning with their greater inclination toward knowledge acquisition goals (Carstensen et al., 1999). This underscores the need for organizations, once they have identified high-value technologies for their business, to clearly articulate the individual benefits these technologies offer. Effectively communicating the added value of technology to all users, but especially to younger workers, can enhance engagement by demonstrating how its use contributes to personal and professional growth.

Recommendation #2. Clearly communicate to all users, particularly younger workers, the benefits of using a technological system to enhance their performance and advance their careers.

Our findings also indicate that facilitating conditions play a crucial role in older workers' decisions to adopt technology (Evidence 5), aligning with their greater need for compensatory mechanisms (Baltes & Baltes, 1990). In this regard, organizations should place particular emphasis on support mechanisms, such as IT assistance and knowledge-sharing initiatives, to encourage technology adoption, especially among older employees. While facilitating conditions are generally less critical for predicting technology use among younger workers, certain factors (i.e., availability and accessibility) have emerged as important for them. This highlights the practical need for organizations to tailor their approach to technology adoption, prioritizing different facilitating conditions based on the age of users.

Recommendation #3. Design conditions and characteristics of technology based on users' age, with a particular focus on ensuring facilitating conditions for older workers.

Finally, across multiple evidences (1, 2, 3, 4, 5, 6), several age-related factors appear to influence the relationship between age and technology adoption. First, the type of technology plays a crucial role in shaping this relationship. For instance, while older workers generally exhibit higher performance expectancy, younger employees tend to perceive greater usefulness in collaboration and e-learning technologies. Additionally, gender emerges as an important factor in conjunction with age, influencing various dimensions of technology adoption. These findings emphasize the importance of considering users within their broader life cycle when implementing technology in organizations. Moreover, factors such as organizational sector and Country-specific contexts also play a role, underscoring the need for a tailored approach to technology adoption and implementation.

Recommendations #4. Consider the specificity of the technology, as well as organizational and individual characteristics, when managing technology adoption among workers of different ages.

Limitations

It is important to acknowledge that there are some limitations in the literature reviewed and our work itself.

Firstly, a predominant proportion of the analyzed articles adopted a cross-sectional design, thereby some potential criticisms need to be taken into account in the overall validity of the research. The use of a cross-sectional design is widely acknowledged as a limitation in the field of aging workforce research, extending beyond its application to technology adoption (Beier et al., 2022). This poses a significant challenge for findings in this domain, as it relies on a between-person design to examine a within-person phenomenon, such as the effects of aging.

Limitation #1. Predominant use of cross-sectional design.

Moreover, the findings across studies are based on samples that vary widely in both mean age and age dispersion. Additionally, the articles handle the age variable differently, treating it either as a continuous measure or as a categorical variable. This issue presents a significant challenge for comparing studies. While heterogeneity in terms of age can be an integral part of contextual analysis (e.g., Country, sector), the decision to operationalize age as a continuous or categorical variable, along with the number of categories used, is often not well justified in existing literature.

Limitation #2. High differences across studies in terms of age mean, distribution and operationalization.

Thirdly, more than half of the papers analyzed don't consider theoretical models of technology adoption, potentially lacking in considering all the relevant influential dimensions. This also resulted in diverse operationalizations of factors influencing technology adoption, such as attitudes toward technology and facilitating conditions. The lack of a solid theoretical framework raises concerns about research grounded in previous evidence and may partially limit the depth of insights that can be drawn from this review.

Limitation #3. Lack of consolidated theoretical frameworks.

Also, the examined articles exhibited considerable heterogeneity, encompassing different sectors (i.e., n = 16), Countries (i.e., n = 16), and technologies (i.e., n = 8). This heterogeneity engendered occasional discordant findings, thereby complicating the generalization of the results. Furthermore, certain Countries (e.g., the USA) and technologies (e.g., ICT) were overrepresented, making the generalizability of the findings more reflective of this specific combination rather than a broader, more diverse context.

Limitation #4. High heterogeneity and overrepresentation of certain Countries (e.g., USA) and technologies (e.g., ICT).

Finally, the present review only focused on the influence of age on technology adoption, failing to consider how workers use the technology once it is adopted, which may affect the impact of technology on workers and organizations. This is a significant shift, especially with the emergence of new artificial intelligence tools that enable a wide range of applications (e.g., content creation, self-learning, communication).

Limitation #5. Lacking to consider how workers use technology once is adopted.

Future research

Based on our findings and limitations, several considerations for future research are necessary. Future research should prioritize investigating the conditions that shape the influence of age on technology adoption, particularly in relation to intersectionality with other characteristics (e.g., gender) and the type of technology (e.g. Artificial intelligence). Our findings indicate that the interaction between age and gender can substantially modify the role of age in technology adoption, as can the specific type of technology. However, the literature review highlights a significant gap in studies exploring these variations, underscoring the need for further research on both the differences between technologies and the intersectionality of age with other factors.

Future research questions #1. How does the type of technology change the influence of age on technology adoption and its antecedents? In what contexts is the intersection of age and gender more insightful than age alone in explaining technology adoption in the workplace?

Moreover, there is a notable gap in the literature regarding the relationship between technology adoption and age-related outcomes, such as job attitudes or career choices. To address this gap, more intervention-based research is needed, which remains limited in the current body of literature.

Future research questions #2. How does technology adoption influence job attitudes among workers of different age groups? How does technology adoption impact career choices across different age groups in the workforce?

Also, the few existing interventions primarily focus on individual-level approaches, such as training programs or IT support. Considering the significant role of organizational factors (e.g., work design) in both technology adoption (Brown et al., 2010) and age-related job attitudes (Truxillo et al., 2012), future research should expand beyond individual-level interventions to examine the effectiveness of organizational-level strategies.

Future research questions #3. How do organizational factors, such as work design, influence technology adoption among workers of different age groups? How do organizational factors, such as work design, affect the relationship between technology adoption and job attitudes among workers of different age groups?

References

Abeni, F., Petrera, F., & Galli, A. (2019). A Survey of Italian Dairy Farmers' Propensity for Precision Livestock Farming Tools. *Animals, 9*(5), 13. doi:https://doi.org/10.3390/ani9050202

Adams, A., Jumpah, E. T., & Caesar, L. D. (2021). The nexuses between technology adoption and socioeconomic changes among farmers in Ghana. *Technological Forecasting and Social Change, 173*, 1-9. doi:https://doi-org.ezproxy.unibo.it/10.1016/j.techfore.2021.121133

Agwu, A. E., Ekwueme, J. N., & Anyanwu, A. C. (2008). Adoption of improved agricultural technologies disseminated via radio farmer programme by farmers in Enugu State, Nigeria. *African Journal of Biotechnology, 7*(9), 1277-1286.

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes, 50*(2), 179-211. doi:https://doi-org.ezproxy.unibo.it/10.1016/0749-5978(91)90020-T

Ajzen, I., & Fishbein, M. (1977). Attitude-behavior relations: A theoretical analysis and review of empirical research. *Psychological bulletin, 84*(5), 888. doi:https://doi.org/10.1037/0033-2909.84.5.888

Alarima, C. I., Kolawole, A., Sodiya, C. I., Oladele, O. I., Masunaga, T., & Wakatsuki, T. (2011). Factors affecting the adoption of sawah technology system of rice production in Nigeria. *Journal of Food, Agriculture and Environment, 9*(3), 177-182.

Al-Gahtani, S. (2008). Testing for the applicability of the TAM model in the arabic context: Exploring an extended TAM with three moderating factors. *Information Resources Management Journal, 21*(4), 1-26.

Al-Gahtani, S. S., Hubona, G. S., & Wang, J. (2007). Information technology (IT) in Saudi Arabia: Culture and the acceptance and use of IT. *Information & management, 44*(8), 681-691. doi:https://doi-org.ezproxy.unibo.it/10.1016/j.im.2007.09.002

Autry Jr, A. J., & Berge, Z. (2011). Digital natives and digital immigrants: getting to know each other. *Industrial and commercial training, 43*(7), 460-466. doi:10.1108/00197851111171890

Baltes, P. B., & Baltes, M. M. (1990). Psychological perspectives on successful aging: The model of selective optimization with compensation. *Successful aging: Perspectives from the behavioral sciences, 1*, 1-34. doi:https://doi.org/10.1017/CBO9780511665684.003

Bandura, A. (1977). *Social Learning Theory.* Englewood Cliffs.

Barchielli, C., Marullo, C., Bonciani, M., & Vainieri, M. (2021). Nurses and the acceptance of innovations in technology-intensive contexts: the need for tailored management strategies. *BMC Health Services Research, 21*(1), 11. doi:https://doi.org/10.1186/s12913-021-06628-5

Bardach, H. S., Rhodus, K. E., Parsons, K., & Gibson, K. A. (2021). Older adults' adaptations to the call for social distancing and use of technology: insights from socioemotional selectivity theory and lived experiences. *Journal of Applied Gerontology, 40*(8), 814-817. doi:10.1177/0733464821996864

Bayramzadeh, S., & Alkazemi, M. F. (2014). Centralized vs. Decentralized Nursing Stations: An Evaluation of the Implications of Communication Technologies in Healthcare. *Health Environments Research and Design Journal, 7*(4), 62-80. doi:https://doi-org.ezproxy.unibo.it/10.1177/193758671400700406

Becker, K. L., Richards, M. B., & Stollings, J. (2020). Better Together? Examining Benefits and Tensions of Generational Diversity and Team Performance. *Journal of Intergenerational Relationships*, 1-21. doi:https://doi-org.ezproxy.unibo.it/10.1080/15350770.2020.1837708

Beier, E. M., Kanfer, R., Kooij, T. D., & Truxillo, M. D. (2022). What's age got to dowith it? A primer and review of theworkplace aging literature. *Personnel Psychology, 75*(4), 779-804. doi:10.1111/peps.12544

Blut, M., Choong, A., Tsiga, Z., & Venkatesh, V. (2021). Meta-analysis of the unified theory of acceptance and use of technology (UTAUT): challenging its validity and charting A research agenda in the red ocean. *Journal of the association for information systems*, 1-128. doi:http://dx.doi.org/10.17705/1jais.00719

Bortamuly, A. B., & Goswami, K. (2015). Determinants of the adoption of modern technology in the handloom industry in Assam. *Technological Forecasting and Social Change, 90*, 400-409. doi:https://doi-org.ezproxy.unibo.it/10.1016/j.techfore.2014.04.018

Brown, P., Daigneault, A., & Dawson, J. (2019). Age, values, farming objectives, past management decisions, and future intentions in New Zealand agriculture. *Journal of Environmental Management, 231*(0), 110-120. doi:https://doi.org/10.1016/j.jenvman.2018.10.018

Brown, S. A., Dennis, A. R., & Venkatesh, V. (2010). Predicting collaboration technology use: integrating technology adoption and collaboration research. *Journal of Management Information Systems, 27*(2), 9-54. doi:https://doi-org.ezproxy.unibo.it/10.2753/MIS0742-1222270201

Carstensen, L. L., Isaacowitz, D. M., & Charles, S. T. (1999). Taking time seriously: A theory of socioemotional selectivity. *American psychologist, 54*(3), 165. doi:https://doi.org/10.1037//0003-066x.54.3.165

Chedid, R. J., Dew, A., & Veitch, C. (2013). Barriers to the use of information and communication technology by occupational therapists working in a rural area of New South Wales, Australia. *Australian Occupational Therapy Journal, 600*(3), 197-205. doi:https://doi-org.ezproxy.unibo.it/10.1111/1440-1630.12016

Chen, I., Yang, K., Tang, F., Huang, C., & Yu, S. (2008). Applying the technology acceptance model to explorepublic health nurses' intentions towards web-based learning: A cross-sectional questionnaire survey. *International Journal of Nursing Studies, 45*(6), 869-878. doi:https://doi.org/10.1016/j.ijnurstu.2006.11.011

Cheng, B., Wang, M. H., Yang, S. J., Kinshuk, & Peng, J. (2011). Acceptance of competency-based workplace e-learning systems: Effects of individual and peer learning support. *Computers & Education, 57*(1), 1317-1333. doi:https://doi.org/10.1016/j.compedu.2011.01.018

Chien, C., Hsu, C., & Huss, J. J. (1998). Computer use in independent restaurants. *Journal of Hospitality and Tourism Research, 22*(2), 158-173. doi:https://doi-org.ezproxy.unibo.it/10.1177/109634809802200204

Chung, J., & Chulhee, L. (2023). Technology, job characteristics, and retirement of aged workers: evidence from automation and IT adoption of firms in Korea. *Industrial and Corporate Change, 32*, 930-955. doi:https://doi-org.ezproxy.unibo.it/10.1093/icc/dtad001

Czaja, S. J., & Sharit, J. (1993). Age differences in the performance of computer-based work. *Psychology and Aging, 8*, 59-67. doi:https://doi.org/10.1037/0882-7974.8.1.59

Czaja, S., Hammond, K., Blascovich, J., & Swede, H. (1989). Age related differences in learning to use a text-editingsystem. *Behaviour and Information Technology, 8*(4), 309-319. doi:https://doi-org.ezproxy.unibo.it/10.1080/01449298908914562

Davis, F. D. (1987). Technology acceptance model: TAM. *Al-Suqri, MN, Al-Aufi, AS: Information Seeking Behavior and Technology Adoption*, 205-219.

De Koning, J., & Gelderblom, A. (2006). ICT and older workers: No unwrinkled relationship. *International Journal of Manpower, 27*(5), 467-490. doi:http://dx.doi.org/10.1108/01437720610683967

DelCampo, R. G., Haggerty, L. A., & Knippel, L. A. (2017). *Managing the Multi-Generational Workforce: From the GI Generation to the Millennials.* Routledge. doi:https://doi-org.ezproxy.unibo.it/10.1108/hrmid.2012.04420baa.017

Dominici, G., & Palumbo, F. (2013). How to build an e-learning product: Factors for student/customer satisfaction. *Business Horizons, 56*(1), 87-96. doi:https://doi-org.ezproxy.unibo.it/10.1016/j.bushor.2012.09.011

Dutta, P., & Borah, A. S. (2018). A Study on Role of Moderating Variables in Influencing Employees’ Acceptance of Information Technology. *The Journal of Business Perspective, 22*(4), 387-394. doi:https://doi-org.ezproxy.unibo.it/10.1177/0972262918803467

Eley, R., Fallon, T., Soar, J., Buikstra, E., & Hegney, D. (2009). Barriers to use of information and computer technology by Australia's nurses: A national survey. *Journal of Clinical Nursing, 18*(8), 1151-1158. doi:https://doi-org.ezproxy.unibo.it/10.1111/j.1365-2702.2008.02336.x

Elias, S. M., Smith, W. L., & Barney, C. E. (2012). Age as a moderator of attitude towards technology in the workplace: work motivationand overall job satisfaction. *Behaviour and Information Technology, 31*(5), 453-467. doi:https://doi-org.ezproxy.unibo.it/10.1080/0144929X.2010.513419

Fasbender, U., Gerpott, F. H., & Rinker, L. (2023). Getting Ready for the Future, Is It Worth It? A Dual Pathway Model of Age and Technology Acceptance at Work. *Work, Ageing and Retirement, 9*, 358-375. doi:10.1093/workar/waac035

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: An introduction to theory and research.* Boston: Addison-Wesley.

Friedberg, L. (2003). The impact of technological change on older workers: Evidence from data on computer use. *Industrial & Labor Relations Review, 56*(3), 511-529. doi:https://doi.org/10.2307/3590922

Grünloh, C., Cabrita, M., Dantas, C., & Ortet, S. (2022). Opportunities, ethical challenges, and value implications of pervasive sensing technology for supporting older adults in the work environment. *Australasian Journal of Information Systems, 26*(0), 1-22. doi:https://doi.org/10.3127/ajis.v26i0.3133

Herden, C. J., Alliu, E., Cakici, A., Cormier, T., Deguelle, C., Gambhir, S., . . . Kiratli, Y.-S. (2021). Corporate Digital Responsibility. New corporate responsibilities in the digital age. *Sustainability Management Forum, 29*(1), 13-29. doi:https://link.springer.com/article/10.1007/s00550-020-00509-x

Horn, J. L., & Raymond, C. B. (1967). Age differences in fluid and crystallized intelligence. *Acta psychologica, 26*, 107-129. doi:10.1016/0001-6918(67)90011-X

International Labour Organization. (2025, 03 10). *ILOSTAT data explorer*. Tratto da International Labour Organization: https://rshiny.ilo.org/dataexplorer37/?lang=en&id=POP_XWAP_SEX_AGE_NB_A

Jeffrey, D., & Dafoe, A. (2021). The logic of strategic assets: From oil to AI. *Security Studies, 30*(2), 182-212. doi:https://doi-org.ezproxy.unibo.it/10.1080/09636412.2021.1915583

Jelinsky, M., Bergen, R., Grant, B., & Waldner, C. (2019). Adoption of technology and management practices by Canadian cow-calf producers. *Canadian Veterinary Journal, 60*(3), 287-293.

Jimoh, L., Pate, M. A., Lin, L., & Schulman, K. A. (2012). A model for the adoption of ICT by health workers in Africa. *International Journal of Medical Informatics, 81*(11), 773-781. doi:https://doi.org/10.1016/j.ijmedinf.2012.08.005

Katou, A. A., & Vogiatzi, M. A. (2011). Employee behavioral intentions in adopting information technology: The case of the Greek hotel industry. *International Journal of Social Ecology and Sustainable Development, 2*(2), 17-30. doi:10.4018/jsesd.2011040102

Kelkay, J. M., Wubante , S. M., Anteneh, D. S., Takilo, M. K., Gebeyehu, C. D., Alamer, T. A., & Gashu, K. D. (2025). Intention to use eLearning-based continuing professional development and its predictors among healthcare professionals in Amhara region referral hospitals, Ethiopia, 2023: using modified UTAUT-2 model. *BMC Health Services Research, 25*, 178. doi:10.1186/s12913-025-12317-4

Khan, S. (2024). Impact of AI on Work Life Balance of Working Women in Hotel Industry. *International Journal of Scientific Research in Engineering and Management, 8*(10), 1-23. 10.55041/IJSREM38120

Kim, Y., Blazquez, V., & Oh, T. (2024). Determinants of Generative AI System Adoption and Usage Behavior in Korean Companies: Applying the UTAUT Model. *Behavioral Science, 14*, 1-23. doi:10.3390/bs14111035

Knight, T. J., Yuan, X., & Bennett Gayle, D. (2022). Illuminating Privacy and Security Concerns in Older Adults' Technology Adoption. *Work, Aging and Retirement, 10*(1), 57-60. doi:https://doi-org.ezproxy.unibo.it/10.1093/workar/waac032

Larsen, T. J., & Sørebø, Ø. (2005). Impact of personal innovativeness on the use of the internet among employees at work. *Journal of Organizational and End User Computing, 17*(2), 43-63. doi:http://dx.doi.org/10.4018/joeuc.2005040103

Laumer, S., Maier, C., Eckhardt, A., & Weitzel, T. (2016). User personality and resistance tomandatory information systems inorganizations: a theoretical model andempirical test of dispositional resistance tochange. *Journal of Information Technology, 31*(1), 67-82. doi:http://dx.doi.org/10.1057/jit.2015.17

Lobschat, L., Mueller, B., Eggers, F., Brandimarte, L., Diefenbach, S., Kroschke, M., & Wirtz, J. (2021). Corporate digital responsibility. *Journal of Business Research, 122*, 875-888. doi:https://doi-org.ezproxy.unibo.it/10.1016/j.jbusres.2019.10.006

Longo, F., Padovano, A., & Umbrello, S. (2020). Value-Oriented and Ethical Technology Engineering in Industry 5.0: A Human-Centric Perspective for the Design of the Factory of the Future. *Applied Sciences, 10*(12), 4182. doi:http://dx.doi.org/10.3390/app10124182

Marzi, G., Balzano, M., Caputo, A., & Pellegrini, M. M. (2024). Guidelines for Bibliometric-Systematic Literature Reviews: 10 steps to combine analysis, synthesis and theory development. *International Journal of Management Reviews, 27*(1), 81–103. doi:10.1111/ijmr.12381

Morris, M. G., & Venkatesh, V. (2000). Age differences in technology adoption decisions: implications for a changing workforce. *Personnel Psychology, 53*(2), 375-403. doi:https://doi-org.ezproxy.unibo.it/10.1111/j.1744-6570.2000.tb00206.x

Morris, M. G., Venkatesh, V., & Ackerman, P. L. (2005). Gender and Age Differences in Employee DecisionsAbout New Technology: An Extensionto the Theory of Planned Behavior. *IEEE*

Transactions on Engineering Management, 52(1), 69-84. doi:http://dx.doi.org/10.1109/TEM.2004.839967

Moura, I. V., De Almeida, L. B., Da Silva, W. V., De Veiga, C. P., & Costa, F. (2020). Predictor Factors of Intention to Use Technological Resources: A Multigroup Study About the Approach of Technology Acceptance Model. *Sage Open, 10*(4), 17. doi:https://doi-org.ezproxy.unibo.it/10.1177/2158244020967942

Mueller, B. (2022). Corporate digital responsibility. *Business & Information Systems Engineering, 64*(5), 689-700.

Negera, D., Zewdie, A., Kera, A. M., & Degefa, G. H. (2023). Health information use and associated factors among healthcare professionals in Ilu Aba Bor zone, Oromia region, Ethiopia: an institution-based cross-sectional study. *BMJ Open, 13*. doi:10.1136/

Newby, M., Nguyen, T. H., & Waring, T. S. (2014). Understanding customer relationship management technology adoption in small and medium-sized enterprises: An empirical study in the USA. *Journal of Enterprise Information Management, 27*(5), 541-560. doi:http://dx.doi.org/10.1108/JEIM-11-2012-0078

Nimrod, G. (2019). Aging Well in the Digital Age: Technology in Processes of Selective Optimization with Compensation. *Journals of Gerontology: Social Sciences, 75*(9), 2008-2017. doi:10.1093/geronb/gbz111

Nord, J. H., Espinosa, S. D., Paliszkiewicz, J., & Madra-Sawicka, M. (2020). Do technology and social media preferences differ with age? A study of the use of social technologies for business purposes in Spain. *Journal of Computer Information Systems, 60*(2), 101-112. doi:http://dx.doi.org/10.1080/08874417.2018.1423892

Ouzzani, M., Hammady, H., Fedorowicz, Z., & Elmagarmid, A. (2016). Rayyan — a web and mobile app for systematic reviews. *Systematic Reviews, 5*(210), 1-10. doi:10.1186/s13643-016-0384-4

Owombo, P. T., & Idumah, F. O. (2017). Determinants of agroforestry technology adoption among arable crop farmers in Ondo state, Nigeria: an empirical investigation. *Agroforestry Systems, 91*(5), 919-926. doi:10.1007/s10457-016-9967-2

Park, C.-Y., Shin, K., & Kikkawa, A. (2021). Aging, automation, and productivity in Korea. *Journal of The Japanese and International Economies, 59*, 1-20. doi:https://doi.org/10.1016/j.jjie.2020.101109

Park, H., Kim, K., Soh, J., Hyun, Y., Jang, S., Lee, S., . . . Kim, H. (2020). Factors Influencing Acceptance of Personal Health Record Apps for Workplace Health Promotion: Cross-Sectional Questionnaire Study. *JMIR MHEALTH AND UHEALTH, 8*(24), 24. doi:https://doi.org/10.2196%2F16723

Pearson, M. J., Bahmanziari, T., Crosby, L., & Conrad, E. (2002). An Empirical Investigation into the Relationshipbetween Organizational Culture and Computer Efficacy as Moderated by Age and Gender. *Journal of Computer Information Systems, 43*(2), 58-70. doi:https://doi-org.ezproxy.unibo.it/10.1080/08874417.2003.11647086

Rantanen, T., & Toikko, T. (2017). Employees' attitudes towards welfare technology in substance abuse treatment in Finland. *Nordic Studies on Alcohol and Drugs, 34*(2), 131-144. doi:https://doi-org.ezproxy.unibo.it/10.1177/1455072517691060

Raymundo, T. M., & Silva Santana, C. (2019). Specific ICT training of older Brazilian workers. *Gerontechnology, 18*(3), 168-179.

Savolainen, R. (2015). Cognitive barriers to information seeking: A conceptual analysis. *Journal of Information Science, 41*(5), 613-623. doi:10.1177/0165551515587850

Schleife, K. (2006). Computer use and employment status of older workers - An analysis based on individual data. *Labour, 20*(2), 325-348. doi:http://dx.doi.org/10.1111/j.1467-9914.2006.00341.x

Sengpiel, M., & Wandke, H. (2010). Compensating the effects of age differences in computer literacy on the use of ticket vending machines through minimal video instruction. *Occupational Ergonomics, 9*(2), 87-98. doi:http://dx.doi.org/10.3233/OER-2010-0174

Shah, M. S., Iqbal, N., Janjua, S. Y., & Amjad, S. (2013). Employee Behavior Towards Adoption of E-learning Courses:Validating Technology Acceptance Model. *Mediterranean Journal of Social Sciences, 4*(14), 765 - 774. doi:http://dx.doi.org/10.5901/mjss.2013.v4n14p765

Singh, B., & Acharjya, D. P. (2016). Nurse's attitude towards computerization in private hospitals of Tamil Nadu, India. *Research Journal of Pharmacy and Technology, 9*(12), 1451-1456. doi:http://dx.doi.org/10.5958/0974-360X.2016.00446.7

Soja, E., & Soja, P. (2020). Fostering ICT use by older workers: Lessons from perceptions of barriers to enterprise system adoption. *Journal of Enterprise Information Management, 33*(2), 407-434. doi:http://dx.doi.org/10.1108/JEIM-12-2018-0282

Tam, S., Grover, V., & Thatcher, J. (2014). Modern information technology in an old workforce: Toward a strategic research agenda. *The journal of strategic information systems, 23*(4), 284-304. doi:https://doi-org.ezproxy.unibo.it/10.1016/j.jsis.2014.10.001

Tams, S., & Dulipovici, A. M. (2019). The creativity model of age and innovation with IT: How to counteract the effects of age stereotyping on user innovation. doi:http://hdl.handle.net/10125/60089

Tarcan, E., & Varol, E. (2010). Role of the demographic factors in the process of hotel information systems adoption. *Tourism: An International Interdisciplinary Journal, 52*(2), 127-144.

Thrasher, G. R., Wynne, K., Baltes, B., & Bramble, R. (2022). The intersectional effect of age and gender on the work–life balance of managers. *Journal of Managerial Psychology, 37*(7), 683-696. doi:10.1108/JMP-03-2021-0169

Truxillo, D. M., Cadiz, D. M., Rineer, J. R., Zaniboni, S., & Fraccaroli, F. (2012). A Lifespan Perspective on Job Design: Fitting the Worker to the Job to Promote Job Satisfaction, Engagement, and Performance. *Organizational Psychology Review, 2*(4), 340-360. doi:10.1177/2041386612454043

Urhuogo, I., Williams, V., & Hart, D. W. (2013). Root Cause Analysis: Using Theory of Constraints Application to Measure the Impact of EmployeeDemographics on the Adoption of InformationTechnology Equipment. *Journal of Information & Knowledge Management, 12*(1), 1-15.

Van der Aalst, W. M., Hinz, O., & Weinhardt, C. (2023). Sustainable Systems Engineering. Opportunities and Challenges. *Business & Information Systems Engineering*, 1-6. doi:http://dx.doi.org/10.1007/s12599-022-00784-6

Venkatesh, V., & Zhang, X. (2010). Unified theory of acceptance and use of technology: U.S. vs. China. *Journal of Global Information Technology Management, 13*(1), 5-27. doi:http://dx.doi.org/10.1080/1097198X.2010.10856507

Venkatesh, V., Brown, S. A., Maruping, L. M., & Bala, H. (2008). Predicting different conceptualizations of system use: The competing roles of behavioral intention, facilitating conditions, and behavioral expectation. *MIS quarterly*, 483-502. doi:http://dx.doi.org/10.2307/25148853

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). *User acceptance of information technology: Toward a unified view* (Vol. 27). MIS Quarterly. doi:https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, 157-178. doi:https://doi.org/10.2307/41410412

Violante, M., & Vezzetti, E. (2014). Implementing a new approach for the design of an e-learning platform in engineering education. *Computer Applications in Engineering Education, 22*(4), 708-727. doi:http://dx.doi.org/10.1002/cae.21564

Waterson, P., Robertson, M. M., Cooke, N. J., Militello, L., Roth, E., & Stanton, N. A. (2015).

Defining the methodological challenges and opportunities for an effective science of sociotechnical systems and safety. Ergonomics, 58(4), 565-599. doi: http://dx.doi.org/10.1080/00140139.2015.1015622

Welch, R., Alade, T., & Nichol, L. (2020). Using the unified theory of acceptance and use of technology (UTAUT) model to determine factors affecting mobile learning adoption in the workplace: A study of the science museum group. *International Journal on Computer Science and Information Systems, 15*(1), 85-98. doi:http://dx.doi.org/10.33965/ijcsis_2020150107

Werner, S., & Landau, R. (2011). Social Workers' and Students' Attitudes toward Electronic Tracking of People with Alzheimer's Disease. *Social Work Education, 30*(5), 541-557. doi:http://dx.doi.org/10.1080/02615479.2010.508090

Wilder, J. L., Nadar, D., Gujral, N., Ortiz, B., Stevens, R., Holder-Niles, F., . . . Gaffin, J. M. (2019). Pediatrician Attitudes toward Digital Voice Assistant Technology Use in Clinical Practice. *Applied Clinical Informatics, 10*(2), 286-294. doi:https://doi.org/10.1055/s-0039-1687863

Yang, C.-C., Shang, K.-C., Lai, P.-L., & Madhavan, M. (2022). Adoption of socially interactive technologies for shipping services. *Maritime Policy and Management*. doi:https://doi-org.ezproxy.unibo.it/10.1080/03088839.2022.2116751

Zacher, H., & Frese, M. (2009). Remaining Time and Opportunities at Work: Relationships Between Age, Work Characteristics, and Occupational Future Time Perspective. *Psychology and Ageing, 24*(2), 487-493. doi:10.1037/a0015425

Zeffane, R., & Cheek, B. (1993). Profiles and correlates of computer usage - A study of the Australian Telecommunications industry. *Computers in Industry, 22*(1), 53-69. doi:https://doi-org.ezproxy.unibo.it/10.1016/0166-3615(93)90081-B

Appendix A

Table 2

Summary of literature review findings

Reference	Technology type	Sector	Country	N, study design and data collection	Attitudes toward using technology	Performance expectancy	Effort expectancy	Social influence	Facilitating conditions	Behavior intentions and use behavior
Abeni et al., (2019)	Productivity technology	Agricultural	IT	*n* = 490 C QN						AD. Negative relation between age and behavior intention
Adams et al., (2021)	Productivity technology	Agricultural	GH	*n* = 463 C QN						AD. Negative relation between age and use behavior
Agwu et al., (2008)	Technology (no specified)	Agricultural	NG	*n* = 135 C QN						AD. Negative relation between age and use behavior
Alarima et al., (2011)	Productivity technology	Agricultural	NG	*n* = 124 C QN						AD. Negative relation between age and use behavior
Al-Gahtani (2008)	Technology (no specified)	-	SA	*n* = 722 C QN		AI. The relationship between perceived usefulness and behavior intention to use technology it was stronger for younger than older workers	AI. NS			
Al-Gahtani et al., (2007)	Information and communication technology	-	SA	*n* = 1190 C QN		AI. NS	AI. NS	AI. The relationship between social influence and behavior intention to use technology it was stronger for younger than older workers	AI. The relationship between facilitating condition and technology use it was stronger for younger than older workers	
Barchielli et al., (2021)	Technology (no specified)	Healthcare	IT	*n* = 54 C QN		AI. The relationship between performance expectancy and behavior intention to use technology it was stronger for younger than older workers	AI. The relationship between effort expectancy and behavior intention to use technology it was stronger for younger than older workers	AI. The relationship between social influence and behavior intention to use technology it was stronger for younger than older workers	AI. The relationship between facilitating condition and technology use it was stronger for older than younger workers	
Bayramzadeh & Alkazemi (2014)	Information and communication technology	Healthcare	USA	*n* = 70 C QN	AD. Younger nurses assessed more favorably					

					tech-based communication over face-to-face interactions					
Becker et al., (2020)	Technology (no specified)	Utility	USA	*n* = 261 C QL					AD. Confidence in use technology was lower for older than younger workers	
Bortamuly & Goswami (2015)	Technology (no specified)	Manufacturing	IND	*n* = 500 C QL						AD. Negative relation between age and use behavior
Brown et al., (2019)	Technology (no specified)	Agricultural	NZ	*n* = 1984 C QL						AD. Negative relation between age and use behavior
Brown et al., (2010)	Information and communication technology	-	FI	*n* = 447 L QN		AD. Performance expectancy was higher for younger than older workers	AD. Effort expectancy was higher for younger than older workers	AD. Social influence was higher for older than younger workers AI. NS	AD. Facilitating conditions was higher for younger than older workers AI. The relationship between facilitating condition and technology use it was stronger for older than younger workers	AD. Negative relation between age and behavior intention and use behavior
Chedid et al., (2013)	Technology (no specified)	Healthcare	AU	*n* = 13 C QL					AD. Confidence in use technology was lower for older than younger workers	
Cheng et al., (2011)	Training technology	-	CN	*n* = 202 C QN		AI. NS			AI. NS	
Chen et al., (2008)	Training technology	Healthcare	TW	*n* = 222 C QN		AD. NS				
Chien et al., (1998)	Computer and software	Retail	USA	*n* = 144 C QN						AD. Over thirty-nine years old workers less computer use than workers under forty years old
De Koning & Gelderblom (2006)	Computer and software	Retail	NL	*n* = 538 C QN						AD. Negative relation between age and use behavior among workers older than fifty years
Dutta & Borah (2018)	Information and communication technology	Public administration	IND	*n* = 93 C QN	NS	AD. Higher level of performance expectancy among workers older than 50 years old	AD. Higher level of effort expectancy among workers		AD. Higher concern about facilitating conditions among	

							younger than 50 years old		older than younger workers	
Eley et al., (2009)	Computer and software	Healthcare	USA	*n* = 3680 C QN					AD. Location of computers and insufficient number of computers were considered more relevant barriers for younger nurses. IT knowledge, lack of technical support and confidence in use were considered more relevant barriers for older nurses.	
Fasbender et al., (2023)	Information and communication technology	-	DE	*n* = 470 C QN	AD. NS	AD. NS	AD. Perceived ease of use was higher for older than younger workers			
Friedberg (2003)	Computer and software	-	USA	*n* = 60000 L QN						AD. Percentage of computer use decrease with age
Jelinski et al., (2019)	Technology (no specified)	Agricultural	CA	*n* = 72820 C QN						AD. Over forty-nine years old workers less computer use than workers under fifty years old
Jimoh et al., (2012)	Information and communication technology	Healthcare	NG	*n* = 200 C QN		AD. NS	AD. Perceived ease of use was higher for older than younger workers			
Katou & Vogiatzi (2011)	Information and communication technology	Tourism	GR	*n* = 215 C QN						AD. Negative relation between age and use behavior
Kelkay et al., (2025)	Training technology	Healthcare	ET	*n* = 1056 C QN		AI. NS	AI. NS	AI. NS	AI. NS	
Kim et al., (2024)	Artificial Intelligence	-	KR	*n* = 300 C QN		AI. NS	AI. The relationship between effort expectancy and behavior intention to use technology was stronger for younger than older workers	AI. NS	AI. NS	
Larsen & Sørebø (2005)	Information and communication technology	Oil and Gas	NO	*n* = 500 C QN						AD. Negative relation between age and use behavior

Laumer et al., (2016)	Information and communication technology	Automotive	-	*n* = 106 C QN		AD. Performance expectancy was higher for older than younger workers	AD. Perceived ease of use was higher for older than younger workers			
Morris & Venkatesh (2000)	Information and communication technology	Finance	USA	*n* = 118 L QN	AD. Younger workers reported higher pleasure of tech use. AI. The relationship between pleasure to use the system and tech use intention was stronger for younger workers.				AI. The relationship between facilitating condition and technology use it was stronger for older than younger workers	
Morris et al., (2005)	Technology (no specified)	-	USA	*n* = 342 L QN	AI. The relationship between attitudes toward using technology and behavior intention to use technology it was stronger for older than younger workers			AI. The relationship between subjective norms and behavior intention to use technology it was stronger for older than younger workers	AI. NS	
Moura et al., (2020)	Information and communication technology	Academic	BR	*n* = 147 C QN		AI. NS	AI. NS	AI. NS	AI. NS	
Newby et al., (2014)	Management technology	Retail	USA	*n* = 126 C QN					AD. NS	
Negera et al., (2023)	Management technology	Public administration	ET	*n* = 397 C QN						AD. Positive relation between age and use behavior
Nord et al., (2018)	Information and communication technology	-	SP	*n* = 104 C QN						AD. Workers between thirty-six- and forty-five-years old use more social media for business purpose
Owombo & Idumah (2017)	Productivity technology	Agricultural	NG	*n* = 240 C QN						AD. Negative relation between age and use behavior
Park et al., (2020)	Management technology	Healthcare	KR	*n* = 866 C QN		AI. The relationship between performance expectancy and behavior intention to use technology it was stronger for younger than older workers	AI. NS	AI. NS		

Rantanen & Toikko (2017)	Welfare technology	NGO	FI	*n* = 129 C QN	AD. NS			AD. NS	AD. Perceived behavioral control was higher for younger than older workers	AD. Negative relation between age and behavior intention
Schleife (2007)	Computer and software	-	DE	*n* = 581 L QN						AD. Older age group show a significantly smaller probability to use a computer at work
Shah et al., (2013)	Training technology	Finance	PK	*n* = 172 C QN		AD. Performance expectancy was higher for younger than older workers	AD. NS			
Singh & Acharjya (2016)	Computer and software	Healthcare	IND	*n* = 164 C QN		AD. Higher performance expectancy among age group 31 - 50 years old than among age group 26 - 30 years old				
Soja & Soja (2020)	Management technology	-	PL	*n* = 187 C QL					AD. Higher concern about facilitating conditions among older than younger workers	
Tarcan & Valor (2010)	Information and communication technology	Tourism	TK	*n* = 396 C QN		AD. Performance expectancy was higher for older than younger workers	AD. NS			
Urhuogo et al., (2013)	Information and communication technology	Academic	USA	*n* = 216 C QL					AD. Confidence in use technology was lower for older than younger workers	AD. Negative relation between age and use behavior
Venkatesh & Zhang (2010)	Technology (no specified)	-	USA / CN	*n* = 149 L QN		AI. The relationship between performance expectancy and behavior intention to use technology it was stronger for younger man than older workers	AI. The relationship between effort expectancy and behavior intention to use technology it was stronger for younger women in the early stages of their experience	AI. NS		
Venkatesh et al., (2008)	Information and communication technology	Telecommunication	USA	*n* = 321 L QN					AI. NS	
Venkatesh et al., (2003)	Technology (no specified)	-	USA	*n* = 215 L QN	AI. NS	AI. The relationship between performance expectancy and	AI. The relationship between effort expectancy and	AI. The relationship between social influence and behavior intention	AI. The relationship between facilitating	

						behavior intention to use technology it was stronger for younger man than older workers	behavior intention to use technology it was stronger for older women than younger workers	to use technology it was stronger for older than younger workers	condition and technology use it was stronger for older than younger workers	
Welch et al., (2020)	Training technology	Museum	EN	*n* = 118 C QN		AI. The relationship between performance expectancy and behavior intention to use technology it was stronger for younger than older workers	AI. The relationship between effort expectancy and behavior intention to use technology it was stronger for older than younger workers	AI. The relationship between social influence and behavior intention to use technology it was stronger for younger than older workers		
Werner & Landau (2011)	Welfare technology	Healthcare	IL	*n* = 116 C QN	AD. NS					
Wilder et al., (2019)	Welfare technology	Healthcare	USA	*n* = 114 C QN						AD. Younger workers were more likely to be willing to try voice technology
Yang et al., (2022)	Information and communication technology	Shipping service	-	-		AI. The relationship between performance expectancy and behavior intention to use technology it was stronger for older than younger workers		AI. The relationship between social influence and behavior intention to use technology it was stronger for older than younger workers		
Zeffane & Cheek (1993)	Computer and software	Telecommunicat ion	AU	*n* = 1300 C QN						AD. Negative relation between age and use behavior

Notes. AU = Australia; BR = Brazil; CA = Canada; CN = China; DE = Germany; EN = England; ET = Ethiopia; FI = Finland; GH = Ghana; GR = GREECE; IL = Israel; IND = India; IT = Italy; KR = Korea; NG = Nigeria; NL = Netherlands; NO = Norway; NZ = New Zeland; PK = Pakistan; PL = Poland; SA = Saudi Arabia; SP = Spain; TK = Turkey; TW = Taiwan; USA = United States. C = Cross-sectional study; L = Longitudinal study. QN = Quantitative data collection; QL = Qualitative data collection. AD = Age differences; AI = Age interaction. NS = non-significant findings.

CHAPTER IV | STUDY 2. Navigating Ethical Boundaries in Workers' Use of Technology: A Review and Integrative Model

Abstract

Technology increasingly mediates human interactions in the workplace, transforming how employees engage with their tasks, colleagues, and organizations. While significant attention has been devoted to the ethical design of workplace technologies, less is understood about how employees behave through technology and the ethical implications of those behaviors. The present contribution aims, first, to clarify the main directions emerging from the literature on workers' ethical use of technology by addressing the question: What ethical use behaviors have been studied? Second, it seeks to develop an integrative framework that identifies why and when a particular use behavior can be considered ethical. To achieve these goals, a bibliometric systematic literature review was conducted, identifying eight thematic clusters across 122 articles included in the analysis. These clusters were critically examined, and based on the existing literature, we developed a framework that integrates key ethical principles with the specific impacts of technology use behaviors on various stakeholders. Finally, limitations and directions for future research are also discussed.

Keywords: Human behavior, Ethical use of technology, Workplace, Bibliometric-Systematic Literature Review, Decision-making

Introduction

The ethical design and use of technology in the workplace is a central factor shaping the impacts of digitalization in the present and near future (Floridi et al., 2018). Three key actors are involved in this dynamic with ethical implications. First, the technical experts who develop new technologies and define the functionalities of digital tools. Second, organizations that, as moral agents (Pedro, 2024), make choices about the adoption and use of technology. Third, the individuals within organizations who use these technologies in their daily work. To establish and manage an ethical approach for the first two groups, research and practice typically rely on universal ethical principles that are intended to guide the behavior of these moral agents (Correa, 2023; Floridi et al., 2018). Based on this perspective, many organizations have attempted to influence technology-related behavior by developing policies that define boundaries for ethical use, both for well-established digital systems (Pierce & Henry, 2000) and for emerging tools such as Artificial Intelligence (Correa, 2023). However, despite the necessity of such governance, these efforts often clash with individual discretion (Green, 2024). Today, this discretion is amplified by the widespread availability of digital tools, often free or low-cost, which can be accessed by employees can access independently from formal organizational adoption, but can also have significant ethical consequences within organizational contexts (Green, 2024). For instance, any employee can choose to use generative AI tools such as ChatGPT or DeepSeek to analyze a document, potentially saving time but also taking risks (e.g., privacy, reliability of outcomes). Moreover, individuals in their everyday behavior often encounter conflicting interests and perspectives from various stakeholders, for example, a co-worker might view it as supportive if I share useful data with them, but from an organizational perspective, the same action could be seen as a breach of privacy. As a result, the ethical challenge is not whether to act ethically, but rather toward whom to act ethically, leading to 'moral stress' (i.e., an incongruence between organizational and individual perspectives on ethical matters) for those striving to navigate these competing ethical demands (Pierce & Henry, 2000). In this context, top-down regulatory approach based on universal ethical principles is not fully capable of guiding individual behavior.

Rather, what is needed is a shift toward distributed responsibility, an ethical model that recognizes and supports the moral agency of individual users while also upholding the ethical boundaries established by organizations. This requires integrating an absolutist approach, grounded in core ethical principles, with a more relativistic perspective that considers when and for whom a particular behavior may be deemed ethical. Grounded in this need, the aim of this article is twofold. First, we would like to clarify the main directions emerging from the literature regarding the workers' ethical use of technology. In particular, we synthesize existing research on individual technology use behaviors inside organizations that may carry ethical implications, addressing the question of *what* ethical use behaviors have been studied. According to Treviño et al. (2014), workers may act in ways that violate ethical principles and harm stakeholders (i.e., unethical), comply with the minimum accepted standards of ethical behavior (i.e., ethical), or go beyond basic compliance to actively promote positive outcomes for stakeholders (i.e., extraordinarily ethical). To the best of our knowledge, no existing work provides a comprehensive summary of the various types of unethical, ethical, and extraordinarily ethical use behaviors explored in the literature. Second, we critically analyze the literature to examine the assumptions under which each technology use behavior has been classified as unethical, ethical, or extraordinarily ethical. Through this analysis, we offer an integration of core ethical principles with the impacts of these behaviors, thereby addressing the *why* and *when* a use behavior can be considered ethical.

Materials and Methods

We followed the Bibliometric-Systematic Literature Reviews (B-SLRS) approach (Marzi et al., 2024). The first step was the definition of research questions and boundaries of the study. In doing so, we took an initial informal literature screening on ethical use of technology, using the keywords ("technology" AND "adoption" OR "use" AND "ethic*" OR "moral*" AND "work*"). Based on this, we defined our research question as follows: What the state of the art on workers' ethical use of technology in the workplace? So, we came out with the following inclusion and exclusion criteria: Studies focusing on workplace use of technology were included. In doing so, we included studies that do not merely refers to use or not use, but instead to the type of use / behavior expressed through technology. In contrast, studies examining the use of technology outside organizational populations (e.g., students) and those not centered on specific behavior expressed through technology (e.g., use behavior as a dichotomous variable, yes/no) were excluded. Only empirical studies employing both quantitative and qualitative data collection methods were included. No restrictions were imposed regarding the publication year, Country, or type of technology examined. As step two we created and validated the set of keywords involving three experts in workplace behavior. Our search query as follows: ("ethic*" OR "moral*" OR "dilemma*") AND ("technology" OR "ct" OR "ict" OR "digit*" OR "Artificial Intelligence" OR "AI" OR "cyber*") AND ("use" OR "performance" OR "utiliz*" OR "behavior*" OR "counterproductive" OR "misuse" OR "citizenship" OR "proactive") AND ("workplace" OR "employee*" OR "worker*" OR "work environment" OR "organization*") AND NOT ("child" OR "children" OR "home" OR "student*" OR "schoolchildren" OR "school"). Third step was the database selection. We conducted our search across multiple databases, selecting two major sources in management studies (i.e., Web of Science and Scopus) as well as three databases highly regarded in organizational and social psychology (i.e., PsycINFO, APA PsycArticles, Psychology Database). Then, our comprehensive literature search was performed using the databases Web of Science (i.e., Clarivate), Scopus (i.e., Elsevier), PsycINFO and APA PsycArticles (i.e., EBSCO), and Psychology Database (i.e., ProQuest). A total of n = 6789 articles were found, published from 1967 to 2025. In the fourth and fifth steps we screened the data, selecting only peer-reviewed articles published in English while excluding dissertations, conference proceedings, and book chapters. Two researchers independently conducted the analysis and cross-validated the data. The screening processes have been conducted by the two researchers using Rayyan online software (Ouzzani et al., 2016), which align with the PRISMA guidelines (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). Table 1 provides a summary of the inclusion and exclusion criteria, structured according to the PICO search framework.

Table 1

Summary of inclusion and exclusion criteria based on PICO method

	Inclusion	Exclusion
Population	Workers	All the others (e.g., customers, users)
Intervention	Quantitative and qualitative empirical studies	Theoretical and conceptual contribution
Comparison	Type of technology use behavior invesitgated	Papers which consider only technology adoption
Outcome	Drivers to evaluate the technology use behavior as ethical, unethical or extraordinary ethical	Ethical behavior no related to technology use

After removing the duplicates, abstracts and full texts were screened. Finally, n = 122 empirical articles were identified and retained. The resulting flow chart is shown in Figure 1. The excluded articles fell into one or more of the following categories: those examining an irrelevant population (e.g., non-working individuals), an unsuitable publication type (e.g., conference proceedings), or an unrelated topic (e.g., the ethical use of AI by organizations rather than individual workers). We also assessed the quality of the sources using the Scimago Quartiles (Marzi et al., 2023). Based on Scimago Quartiles, 48% of the sources were ranked in Q1, 18% were ranked in Q2, the 16% were ranked in Q3 and the remaining 17% in Q4 (Figure 2). After completing the initial five steps, we had a methodological checkpoint as recommended by the B-SLR method. The literature presented contrasting and often disconnected evidence regarding which technology use behaviors are considered ethical, and the reasons behind these judgments. These conceptual inconsistencies highlight the need for further investigation to address our earlier question. Consequently, we formulated our final research questions as follows: What worker behaviors related to the ethical use of technology have been considered in the literature? Additionally, why are these behaviors classified as unethical, ethical or extraordinary ethical?

To address our research questions, the sixth step involved conducting a bibliometric analysis of the selected articles, utilizing both bibliometric indicators and science mapping techniques. For bibliometric indicators, we examined key aspects of each article, including country of origin, type of technology, publication year, and sector. The findings from this analysis are presented in the

Results section. For science mapping, we performed a co-occurrence analysis of keywords using VOSviewer software (van Eck & Waltman, 2010). This allowed us to construct a keyword network and apply overlay visualization to identify topics that have gained increased interest over time. This approach helped us recognize, in the seventh step, clusters of analysis. In the eighth step, we organized and selected articles within each cluster, categorizing them based on the specific types of behaviors expressed, which led to the unification of two clusters in one (i.e., black and pink). This allowed for a more structured analysis of ethical technology use across different contexts. The second methodological checkpoint confirmed our aggregation.

Figure 1

Flowchart of the study selection for the systematic review

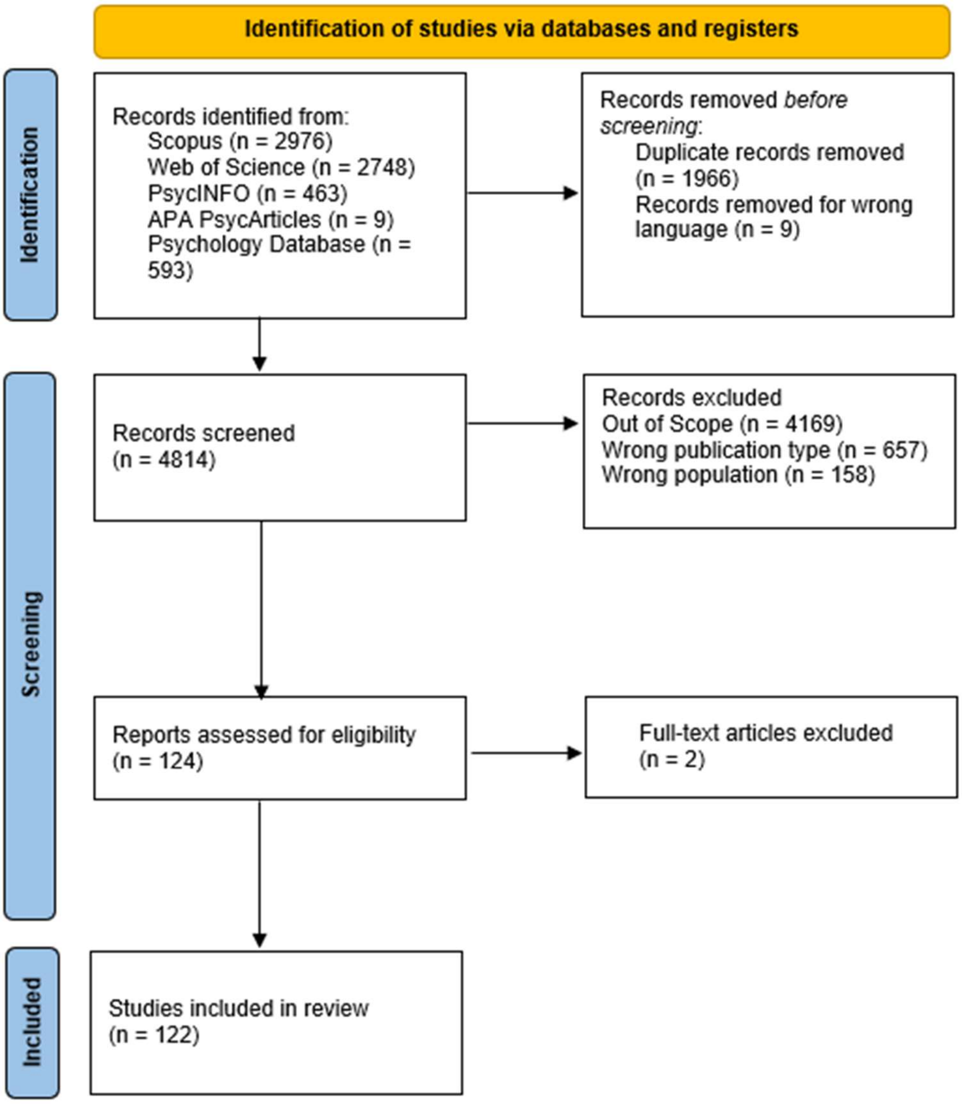
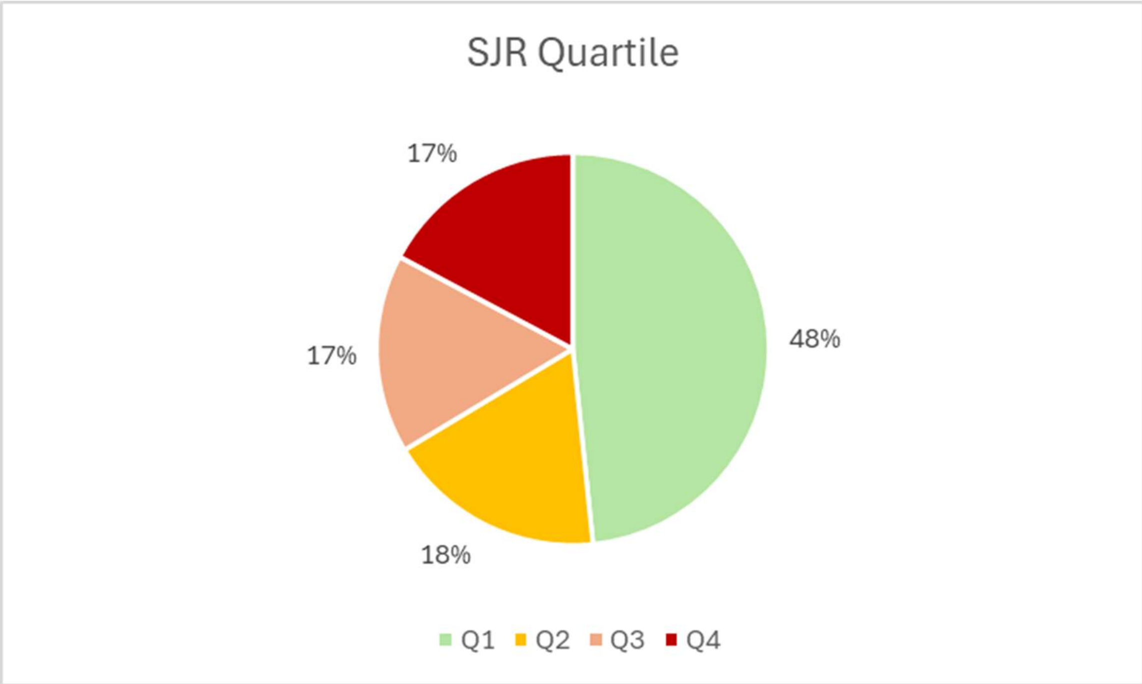


Figure 2

Sources Journal Ranking based on Scimago Quartiles



Results

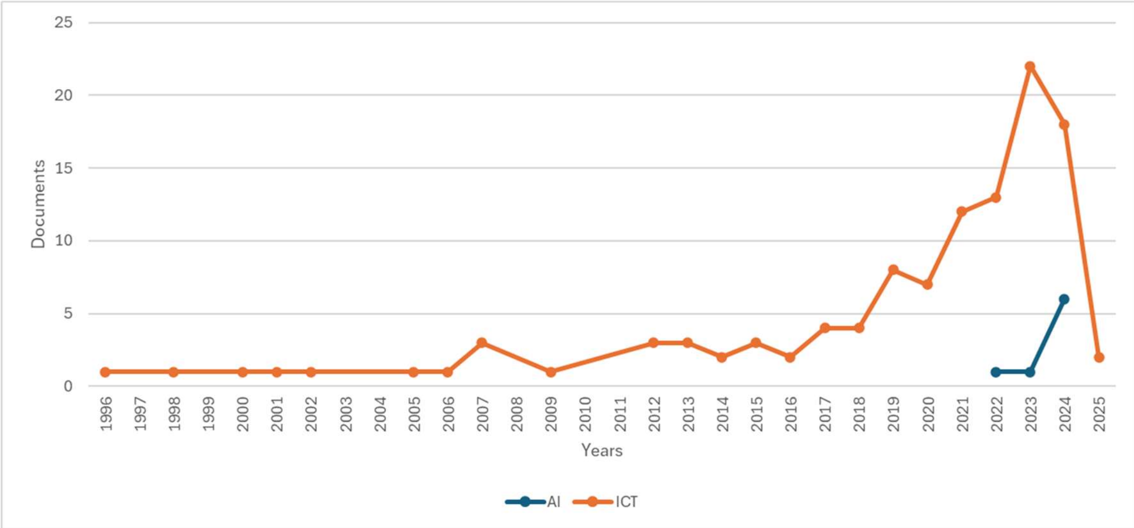
In this section, we first present the main results of applying the bibliometric indicators (i.e., the publication trend, publication by Country, sector, and co-occurrence analysis based on the keywords). Thereafter, we present the analysis of the clusters identified through the bibliographic coupling.

Bibliometric indicators

The first analysis examined how interest in different types of technology use behaviors in the workplace has evolved over time. The earliest paper we identified was published in 1996 and focused on the ethical use of computers at work. Notably, the majority of articles were published after 2018. Specifically, all publications before 2021 explored the use of various forms of Information and Communication Technology (ICT). However, since 2022, a growing number of studies have started to focus on the use of Artificial Intelligence (AI) (Figure 3).

Figure 3

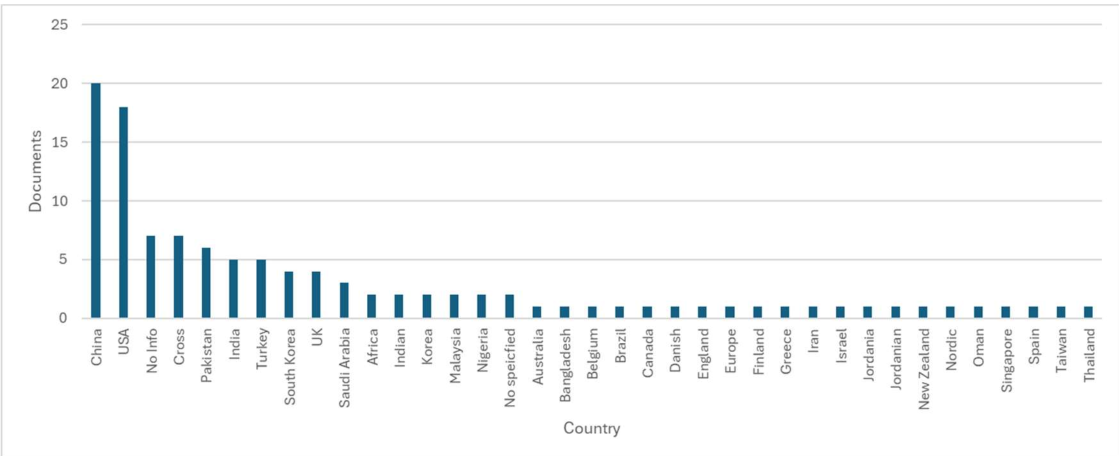
Publication trend for ICT and Artificial Intelligence technology



Nevertheless, the vast majority of articles (96%) focused on technology use behavior related to ICT. This trend highlights that research has so far concentrated more on the ethical design and organizational use of AI tools, while the individual ethical use of these technologies in the workplace remains largely unexplored. This shift may be linked to the rapid rise of generative AI models (e.g., ChatGPT) and the increasing attention to how they are being used in the workplace. Next, we analyzed the geographic distribution of these studies (Figure 4).

Figure 4

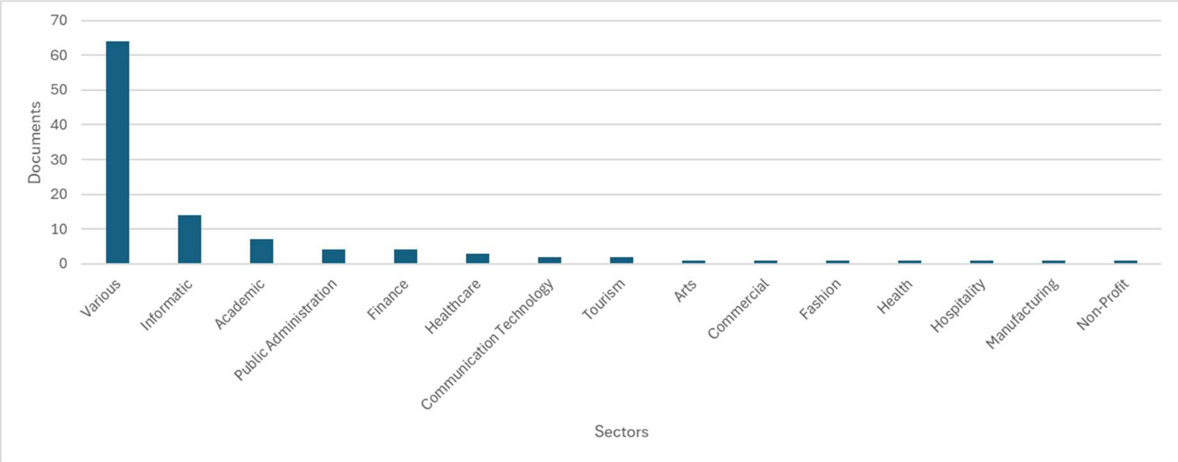
Publication by Country



Interestingly, 30% of the papers were produced in either China or the United States. In contrast, all other countries contributed significantly fewer publications on this topic. We also looked at the sectoral distribution of the research (Figure 5).

Figure 5

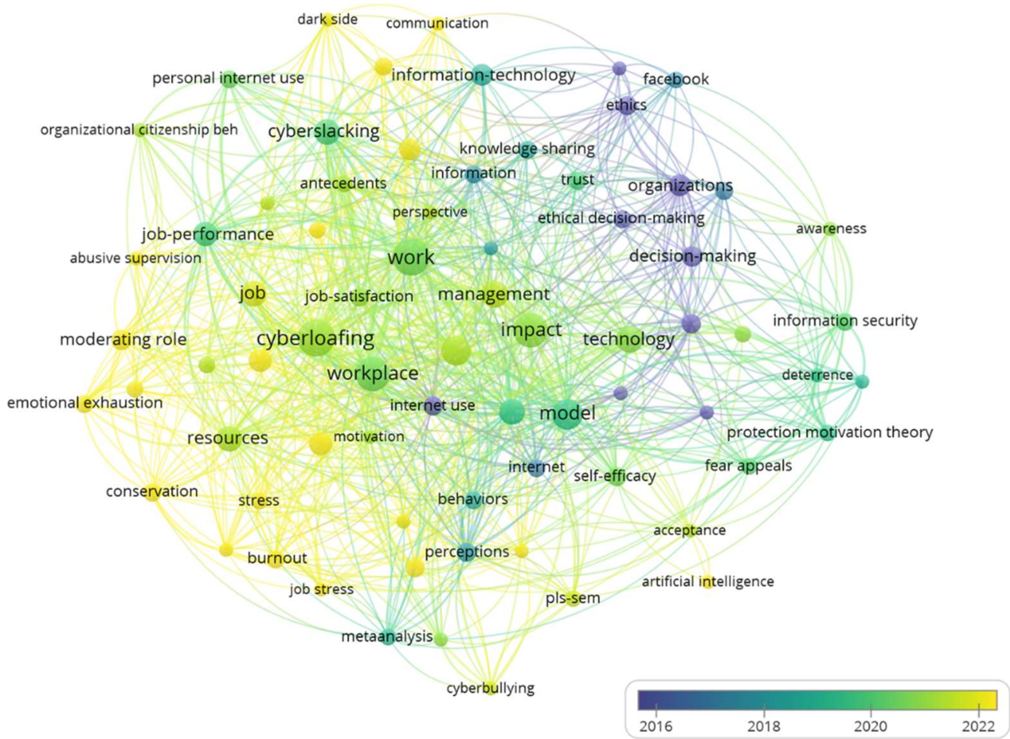
Publication by Sector



Over half of the studies (52%) did not focus on a single sector, instead collecting data across multiple industries. Among those with a specific sectoral focus, most were centered on information technology and IT service organizations (11%), followed by academia (6%), public administration, and finance (3%). Finally, the overlay visualization of the co-occurrence analysis using "all keywords" revealed a range of thematic focuses across the papers which change overtime (Figure 6).

Figure 6

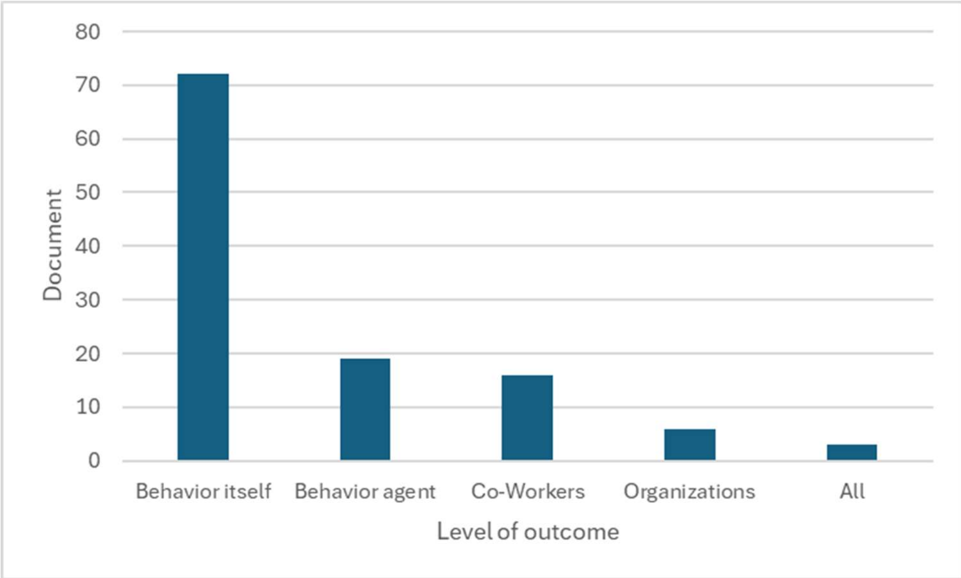
Co-occurrence analysis with "All keywords" (the minimum number of occurrences for a document is 4). Overlay visualization



Some keywords referred to specific technologies, such as artificial intelligence and various types of ICT (e.g., internet, information technology). A significant portion of the keywords related to specific types of use behaviors, including terms like cyberloafing, cyberslacking and knowledge sharing. Additionally, studies included keywords pointing to antecedents (e.g., abusive supervisor) and outcomes of technology use behaviors (e.g., stress, job satisfaction). Interestingly, the majority of the articles concentrated on the antecedents of technology use behavior, with limited attention given to its outcomes, particularly in relation to the stakeholders affected by such behavior. Specifically, 59% of the studies examined the antecedents of technology use, considering the use behavior itself as the outcome of their model, while 15% focused on its consequences for the individual engaging in the behavior. Notably, just 19% of the papers addressed the impact of technology use on stakeholders, such as coworkers or organizations (Figure 7).

Figure 7

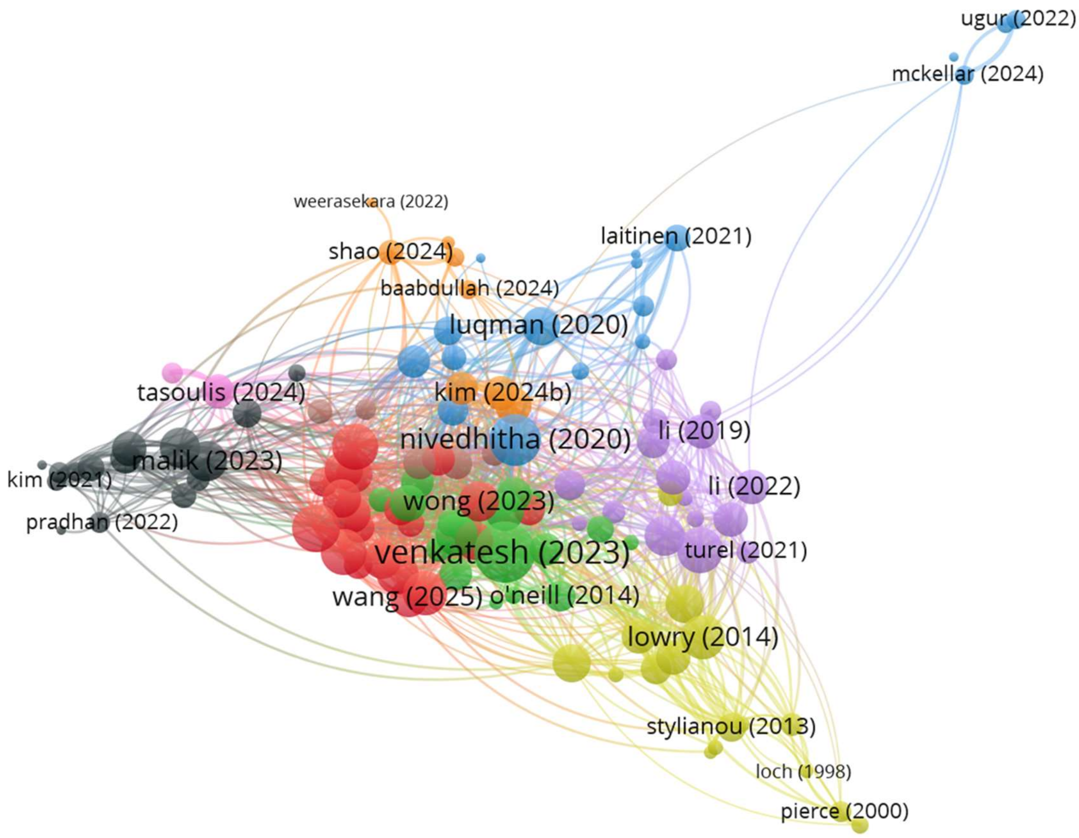
Level of outcome considered in the literature



Bibliographic coupling

Figure 8

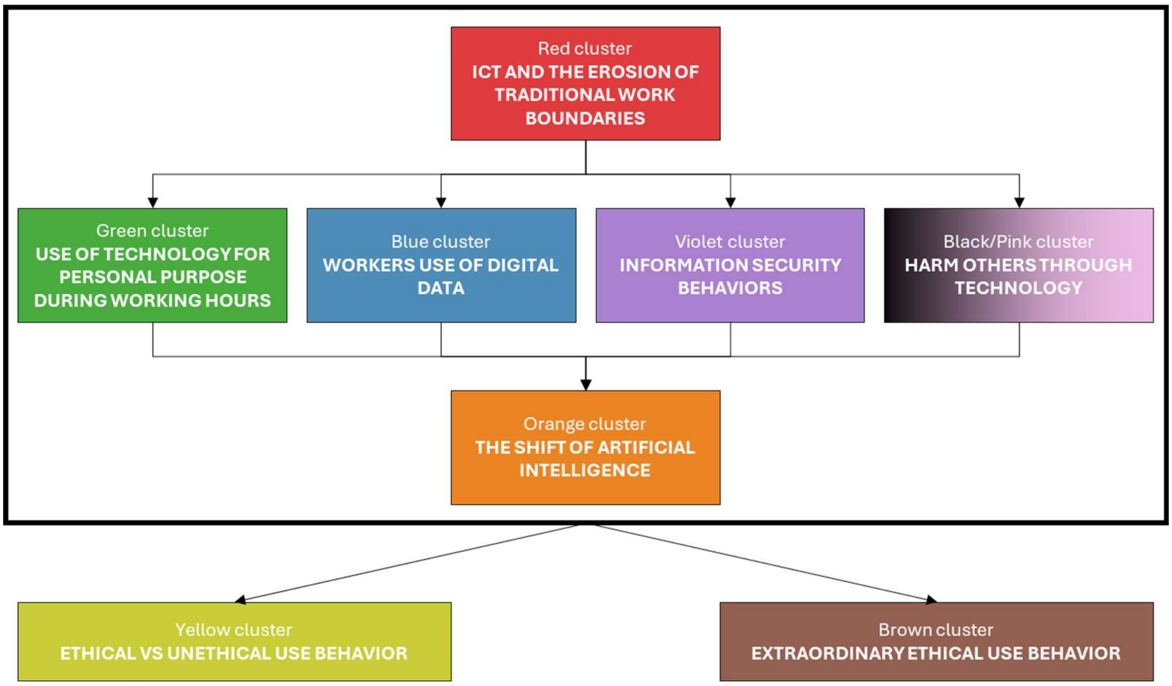
VOS results of bibliographic coupling



In Figure 8 the map is available resulting from the VOSviewer analysis, while Figure 9 represents the clusters topic and flow, based on author map analysis. Through bibliographic coupling, eight distinct clusters emerged, representing the evolution of literature on the ethical use of technology in the workplace and the various types of behaviors it enables. Since usage behaviors are shaped and facilitated by technology itself, the first cluster (red) focuses on how the introduction of ICT in the workplace has altered individual behavior, creating both new opportunities and risks. Building on this foundation, the next four clusters (green, blue, violet, and black/pink) explore different types of technology-enabled behaviors in the workplace. Both green and blue clusters address proactive use behaviors, but with different intents. The green cluster relates to personal use of technology for detachment from work, such as using social media during office hours, whereas the blue cluster centers on technology used for information gathering and sharing, like knowledge exchange among colleagues. The violet cluster focuses on involuntary use behaviors or the avoidance of certain actions that could lead to information security risks, while the black/pink cluster represents voluntary harmful behaviors toward colleagues, such as cyber harassment or workplace incivility enabled by digital tools. The orange cluster extends the discussion to new ethical concerns brought by emerging technologies like AI, highlighting additional behaviors made possible by these innovations. Finally, the yellow and brown clusters focus on categorizing technology use behaviors as unethical, ethical, or exceptionally ethical. The literature within these clusters often does so without strong empirical evidence, relying instead on assumptions about the impact of these behaviors, and typically considering the effects on a single stakeholder group, such as coworkers or the organization, rather than taking a broader, multi-stakeholder view.

Figure 9

Summary of the research on technology ethical use behavior in the workplace



Following a description of each cluster, the most influential articles of each are listed in Table 2.

Table 2

The most influential paper per cluster (source: VOSviewer Software)

Cluster	Authors	Publication year	Citations	Total link strength
Red	Wong, G.Y.-L. and Kwok, R.C.-W. and Zhang, S., Lai, G.C.-H. & Cheung, J.C.-F.	2023	77	43
	Bhattacharjee, A. & Sarkar, A.	2024	74	62
	Khorakian, A., Jahangir, M., Rahi, S., Eslami, G. & Muterera, J.	2023	73	27
	She, Z., Li, Q. & Ma, L.	2025	71	40
	Murtaza, G., Neveu, J., Khan, R. & Talpur, Q.	2022	71	39
	Reizer, A., Galperin, B.L., Chavan, M., Behl, A & Pereira, V.	2022	70	37
Green	Venkatesh, V., Cheung, C.M.K., Davis, F.D. & Lee, Z.W.Y.	2023	72	100
	Elciyar, K. & Simsek, A.	2021	71	28
	Koay, K.Y., Soh, P.C.-H. & Chew, K.W.	2017	70	40
	Güğerçin, U.	2020	68	31
	Giordano, C. & Mercado, B.K.	2023	65	35
	Narwal, M.	2023	62	20
Blue	KS, N. & AK, S.M.	2020	78	71
	Luqman, A., Masood, A., Shahzad, F., Rasheed, M.I. & Weng, Q.X.	2020	69	39
	Chen ,R.R. , Huang ,Q., Dou ,G.	2024	51	28
	Zhang, Z. & Ji, X.	2023	47	17
	Farivar, F. & Richardson, J.	2021	46	26
	Chen, L.M., Xu, Y. & He, Y.	2024	34	21
Violet	Nwankpa, J. K., & Datta, P. M.	2023	65	25

	Li, L., He, W., Xu, L., Ash, I., Anwar, M., & Yuan, X.	2019	64	31
	Yoon, C., & Kim, H.	2013	62	30
	Yazdanmehr, A., Jawad, M., Benbunan-Fich, R., & Wang, J.	2024	61	54
	Chen, H., Chau, P. Y., & Li, W.	2019	61	41
	Onumo, A., Ullah-Awan, I., & Cullen, A.	2021	49	28
Black / Pink	Malik, O. F., & Pichler, S.	2023	65	44
	Anwar, A., Kee, D. M. H., & Ahmed, A.	2020	65	16
	Akram, Z., Khan, A. G., Akram, U., Ahmad, S., & Song, L. J.	2022	59	42
	Tasoulis, K., Theriou, G., Louzi, N., & Chatzoudes, D.	2023	59	27
	Gardner, D., O'Driscoll, M., Cooper-Thomas, H. D., Roche, M., Bentley, T., Catley, B., ... & Trenberth, L.	2016	52	25
	Vranjes, I., Baillien, E., Vandebosch, H., Erreygers, S., & De Witte, H.	2018	49	33
Yellow	Lowry, P.B., Posey, C., Roberts, T.L., & Bennett, R.J.	2014	71	51
	Chu, A. M., Chau, P. Y., & So, M. K.	2015	56	39
	Venkatraman, S., MK Cheung, C., Lee, Z. W., D. Davis, F., & Venkatesh, V.	2018	66	39
	Rahman, M. S., Hossain, M. A., Abdel Fattah, F. A. M., & Ibne Mokter, A. M.	2022	63	33
	D'Arcy, J., & Devaraj, S.	2012	66	30
	Roberts, J.A. & Wasieleski, D.M.	2012	69	24
Brown	Bhatti, S.H., Kiyani, S.K., Dust, S.B. & Zakariya, R.	2021	23	13
	Jin, Y., Lu, N., Deng, Y., Lin, W., Zhan, X., Feng, B., & Li, G.	2024	39	16
	Zoghbi-Manrique-de-Lara, P., & Viera-Armas, M.	2017	58	29
	Zoghbi-Manrique-de-Lara, P., & Melián-González, S.	2009	53	17
	Zoghbi-Manrique-de-Lara, P., & Sharifiatashgah, M.	2021	67	25
Orange	Kim, B.J. & Kim, M.J.	2024	66	36
	Hong, Y.S., Kim, M.J. & Roh, T.	2023	59	28
	Shao, Y., Huang, C., Song, Y., Wang, M., Song, Y. H., & Shao, R.	2024	47	18
	Kim, B. J., Kim, M. J., & Lee, J.	2024	43	31
	Baabdullah, A. M.	2024	42	11
	Chen, A., Yang, T., Ma, J., & Lu, Y.	2023	17	10

See Table 3 for a summary of the technology use behaviors and the definitions for each use behavior.

Table 3

Summary and definitions of (un)ethical technology use behavior in the workplace.

Cluster / Section	Use behavior	Definition	Reference
Green cluster - Use of technology for	Cyberloafing	Voluntary behavior in which employees during work hours use the company's internet for their	Lim, Teo, & Loo, 2002

personal purpose during working hours		individual purposes rather than for their work	
	Cyberslacking	Use of IT for nonwork activities in the workplace during work hours	Whitty & Carr, 2006
Blue cluster - Workers use of digital data	Digital hoarding	The acquisition of and failure to discard digital content, leading to the accumulation of digital clutter’	Sedera and Lokuge 2018
	Knowledge sharing	The process of exchanging, disseminating, or mutually providing knowledge, expertise, and information among individuals, teams, or organizations	Ritala et al., 2015
Violet cluster - Information security behaviors	Information security policy violation	Occurs when an employee does not follow the established rules and policies regarding the use of an organization's IT resource	Yazdanmehr et al., 2024
	Cybersecurity behavior	Behaviors or actions recommended to negate the harm related to threats	Li et al., 2022
Black/Pink cluster - Harm others through technology	Cyberbulling	Intentional, aggressive, and repetitive behaviour perpetrated by a more powerful individual against someone more vulnerable using technology such as the internet, social media, and cellular phones	Agatston, 2007
	Cybeincivility	A communication behaviour manifested in computer-mediated interactions that violates workplace norms of mutual respect	Lim & Chin, 2006
	Online harassement	Repeated and persistent attempts by one person to wear down and frustrate another person	Salin, 2008
	Sexual harassment	Unwelcome sexual advances, requests for sexual favors, and other verbal or physical harassment of a sexual nature	Scarduzio et al., 2021
Yellow cluster - Ethical Vs Unethical use behavior	Threat avoidance	The actions taken by individuals to avoid engaging in tasks that they perceive as posing security or privacy threats	Liang & Xue, 2009
	Whistleblowing	It is when current or former employees disclose illegal, immoral, or illegitimate organizational activity to parties they believe may be able to stop it	Miceli et al., 2008
	Digital citizenship	The norms of appropriate, responsible behaviour with regard to technology use	Ribble, 2012
	Misuse of ICT	The misuse or unauthorized use of ICT resources including applications, the Internet, and networks while at work to be a relatively serious and common type of ICT-related unethical behavior in the workplace	Chu et al., 2015
Brown cluster - Extraordinary ethical use behavior	Cybercivism	The one IT extra-role behavior that includes any voluntary act by employees, while using internet access during office hours, to care for the company’s information system and to help its users, that are not directly or explicitly recognized by the formal reward system	Zoghbi-Manrique-de-Lara & Melián-González, 2009

ICT and the erosion of traditional work boundaries (Red cluster)

The overarching theme emerging from the red cluster (20 items) is hyperconnectivity induced by ICT and the consequent blurring of boundaries between work and personal life. The central node within this cluster is the study by Wong et al. (2023), which examined the impact of cyberloafing and cyber-life interruptions on employee exhaustion. This work highlights the potentially detrimental role of ICT in both work and non-work domains, emphasizing how it can amplify personal and professional demands, thereby eroding traditional work-life boundaries. Other key contributions within the cluster (e.g., Khorakian et al., 2023; Reizer et al., 2022) underscore how these pressures intensified during the COVID-19 pandemic, when remote work further contributed to the blurring of professional and personal spheres. In light of these ICT-enabled dynamics, the literature in this cluster generally adopts two main perspectives in studying use behaviors. On one hand, some studies adopt an organizational viewpoint, exploring the reasons why employees engage in time theft (i.e., using ICT during work hours to address personal matters) often explained through mechanisms such as moral disengagement. On the other hand, another body of research focuses on the coworkers of such individuals, analyzing the negative effects of ICT-mediated workplace gossip on colleagues.

Use of technology for personal purpose during working hours (Green cluster)

The green cluster centers on cyberloafing / cyberslacking, comprising 18 items. The most central node is the study by Venkatesh et al. (2023), which highlights the negative impact of this use behavior on employees' job performance. Another key study within the cluster, however, found that using technology for personal purpose during work hours can enhance innovative work behavior (Narwal, 2023). Although these studies do not directly examine the impact on stakeholders, they imply that such behaviors could influence the organization in both harmful (i.e., decreasing employees' performance) and beneficial (i.e., increasing employees' innovative behavior) ways. Notably, the majority of studies in this cluster (13 out of 18) focus on the antecedents of the use behavior, largely overlooking its consequences for stakeholders such as coworkers and the organization.

Worker' use of digital data (Blue cluster)

The 17 items in the blue cluster focus on workers' behaviors related to acquisition and use of information through technology. Access to ICTs, such as social media, enables employees to gather information about their peers, often triggering social comparison. This process can have negative effects on altruistic behavior (Chen et al., 2024), ultimately impacting coworkers adversely. Differently, technology can also be leveraged to acquire knowledge and develop skills, potentially benefiting the individual (Pammer-Schindler & Rosé, 2022). Once data is acquired, employees may engage in digital hoarding, either storing irrelevant information or organizing it inefficiently. Such behavior has been associated with negative outcomes for both individuals (e.g., reduced psychological well-being) and organizations (e.g., cybersecurity risks) (Sweeten et al., 2018; Ugur & Caliskan, 2022). Knowledge sharing, by contrast, is often seen as a positive use behavior that benefits stakeholders. For instance, Ritala et al. (2015) found that employees who share knowledge contribute positively to a firm's innovative performance. However, this behavior also carries risks: sharing sensitive information can lead to knowledge leakage (Ritala et al., 2015), potentially harming the organization's competitive advantage.

Information security behaviors (Violet cluster)

The violet cluster centers on employee behavior and its potential to either threaten or enhance digital data security (16 items). At the core of this cluster is the study by Nwankpa and Datta (2023), which explores how remote work influences employees' cybersecurity awareness and precautionary actions. They found that remote working positively affects cybersecurity awareness and behavior, explaining this finding based on the lower moral hazard among remote workers, who tend to perceive higher negative consequences for security breaches and greater assumption of responsibility (Peltzman, 1975). Other studies within the violet cluster examine both positive behaviors, such as threat avoidance and compliance with information security protocols, and negative behaviors, like information security violations.

Harm others through technology (Black / Pink cluster)

The 18 items in this cluster examine various forms of ICT misuse that harm co-workers and organizations, such as cyberbullying, cyber incivility, and online harassment. Unlike other usage behaviors, those captured in this cluster are consistently associated with negative consequences. For instance, cyberbullying has been linked to increased depression, stress, and turnover intentions among victims, as well as decreased employee engagement. Similarly, cyber incivility has been found to negatively affect service innovation. Across all studies, the evidence consistently highlights the detrimental impact of these behaviors, emphasizing their unethical nature.

The shift of Artificial Intelligence (Orange cluster)

The orange cluster (8 items) represents the emerging body of literature on the use behavior of Artificial Intelligence (AI). The most representative node in this cluster suggests that employees' beliefs in their ability to learn and effectively use AI tools can help them manage work overload, ultimately influencing their cybersecurity behaviors (Kim & Kim, 2024). Beyond cybersecurity, which represents a central issue in workplace AI use, as it was with ICT, the literature recognizes that AI has introduced new patterns of use behavior with potential ethical implications. For instance, Shao et al. (2024) found that learning through AI can enhance task performance, which is ethically favorable when it contributes positively to organizational outcomes. However, they also noted that AI-based learning can increase information overload and hinder psychological detachment, thus negatively affecting the well-being of the user. Another node highlights that AI-driven information seeking can influence decision-making efficiency (Baabdullah, 2024), with potentially positive or negative consequences for various stakeholders. In sum, the use behaviors examined in this cluster primarily involve leveraging AI to gain information for various purposes, such as learning and decision-making. However, there is no evidence regarding the ethical implications of these behaviors. Moreover, other types of use behavior are not represented, for instance, the use of AI for content creation, task automation or document analysis.

Ethical vs Unethical use behavior (Yellow cluster)

In contrast to the previous clusters, which focus on specific use behaviors, the yellow cluster (15 items) addresses the broader distinction between technology use that aligns with social norms (i.e., ethical use) and that which deviates from them (i.e., unethical use), mainly through ICT. Within this cluster, several papers explore what constitutes ethical technology use, such as digital citizenship and general ethical conduct. For example, Pierce and Henry (1996) examined how employees adhere to formal, informal, or personal codes of ethics when using computers in the workplace. Similarly, Verma and Garg (2024) investigated digital citizenship, proposing that individuals who practice strong digital citizenship can positively influence an organization's ethical climate. Whistleblowing is also highlighted within this cluster as a distinct form of ethical ICT behavior. On the other hand, other studies in the yellow cluster examine unethical or deviant ICT use, including abuse and counterproductive behaviors. Lowry et al. (2014), for instance, analyzed how cultural dimensions, such as individualism and collectivism, affect abusive actions like deliberate errors or system sabotage. A contribution from Pierce and Henry (2000) explored how individuals perceive moral judgments differently across themselves, their co-workers, and their organizations. They found discrepancies in these judgments, which can give rise to "moral stress" (Wyld & Jones, 1997), a tension experienced when trying to navigate and satisfy the ethical expectations of various stakeholders in technology-related decisions.

Extraordinary ethical use behavior (Brown cluster)

The brown cluster (5 items) focuses on employees' voluntary prosocial behaviors expressed through technology, primarily aimed at supporting others, particularly co-workers. These behaviors are conceptualized as forms of organizational citizenship behavior (OCB) enacted via digital means. They are consistently framed in a positive light and regarded as extraordinary ethical actions, largely because they are voluntary and typically go unrecognized by formal organizational reward systems. Key factors influencing these behaviors, as highlighted in the cluster, include leadership style, especially ethical leadership, and perceptions of organizational justice. Two studies within the cluster specifically explore knowledge sharing (Bhatti et al., 2021; Jin et al., 2024), identifying it as a notable example of extraordinary ethical behavior, particularly because it is voluntary and lacks formal recognition in the contexts examined. One study (Bhatti et al., 2021) emphasizes the positive impact of knowledge sharing on project success and, by extension, organizational performance. In contrast, other studies in the cluster address the behavior itself without explicitly examining its effects on stakeholders.

Discussion

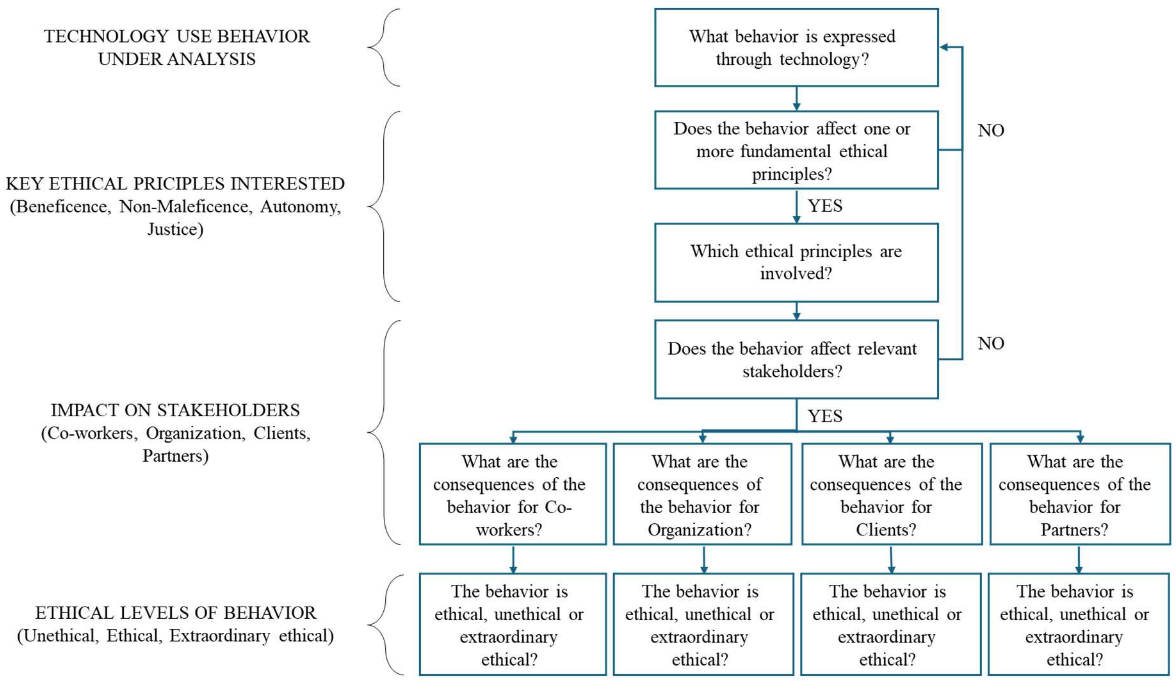
Analyzing the literature on technology use behavior in the workplace, we identified evidence of unethical, ethical, and extraordinary ethical use behaviors. However, the literature offers limited insight into when such behaviors result in positive versus negative outcomes. Most existing studies concentrate on the antecedents of these behaviors, frequently assuming their ethicality from a predominantly organizational perspective. This organizational-centric bias has led to assumptions about the ethical nature of certain behaviors, often without adequately considering their broader impact on stakeholders. Our findings suggest that while some behaviors can be easily classified within ethical categories (e.g., cyber incivility, online harassment), others (e.g., cyberloafing, knowledge sharing) can have both positive and negative consequences for stakeholders, making it more difficult to determine whether they are truly ethical or not. For instance, while cyberloafing may be seen as time theft from an organization point of view, it can also serve as a recovery mechanism for employees, potentially enhancing their collaboration with coworkers and increasing innovation (Narwal, 2023), benefits that ultimately support the organization too. An organizational-centric bias in the literature on individual technology use is also evident in the predominantly negative framing of use behaviors. Many studies label certain actions (e.g., cyberloafing or digital hoarding) as unethical, often without a thorough examination of their broader or nuanced outcomes. Interestingly, the stream of literature that does focus on the consequences of technology use tends to examine behaviors that directly affect individuals (e.g., cyber incivility, online harassment). In these cases, the emphasis is frequently on outcomes like stress, seemingly in an effort of the literature to redirect the conversation toward their organizational implications. In doing so, literature fails to explore the conditions under which individual technology use behaviors can be considered ethical, unethical or extraordinary ethical from a stakeholders perspective.

The emergence of new technologies, particularly artificial intelligence, further complicates this landscape. Technology-enabled behaviors are becoming more diverse, and their potential impacts more significant for every stakeholder. In today's context, steering user behavior through policies or top-down initiatives, often based on a narrow set of ethical principles reflecting the organization's viewpoint, is no longer sufficient to ensure ethical technology use at the individual level. These approaches may not only fail to prevent undesirable behaviors but can also hinder organizations from fully leveraging employees' proactivity and discretionary actions, which are essential sources of value in modern workplaces (Schmidt et al., 2024). For example, banning the use of generative AI due to privacy concerns may, on one hand, restrict workers' ability to perform their tasks more efficiently and effectively, while on the other, it fails to guarantee that such widely available tools are not being used informally or unknowingly (Handa et al., 2025; Shao et al., 2025). What is needed instead is a balanced integration of universal ethical principles, which serve as boundaries for acceptable action, and an individual-level understanding of the impact of specific behaviors. This approach aimed to guide personal discretion, rather than restriction, fostering more responsible and empowered technology use.

Based on this evidence, we propose a model in the form of a decision diagram (please see Figure 10).

Figure 10

Technology use behavior ethical impacts



Similar to the Sociotechnical System, which aims to guide conscious choices about how a decision on one part of the system affects the others (Hughes et al., 2017), our model is designed to help make explicit choices about technology use behavior by considering how these behaviors impact stakeholders. The process is straightforward, and can be summarized in four broad stages. First, the model makes the user's technology use behavior explicit. In this way, users can define the boundaries of their actions and consciously reflect on what they are doing and what they are not doing. Second, the process intends to steer users to reflect about ethical principles involved. The ethical principles most commonly referenced in discussions about technology are the bioethical principles of beneficence, non-maleficence, autonomy, and justice (Floridi et al., 2018). These principles are highly relevant in the context of technology use and can serve as ethical anchors to guide individual behavior in digital environments. Following this process leads to a brief assessment of the ethical principles involved in the use behavior. Third, the next step is to analyze the stakeholders affected by the behavior. In fact, literature shows that the impact of use behavior on different stakeholders can vary depending on the behavior itself, which can challenge assumptions about its ethicality. To address this tension, it is essential to evaluate the outcomes of a behavior across different stakeholders (i.e., organization, co-workers, clients, partners), not with the unrealistic goal of avoiding all negative consequences, but rather to make a conscious and informed decision about the kind of impact we intend to generate, and consequently, the behavior we choose to enact. Based on the first three steps, the final phase of the process is to evaluate the use behavior as unethical, ethical, or extraordinary ethical for the different stakeholders affected. This evaluation can be based on the expected consequences of the use behavior in question. Depending on how these consequences align with ethical principles, the behavior may violate, uphold, or actively promote those principles, resulting in unethical, ethical, or exceptionally ethical conduct, respectively (Treviño et al., 2014).

Conclusion and Future Research

Our aim was to clarify which technology use behaviors have been examined in the literature and to understand the criteria by which these behaviors are classified as unethical, ethical, or extraordinary ethical. We found evidence of various use behaviors, but in many cases, the rationale for their ethical classification remains unclear. Most studies focused on the antecedents of the technology use behaviors under investigation, often overlooking their outcomes. Typically, authors framed these behaviors as either positive or negative based on organizational perspectives or prevailing mainstream interpretations. This approach leaves the actual impact of such behaviors on coworkers, organizations, and other stakeholders, unclear. Moreover, it tends to assume the ethicality of a use behavior a priori, rather than assessing whether a behavior is ethical based on its consequences. Future research should shift focus toward examining the outcomes of technology use behaviors and aim to clarify not whether, but under what conditions, a given behavior can be considered ethical. Also, much of the existing literature on technology use in the workplace primarily focuses on unethical behaviors or tends to interpret certain practices, such as cyberloafing, primarily through an unethical lens. By concentrating primarily on negative or deviant uses, literature risks overlooking or underrepresenting positive technology-related behaviors. As a result, research may prioritize risk avoidance over opportunity promotion. While this risk-averse inclination is natural to human decision-making (Kahneman & Tversky, 1979) and beneficial in preventing harmful practices, it also risks overlooking the value of individual proactive initiatives. Such initiatives can be particularly impactful in work environments where personal agency plays a key role (Bhatti et al., 2021). Therefore, we encourage future research to place greater emphasis on the proactive and positive use of technology in the workplace. To address these biases in the literature, we propose a model aimed at fostering distributed responsibility among individuals who engage with technology in the workplace. The model seeks to bridge key ethical principles with their practical, everyday application in individual technology use. Based on the evidence we found, we argue that in the high-tech context in which organizations operate, responsibility distributed among all individuals, who make daily choices about technology use, is the key way to generate a positive impact with technological tools. This is especially true in a highly connected environment, where different stakeholders can be affected in different ways by the same technology use behavior. Navigating these 'moral stress' is essential for making responsible choices in technologically mediated work environments.

References

Akram, Z., Khan, A., Akram, U., Ahmad, S., & Song, L. (2022). A contemporary view of interpersonal aggression and cyberbullying through ICT: multilevel insights from LMX differentiation. *INTERNET RESEARCH*, *32*(5), 1700–1724. https://doi.org/10.1108/INTR-11-2020-0659

Alanazi, S., Anbar, M., Ebad, S., Karuppayah, S., & Al-Ani, H. (2020). Theory-Based Model and Prediction Analysis of Information Security Compliance Behavior in the Saudi Healthcare Sector. *SYMMETRY-BASEL*, *12*(9). https://doi.org/10.3390/sym12091544

Alanazi, S. T., Anbar, M., A. Ebad, S., Karuppayah, S., & Al-Ani, H. A. (2020). Theory-Based Model and Prediction Analysis of Information Security Compliance Behavior in the Saudi Healthcare Sector. *SYMMETRY-BASEL*, *12*(9), 1544. https://doi.org/10.3390/sym12091544

Alomar, N., Alsaleh, M., & Alarifi, A. (2019). Uncovering the predictors of unsafe computing behaviors in online crowdsourcing contexts. *COMPUTERS & SECURITY*, *85*, 300–312. https://doi.org/10.1016/j.cose.2019.05.001

Alqahtani, N., Innab, A., Alammar, K., Alkhateeb, R., Kerari, A., & Alharbi, M. (2022). Cyberloafing behaviours in nursing: The role of nursing stressors. *International Journal of Nursing Practice*, *28*(5), 1–10. https://doi.org/10.1111/ijn.13079

Alrawashdeh, M., Alsawalqa, R., Alnajdawi, A., Aljboor, R., Altwahya, F., & Ibrahim, A. (2024). Workplace cyberbullying and social capital among Jordanian university academic staff: A cross-sectional study. *HUMANITIES & SOCIAL SCIENCES COMMUNICATIONS*, *11*(1). https://doi.org/10.1057/s41599-024-02805-z

Al-Shanfari, I., Yassin, W., Tabook, N., Ismail, R., & Ismail, A. (2022). Determinants of Information Security Awareness and Behaviour Strategies in Public Sector Organizations among Employees. *International Journal of Advanced Computer Science and Applications*, *13*(8), 479–490. https://doi.org/10.14569/IJACSA.2022.0130855

Anderson, S. C., & Guyton, M. R. (2013). Ethics in an Age of Information Seekers: A Survey of

Licensed Healthcare Providers about Online Social Networking. *Journal of Technology in Human Services*, *31*(2), 112–128. https://doi.org/10.1080/15228835.2013.775901

Anwar, A., Kee, D. M. H., & Ahmed, A. (2020). Workplace Cyberbullying and Interpersonal Deviance: Understanding the Mediating Effect of Silence and Emotional Exhaustion. *Cyberpsychology, Behavior, and Social Networking*, *23*(5), 290–296. https://doi.org/10.1089/cyber.2019.0407

Baabdullah, A. (2024). Generative conversational AI agent for managerial practices: The role of IQ dimensions, novelty seeking and ethical concerns. *TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE*, *198*. https://doi.org/10.1016/j.techfore.2023.122951

Baheer, R., Khan, K. I., Rafiq, Z., & Rashid, T. (2023). Impact of dark triad personality traits on turnover intention and mental health of employees through cyberbullying. *Cogent Business and Management*, *10*(1). https://doi.org/10.1080/23311975.2023.2191777

Bhattacharjee, A., & Sarkar, A. (2024). Abusive supervision and cyberloafing: An investigation based on Stressor-Emotion-CWB theory. *Information Technology & People*, *37*(3), 1126–1155. https://doi.org/10.1108/ITP-05-2022-0353

Bhatti, S., Kiyani, S., Dust, S., & Zakariya, R. (2021). The impact of ethical leadership on project success: The mediating role of trust and knowledge sharing. *INTERNATIONAL JOURNAL OF MANAGING PROJECTS IN BUSINESS*, *14*(4), 982–998. https://doi.org/10.1108/IJMPB-05-2020-0159

Bock, G.-W., Zmud, R., Kim, Y.-G., & Lee, J.-N. (2005). Behavioral Intention Formation in Knowledge Sharing: Examining the Roles of Extrinsic Motivators, Social-Psychological Forces, and Organizational Climate. *MIS Quarterly*, *29*, 87–111. https://doi.org/10.2307/25148669

Caballero, J., & Sora-Domenjó, C. (2024). Automation and creativity in AI-driven film editing: G: The view from the professional documentary sector. *COMMUNICATION & SOCIETY-SPAIN*, *37*(3). https://doi.org/10.15581/003.37.3.201-218

Chanda, A. K. (2024). HUMAN JUDGMENT IN ARTIFICIAL INTELLIGENCE FOR BUSINESS DECISION-MAKING: AN EMPIRICAL STUDY. *International Journal of Innovation Management*. https://doi.org/10.1142/S136391962450004X

Chen, A., Yang, T., Ma, J., & Lu, Y. (2023). Employees' learning behavior in the context of AI collaboration: A perspective on the job demand-control model. *INDUSTRIAL MANAGEMENT & DATA SYSTEMS*, *123*(8), 2169–2193. https://doi.org/10.1108/IMDS-04-2022-0221

Chen, H., Chau, P. Y., & Li, W. (2019). The effects of moral disengagement and organizational ethical climate on insiders' information security policy violation behavior. *Information Technology & People*, *32*(4), 973–992. https://doi.org/10.1108/ITP-12-2017-0421

Chen, L., Xu, Y., & He, Y. (2024). Social media use in the workplace: The role of social comparison in negative behaviors. *ACTA PSYCHOLOGICA*, *243*. https://doi.org/10.1016/j.actpsy.2024.104144

Chen, R. R., Huang, Q., & Dou, G. (2024). Exploring the impact of social media use on altruistic behaviours: An affordance approach. *Behaviour & Information Technology*, *43*(11), 2589–2607.

Cheng, B., Zhang, Z., & Peng, Y. (2024). Linking negative workplace gossip to deviant workplace behavior: A social cognitive perspective. *Current Psychology*, *43*(7), 6613–6626. https://doi.org/10.1007/s12144-023-04854-0

Cheng, H., Zheng, W., Zhou, J., Zhang, G., & Tang, S. (2023). The effects of work-related electronic communication during nonwork time on employee workplace deviance. *Applied Psychology*. https://doi.org/10.1111/apps.12506

Chu, A. M. Y., Chau, P. Y. K., & So, M. K. P. (2015). Explaining the Misuse of Information Systems Resources in the Workplace: A Dual-Process Approach. *Journal of Business Ethics*, *131*(1), 209. https://doi.org/10.1007/s10551-014-2250-4

Connolly, R., & McParland, C. (2012). Dataveillance: Employee monitoring & information privacy concerns in the workplace. *Journal of Information Technology Research*, *5*(2), 31–45. https://doi.org/10.4018/jitr.2012040103

Cornish, R. (2022). Unsilenced Employee Voice in South Africa: Social Media Misconduct Dismissals as Evidence of E-Voice**. *MANAGEMENT REVUE*, *33*(3), 356–396. https://doi.org/10.5771/0935-9915-2022-3-356

Daniels, S., & Thornton, L. (2019). Race and workplace discrimination The mediating role of cyber incivility and interpersonal incivility. *EQUALITY DIVERSITY AND INCLUSION*, *39*(3), 319–335. https://doi.org/10.1108/EDI-06-2018-0105

D'Arcy, J., & Devaraj, S. (2012). Employee Misuse of Information Technology Resources: Testing a Contemporary Deterrence Model. *DECISION SCIENCES*, *43*(6), 1091–1124. https://doi.org/10.1111/j.1540-5915.2012.00383.x

Dearden, T. E., Parti, K., Hawdon, J., Gainey, R., Vandecar-Burdin, T., & Albanese, J. (2023). Differentiating Insider and Outsider Cyberattacks on Businesses. *American Journal of Criminal Justice : AJCJ*, *48*(4), 871–886. https://doi.org/10.1007/s12103-023-09727-7

Eastin, M., Glynn, C., & Griffiths, R. (2007). Psychology of communication technology use in the workplace. *CYBERPSYCHOLOGY & BEHAVIOR*, *10*(3), 436–443. https://doi.org/10.1089/cpb.2006.9935

Elciyar, K., & Simsek, A. (2021). An investigation of cyberloafing in a large-scale technology organization from the perspective of the theory of interpersonal behavior. *Online Journal of Communication and Media Technologies*, *11*(2). https://doi.org/10.30935/ojcmt/10823

Farivar, F., & Richardson, J. (2021). Workplace digitalisation and work-nonwork satisfaction: The role of spillover social media. *BEHAVIOUR & INFORMATION TECHNOLOGY*, *40*(8), 747–758. https://doi.org/10.1080/0144929X.2020.1723702

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., & Rossi, F. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines*, *28*, 689–707. https://doi-org /10.1007/s11023-018-9482-5

Gardner, D., O'Driscoll, M., Cooper-Thomas, H. D., Roche, M., Bentley, T., Catley, B., Teo, S. T. T., & Trenberth, L. (2016). Predictors of workplace bullying and cyber-bullying in New Zealand. *International Journal of Environmental Research and Public Health*, *13*(5). https://doi.org/10.3390/ijerph13050448

Gaur, N., & Gupta, V. (2023). Analyzing the Concatenation Between Ethics and Knowledge Culture in Indian IT Sector. *SAGE OPEN*, *13*(4). https://doi.org/10.1177/21582440231209141

Gillam, A., & Waite, A. (2021). Gender differences in predictors of technology threat avoidance. *INFORMATION AND COMPUTER SECURITY*, *29*(3), 393–412. https://doi.org/10.1108/ICS-01-2020-0008

Giordano, C., & Mercado, B. (2023). Cyberloafing: Investigating the Importance and Implications of New and Known Predictors. *COLLABRA-PSYCHOLOGY*, *9*(1). https://doi.org/10.1525/collabra.57391

Green, B. (2021). The contestation of tech ethics: A sociotechnical approach to technology ethics in practice. *Journal of Social Computing*, *2*(3), 209–225. https://doi.org/10.23919/JSC.2021.0018

Güğerçin, U. (2020). Does techno-stress justify cyberslacking? An empirical study based on the neutralisation theory. *Behaviour and Information Technology*, *39*(7), 824–836. https://doi.org/10.1080/0144929X.2019.1617350

Hammouri, G., Esenyel, I., & Aljawarneh, N. (2024). Sustainable Cyber Incivility and Service Innovation: Does Transformational Leadership Matter? *SAGE OPEN*, *14*(2). https://doi.org/10.1177/21582440241249153

Handa, K., Tamkin, A., McCain, M., Huang, S., Durmus, E., Heck, S., Mueller, J., Hong, J., Ritchie, S., & Belonax, T. (2025). Which economic tasks are performed with ai? Evidence from millions of claude conversations. *arXiv Preprint arXiv:2503.04761*.

Hong, Y., Kim, M., & Roh, T. (2023). Mitigating the Impact of Work Overload on Cybersecurity Behavior: The Moderating Influence of Corporate Ethics-A Mediated Moderation Analysis. *SUSTAINABILITY*, *15*(19). https://doi.org/10.3390/su151914327

Hughes, H. P., Clegg, C. W., Bolton, L. E., & Machon, L. C. (2017). Systems scenarios: A tool for facilitating the socio-technical design of work systems. *Ergonomics*, *60*(10), 1319–1335. https://doi.org/10.1080/00140139.2017.1288272

Jin, Y., Lu, N., Deng, Y., Lin, W., Zhan, X., Feng, B., & Li, G. (2024). Becoming reluctant to share? Roles of career age and career plateau in the relationship between ethical leadership and knowledge sharing. *Current Psychology*, *43*(2), 1483–1495. https://doi.org/10.1007/s12144-023-04357-y

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 363–391.

Kaptangil, K., Asan, K., & Kinay, A. G. (2021). The effect of the cyberloafing behaviors of tourism business employees on business motivations and organizational identification. *Tourism and Management Studies*, *17*(1), 31–43. https://doi.org/10.18089/TMS.2021.170103

Khorakian, A., Jahangir, M., Rahi, S., Eslami, G., & Muterera, J. (2023). Remote working and work performance during the covid-19 pandemic: The role of remote work satisfaction, digital literacy, and cyberslacking. *Behaviour & Information Technology*. https://doi.org/10.1080/0144929X.2023.2235026

Kim, B., & Kim, M. (2024). The influence of work overload on cybersecurity behavior: A moderated mediation model of psychological contract breach, burnout, and self-efficacy in AI learning such as ChatGPT. *TECHNOLOGY IN SOCIETY*, *77*. https://doi.org/10.1016/j.techsoc.2024.102543

Kim, B.-J., Kim, M.-J., & Lee, J. (2024). Examining the impact of work overload on cybersecurity behavior: Highlighting self-efficacy in the realm of artificial intelligence. *Current Psychology*, *43*(19), 17146–17162. https://doi.org/10.1007/s12144-024-05692-4

Kim, H., & Scott, C. (2019). Change communication and the use of anonymous social media at work; Implications for employee engagement. *Corporate Communications*, *24*(3), 410–424. https://doi.org/10.1108/CCIJ-07-2018-0076

Kim, K. H., & Chon, M.-G. (2022). When work and life boundaries are blurred: The effect of after-hours work communication through communication technology on employee outcomes. *Journal of Communication Management*, *26*(4), 386–400. https://doi.org/10.1108/JCOM-06-2022-0073

Kim, Y., Qian, L., & Aslam, M. (2021). Cyberbullying Among Traditional and Complementary Medicine Practitioners in the Workplace: Protocol for a Cross-sectional Descriptive Study. *JMIR RESEARCH PROTOCOLS*, *10*(8). https://doi.org/10.2196/29582

Koay, K. Y., Soh, P. C.-H., & Chew, K. W. (2017). Antecedents and consequences of cyberloafing: Evidence from the Malaysian ICT industry. *First Monday*, *22*(3). https://doi.org/10.5210/fm.v22i3.7302

Kompella, S. (2022). Persisting Menace: A Case-Based Study of Remote Workplace Bullying in India. *International Journal of Bullying Prevention*. https://doi.org/10.1007/s42380-022-00152-8

Kont, K.-R. (2024). The Role of Libraries in Creating a Safer Cyberspace: Awareness of Estonian Library Employees in Information Security. *International Information and Library Review*. https://doi.org/10.1080/10572317.2024.2315630

KS, N., & AK, S. M. (2020). Get employees talking through enterprise social media! Reduce cyberslacking: A moderated mediation model. *Internet Research*, *30*(4), 1167–1202. https://doi.org/10.1108/INTR-04-2019-0138

Kwala, A., & Agoyi, M. (2024). The nexus between cyberloafing and employee well-being: Role of creativity in the Nigerian service sector. *HUMANITIES & SOCIAL SCIENCES COMMUNICATIONS*, *11*(1). https://doi.org/10.1057/s41599-024-03928-z

Laitinen, K., & Sivunen, A. (2021). Enablers of and constraints on employees' information sharing on enterprise social media. *Information Technology & People*, *34*(2), 642–665. https://doi.org/10.1108/ITP-04-2019-0186

Leclercq-Vandelannoitte, A. (2019). Is Employee Technological “Ill-Being” Missing from Corporate Responsibility? The Foucauldian Ethics of Ubiquitous IT Uses in Organizations. *Journal of Business Ethics*, *160*(2), 339–361. https://doi.org/10.1007/s10551-019-04202-y

Lee, C., Boyd, L. D., Laspina, L., & Vineyard, J. (2023). Prevalence of Workplace Cyberbullying among Dental Hygienists. *Journal of Dental Hygiene*, *97*(2), 22–30.

Leonard, L. N. K., & Haines, R. (2007). Computer-mediated group influence on ethical behavior. *Computers in Human Behavior*, *23*(5), 2302–2320. https://doi.org/10.1016/j.chb.2006.03.010

Li, L., He, W., Xu, L., Ash, I., Anwar, M., & Yuan, X. (2019). Investigating the impact of cybersecurity policy awareness on employees’ cybersecurity behavior. *International Journal of Information Management*, *45*, 13–24. https://doi.org/10.1016/j.ijinfomgt.2018.10.017

Li, L., Xu, L., & He, W. (2022). The effects of antecedents and mediating factors on cybersecurity protection behavior. *COMPUTERS IN HUMAN BEHAVIOR REPORTS*, *5*. https://doi.org/10.1016/j.chbr.2021.100165

Lim, V. (2002). The IT way of loafing on the job: Cyberloafing, neutralizing and organizational justice. *JOURNAL OF ORGANIZATIONAL BEHAVIOR*, *23*(5), 675–694. https://doi.org/10.1002/job.161

Lock, K. D., Conger, S., & Oz, E. (1998). Ownership, privacy and monitoring in the workplace: A debate on technology and ethics. *Journal of Business Ethics*, *17*(6), 653.

Lowe-Calverley, E., & Grieve, R. (2017). Web of deceit: Relationships between the dark triad, perceived ability to deceive and cyberloafing. *CYBERPSYCHOLOGY-JOURNAL OF PSYCHOSOCIAL RESEARCH ON CYBERSPACE*, *11*(2). https://doi.org/10.5817/CP2017-2-5

Lowry, P. B., Posey, C., Roberts, T. L., & Bennett, R. J. (2014). Is Your Banker Leaking Your Personal Information? The Roles of Ethics and Individual-Level Cultural Characteristics in Predicting Organizational Computer Abuse. *Journal of Business Ethics*, *121*(3), 385. https://doi.org/10.1007/s10551-013-1705-3

Luqman, A., Masood, A., Shahzad, F., Rasheed, M., & Weng, Q. (2020). Enterprise Social Media and Cyber-slacking: An Integrated Perspective. *INTERNATIONAL JOURNAL OF HUMAN-COMPUTER INTERACTION*, *36*(15), 1426–1436. https://doi.org/10.1080/10447318.2020.1752475

Lyu, M., Sun, B., & Zhang, Z. (2023). Linking online voice to workplace cyberbullying: Roles of job strain and moral efficacy. *Kybernetes*, *52*(5), 1778–1794. https://doi.org/10.1108/K-03-2021-0246

Mainiero, L. A., & Jones, K. J. (2013). Workplace Romance 2.0: Developing a Communication Ethics Model to Address Potential Sexual Harassment from Inappropriate Social Media Contacts Between Coworkers. *Journal of Business Ethics*, *114*(2), 367. https://doi.org/10.1007/s10551-012-1349-8

Malik, O. F., & Pichler, S. (2023). Linking Perceived Organizational Politics to Workplace Cyberbullying Perpetration: The Role of Anger and Fear. *Journal of Business Ethics*, *186*(2), 445–463. https://doi.org/10.1007/s10551-022-05234-7

Marzi, G., Balzano, M., Caputo, A., & Pellegrini, M. M. (2025). Guidelines for bibliometric-systematic literature reviews: 10 steps to combine analysis, synthesis and theory development. *International Journal of Management Reviews*, *27*(1), 81-103. https://doi-org /10.1111/ijmr.12381

Masi, D., & Freedman, M. (2001). The use of telephone and on line technology in assessment, counseling, and therapy. *Employee Assistance Quarterly*, *16*(3), 49–63. https://doi.org/10.1300/J022v16n03_05

Mastrangelo, P. M., Everton, W., & Jolton, J. A. (2006). Personal Use of Work Computers:

Distraction versus Destruction. *CyberPsychology & Behavior*, *9*(6), 730–741. https://doi.org/10.1089/cpb.2006.9.730

McKellar, K., Sillence, E., Neave, N., & Briggs, P. (2024). Digital accumulation behaviours and information management in the workplace: Exploring the tensions between digital data hoarding, organisational culture and policy. *Behaviour & Information Technology*, *43*(6), 1206–1218. https://doi.org/10.1080/0144929X.2023.2205970

Mei, W., Wu, J., Zoghbi-Manrique-de-Lara, P., Liu, L., He, Y., & Song, M. (2023). Lose at sunrise, but gain at sunset: Linking social cyberloafing to psychological detachment, personal life enhancement of work, and mental health. *Work: Journal of Prevention, Assessment & Rehabilitation*, *75*(1), 339–348.

Miceli, M. P., & Near, J. P. (1985). Characteristics of organizational climate and perceived wrongdoing associated with whistle-blowing decisions. *Personnel Psychology*, *38*(3), 525–544.

Murtaza, G., Neveu, J., Khan, R., & Talpur, Q. (2022). Gossip 20: The role of social media and moral attentiveness on counterproductive work behaviour. *Applied Psychology: An International Review*. https://doi.org/10.1111/apps.12449

Narwal, M. (2023). DIGITAL DISTRACTIONS IN THE WORKPLACE: EXPLORING CYBERLOAFING IMPACT ON EMPLOYEE BEHAVIOUR AND INNOVATION. *Virtual Economics*, *6*(4), 7–24. https://doi.org/10.34021/ve.2023.06.04(1)

Nguyen, T. (2024). Understanding Shadow IT usage intention: A view of the dual-factor model. *ONLINE INFORMATION REVIEW*, *48*(3), 500–522. https://doi.org/10.1108/OIR-04-2022-0243

Nusrat, A., He, Y., Luqman, A., Nijjer, S., & Gugnani, R. (2024). From slack to strength: Examining ESNs impact on mental toughness and cyberslacking in the workplace. *TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE*, *198*. https://doi.org/10.1016/j.techfore.2023.122950

Nwankpa, J., & Datta, P. (2023). Remote vigilance: The roles of cyber awareness and cybersecurity policies among remote workers. *COMPUTERS & SECURITY*, *130*. https://doi.org/10.1016/j.cose.2023.103266

Ohana, M., Murtaza, G., ul Haq, I., Al-Shatti, E., & Chi, Z. (2024). Why and When can CSR toward Employees Lead to Cyberloafing? The Role of Workplace Boredom and Moral Disengagement. *JOURNAL OF BUSINESS ETHICS*, *189*(1), 133–148. https://doi.org/10.1007/s10551-023-05358-4

O'Neill, T. A., Hambley, L. A., & Bercovich, A. (2014). Prediction of cyberslacking when employees are working away from the office. *Computers in Human Behavior*, *34*, 291–298. https://doi.org/10.1016/j.chb.2014.02.015

Onumo, A., Ullah-Awan, I., & Cullen, A. (2021). Assessing the Moderating Effect of Security Technologies on Employees Compliance with Cybersecurity Control Procedures. *ACM Transactions on Management Information Systems*, *12*(2). https://doi.org/10.1145/3424282

Oz, E. (2001). Organizational commitment and ethical behavior: An empirical study of information system professionals. *Journal of Business Ethics*, *34*(2), 137. https://doi.org/10.1023/A:1012214017119

Page, D. (2015). Teachers' personal web use at work. *BEHAVIOUR & INFORMATION TECHNOLOGY*, *34*(5), 443–453. https://doi.org/10.1080/0144929X.2014.928744

Pammer-Schindler, V., & Rosé, C. (2022). Data-Related Ethics Issues in Technologies for Informal Professional Learning. *INTERNATIONAL JOURNAL OF ARTIFICIAL INTELLIGENCE IN EDUCATION*, *32*(3), 609–635. https://doi.org/10.1007/s40593-021-00259-x

Peltzman, S. (1975). The effects of automobile safety regulation. *Journal of Political Economy*, *83*(4), 677–725.

Pierce, M. A., & Henry, J. W. (1996). Computer ethics: The role of personal, informal, and formal codes. *Journal of Business Ethics*, *15*(4), 425. https://doi-org /10.1007/BF00380363

Pierce, M. A., & Henry, J. W. (2000). Judgements about computer ethics: Do individual, co-worker, and company judgements differ? Do company codes make a difference? *Journal of Business Ethics*, *28*(4), 307.

Pradhan, S., Agrawal, S., & Srivastava, A. (2022). Cyberbullying and Depression: An empirical study of Indian executives. *Vision*. https://doi.org/10.1177/09722629221074752

Rahman, M., Hossain, M., Fattah, F., & Mokter, A. (2022). Avoidance behaviour towards using pirated software: Testing a seven-component model on SME employees. *INFORMATION TECHNOLOGY & PEOPLE*, *35*(1), 316–343. https://doi.org/10.1108/ITP-12-2019-0621

Razmerita, L., Kirchner, K., & Nielsen, P. (2016). What factors influence knowledge sharing in organizations? A social dilemma perspective of social media communication. *Journal of Knowledge Management*, *20*(6), 1225–1246. https://doi.org/10.1108/JKM-03-2016-0112

Reizer, A., Galperin, B., Chavan, M., Behl, A., & Pereira, V. (2022). Examining the relationship between fear of COVID-19, intolerance for uncertainty, and cyberloafing: A mediational model. *JOURNAL OF BUSINESS RESEARCH*, *145*, 660–670. https://doi.org/10.1016/j.jbusres.2022.03.037

Ritala, P., Olander, H., Michailova, S., & Husted, K. (2015). Knowledge sharing, knowledge leaking and relative innovation performance: An empirical study. *TECHNOVATION*, *35*, 22–31. https://doi.org/10.1016/j.technovation.2014.07.011

Roberts, J. A., & Wasieleski, D. M. (2012). Moral Reasoning in Computer-Based Task Environments: Exploring the Interplay between Cognitive and Technological Factors on Individuals' Propensity to Break Rules. *Journal of Business Ethics*, *110*(3), 355–376. https://doi.org/10.1007/s10551-011-1196-z

Sarfraz, M., Khawaja, K., & Um-e-Farwah. (2023). Is the internet a double-edged sword for organizations? An empirical study on cyberloafing. *INFORMATION TECHNOLOGY & MANAGEMENT*. https://doi.org/10.1007/s10799-022-00385-5

Scarduzio, J. A., Redden, S. M., & Fletcher, J. (2021). Everyone's 'uncomfortable' but only some people report: Privacy management, threshold levels, and reporting decisions stemming from coworker online sexual harassment. *Journal of Applied Communication Research*, *49*(1), 66–85. https://doi.org/10.1080/00909882.2020.1849771

Schmidt, A. C., Fellmann, M., & Voigt, J. (n.d.). *Job Crafters Going Digital: A Framework for IT-Based Workplace Adaption*.

Seymour, L., & Nadasen, K. (2007). Web access for IT staff: A developing world perspective on web abuse. *ELECTRONIC LIBRARY*, *25*(5), 543–557. https://doi.org/10.1108/02640470710829532

Shao, Y., Huang, C., Song, Y., Wang, M., Song, Y. H., & Shao, R. (2024). Using augmentation-based AI tool at work: A daily investigation of learning-based benefit and challenge. *Journal of Management*, 01492063241266503.

Shao, Y., Zope, H., Jiang, Y., Pei, J., Nguyen, D., Brynjolfsson, E., & Yang, D. (2025). Future of Work with AI Agents: Auditing Automation and Augmentation Potential across the US Workforce. *arXiv Preprint arXiv:2506.06576*.

She, Z., Li, Q., & Ma, L. (2025). Witnessing Cyberloafing: A Daily Diary Study of Observers' Reactions to Cyberloafers. *Journal of Business Ethics*, 1–19.

Stylianou, A. C., Winter, S., Niu, Y., Giacalone, R. A., & Campbell, M. (2013). Understanding the Behavioral Intention to Report Unethical Information Technology Practices: The Role of Machiavellianism, Gender, and Computer Expertise. *Journal of Business Ethics*, *117*(2), 333. https://doi.org/10.1007/s10551-012-1521-1

Sweeten, G., Sillence, E., & Neave, N. (2018). Digital hoarding behaviours: Underlying motivations and potential negative consequences. *Computers in Human Behavior*, *85*, 54–60. https://doi.org/10.1016/j.chb.2018.03.031

Syrek, C. J., Kühnel, J., Vahle-Hinz, T., & De Bloom, J. (2018). Share, like, twitter, and connect: Ecological momentary assessment to examine the relationship between non-work social media use at work and work engagement. *Work and Stress*, *32*(3), 209. https://doi.org/10.1080/02678373.2017.1367736

Tasoulis, K., Theriou, G., Louzi, N., & Chatzoudes, D. (2023). Scylla and Charybdis: The relationships between supervisor active and passive cyber incivility with job stress, work engagement, and turnover intentions. *European Management Journal*. https://doi.org/10.1016/j.emj.2023.10.002

Tenório, N., & Bjørn, P. (2019). Online Harassment in the Workplace: The Role of Technology in Labour Law Disputes. *Computer Supported Cooperative Work: CSCW: An International Journal*, *28*(3), 293–315. https://doi.org/10.1007/s10606-019-09351-2

Terlizzi, M., Meirelles, F., & da Cunha, M. (2017). Behavior of Brazilian Banks Employees on Facebook and the Cybersecurity Governance. *JOURNAL OF APPLIED SECURITY RESEARCH*, *12*(2), 224–252. https://doi.org/10.1080/19361610.2017.1277886

Tiamboonprasert, W., & Charoensukmongkol, P. (2020). Effect of Ethical Leadership on Workplace Cyberbullying Exposure and Organizational Commitment. *JOURNAL OF BEHAVIORAL SCIENCE*, *15*(3), 85–100.

Treviño, L. K., Den Nieuwenboer, N. A., & Kish-Gephart, J. J. (2014). (Un) ethical behavior in organizations. *Annual Review of Psychology*, *65*(1), 635–660. https://doi.org/10.1146/annurev-psych-113011-143745

Turel, O., He, Q., & Wen, Y. (2021). EXAMINING THE NEURAL BASIS OF INFORMATION SECURITY POLICY VIOLATIONS: A NONINVASIVE BRAIN STIMULATION APPROACH. *MIS QUARTERLY*, *45*(4), 1715–1744. https://doi.org/10.25300/MISQ/2021/15717

Ugur, N., & Caliskan, K. (2022). Time for De-cluttering: Digital clutter scaling for individuals and enterprises. *COMPUTERS & SECURITY*, *119*. https://doi.org/10.1016/j.cose.2022.102751

Ul Hassan, S., Kiran, S., Gul, S., Khatatbeh, I., & Zainab, B. (2023). The perception of accountants/auditors on the role of corporate governance and information technology in fraud detection and prevention. *JOURNAL OF FINANCIAL REPORTING AND ACCOUNTING*. https://doi.org/10.1108/JFRA-05-2023-0235 van Eck, N. J., & Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics*, *84*(2), 523–538. https://doi.org/10.1007/s11192-009-0146-3

Venkatesh, V., Cheung, C., Davis, F., & Lee, Z. (2023). CYBERSLACKING IN THE WORKPLACE: ANTECEDENTS AND EFFECTS ON JOB PERFORMANCE. *MIS QUARTERLY*, *47*(1), 281–316. https://doi.org/10.25300/MISQ/2022/14985

Venkatraman, S., Cheung, C., Lee, Z., Fred, F., & Venkatesh, V. (2018). The "Darth" Side of Technology Use: An Inductively Derived Typology of Cyberdeviance. *JOURNAL OF MANAGEMENT INFORMATION SYSTEMS*, *35*(4), 1060–1091. https://doi.org/10.1080/07421222.2018.1523531

Verma, S., & Garg, N. (2023). Exploring intergenerational differences in technology-oriented ethical behavior. *KYBERNETES*, *52*(6), 2164–2180. https://doi.org/10.1108/K-09-2021-0897

Verma, S., & Garg, N. (2024). New ethical frontier: Exploring the nexus of techno-ethical orientation and corporate ethical values moderated by digital citizenship behaviour. *Journal of Organizational Change Management*, *37*(2), 391–407. https://doi.org/10.1108/JOCM-04-2023-0107

Vranjes, I., Baillien, E., Vandebosch, H., Erreygers, S., & De Witte, H. (2018). Kicking someone in cyberspace when they are down: Testing the role of stressor evoked emotions on exposure to workplace cyberbullying. *Work and Stress*, *32*(4), 379–399. https://doi.org/10.1080/02678373.2018.1437233

Wang, M., Liu, Y., & Lang, Y. (2025). Does perceived overqualification lead to cyberloafing? A moderated-mediation model based on social cognitive theory. *CHINESE MANAGEMENT STUDIES*, *19*(2), 549–566. https://doi.org/10.1108/CMS-12-2023-0690

Weerasekara, M., & Smedberg, Å. B. (2022). The use of online communities of practice in the software industry: Learnings from Facebook communities in Sri Lanka. *International*

Journal of Web Based Communities, *18*(2), 186–209. https://doi.org/10.1504/IJWBC.2022.10047191

Wong, G. Y.-L., Kwok, R. C.-W., Zhang, S., Lai, G. C.-H., & Cheung, J. C.-F. (2023). Mutually complementary effects of cyberloafing and cyber-life-interruption on employee exhaustion. *Information and Management*, *60*(2). https://doi.org/10.1016/j.im.2022.103752

Wyld, D. C., & Jones, C. A. (1997). The importance of context: The ethical work climate construct and models of ethical decision making—An agenda for research. *Journal of Business Ethics*, *16*, 465–472.

Xu, C., Yao, Z., & Xiong, Z. (2023). The Impact of Work-Related Use of Information and Communication Technologies After Hours on Time Theft. *Journal of Business Ethics*, *187*(1), 185–198. https://doi.org/10.1007/s10551-022-05167-1

Yao, S., Lu, J., Wang, H., Wark Montgomery, J. J., Gorny, T., & Ogbonnaya, C. (2024). Excessive technology use in the post-pandemic context: How work connectivity behavior increases procrastination at work. *Information Technology & People*, *37*(2), 583–604. https://doi.org/10.1108/ITP-08-2022-0573

Yazdanmehr, A., Jawad, M., Benbunan-Fich, R., & Wang, J. (2024). The role of ethical climates in employee information security policy violations. *DECISION SUPPORT SYSTEMS*, *177*. https://doi.org/10.1016/j.dss.2023.114086

Yildiz Durak, H., & Saritepeci, M. (2019). Occupational burnout and cyberloafing among teachers: Analysis of personality traits, individual and occupational status variables as predictors. *Social Science Journal*, *56*(1), 69–87. https://doi.org/10.1016/j.soscij.2018.10.011

Yildiz, S., Kutlu, D., & Yildiz, R. (2023). THE EFFECT OF NOMOPHOBIA ON CYBERLOAFING AMONG EMPLOYEES IN TOURISM ENTERPRISES. *VIVAT ACADEMIA*, *156*, 173–198. https://doi.org/10.15178/va.2023.156.e1465

Yoon, C., & Kim, H. (2013). Understanding computer security behavioral intention in the workplace; An empirical study of Korean firms. *Information Technology & People*, *26*(4),

401. https://doi.org/10.1108/ITP-12-2012-0147

Young, J. A., Courtney, J. F., Bennett, R. J., Timothy Selwyn Ellis, & Posey, C. (2021). The impact of anonymous, two-way, computer-mediated communication on perceived whistleblower credibility. *Information Technology & People*, *34*(3), 1119–1151. https://doi.org/10.1108/ITP-03-2019-0138

Zhang, J., Akhtar, M., Zhang, Y., & Sun, S. (2020). Are overqualified employees bad apples? A dual-pathway model of cyberloafing. *INTERNET RESEARCH*, *30*(1), 289–313. https://doi.org/10.1108/INTR-10-2018-0469

Zhang, J., Xie, K., Zhang, Y., & Wang, Y. (2024). Unintended influence of leader forgiveness: Increased employee cyberloafing. *MANAGEMENT DECISION*, *62*(1), 107–128. https://doi.org/10.1108/MD-10-2022-1426

Zhang, Z., & Ji, X. (2023). A Virtual Net Locks Me In: How and When Information and Communication Technology Use Intensity Leads to Knowledge Hiding. *Journal of Business Ethics*, *187*(3), 611–626. https://doi.org/10.1007/s10551-022-05245-4

Zoghbi-Manrique-de-Lara, P., & Maryamsadat, S. (2021). The relationship between perceived crowding and cyberloafing in open offices at Iranian IT-based companies. *Cognition, Technology & Work*, *23*(2), 331–342. https://doi.org/10.1007/s10111-020-00627-y

Zoghbi-Manrique-de-Lara, P., & Melián-González, S. (2009). The role of anomia on the relationship between organisational justice perceptions and organisational citizenship online behaviours. *Journal of Information, Communication and Ethics in Society*, *7*(1), 72–85. https://doi.org/10.1108/14779960910938106

Zoghbi-Manrique-de-Lara, P., & Viera-Armas, M. (2017). Corporate Culture as a Mediator in the Relationship Between Ethical Leadership and Personal Internet Use. *JOURNAL OF LEADERSHIP & ORGANIZATIONAL STUDIES*, *24*(3), 357–371. https://doi.org/10.1177/1548051817696877

CHAPTER V | STUDY 3. Craft your work through Artificial Intelligence: An investigation of workers' AI Augmented Crafting behavior

Abstract

New AI tools are creating opportunities for workers to augment their own abilities, transforming how work can be performed. Understanding how employees proactively enhance their capabilities through the use of AI is crucial, as this behavior shapes how work is adapted and redesigned from the bottom up. To address this, we introduce the concept of AI Augmented Crafting (AIAC), defined as workers' proactive use of AI tools to expand their skills and effectiveness. In this article, we first develop the AIAC construct, conceptualizing it as formative in nature. Through a qualitative approach, we develop measurement items of the construct. Then, drawing on data from multiple field studies, we test its content and construct validity. We also examine its nomological network by exploring its antecedents and potential consequences. We conclude by discussing the implications of AIAC for research and practice, highlighting how this new construct advances our understanding of work crafting in the age of AI.

Keywords: Artificial Intelligence; Human behavior; Augmentation, Job Crafting; AI Augmented Crafting

Introduction

New Artificial Intelligence tools (AI) (e.g., ChatGPT, Perplexity, Gemini) can be used by workers even without being officially adopted by companies (Budhwar et al., 2023; Handa et al., 2025; Shao et al., 2025). This represents an important switch in the field of workers' bottom-up behavior (e.g., job crafting). For example, every worker in almost every organization can augment his/her capabilities, becoming faster and more effective in performing work tasks, and also carrying out tasks without having the skills to complete them in the absence of AI (Budhwar et al., 2023). This emerging phenomenon is enabled by the augmentation potential of new AI tools (Grote et al., 2024; Handa et al., 2025; Shao et al., 2025a). Unlike earlier systems focused primarily on automating tasks and replacing human agency, these tools create a synthetic environment that supports new forms of partnership between human and artificial intelligence, what has been called collaborative intelligence (Makarius et al., 2020). Within these partnerships, humans can choose to complement and enhance their capabilities through augmentation, drawing on AI for support. For example, individuals can ask AI to generate solutions to a problem, evaluate alternative options, or even handle both tasks within a single prompt. The introduction of this augmentation potential into human work processes can reshape job characteristics (Parker et al., 2025), opening new opportunities for workers to craft their roles (Li et al., 2024). In this sense, the augmentation potential of AI can expand the avenues for work crafting, reflected in the diverse ways workers engage with these tools (Handa et al., 2025; Shao et al., 2025b). Research from this perspective has begun to examine specific forms of workers' AI use behavior (Jia et al., 2024; Jo & Park, 2024; Shao et al., 2024). However, it overlooks the diverse opportunities for work crafting that AI enables and lacks a systematic approach to measuring this phenomenon. Drawing on job crafting theory (Bruning & Campion, 2018; Zhang & Parker, 2019), our study focuses on exploring the ways employees can use AI tools to augment their own abilities, enabling them to proactively craft their work and pursue their individual goals. For this reason, we introduce the concept of AI Augmented Crafting (AIAC), defined as workers' enhancement of their own capabilities through the proactive and goal-directed use of AI tools to alter the work. Then, we introduce the development and validation of the AIAC measure, and to conclude, we test its nomological network using data from multiple field studies. With the introduction of AIAC, we aim to contribute to both theory and practice by offering a novel construct and an associated measurement tool that enables researchers and managers to systematically capture and account for the use of AI in shaping work.

Theoretical framework

Workers' proactive adaptation of their jobs has been conceptualized within job crafting theories (Bruning & Campion, 2018; Zhang & Parker, 2019). Recent developments in job crafting literature have incorporated the use of technology into theoretical models of how employees shape their work (Bruning & Campion, 2018). Bruning and Campion (2018) introduced the goal-directed use of technology to modify one's job and improve work processes as a form of approach resources crafting. This type of technology-based job crafting can take new forms with emerging technologies such as Artificial Intelligence (AI). In fact, whereas traditional technologies primarily automate tasks, new AI tools can augment and enhance human capabilities (Shao et al., 2025). As a result, job crafting in the age of AI involves not only changing tasks and processes but also augmenting one's own capabilities. Following the model of Bruning and Campion (2018), we suggest that AI Augmented Crafting can be seen as a form of approach resources crafting that aims not only to improve work directly but also to enhance workers' own capabilities, which can ultimately lead to changes in how work is performed. Recent literature on Human-AI interaction has highlighted the importance of examining different forms of goal-directed augmentation when studying, for example, how teams interact with AI (Klonek & Parker, 2025). Klonek and Parker (2025) argue that Human-to-Human processes within work teams can also apply to Human-to-AI interactions, suggesting that team members engage with AI for three main purposes (i.e., transition, action, and interpersonal). Building on these three purposes, the authors identified different forms of AI use that help workers enhance their team processes. They examined how these usage behaviors relate to potential outcome, such as stress. Given the growing relevance of new forms of augmentation enabled by AI tools, our goal is to investigate these emerging forms of work crafting made possible by AI technologies (i.e., AIAC). Intuitively, employees must first adopt AI before they can craft their work through it. Prior research has extensively examined the antecedents of AI adoption (Cao et al., 2021). Drawing on the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003), Cao et al. (2021) identified factors influencing the adoption of AI systems for organizational decision-making. Once adopted, AI use enables employees to generate meaningful impact (Jia et al., 2024; Li et al., 2024; Man Tang et al., 2022; Shao et al., 2024; Zhang et al., 2025), such as enhancing creative performance (Jia et al., 2024) or facilitating knowledge acquisition (Shao et al., 2024). Our study examines various forms of goal-directed proactive AI use in the workplace, recognizing that these forms can give rise to divergent outcomes.

To achieve our aim, we first develop the AI Augmented Crafting construct and its corresponding scale. Consistent with recent literature on job crafting (Zhang & Parker, 2019) and information system measurement (Petter et al., 2007), we conceptualize AI-Augmented Crafting as a composite construct (i.e., formative), therefore considering the dimensions and indicators of AI-Augmented Crafting as defining characteristics of the focal construct. In this view, the AI-Augmented Crafting construct is formed by its sub-dimensions, each of which is in turn shaped by its respective indicators. Consequently, a change in any single sub-dimension may result in a change in the overall construct. Next, we test the validity of the scale following established guidelines for formative constructs (Jarvis et al., 2003; MacKenzie et al., 2005, 2011; Wang et al., 2015). Finally, we examine its nomological network by testing its antecedents and potential consequences. We based our results on five different field studies, each conducted in distinct organizations and samples. Implications for research and practice are then discussed.

Scale development and validation

We followed recommended practices for construct and scale development (Colquitt et al., 2019; Jarvis et al., 2003; MacKenzie et al., 2005, 2011; Wang et al., 2015) to validate the AI

Augmented Crafting scale. We preregistered the study on the Open Science Framework (OSF; https://osf.io/x2b57).

Construct development and item generation

The proliferation of AI tools in organizational contexts has created new opportunities for employee engagement, a development explored in recent literature (Boussioux et al., 2024; Jo, 2023; Shao et al., 2024). Studies have identified distinct patterns of AI use, each serving different objectives and potentially operating independently from one another. For instance, some research has examined AI use for knowledge acquisition (Shao et al., 2024), while others have focused on its role in supporting decision-making processes (Cao et al., 2021), both examples of goal-directed usage, yet functionally distinct. In line with MacKenzie et al. (2005), we argue that the dimensions of AI-Augmented Crafting should be conceptualized as formative constructs. That is, the indicators define the construct itself, and changes in the overall construct do not necessarily require changes across all individual indicators. Based on this reasoning, we proceeded with item generation, treating the AI Augmented Crafting dimensions as formative. This perspective is also aligned with recent job crafting literature, which suggests the use of formative scales to capture these behaviors more accurately (Zhang & Parker, 2019).

Method

We adopted an inductive approach, as recommended when the conceptual foundation of a construct is not easily identifiable (Hinkin, 1998). This was particularly appropriate in our case, where use behaviors can vary significantly depending on the specific purposes that different technological functions are intended to support. Then, to develop the AI Augmented Crafting construct and its dimensions, we drew on existing literature on AI use. Also, we conducted one-on-one interviews with four professionals who regularly and proactively use AI in their daily work. The participants represented diverse roles and sectors, including a programmer, two business consultants, and a psychotherapist, with 7, 3, 15, and 7 years of work experience, respectively.

During the interviews, we asked participants to describe how they use AI in their work (see summary in Table 1).

Table 1

AI use behaviors described during the interviews.

	Gender/Age	Years of work experience	Role	Type of use described
Participant 1	Male/33	7	Programmer	• Write code and add comments to it • Search for technical documentation and information • Review and edit documents
Participant 2	Female/26	3	Business Consultant	• Translate documents and optimize written communications • Generate ideas, for example, for LinkedIn posts and professional outreach
Participant 3	Female/39	15	Business Consultant	• Generate creative ideas • Write proposals and offers • Suggest Excel formulas and solutions • Find and gather relevant information
Participant 4	Female/32	7	Psychotherapist	• Create templates and questions, for example, for structured interviews • Generate ideas, such as engaging prompts or requests for event participants • Gather information without relying solely on Google search

Results

First, our analysis indicates that AI can play a significant role in supporting organizational decision-making processes (Cao et al., 2021; Ulfert et al., 2022), for example by generating or evaluating alternative courses of action. Decision-making in organizational contexts requires the identification of problems, the systematic assessment of advantages and disadvantages across alternatives, and the selection of the option most likely to yield optimal outcomes for the organization (Yang et al., 2022). Job demands may exacerbate the complexity of decision-making tasks (Ganster, 2005). In contrast, the proactive integration of AI may function as a valuable resource that alleviates task difficulty and facilitates more effective decision-making. Second, AI can serve as a learning companion (Jo & Park, 2024; Shao et al., 2024), enabling workers to acquire knowledge and develop skills on demand. Prior research indicates that users perceive AI systems (e.g., ChatGPT) as valuable sources of information (Jo & Park, 2024) and actively help them to enhance their knowledge (Jia et al., 2024; Shao et al., 2024). This behavior also emerged in the interviews, where participants reported using AI to, for example, "gather information without relying solely on Google search" or "search for technical documentation and information". Third, AI tools can also support workplace relationships by enhancing communication with colleagues (Esplugas, 2023) and expanding professional networks (Hostetter & Rodríguez Abitia, 2025; Kumar et al., 2024). For instance, Hostetter and Rodríguez Abitia (2025) found that AI is perceived as a valuable resource for networking, a pattern also confirmed in our interviews (e.g., "Generating ideas for LinkedIn posts and professional outreach"). Finally, AI can be employed to perform and monitor work tasks (Klonek & Parker, 2025; Tanaka et al., 2021; Yu et al., 2024). For instance, workers may use AI to create videos (Yu et al., 2024) or to read and process documents (Tanaka et al., 2021; Yu et al., 2024). Such task-oriented applications are valuable even when workers lack the full set of competencies to accomplish them independently. This was also reflected in our interviews, where one participant reported using AI to "Translate documents and optimize written communications" even in languages she does not know well.

Drawing on the literature and the interviews, we identified 14 different use behaviors that may occur in interactions with AI, grouped into four overarching constructs that capture different aspects of the proactive use of AI. Task Augmentation, that is the use of AI to directly enhance the efficiency, scope, or quality of tasks within a worker's role, also completing tasks without having skills to do it; Decision Making Augmentation, that is the use of AI to support and enhance the decision-making process; Learning Augmentation, that is the use of AI to develop and refine job-relevant skills and knowledge; Relational Augmentation, that is the use of AI to strengthen interpersonal and collaborative aspects of work. All use behaviors and their categorization are presented in Table 2.

Study 1: Content validation

Method

We content validate the AI Augmented Crafting scale using the Anderson and Gerbing (1991) methodology (Colquitt et al., 2019). To ensure that the orbiting constructs (1) are at the same stage of the causal flow, (2) share the same referent as the focal construct, and (3) do not have a part–whole relationship with the focal construct, we used the four dimensions of the AIAC as orbiting constructs, comparing each dimension to the others (Colquitt et al., 2019). Considering that 14 items were assessed, a sample size of 50 participants was considered sufficient to test the validity of the dimensions. Then, we sent the link to 75 participants to rate the correspondence between items and definitions of various theoretical constructs. Finally, 66 participants completed the whole questionnaire. 97% (64) were workers from different organizations and jobs, while 3% (2) were PhD students. 50% (33) were female. The average age was 36.89 and the standard deviation was 8.59. 6% (4) of participants were high school graduates, all the other had bachelor's degree or higher. Participants were first asked to practice by associating a general constructs (i.e., work motivation, work satisfaction, work place) with related items (e.g., I work hard in my job, I work in a basement, I lack energy when working)(see Colquitt et al., 2019). After successfully completing this practice task, they proceeded to finalize the association between items and the constructs of AI Augmented Crafting. The items were presented randomly.

Results

In Table 2 the results of the analysis are shown. We changed two items which showed weak content validity as follows: "*I use AI to generate multiple solutions*" was changed in "*I use AI to generate multiple solutions before making a decision*", and "*I use AI to receive feedback on my performance (for example, by asking for feedback on my outputs)*" was changed in "*I use AI to learn new ways of doing things (for example, by asking for feedback on my outputs)*".

Table 2

Results of the content validation.

		Psa	*Csv*	*Interpratation Psa*	*Interpratation Csv*
TASK AUGMENTATION	TA1 - I use AI to automate repetitive tasks (e.g., creating automated document archiving workflows)	0.894	0.788	Strong	Strong
	TA2 - I use AI to perform tasks that I wouldn't normally be able to accomplish (e.g., creating visualizations, reports, or other content that would require skills I don't have)	0.909	0.818	Strong	Very strong
	TA3 - I use AI to complete my tasks better (e.g., by asking it to correct errors in my outputs)	0.924	0.848	Very strong	Very strong
	TA4 - I use AI to complete my tasks faster (e.g., reading and summaryze pdf documents)	0.970	0.939	Very strong	Very strong
DECISION MAKING AUGMENTATION	DMA1 - I use AI to gain insights that inform my decisions (e.g., by asking to analyze data)	0.894	0.788	Strong	Strong
	DMA2 - I use AI to generate different solutions	0.576	0.152	Weak	Weak
	DMA3 - I use AI to evaluate options before making a decision	0.909	0.818	Strong	Very strong
	DMA4 - I use AI to develop working strategies and plan	0.591	0.182	Weak	Weak
LEARNING AUGMENTATION	LA1 - I use AI to stay updated with the latest developments and knowledge in my field	0.939	0.879	Very strong	Very strong
	LA2 - I use AI to assess my learning progress (e.g., by asking to provide me with exam simulations)	0.879	0.758	Strong	Strong
	LA3 - I use AI to receive feedback on my performance (for example, by asking for feedback on my outputs)	0.485	-0.030	Weak	Lack of
RELATIONAL AUGMENTATION	RA1 - I use AI to create relationships that align with my goals (e.g., by asking to find new LinkedIN or Facebook connections)	0.803	0.606	Moderate	Strong
	RA2 - I use AI to improve my relational skills (e.g., using a virtual coach)	0.848	0.697	Strong	Strong
	RA3 - I use AI to improve my social image (e.g., by asking for suggestions on how to behave in social situations)	0.939	0.879	Very strong	Very strong

Note. Interpretation of Psa and Csv is based on evaluation criteria not normed to average correlation provided by Colquitt et al. (2019).

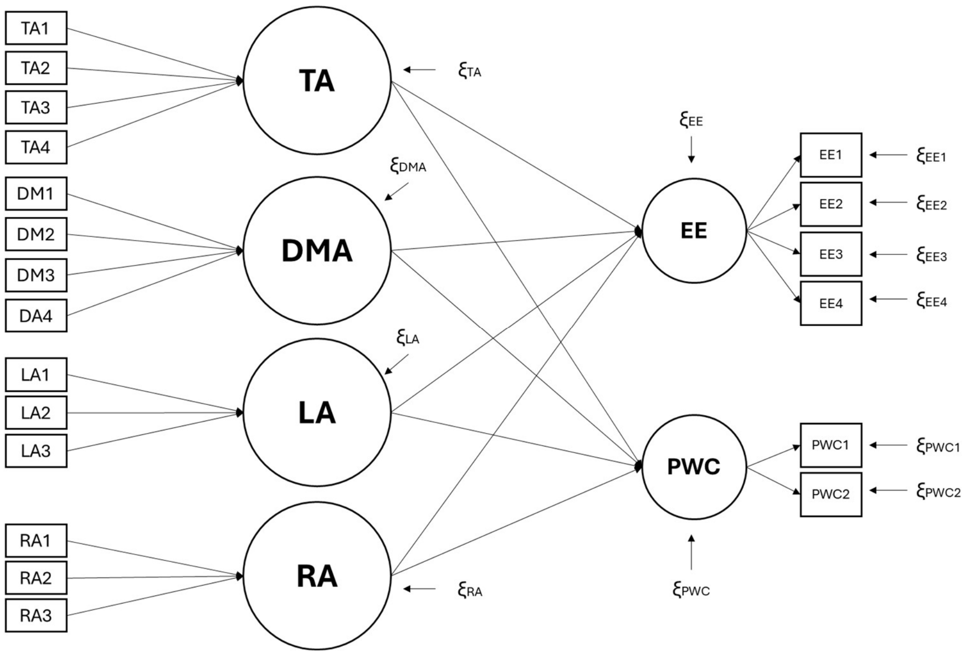
Study 2: Factorial validity

Method

According to MacKenzie et al. (2005), exploratory factor analysis (EFA) is not recommended for formative construct, then we conducted a confirmatory factor analysis (CFA) to assess how well the hypothesized factorial structure of the four formative dimensions fit the observed data. Given the issue of indicator indeterminacy inherent in formative constructs (MacKenzie et al., 2005), we added paths from each formative construct to two theoretically reflective indicators of AI perceptions, Effort Expectancy (EE) and Personal Wellbeing Concerns (PWC) (Cao et al., 2021), to achieve model identification. We selected EE because it has shown consistent relationships with technology use in the literature (Blut et al., 2022; Venkatesh et al., 2003), and PWC because, in the context of AI, the combination of EE and PT allows us to capture users' positive perceptions (EE) and negative perceptions (PWC) toward the tool. According to AI Acceptance–Avoidance Model (IAAAM; Cao et al., 2021), Effort Expectancy (α = .89) is defined as the degree of ease associated with the use of the system. A sample item is "I would find the system easy to use". Personal Wellbeing Concerns (α = .0.77) is defined as an individual's concerns regarding the degree of personal anxiety and stress caused by the use of AI. A sample item is "AI makes me feel relaxed (R)". Both dimensions were measured on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). In line with our conceptual model, we specified four first-order formative dimensions: Learning Augmentation and Relational Augmentation (each measured by three indicators), Task Augmentation and Decision-Making Augmentation (each measured by four indicators). Figure 1 illustrates the model tested. Unlike reflective models assessed through CFA, the validity of formative indicators is primarily evaluated by examining the significance and strength of the path from each indicator to its composite latent construct (MacKenzie et al., 2005). Accordingly, we used these path coefficients to assess the measurement quality of our model. All parameters are shown in Table 3. Moreover, to address potential collinearity, which may indicate redundancy among formative indicators (Jarvis et al., 2003; Petter et al., 2007), we calculated R^2, the Variance Inflation Factor (VIF), and Pearson's correlation coefficients between indicators (Table 4). To these purposes, we collected data from 1372 employees working in three Italian Public Administrations. In our sample, 66% (n=910) were female. The average age was 48.25 and the standard deviation was 10.0. Data was collected online and anonymously.

Figure 1

Representation of the tested model.



Results

The CFA, R^2, the Variance Inflation Factor (VIF), and Pearson's correlation coefficients between indicators were performed using the *lavaan* package in R Studio (version 4.1). The goodness of fit was assessed using six indicators (Hu & and Bentler, 1999): (a) chi-square ($\chi2$ = significant values: $p < 0.01$), (b) chi square over degrees of freedom (df; target: $\chi2/df = < 3$), (c) comparative fit index (CFI; target: >0.90), (d) Tucker–Lewis index (TLI; target = > 0.90), (e) root mean square error of approximation (RMSEA <0.08), and (f) Standardized root mean square residual (SRMR; target = < 0.08) (Kline, 2015). Our hypothesized model shows good fit ($\chi2$ = 949.318, df = 145, $\chi2$ / df = 6.56, CFI = 0.96, TLI = 0.94, RMSEA = 0.06, SRMR = 0.046). All path coefficients were statistically significant (Table 3).

Table 3

Path coefficient from items to dimensions.

Indicator	Latent Factor	Estimate	SE	*z*	*p*
TA1	Task Augmentation (TA)	0.103	0.011	9.26	< .001
TA2	TA	0.110	0.012	9.36	< .001
TA3	TA	0.134	0.014	9.48	< .001
TA4	TA	0.134	0.014	9.63	< .001
DM1	Decision Making (DM)	0.086	0.010	8.91	< .001
DM2	DM	0.080	0.009	8.95	< .001
DM3	DM	0.082	0.009	8.93	< .001

DM4	DM	0.076	0.009	8.81	< .001
LA1	Learning Augmentation (LA)	0.234	0.026	8.92	< .001
LA2	LA	0.225	0.024	9.42	< .001
LA3	LA	0.164	0.018	8.94	< .001
RA1	Relational Augmentation (RA)	0.084	0.013	6.61	< .001
RA2	RA	0.093	0.015	6.29	< .001
RA3	RA	0.081	0.013	6.45	< .001

Note. All estimates are unstandardized loadings from the measurement model. *SE* = Standard Error. *p*-values are based on z-tests. Model fit: χ^2(df) = 949.318 (145), $p < .001$; CFI = .96; TLI = .94; RMSEA = .06; SRMR = .046.

Furthermore, all VIF values were below 3.6, suggesting that multicollinearity is not a concern and falls within acceptable thresholds (RM & Jacob, 2017).

Table 4

R^2, Variance Inflaction Factor (VIF), Correlation.

		TA1		TA2		TA3		TA4	
Target Variable	R-squared	VIF	Pearson's r	VIF	Pearson's r	VIF	Pearson's r	VIF	Pearson's r
TA1	0.5352	-	-	2.0288	0.5547	2.9490	0.5545	2.6260	0.6021
TA2	0.5152	2.1160	0.5547	-	–	2.9854	0.5548	2.6719	0.5875
TA3	0.6659	2.1194	0.5545	2.0571	0.5548	-	–	2.5735	0.6766
TA4	0.6298	2.0914	0.6021	2.0402	0.5875	2.8519	0.6766	-	–
DM1	0.6564	2.1507	0.5597	2.0368	0.6043	2.9903	0.62	2.4772	0.6995
DM2	0.7197	2.1489	0.5586	2.0558	0.5826	2.9871	0.6266	2.6987	0.6205
DM3	0.7044	2.1494	0.5336	2.0628	0.5609	2.9881	0.6019	2.6991	0.5909
DM4	0.6729	2.0982	0.6284	2.0628	0.5739	2.9799	0.6105	2.6765	0.6419
LA1	0.6254	2.1434	0.4855	2.0006	0.5938	2.8955	0.6303	2.6994	0.5842
LA2	0.5966	2.1394	0.5303	2.0619	0.5439	2.9897	0.52	2.6988	0.5301
LA3	0.5689	2.1199	0.5585	2.0622	0.4883	2.9928	0.4494	2.7002	0.4994
RA1	0.5295	2.1479	0.4374	2.0628	0.4574	2.3848	0.7025	2.6860	0.5582
RA2	0.5538	2.1013	0.5439	2.0405	0.4853	2.9876	0.397	2.6976	0.4377
RA3	0.5783	2.1510	0.5086	2.0603	0.4805	2.9906	0.448	2.6959	0.4903

		DM1		DM2		DM3		DM4	
Target Variable	R-squared	VIF	Pearson's r	VIF	Pearson's r	VIF	Pearson's r	VIF	Pearson's r
TA1	0.5352	2.9099	0.5597	3.5645	0.5586	3.3799	0.5336	2.9823	0.6284
TA2	0.5152	2.8742	0.6043	3.5567	0.5826	3.3832	0.5609	3.0580	0.5739
TA3	0.6659	2.9076	0.62	3.5611	0.6266	3.3769	0.6019	3.0440	0.6105
TA4	0.6298	2.6692	0.6995	3.5652	0.6205	3.3802	0.5909	3.0297	0.6419
DM1	0.6564	-	–	3.5447	0.6843	3.2995	0.6871	3.0266	0.6671
DM2	0.7197	2.8912	0.6843	-	–	2.6889	0.7983	2.9408	0.717
DM3	0.7044	2.8388	0.6871	2.8364	0.7983	-	–	3.0104	0.6962
DM4	0.6729	2.8810	0.6671	3.4320	0.717	3.3305	0.6962	-	–

LA1	0.6254	2.8766	0.649	3.5515	0.6487	3.3553	0.6447	3.0421	0.6057
LA2	0.5966	2.8721	0.6186	3.5489	0.6267	3.3579	0.6316	3.0552	0.5923
LA3	0.5689	2.9052	0.5209	3.5633	0.523	3.3696	0.544	3.0208	0.6072
RA1	0.5295	2.9109	0.5123	3.5515	0.5455	3.3823	0.5162	3.0559	0.5077
RA2	0.5538	2.9070	0.4522	3.5627	0.4801	3.3741	0.4993	3.0273	0.5689
RA3	0.5783	2.9087	0.4865	3.5553	0.5353	3.3832	0.5245	3.0176	0.5977

		LA1		LA2		LA3	
Target Variable	R-squared	VIF	Pearson's r	VIF	Pearson's r	VIF	Pearson's r
TA1	0.5352	2.6598	0.4855	2.4655	0.5303	2.2857	0.5585
TA2	0.5152	2.5893	0.5938	2.4784	0.5439	2.3190	0.4883
TA3	0.6659	2.5823	0.6303	2.4762	0.52	2.3191	0.4494
TA4	0.6298	2.6678	0.5842	2.4770	0.5301	2.3186	0.4994
DM1	0.6564	2.6383	0.649	2.4464	0.6186	2.315	0.5209
DM2	0.7197	2.6568	0.6487	2.4656	0.6267	2.3162	0.523
DM3	0.7044	2.6477	0.6447	2.4609	0.6316	2.3104	0.544
DM4	0.6729	2.6559	0.6057	2.4772	0.5923	2.2915	0.6072
LA1	0.6254	-	–	2.1755	0.6778	2.3190	0.4553
LA2	0.5966	2.3426	0.6778	-	–	2.2973	0.5552
LA3	0.5689	2.6690	0.4553	2.4555	0.5552	-	–
RA1	0.5295	2.6682	0.5105	2.4795	0.4507	2.3198	0.4092
RA2	0.5538	2.6627	0.4048	2.4444	0.5309	2.2036	0.6361
RA3	0.5783	2.6573	0.429	2.4563	0.54	2.1397	0.6583

		RA1		RA2		RA3	
Target Variable	R-squared	VIF	Pearson's r	VIF	Pearson's r	VIF	Pearson's r
TA1	0.5352	2.1219	0.4374	2.1891	0.5439	2.3711	0.5086
TA2	0.5152	2.1254	0.4574	2.2172	0.4853	2.3687	0.4805
TA3	0.6659	1.6932	0.7025	2.2369	0.397	2.3692	0.448
TA4	0.6298	2.1133	0.5582	2.2382	0.4377	2.3668	0.4903
DM1	0.6564	2.1254	0.5123	2.2384	0.4522	2.3698	0.4865
DM2	0.7197	2.1151	0.5455	2.2376	0.4801	2.3626	0.5353
DM3	0.7044	2.1248	0.5162	2.2354	0.4993	2.3716	0.5245
DM4	0.6729	2.1240	0.5077	2.2189	0.5689	2.3403	0.5977
LA1	0.6254	2.1241	0.5105	2.2355	0.4048	2.3606	0.429
LA2	0.5966	2.1254	0.4507	2.2097	0.5309	2.3495	0.54
LA3	0.5689	2.1254	0.4092	2.1292	0.6361	2.1876	0.6583
RA1	0.5295	-	–	2.2410	0.3765	2.3343	0.4552
RA2	0.5538	2.1250	0.3765	-	–	2.1350	0.6603
RA3	0.5783	2.0920	0.4552	2.0177	0.6603	-	–

Study 3: Convergent Validity

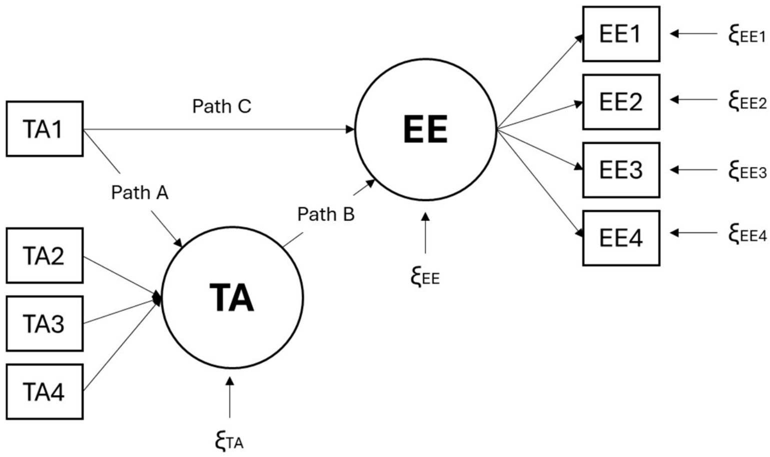
Method

Convergent validity refers to the degree to which the construct converges on other constructs to which it should be theoretically similar. We assessed convergent validity following the procedure proposed by Wang et al. (2015) for evaluating convergent validity in formative constructs. According to Wang et al. (2015), to establish convergent evidence for a formative construct (e.g., Task Augmentation, TA), if an indicator (e.g., TA1) truly belongs to that construct, its effect on another theoretically related construct should be mediated by the formative construct itself (i.e., TA). This mediator perspective involves three steps. First, test the path from the indicator to the formative construct (Path A). Second, test the direct path from the indicator to the dependent construct (Path C). Third, test the same direct path (Path C) while controlling for the indirect effect of the indicator on the dependent construct through the mediator. In this last step, the strength of Path C should decrease, indicating that the effect of the indicator on the dependent construct is mediated by the formative construct. Figure 2 illustrates an example of this mediator perspective, using Task Augmentation as the mediator and Effort Expectancy as the dependent construct.

We then applied this procedure to test the convergent validity of our four AIAC dimensions, using Effort Expectancy ($\alpha = .91$) and Perceived Wellbeing Concerns ($\alpha = .0.80$) as the related constructs (Cao et al., 2021). To assess convergent validity, we collected data from 319 employees: 77% were employed in a service company and 23% in an international airport in Italy. Of the participants, 73% ($n = 231$) were female, with a mean age of 48.2 years ($SD = 10.6$). Data were collected online and anonymously.

Figure 2

Example of the mediator perspective for our scale. Convergent validity.



Results

We tested convergent validity using Jamovi 2.3.28 software. The results of this analysis are reported in Table 5 for Effort Expectancy and in Table 6 for Personal Wellbeing Concerns. As expected, both Path A and Path B were significant. Path C was also significant before controlling for A and B. After controlling for A and B, the strength of Path C either became non-significant or decreased, indicating that the indicators affect the dependent variable primarily through the mediator. According to Wang et al. (2015), this pattern supports good convergent validity.

Table 5

Convergent validity path coefficient between AIAC dimensions, AIAC dimensions' indicators and Effort Expectancy.

	Path A	Path B	Path C (before controlling Path A)	Path C (after controlling Path A)
TA1	0.826***	0.714***	0.493***	-0.288
TA2	0.775***	0.714***	0.504***	-0.179
TA3	0.640***	0.714***	0.492***	0.134
TA4	0.702***	0.714***	0.559***	0.262
DM1	0.762***	0.675***	0.594***	0.435**
DM2	0.839***	0.675***	0.501***	-0.382*
DM3	0.837***	0.675***	0.566***	0.007
DM4	0.836***	0.675***	0.531***	-0.142
LA1	0.709***	0.683***	0.488***	0.015
LA2	0.905***	0.683***	0.571***	-0.144
LA3	0.679***	0.683***	0.484***	0.090
RA1	0.748***	0.543***	0.424***	0.096
RA2	0.805***	0.543***	0.488***	0.414
RA3	0.915***	0.543***	0.391**	-0.433

Note. Standardized Regression Coefficient are reported. *p < 0.05. **p < 0.01. ***p < 0.001.

Table 6

Convergent validity path coefficient between AIAC dimensions, AIAC dimensions' indicators and Personal Wellbeing Concerns.

	Path A	Path B	Path C (before controlling Path A)	Path C (after controlling Path A)
TA1	0.826***	-0.539***	-0.364***	0.241
TA2	0.775***	-0.539***	-0.434***	-0.059
TA3	0.640***	-0.539***	-0.371***	-0.097
TA4	0.702***	-0.539***	-0.387***	-0.038
DM1	0.762***	-0.522***	-0.389***	0.049
DM2	0.839***	-0.522***	-0.436***	0.015
DM3	0.837***	-0.522***	-0.433***	0.028
DM4	0.836***	-0.522***	-0.455***	-0.079
LA1	0.709***	-0.529***	-0.410***	-0.165
LA2	0.905***	-0.529***	-0.335***	0.434**
LA3	0.679***	-0.529***	-0.395***	-0.166
RA1	0.748***	-0.473***	-0.358***	-0.018
RA2	0.805***	-0.473***	-0.412***	-0.257
RA3	0.915***	-0.473***	-0.380***	0.217

Note. Standardized Regression Coefficient are reported. *p < 0.05. **p < 0.01. ***p < 0.001.

Study 4: Discriminant validity

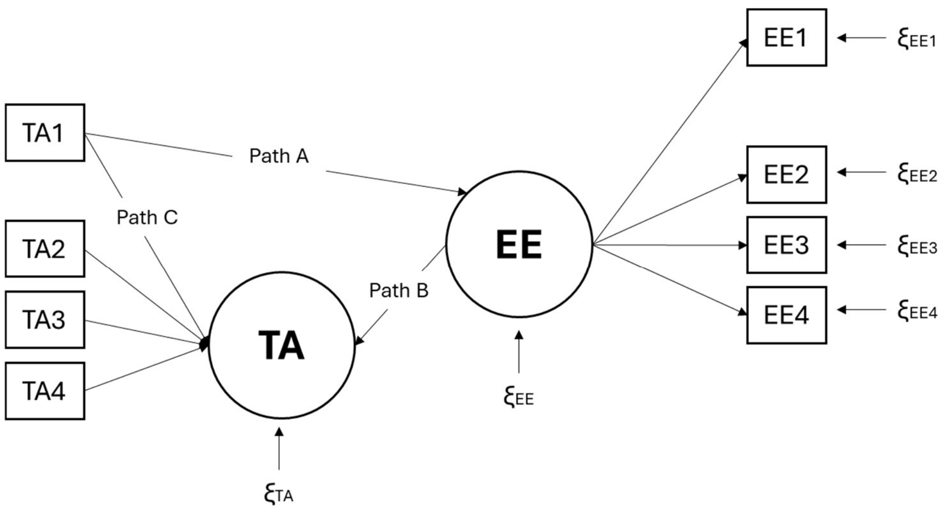
Method

Discriminant validity refers to the degree to which the construct measured diverges from other constructs from which it should theoretically differ. Following Wang et al. (2015), we assessed discriminant validity using the same mediation-based procedure applied for convergent validity. In this case, the AIAC dimensions' indicators were treated as independent variables, Effort Expectancy (α = .85) and Personal Wellbeing Concerns (α = .71) were modeled as mediators, and the AIAC dimensions were specified as dependent variables. Figure 3 illustrates an example of this mediator perspective, using Task Augmentation indicators as independent variable, Effort Expectancy as mediator and Task Augmentation as dependent variable.

To assess discriminant validity, we collected data from 326 employees, of whom 91% worked in two organizations within the Italian public administration sector and 9% in a multinational corporation in the retail industry. 58% (188) were female. The average age was 50.5 and the standard deviation was 8.89. Data was collected online and anonymously.

Figure 3

Example of the mediator perspective for our scale. Discriminant validity.



Results

We tested discriminant validity using Jamovi 2.3.28 software. The results of this analysis are reported in Table 7 for Effort Expectancy and in Table 8 for Personal Wellbeing Concerns. As expected, both Path A and Path B were significant, except for one item of Relational Augmentation, which showed a non-significant Path A. Path C was also significant before controlling for A and B. After controlling for A and B, the strength of Path C was still significant and decreased little, indicating that Effort Expectancy and Personal Wellbeing Concerns did not mediate the influence of AIAC dimensions' indicators and AIAC dimensions. According to Wang et al. (2015), this pattern supports good discriminant validity.

Table 7

Discriminant validity path coefficient between AIAC dimensions' indicators, Effort expectancy and AIAC dimensions.

	Path A	Path B	Path C (before controlling Path A)	Path C (after controlling Path A)
TA1	0.405***	0.332***	0.761***	0.711***
TA2	0.361***	0.332***	0.737***	0.688***
TA3	0.358***	0.332***	0.647***	0.609***
TA4	0.336***	0.332***	0.659***	0.626***
DM1	0.363***	0.295***	0.671***	0.649***
DM2	0.368***	0.295***	0.776***	0.748***
DM3	0.330***	0.295***	0.752***	0.717***
DM4	0.385***	0.295***	0.776***	0.737***
LA1	0.284***	0.203***	0.614***	0.594***
LA2	0.259**	0.203***	0.786***	0.755***
LA3	0.355***	0.203***	0.616***	0.602***
RA1	0.180	0.070**	0.737***	0.732***
RA2	0.247**	0.070**	0.691***	0.689***
RA3	0.268*	0.070**	0.810***	0.804***

Note. Standardized Regression Coefficient are reported. *p < 0.05. **p < 0.01. ***p < 0.001.

Table 8

Discriminant validity path coefficient between AIAC dimensions' indicators, Personal Wellbeing Concerns and AIAC dimensions.

	Path A	Path B	Path C (before controlling Path A)	Path C (after controlling Path A)
TA1	-0.336***	-0.295***	0.761***	0.712***
TA2	-0.378***	-0.295***	0.737***	0.694***
TA3	-0.360***	-0.295***	0.647***	0.613***
TA4	-0.388***	-0.295***	0.659***	0.638***
DM1	-0.349***	-0.276***	0.671***	0.642***
DM2	-0.460***	-0.276***	0.776***	0.759***
DM3	-0.371***	-0.276***	0.752***	0.718***
DM4	-0.389***	-0.276***	0.776***	0.734***
LA1	-0.381***	-0.216***	0.614***	0.592***
LA2	-0.312***	-0.216***	0.786***	0.745***
LA3	-0.399***	-0.216***	0.616***	0.593***
RA1	-0.183	-0.071**	0.737***	0.730***
RA2	-0.302**	-0.071**	0.691***	0.689***
RA3	-0.324**	-0.071**	0.810***	0.804***

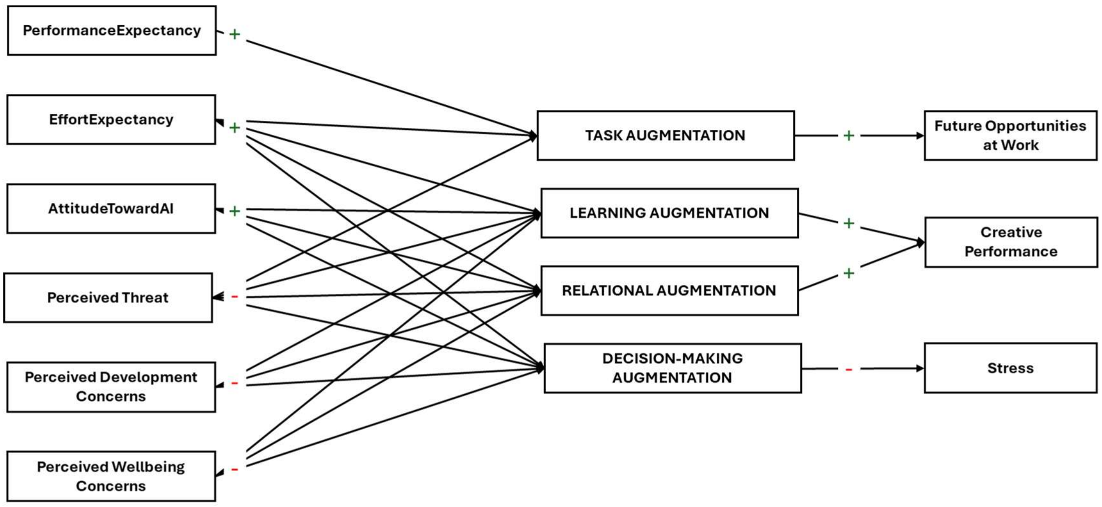
Note. Standardized Regression Coefficient are reported. *p < 0.05. **p < 0.01. ***p < 0.001.

Study 5: Nomological network

The sixth and final stage is to test the nomological network of AI Augmented Crafting dimensions, including antecedents and potential outcomes. The tested model is presented in Figure 4.

Figure 4

Representation of the tested paths derived from the research hypotheses.



Task Augmentation

Expected Antecedents. With Task Augmentation, workers approach AI as a valuable resource that enables individuals to perform tasks more efficiently and effectively, either by saving time or by improving the quality of output. Workers who perceive AI tools as useful for enhancing their performance are therefore more likely to adopt them as companions in task completion. Furthermore, perceiving the tool as easy to use may strengthen the belief that AI serves as a time-saver, allowing workers to maintain a positive balance between effort invested and benefits gained. Based on this reasoning, we expect that Performance Expectancy and Effort Expectancy will be both positively associated with Task Augmentation. In contrast, when AI is perceived as dangerous or harmful, workers may be discouraged from using it to complete tasks. In such cases, attention is directed more toward potential losses (Kahneman & Tversky, 1979) than toward the anticipated efficiency and effectiveness gains. Accordingly, we hypothesize that Perceived Threat will be negatively associated with Task Augmentation.

Hypothesis 1a. Performance Expectancy and Effort Expectancy are positively related, whereas Perceived Threat is negatively related to Task Augmentation.

Expected Outcomes. The use of AI to augment work tasks can serve as a valuable resource, helping employees address job demands more efficiently and effectively, with immediate benefits. For example, employing AI to complete tasks can save workers time (Do et al., 2020; Elmsellem et al., 2025; Uhunoma, n.d.; Wang et al., 2025). With the introduction of this new resource, employees may find more opportunities for their future, gaining valuable support to meet workplace demands (Bakker & Demerouti, 2007; Rudolph et al., 2018). Based on this reasoning, we hypothesize that higher level of Task Augmentation will be positively associated with Future Opportunities at Work.

Hypothesis 1b. Task Augmentation is positively related to Future Opportunities at Work.

Learning Augmentation

Expected Antecedents. In the context of Learning Augmentation, workers may employ AI to enhance their knowledge and skills, thereby deriving personal benefits from the interaction. Research on the adoption of learning-oriented systems has shown that Effort Expectancy is a key determinant of adoption (Fazi et al., 2025). Moreover, positive attitudes toward such systems have been found to strengthen the intention to use them (Blut et al., 2022). Accordingly, we predict that Effort Expectancy and Attitude Toward AI will be positively related to Learning Augmentation. Conversely, concerns about the potential harmfulness of AI systems, as well as their possible negative effects on personal development and wellbeing, may discourage workers from using AI for learning purposes(Cao et al., 2021). In line with risk avoidance theory (Kahneman & Tversky, 1979), perceiving high risks to one's development or wellbeing could reduce willingness to engage with AI in this domain. Therefore, we expect that Perceived Threat, Perceived Wellbeing Concerns, and Perceived Development Concerns will be negatively related to Learning Augmentation.

Hypothesis 2a. Effort Expectancy and Attitude Toward AI are positively related, whereas Perceived Threat, Perceived Wellbeing Concerns and Perceived Development Concerns are negatively related to Learning Augmentation.

Expected Outcomes. Through Learning Augmentation, workers can acquire valuable resource, such as knowledge and skills, that can be invested in the future to meet job demands (Bakker & Demerouti, 2007). Furthermore, using AI as a tool that provides learning stimuli may serve as an enabler of divergent thinking and novel solutions (Jia et al., 2024; Raisch & Krakowski, 2021). Since learning and resources are a fundamental driver of creativity (Gong et al., 2009), AI can be a valuable resource for acquiring knowledge that enables workers to approach problems in new ways (Raisch & Fomina, 2025) and to generate original ideas (Raisch & Krakowski, 2021). Therefore, we expect that greater use of AI as a learning companion will be positively associated with workers' creative performance in the workplace.

Hypothesis 2b. Learning Augmentation is positively related to Creative Performance.

Relational Augmentation

Expected Antecedents. Similar to Learning Augmentation, the use of AI for relational purposes may enable workers to obtain personal benefits, such as expanding their professional networks or fostering positive workplace relationships. This holds true only if the effort required and the negative emotions associated with using AI do not outweigh the perceived benefits; otherwise, workers may be discouraged from relying on AI to enhance their work relationships. Accordingly, we expect that Effort Expectancy and Attitude Toward AI will be positively related to Relational Augmentation. Conversely, perceiving AI as a threat to one's development or wellbeing in the workplace may inhibit its use for relational purposes. Therefore, we expect that Perceived Threat, Perceived Wellbeing Concerns, and Perceived Development Concerns will be negatively related to Relational Augmentation.

Hypothesis 3a. Effort Expectancy and Attitude Toward AI are positively related, whereas Perceived Threat, Perceived Wellbeing Concerns and Perceived Development Concerns are negatively related to Relational Augmentation.

Expected Outcomes. As with Learning Augmentation, the use of AI for relational purposes may enable workers to acquire resources, such as professional networks or positive workplace relationships, that can be invested in the future to cope with job demands (Bakker & Demerouti, 2007). Also, finding new stimuli and ideas from others might help workers to come out with different ideas theirselves (Fetrati & Nielsen, 2018). In this sense, workers who use AI for Relational Augmentation might gain good relationships to be used in gaining stimuli to solve problems and generate creative ideas. Therefore, we argue that higher level of Relational Augmentation will be positively associated with workers' creative performance in the workplace.

Hypothesis 3b. Relational Augmentation is positively related to Creative Performance.

Decision Making Augmentation

Expected Antecedents.

Cao et al. (2021), within the IAAAM framework, examined ten potential antecedents of workers' intentions to adopt organization-implemented AI for decision making. Four antecedents, such that attitude toward AI, perceived development concerns, perceived well-being concerns, and perceived threat, significantly predicted intention to use AI for decision making. Consistent with these findings, we treat these dimensions as antecedents of Decision Making Augmentation. Specifically, we expect attitude toward AI to be positively associated with, whereas perceived development concerns, perceived well-being concerns, and perceived threat to be negatively associated with Decision Making Augmentation. Moreover, unlike Cao et al. (2021), our construct of Decision-Making Augmentation captures proactive AI use even when AI has not been formally implemented by the organization. Because perceived ease of use is a key determinant of users' adoption decisions (Blut et al., 2022), we hypothesize a positive association between effort expectancy and Decision Making Augmentation.

Hypothesis 4a. Effort Expectancy and Attitude Toward AI are positively related, whereas Perceived Threat, Perceived Wellbeing Concerns and Perceived Development Concerns are negatively related to Decision Making Augmentation.

Expected Outcomes. Decision making is effortful and can elicit ego depletion, resulting in decision fatigue (Pignatiello et al., 2020). When faced with demanding choices, employees may use

AI tools as a coping resource that offloads cognitive effort and, in turn, reduces stress; accordingly, we hypothesize that greater use of AI for decision-making will be associated with lower stress.

Hypothesis 4b. Decision Making Augmentation is negatively related to stress.

Method

To test our hypotheses, we collected data at three time points, each separated by a time lag of approximately three to four weeks. Data were collected anonymously from employees across multiple organizations using an online questionnaire. To match responses from the same participants across different time points, participants were asked to generate a unique code consisting of the first two letters of their mother's name, the last three digits of their phone number, and their birth month in numerical form. We invited 1,270 employees to take part in the study. Of these, 443 completed the survey at T1, 393 at T2, and 335 at T3. A total of 151 participants completed the survey at all three time points. To ensure data quality, two attention check items were included. Only participants who answered both items correctly were included in the final sample. Finally, 142 out of 151 participants met this criterion and were included in the analysis. Of the final sample, 92% of participants were employed in the public administration sector, while 8% worked in the service sector. The sample was 58.9 % (77) female, with an average age of 49.8 years (SD = 9.99).

Performance expectancy (α = .69), effort expectancy (α = .87), attitude toward using AI (α = .50), perceived threat (α = .73), personal development concerns (α = .63), and personal wellbeing concerns (α = .73) were measured using the AI Acceptance-Avoidance Model (IAAAM) scale developed by Cao et al. (2021), with items rated on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Creative performance (α = .94) was assessed using the 4-item scale from Zhou and George (2001) measure of this construct, also rated on a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). Stress (α = .70) was measured using the 4-item scale adapted from Mondo et al. (2021), with responses ranging from 0 (never) to 5 (very often). Future

Opportunities at Work was measured using the four items from Zacher and Frese (2009), with responses ranging from 1 (does not apply at all) to 7 (applies completely).

Results

A path analysis was conducted using Jamovi 2.3.28 software, to examine the effects of the proposed antecedents on the dimensions of AI Augmented Crafting, as well as the effects of these dimensions on the expected outcomes. The hypothesized model shows acceptable fit ($\chi2$ = 70.1, df = 33, $\chi2$ / df = 2.12, CFI = 0.92, TLI = 0.86, RMSEA = 0.089, SRMR = 0.076).

Task Augmentation. According to H1a, performance expectancy (B = 0.16, SE = 0.05, β = 0.22, z = 3.42, $p < .001$) and effort expectancy (B = 0.18, SE = 0.05, β = 0.27, z = 3.43, $p < .001$) were both positively and significantly related to task augmentation. Differently, perceived threat (B = -0.13, SE = 0.05, β = -0.21, z = -2.67, $p < .01$) was negatively and significantly related to task augmentation. Task Augmentation was significantly and positively related to Future Opportunities at Work (B = 0.24, SE = 0.08, β = 0.23, z = 2.94, $p < .01$). Thus, Hypothesis 1a was supported while Hypothesis 1b was supported.

Leaning Augmentation. According to H2a, effort expectancy (B = 0.12, SE = 0.05, β = 0.24, z = 2.68, $p < .01$) was found significantly positive related, while perceived wellbeing concerns (B = -0.11, SE = 0.04, β = -0.21, z = -2.56, $p < .05$) was found significantly negative related to Learning Augmentation. No significant relations were found between attitude toward AI, perceived threat, perceived development concerns and Learning Augmentation. Thus, H2a was partially supported. According to H2b, Learning Augmentation was positively and significantly related to creative performance (B = 0.53, SE = 0.15, β = 0.32, z = 3.56, $p < .001$). Thus, H2b was supported.

Relational Augmentation. According to H3a, perceived threat (B = -0.08, SE = 0.02, β = -0.32, z = -3.02, $p < .01$) was found significantly negative related to Relational Augmentation. No significant relationship was found between the other hypothesized antecedents and Relational Augmentation, thus resulting in partial support for H3a. No support was found for H3b.

Decision Making Augmentation. According to H4a, effort expectancy (B = 0.14, SE = 0.06, β = 0.21, z = 2.46, $p < .05$) was found significantly positive related, while perceived wellbeing concerns (B = -0.13, SE = 0.05, β = -0.19, z = -2.73, $p < .01$) and perceived threat (B = -0.12, SE = 0.06, β = -0.19, z = -2.11, $p < .05$) were found significantly negative related to Decision Making Augmentation. No significant relationship was found for attitude toward AI and perceived development concerns. Thus, H4a was partially supported. Finally, Decision Making Augmentation was found not significantly related to stress. Thus, H4b was not supported.

Supplementary analyses

In this section, we provide supplementary information on the psychometric properties of the AIAC scale.

Frequencies

Frequencies are calculated based on the time-lagged data from Study 5. Average frequencies for each AI use behavior are reported in Table 9. All behaviors showed mean scores below 2 on a scale from 1 (never) to 5 (always), indicating that the phenomenon is still in its early stages. This result may also be influenced by the composition of Study 5, which was conducted primarily within the public administration sector (92% of the sample). The most frequently reported behaviors were T4 - "I use AI to complete my tasks faster (e.g., reading and summarizing PDF documents)", DM1 – "I use AI to gain insights that inform my decisions (e.g., asking it to analyze data)" and LA1 – "I use AI to stay updated with the latest developments and knowledge in my field". Conversely, the least frequently reported behaviors were LA3 – "I use AI to receive feedback on my performance (e.g., asking for feedback on my outputs)" and RA3 – "I use AI to improve my social image (e.g., seeking suggestions on how to behave in social situations)". Given our aim to comprehensively capture diverse AI use behaviors, we retained all items, as each represents a distinct behavior that can be expressed using AI.

Table 9

Frequencies and over time correlations of use behaviors items in the study 6.

Item	Average frequency each time point (from 1-never to 5-always)	Correlation between T1 and T2	Correlation between T2 and T3	Correlation between T1 and T3
TA1	1.41	0.72**	0.62**	0.49**
TA2	1.55	0.52**	0.53**	0.48**
TA3	1.60	0.64**	0.66**	0.57**
TA4	1.71	0.79**	0.59**	0.61**
DM1	1.64	0.70**	0.63**	0.66**
DM2	1.50	0.67**	0.54**	0.54**
DM3	1.52	0.81**	0.52**	0.53**
DM4	1.37	0.62**	0.57**	0.54**
LA1	1.80	0.69**	0.60**	0.56**
LA2	1.52	0.72**	0.53**	0.51**
LA3	1.19	0.67**	0.42**	0.48**
RA1	1.50	0.57**	0.32**	0.21**
RA2	1.51	0.51**	0.55**	0.49**
RA3	1.18	0.68**	0.59**	0.58**

Note. *$p < 0.05$. **$p < 0.01$. ***$p < 0.001$.

Stability

Information on the stability of each AI use behavior over time is presented in Table 9. For each behavior, we calculated correlations between T1 and T2, T2 and T3, and T1 and T3. All behaviors showed significant correlations across the three time points, indicating that they are stable over time. In other words, respondents who use AI for a given purpose tend to continue using it for that same purpose, whereas those who do not use AI for a given purpose generally maintain that pattern as well.

Variance explained by the 14 use behaviors

Following prior research on validating formative indicators (Zhou et al., 2017) and on technology adoption and use (Blut et al., 2022; Venkatesh, 2022), we examined the extent to which the 14 AI use behaviors included in the AIAC account for overall AI use. This analysis allowed us to assess how comprehensively the AIAC indicators capture the broader phenomenon of AI use. It also enabled us to derive indicator weights for re-testing the nomological network and evaluating the robustness of our findings (Zhou et al., 2017). To do so, we combined data from Study 2, Study 3, and Study 4 (N = 2016), in which participants reported how frequently they use AI at work on a scale ranging from 1 (never) to 7 (always). We then regressed overall AI use frequency on all 14 AIAC behaviors simultaneously. The results indicated that the full set of AIAC indicators explained a significant proportion of variance in AI use ($F(14, 1999) = 161$, $p < .001$, $R^2 = .53$). The unstandardized regression coefficients from this model were used as indicator weights to re-test the nomological network in Study 5.

Nomological network test using weighted scores

Using the weights obtained from the regression analysis, we computed weighted scores for all AIAC indicators in the Study 5 sample. Based on these weighted indicator scores, we then calculated the four AIAC dimension scores (i.e., TA, DM, LA, RA). Next, we re-tested the nomological network using the Study 5 data. Across all weighting schemes, the results remained fully consistent with our original findings.

Discussion

The aim of this paper was to develop and validate a measure for assessing employees' proactive use of AI in the workplace. Drawing on job crafting theory and on workers' reported AI-use behaviors, we introduce AI Augmented Crafting and its corresponding measure. The AI Augmented Crafting scale was tested across five field studies to assess its content, factorial, discriminant, convergent, and predictive validity, in line with best practices for developing formative measures.

Contributions for research

The AI Augmented Crafting questionnaire makes it possible to assess how workers proactively use AI to adapt their tasks and empower themselves within the organizational context, opening up new avenues for research. First, the AI Augmented Crafting questionnaire enables researchers to move beyond the traditional binary view of AI use ('use versus non-use'), which has dominated the literature, and instead capture a more nuanced understanding of how employees engage with AI in practice. This is particularly relevant in light of emerging AI technologies, which afford diverse forms of use behaviors among employees. Second, by distinguishing among different types of AI use, the questionnaire allows researchers to refine their hypotheses and better identify the specific behaviors involved, along with their antecedents and potential outcomes. In this sense, the AI Augmented Crafting enables more in-depth analyses both within and between levels, allowing researchers to explore how factors such as industry sector and country context shape employees' proactive engagement with AI. Third, the scale can help uncover how the same AI use behaviors may lead to different outcomes in different contexts. Prior research has shown that workers use AI tools for a variety of purposes (Handa et al., 2025; Shao et al., 2025), but it has often struggled to provide clear insights into the impacts of these different behaviors. The AI Augmented Crafting questionnaire offers a valid tool in this regard, enabling researchers to measure and compare the differential effects of various types of AI use on relevant outcomes. Fourth, the AI Augmented Crafting questionnaire allows researchers to account for use behaviors that, even if they are not the main focus of a study, may still influence the results and should therefore be considered as control variables. When examining the effects of AI use, research on technology adoption and use highlights the importance of considering how familiar workers already are with technology tools (Blut et al., 2022; Shao et al., 2024). Workers' confidence in using AI can, for example, affect their readiness to adopt additional tools or explore other functionalities. Our scale provides a way to capture this dimension, helping researchers control for its potential impact. Fifth, our scale captures the goals that employees pursue when interacting with AI tools, as well as their corresponding usage behaviors. This represents an important contribution to the literature on proactive work behaviors, such as job crafting. Specifically, these AI-enabled behaviors can be understood as a form of approach-oriented resource crafting, uniquely facilitated by AI tools.

Contributions for practice

The AI Augmented Crafting questionnaire is a valuable tool for supporting the organizational management of AI. First, the scale can help assess the diffusion of AI tools within organizational boundaries, providing insight into how employees' goals and tasks align with AI applications. This information can guide organizations in making more informed investment decisions, for example, choosing to implement new AI solutions where they address specific needs, or avoiding unnecessary spending when employees are already meeting those needs with freely available tools. Second, assessing the different types of AI use among employees is a valuable input for organizational risk management. It enables organizations to consider not only the opportunities AI offers but also the potential risks, such as privacy and ethical concerns, that may arise from specific use behaviors. Third, the AI Augmented Crafting questionnaire enables organizations to evaluate differences in proactive AI use across employees, departments, roles, and other relevant areas. This insight is valuable for both IT managers, who need to optimize technology-related costs, and HR managers, who can design targeted interventions to encourage AI use based on employees' actual behaviors. Fourth, organizations can use the AI Augmented Crafting questionnaire to better understand how different types of AI use relate to important job outcomes, such as creative performance, allowing them to steer AI adoption in ways that align with their strategic goals.

Limitations and future research

The article provides an initial validation of AI Augmented Crafting questionnaire. It is important to acknowledge limitations that future research can address. First, although we used multiple samples to test different aspects of validity, three out of five samples consisted primarily of public administration employees, which may limit the generalizability of our findings. Additionally, all participating organizations were based in Italy. We therefore recommend that future studies replicate our results and further validate the scale across different sectors and countries. Second, we measured outcomes using self-report scales, which are subject to biases such as social desirability (Fisher et al., 2024). Although this is a common practice in scale validation (MacKenzie et al., 2011; Parent-Rocheleau et al., 2024), future research should replicate the expected outcomes of the AIAC using alternative measurement approaches. Third, we found that among the four AI Augmented Crafting dimensions, only Learning Augmentation and Task Augmentation was related to outcomes. We didn't find significant relationship between Decision Making Augmentation, Relational Augmentation and hypothesized outcomes. This may be due to several reasons. Some of the outcomes we examined, such as stress, may not be directly or immediately linked to AI Augmented Crafting. Using AI tools can involve a certain level of complexity that may delay its benefits. In other words, the advantages of using AI may not be immediately felt and may depend on other factors, such that the user's level of experience with the technology. For example, an employee approaching AI tools for the first time may initially struggle to understand how they work and therefore may not experience short-term gains in stress reduction, unlike a more experienced user. Because AI Augmented Crafting is still emerging within organizations, more time may be required for its effects to materialize. This is also confirmed by the average level of AI use in our samples, that was low (below 2 on a scale from 1 = "never" to 5 = "always"). This suggests a relatively limited diffusion of AI tools in Italian organizations, particularly in public administration. For our study, this created additional difficulty in detecting potential effects of AI Augmented Crafting and likely reduced statistical power when examining associations between usage behaviors and outcomes. We encourage future research to clarify these relationships in contexts where AI usage is more widespread and frequent.

References

Bakker, A. B., & Demerouti, E. (2007). The job demands-resources model: State of the art. *Journal of Managerial Psychology*, *22*(3), 309–328.

Blut, M., Chong, A. Y. L., Tsiga, Z., & Venkatesh, V. (2022). *Meta-analysis of the unified theory of acceptance and use of technology (UTAUT): Challenging its validity and charting a research agenda in the red ocean*.

Boussioux, L., Lane, J. N., Zhang, M., Jacimovic, V., & Lakhani, K. R. (2024). The crowdless future? Generative AI and creative problem-solving. *Organization Science*, *35*(5), 1589–1607.

Bruning, P. F., & Campion, M. A. (2018). A role–resource approach–avoidance model of job crafting: A multimethod integration and extension of job crafting theory. *Academy of Management Journal*, *61*(2), 499–522.

Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Lee Cooke, F., Decker, S., & DeNisi, A. (2023). Human resource management in the age of generative artificial intelligence: Perspectives and research directions on ChatGPT. *Human Resource Management Journal*, *33*(3), 606–659.

Cao, G., Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2021). Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. *Technovation*, *106*, 102312.

Carstensen, L. L., Isaacowitz, D. M., & Charles, S. T. (1999). Taking time seriously: A theory of socioemotional selectivity. *American Psychologist*, *54*(3), 165.

Chari, P., Pease, C., Raskar, R., & Challapally, A. (2025). *The GenAI Divide: State of AI in Business 2025* (MIT Project NANDA). MIT. https://mlq.ai/media/quarterly_decks/v0.1_State_of_AI_in_Business_2025_Report.pdf?utm_source=chatgpt.com

Chowdhury, S., Budhwar, P., Dey, P. K., Joel-Edgar, S., & Abadie, A. (2022). AI-employee collaboration and business performance: Integrating knowledge-based view, socio-technical systems and organisational socialisation framework. *Journal of Business Research*, *144*, 31–49.

Cole, D. A., & Maxwell, S. E. (2003). Testing mediational models with longitudinal data: Questions and tips in the use of structural equation modeling. *Journal of Abnormal Psychology*, *112*(4), 558.

Colquitt, J. A., Sabey, T. B., Rodell, J. B., & Hill, E. T. (2019). Content validation guidelines: Evaluation criteria for definitional correspondence and definitional distinctiveness. *Journal of Applied Psychology*, *104*(10), 1243.

Do, H. M., Spear, L. G., Nikpanah, M., Mirmomen, S. M., Machado, L. B., Toscano, A. P., Turkbey, B., Bagheri, M. H., Gulley, J. L., & Folio, L. R. (2020). Augmented Radiologist Workflow Improves Report Value and Saves Time: A Potential Model for Implementation of Artificial Intelligence. *Special Issue: Artificial Intelligence*, *27*(1), 96–105. https://doi.org/10.1016/j.acra.2019.09.014

ELMSELLEM, H., ESSADKI, S., EL KHALLOUKI, R., LAMSYAH, R., HAJJAJI, W., & BOUGHOUFA, R. (2025). Artificial Intelligence and Productivity: Essential Tools to Save Time. *International Journal*, *6*(1), 240–253.

Esplugas, M. (2023). The use of artificial intelligence (AI) to enhance academic communication, education and research: A balanced approach. *Journal of Hand Surgery (European Volume)*, *48*(8), 819–822.

Fetrati, M. A., & Nielsen, A. P. (2018). The association between creativity and innovation: A literature review. *ISPIM Conference Proceedings*, 1–14.

Fisher, R. J., Rawal, S., Hochstein, B., & Plouffe, C. R. (2024). Development and validation of the SDR-O: A new measure of socially desirable responding in organizations. *Personality and Individual Differences*, *222*, 112597.

Gagné, M., Forest, J., Gilbert, M.-H., Aubé, C., Morin, E., & Malorni, A. (2010). The motivation at work scale: Validation evidence in two languages. *Educational and Psychological Measurement*, *70*(4), 628–646.

Ganster, D. C. (2005). Executive job demands: Suggestions from a stress and decision-making perspective. *Academy of Management Review*, *30*(3), 492–502.

Gaube, S., Suresh, H., Raue, M., Merritt, A., Berkowitz, S. J., Lermer, E., Coughlin, J. F., Guttag, J. V., Colak, E., & Ghassemi, M. (2021). Do as AI say: Susceptibility in deployment of clinical decision-aids. *NPJ Digital Medicine*, *4*(1), 31.

Gong, Y., Huang, J.-C., & Farh, J.-L. (2009). Employee learning orientation, transformational leadership, and employee creativity: The mediating role of employee creative self-efficacy. *Academy of Management Journal*, *52*(4), 765–778.

Grote, G., Parker, S. K., & Crowston, K. (2024). Taming artificial intelligence: A theory of control-accountability alignment among AI developers and users. *Academy of Management Review*, *ja*, amr. 2023.0117.

Handa, K., Tamkin, A., McCain, M., Huang, S., Durmus, E., Heck, S., Mueller, J., Hong, J., Ritchie, S., & Belonax, T. (2025). Which economic tasks are performed with ai? Evidence from millions of claude conversations. *arXiv Preprint arXiv:2503.04761*.

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

Hostetter, C., & Rodríguez Abitia, G. (2025). *The Future of Networking: AI's Potential to Augment Professional Networking*.

Hu, L., & and Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Jarvis, C. B., MacKenzie, S. B., & Podsakoff, P. M. (2003). A critical review of construct indicators and measurement model misspecification in marketing and consumer research. *Journal of Consumer Research*, *30*(2), 199–218.

Jia, N., Luo, X., Fang, Z., & Liao, C. (2024). When and how artificial intelligence augments employee creativity. *Academy of Management Journal*, *67*(1), 5–32.

Jo, H. (2023). Understanding AI tool engagement: A study of ChatGPT usage and word-of-mouth among university students and office workers. *Telematics and Informatics*, *85*, 102067.

Jo, H., & Park, D.-H. (2024). AI in the workplace: Examining the effects of ChatGPT on information support and knowledge acquisition. *International Journal of Human–Computer Interaction*, *40*(23), 8091–8106.

Kahneman, D., & Tversky, A. (2013). Prospect theory: An analysis of decision under risk. In *Handbook of the fundamentals of financial decision making: Part I* (pp. 99–127). World Scientific.

Kerr, S., & Jermier, J. M. (1978). Substitutes for leadership: Their meaning and measurement. *Organizational Behavior and Human Performance*, *22*(3), 375–403.

Khosravi, M., Zare, Z., Mojtabaeian, S. M., & Izadi, R. (2024). Artificial Intelligence and Decision-Making in Healthcare: A Thematic Analysis of a Systematic Review of Reviews. *Health Services Research and Managerial Epidemiology*, *11*, 23333928241234863. https://doi.org/10.1177/23333928241234863

Klonek, F., & Parker, S. (2025). Does AI at Work Increase Stress? Text Mining Social Media About Human–AI Team Processes and AI Control. *Journal of Organizational Behavior*.

Kumar, K. S., Srihari, P., & Raman, C. J. (2024). AI for Career Growth: Advanced Resume Analysis and LinkedIn Scraping for Personalized Job Recommendations. *2024 2nd International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS)*, 1287–1293.

Li, W., Qin, X., Yam, K. C., Deng, H., Chen, C., Dong, X., Jiang, L., & Tang, W. (2024). Embracing artificial intelligence (AI) with job crafting: Exploring trickle-down effect and employees' outcomes. *Tourism Management*, *104*, 104935.

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, *151*, 90–103.

MacKenzie, S. B., Podsakoff, P. M., & Jarvis, C. B. (2005). The problem of measurement model misspecification in behavioral and organizational research and some recommended solutions. *Journal of Applied Psychology*, *90*(4), 710.

MacKenzie, S. B., Podsakoff, P. M., & Podsakoff, N. P. (2011). Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques. *MIS Quarterly*, 293–334.

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research*, *120*, 262–273.

Man Tang, P., Koopman, J., McClean, S. T., Zhang, J. H., Li, C. H., De Cremer, D., Lu, Y., & Ng, C. T. S. (2022). When conscientious employees meet intelligent machines: An integrative approach inspired by complementarity theory and role theory. *Academy of Management Journal*, *65*(3), 1019–1054.

Mondo, M., Sechi, C., & Cabras, C. (2021). Psychometric evaluation of three versions of the Italian Perceived Stress Scale. *Current Psychology*, *40*(4), 1884–1892.

Morgeson, F. P., & Humphrey, S. E. (2006). The Work Design Questionnaire (WDQ): Developing and validating a comprehensive measure for assessing job design and the nature of work. *Journal of Applied Psychology*, *91*(6), 1321.

Oppioli, M., Sousa, M. J., Sousa, M., & de Nuccio, E. (2023). The role of artificial intelligence for management decision: A structured literature review. *Management Decision*.

Parent-Rocheleau, X., Parker, S. K., Bujold, A., & Gaudet, M.-C. (2024). Creation of the algorithmic management questionnaire: A six-phase scale development process. *Human Resource Management*, *63*(1), 25–44.

Parker, S. K., Trezise, M., & Thomas, C. S. (2025). Healthier Work in the Age of AI: An

Application of the SMART Work Design Model. In *Unlocking Sustainable Wellbeing in the Digital Age: New Avenues for Research and Practice* (pp. 15–31). Springer.

Petter, S., Straub, D., & Rai, A. (2007). Specifying formative constructs in information systems research. *MIS Quarterly*, 623–656.

Pignatiello, G. A., Martin, R. J., & Hickman Jr, R. L. (2020). Decision fatigue: A conceptual analysis. *Journal of Health Psychology*, *25*(1), 123–135.

Raisch, S., & Fomina, K. (2025). Combining human and artificial intelligence: Hybrid problem-solving in organizations. *Academy of Management Review*, *50*(2), 441–464.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, *46*(1), 192–210.

RM, H., & Jacob, J. (2017). Promotional support: A formative scale development. *International Journal of Pharmaceutical and Healthcare Marketing*, *11*(1), 97–110.

Rudolph, C. W., Kooij, D. T., Rauvola, R. S., & Zacher, H. (2018). Occupational future time perspective: A meta-analysis of antecedents and outcomes. *Journal of Organizational Behavior*, *39*(2), 229–248.

Shao, Y., Huang, C., Song, Y., Wang, M., Song, Y. H., & Shao, R. (2024). Using augmentation-based AI tool at work: A daily investigation of learning-based benefit and challenge. *Journal of Management*, 01492063241266503.

Shao, Y., Zope, H., Jiang, Y., Pei, J., Nguyen, D., Brynjolfsson, E., & Yang, D. (2025). Future of Work with AI Agents: Auditing Automation and Augmentation Potential across the US Workforce. *arXiv Preprint arXiv:2506.06576*.

Tanaka, R., Nishida, K., & Yoshida, S. (2021). Visualmrc: Machine reading comprehension on document images. *Proceedings of the AAAI Conference on Artificial Intelligence*, *35*(15), 13878–13888.

Tang, X., Li, X., Ding, Y., Song, M., & Bu, Y. (2020). The pace of artificial intelligence innovations: Speed, talent, and trial-and-error. *Journal of Informetrics*, *14*(4), 101094.

Toderi, S., Balducci, C., Edwards, J. A., Sarchielli, G., Broccoli, M., & Mancini, G. (2013). Psychometric properties of the UK and Italian versions of the HSE stress indicator tool. *European Journal of Psychological Assessment*.

Uhunoma, E. (n.d.). *From Hours to Minutes: The Impact of Generative AI on Work Turnaround Time and Productivity*.

Ulfert, A.-S., Antoni, C. H., & Ellwart, T. (2022). The role of agent autonomy in using decision support systems at work. *Computers in Human Behavior*, *126*, 106987.

Vaccaro, M., Almaatouq, A., & Malone, T. (2024). When combinations of humans and AI are useful: A systematic review and meta-analysis. *Nature Human Behaviour*, *8*(12), 2293–2303.

Varma, A., Dawkins, C., & Chaudhuri, K. (2023). Artificial intelligence and people management: A critical assessment through the ethical lens. *Human Resource Management Review*, *33*(1), 100923.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Wang, J., Kiran, E., Aurora, S. R., Simeone, M., & Lobo, J. (2025). ChatGPT on ChatGPT: An exploratory analysis of its performance in the public sector workplace. *Digital Government: Research and Practice*, *6*(2), 1–28.

Wang, X., French, B. F., & Clay, P. F. (2015). Convergent and discriminant validity with formative measurement: A mediator perspective. *Journal of Modern Applied Statistical Methods*, *14*(1), 83–106.

Warr, P., Cook, J., & Wall, T. (1979). Scales for the measurement of some work attitudes and aspects of psychological well-being. *Journal of Occupational Psychology*, *52*(2), 129–148.

Wiesenberg, M., & Tench, R. (2020). Deep strategic mediatization: Organizational leaders' knowledge and usage of social bots in an era of disinformation. *International Journal of*

Information Management, *51*, 102042.

Wrzesniewski, A., & Dutton, J. (2001). Crafting a Job: Revisioning Employees as Active Crafters of Their Work. *Academy of Management Review*, *26*, 179–201. https://doi.org/10.2307/259118

Yang, F. X., Li, Y., Li, X., & Yuan, J. (2022). The beauty premium of tour guides in the customer decision-making process: An AI-based big data analysis. *Tourism Management*, *93*, 104575.

Yu, T., Yang, W., Xu, J., & Pan, Y. (2024). Barriers to industry adoption of AI video generation tools: A study based on the perspectives of video production professionals in China. *Applied Sciences*, *14*(13), 5770.

Zacher, H., & Frese, M. (2009). Remaining time and opportunities at work: Relationships between age, work characteristics, and occupational future time perspective. *Psychology and Aging*, *24*(2), 487.

Zhang, F., & Parker, S. K. (2019). Reorienting job crafting research: A hierarchical structure of job crafting concepts and integrative review. *Journal of Organizational Behavior*, *40*(2), 126–146.

Zhang, R., Zou, D., Cheng, G., & Xie, H. (2025). Flow in ChatGPT-based logic learning and its influences on logic and self-efficacy in English argumentative writing. *Computers in Human Behavior*, *162*, 108457.

Zhou, J., & George, J. M. (2001). When job dissatisfaction leads to creativity: Encouraging the expression of voice. *Academy of Management Journal*, *44*(4), 682–696.

Zhou, L., Wang, M., Chang, C.-H., Liu, S., Zhan, Y., & Shi, J. (2017). Commuting stress process and self-regulation at work: Moderating roles of daily task significance, family interference with work, and commuting means efficacy. *Personnel Psychology*, *70*(4), 891–922.

CHAPTER VI | General discussion

Key findings of the doctoral research

This doctoral work investigate the adoption and use of technology in the workplace, with particular attention to the shift from traditional digital technologies to new artificial intelligence tools, and to the role of end users in shaping their impact. I approached this topic by building on existing research, first examining technology adoption and then the way technology is used. In line with this progression, the first study of the thesis connected a well-established topic, technology adoption, with an urgent trend: demographic change in the workforce. Although technology adoption has been widely studied across disciplines, the role of age, especially within organizational contexts, is less clear. For this reason, the first study is a systematic literature review aimed at identifying the state of the art and future directions regarding the role of age in technology adoption at work. The findings highlighted several interesting issues, beginning with the observation that older workers tend to adopt new technologies less than younger workers. In fact, the literature shows substantial agreement on a negative relationship between age and technology adoption in the workplace. This is not a comfortable trend for two main reasons. On the one hand, organizations are becoming increasingly digitalized, and technology is now a key asset for most of them. On the other hand, the workforce is ageing: the proportion of older workers is rising in parallel with population ageing. This combination may have several implications. For example, organizations may fail to realize the full return on investment (ROI) of new technologies if older workers do not adopt them. Also, technology can reinforce differences, or even create polarization, between age groups, if younger workers adopt these tools while older workers do not, or do so to a lesser extent. Another key point is that some perceptions about technology have a similar impact across age groups, while others do not. For example, perceptions of how easy technology is to use (i.e., effort expectancy) tend to influence technology adoption in a similar way for workers of different ages. By contrast, beliefs that using the system will improve job performance (i.e., performance expectancy) has been found more relevant for younger workers, whereas beliefs about the organizational and technical support available to use that system (i.e., facilitating conditions) are more relevant for older workers. Drawing on well-established life-span theories, such as socioemotional selectivity theory (Carstensen et al., 1999) and the selection, optimization, and compensation theory (Baltes & Baltes, 1990), it is plausible to argue why these differences occur. Younger workers are likely to be more driven by performance expectancy, because their goals tend to be knowledge- and career-oriented, and they generally perceive a longer future time horizon (Carstensen et al., 1999). In contrast, older workers may place greater value on organizational and technical support, because it can function as a compensatory resource that helps them maintain effectiveness in the face of technological challenge (Baltes & Baltes, 1990). Despite their usefulness in explaining these differences, these theories may not capture the whole picture of the role of age on technology adoption. For example, they do not explain why these age-related differences are absent or less consistent for certain types of technology (e.g., e-learning systems) or in specific work contexts (e.g., shipping services). This highlights the need for greater integration between life-span theories and technology adoption theories to explain the role of age in technology adoption.

Investigating the role of age in technology adoption shows that the literature addresses this topic with a certain degree of consistency, although with divergent focuses and theoretical frameworks. By contrast, when looking at technology use behaviors, the research landscape is highly fragmented and lacks a shared foundation. For example, knowledge sharing, digital hoarding, and cyberbullying are all technology use behaviors, yet they are typically studied in separate domains, without a common framework. This specialization has clear benefits: it allows researchers to examine the specific mechanisms driving each individual behavior in depth, thereby improving understanding of each phenomenon on its own. However, the lack of an overarching, comprehensive view of technology use behavior, and the absence of common analytical drivers, makes it difficult to identify shared patterns and fundamental mechanisms that may underline the broader phenomenon. The second study in this thesis is a bibliographic systematic literature review that shifts the focus from technology adoption to technology use behaviors. Its aim is twofold: first, to identify limitations in how existing research approaches these phenomena; and second, to develop an integrative model to drive technology use behaviors. Grounded in theories of ethical behavior, this study offers a comprehensive analysis of the various technology use behaviors examined in the literature and articulates the assumptions that link these behaviors to individual responsibility in technology use. The findings show broad agreement in the literature about which behaviors are labeled as ethical (e.g., knowledge sharing) and which are labeled as unethical (e.g., cyberloafing). However, this clarity mostly reflects an organizational perspective. For instance, cyberloafing is typically considered unethical because it is framed as a misuse of working time. At the same time, studies also suggest that briefly disengaging from work through cyberloafing can have positive effects afterward, such as helping employees feel more engaged or more innovative. This suggests that the "unethical" label is not as straightforward as it appears. Relying primarily on the organizational point of view is useful in some ways. It simplifies the analysis and allows findings to be translated directly into managerial actions, for example through HR policies and practices. But focusing on a single stakeholder, the organization fails to capture the complexity of the context in which individuals actually operate (Green, 2021). It also overlooks individuals themselves, who are treated as meaningful moral agents across disciplines and sectors. Consistent with this organization-centered framing, study 2 found that the literature tends to focus on the antecedents of technology use behaviors and to classify those behaviors as ethical or unethical a priori. Much less attention is paid to the outcomes of those behaviors. Understanding antecedents is undeniably important, but this lack of attention to consequences leaves us without a clear view of the real impact of technology use behaviors on different actors (e.g., coworkers, suppliers). This gap becomes even more critical considering emerging AI tools, which can create complex, multi-actor effects that cannot be evaluated only from the employer's perspective.

In fact, with the rise of new AI tools, each worker now holds the power to generate unethical, ethical, or even exceptionally ethical outcomes through their own use of these tools. According to the model developed in study 2, the difference lies in individual choices, which should be guided by key ethical principles and by an awareness of the expected impacts of one's actions. Understanding AI use behaviors therefore becomes a necessary step for shifting the discussion toward individual agency and its consequences in AI use. Then, drawing on the findings from Studies 1 and 2, I developed Study 3. Study 1 showed that workers' decisions to adopt technology are shaped by their perceptions, with age playing a significant role. These decisions represent individual choices that create opportunities for action through technology. Study 2 builds on this insight by showing that technology enables diverse patterns of use behavior, reflecting bottom up expressions of agency within organizations. Taken together, the findings from Studies 1 and 2 informed Study 3, highlighting the need to anchor different forms of AI use in the job crafting literature, which conceptualizes work as being modified through bottom up, employee driven processes. Then, following established guidelines for the development of formative constructs, Study 3 introduces the concept of AI Augmented Crafting and develops a corresponding measurement scale, which is validated across five different field studies. AI Augmented Crafting, grounded in Job Crafting theory, is designed to capture the workers' enhancement of their own capabilities through the proactive and goal-directed use of AI tools to alter the work. Drawing on interviews with practitioners and on analyses of different forms of technology use behaviors identified in the literature, Study 3 identifies four distinct forms of AI Augmented Crafting. First, employees can use AI to directly enhance the efficiency, scope, or quality of tasks within a worker's role, also completing tasks without having skills to do it (i.e., Task Augmentation). This emerged as one of the most widespread forms of AI use in the organizations studied. Second, employees use AI to develop and refine job-relevant skills and knowledge. This is defined as Learning Augmentation, and it was also highly prevalent in the organizational contexts analyzed. Third, employees use AI to support and enhance the decision-making process (i.e., Decision Making Augmentation), another proactive form of AI use observed in the field. Fourth, employees use AI to strengthen interpersonal and collaborative aspects of work. This is referred to as Relational Augmentation. Compared to the other forms, this emerged less frequently and appears to represent an emerging pattern of AI use in organizations. These forms of proactive AI use behaviors allow us to observe the phenomenon directly at the level of individual choice expression, which can have multiple implications. For example, Study 3 shows that using AI for learning purposes is positively associated with employees' creative performance. This finding is consistent with prior work linking learning stimuli to creativity (Jia et al., 2024; Raisch & Krakowski, 2021). Moreover, the use of AI as a valuable resource to support work tasks also emerged as positively related to workers' perceptions of future opportunities at work. This suggests that employees view AI as a useful tool to help them manage job demands, not only in the present but also in the future. At the same time, each of these forms of AI use can generate a range of consequences, for the user, for coworkers, and for the organization more broadly, based on individual choices that are themselves influenced by various contextual and personal factors. Indeed, each use behavior may manifest under varying conditions, which can plausibly influence the nature and magnitude of the value created through human–AI interactions. For example, an employee may ask for an AI system to generate an output (e.g., a presentation slide deck or an Excel macro) either within or outside their area of expertise. When the task falls within the employee's expertise, the output remains largely under their control because they can evaluate, edit, and correct it. When the task lies outside their expertise, the output may be effectively outside their control, creating potentially unpredictable consequences for both the individual and the organization, including a decline in output quality (Lazar et al., 2025).

Building on this reasoning, there are two main human-agency factors that can shape whether different forms of AI use lead to positive or negative outcomes. The first factor is awareness, specifically, about what one is doing, and of what is (and is not) expected from the technology. Consistent with Study 2, technology use should be guided primarily by user awareness in order to reduce risk and promote responsible choices. This does not always mean being technically competent in using AI. Rather, it means being aware of one's own (non-)competence and acting accordingly. For example, an employee might ask an AI system to generate a report on a topic outside their area of expertise. This does not necessarily create negative consequences if the employee is consciously aware of their own lack of expertise and therefore treats the AI's output as something they cannot personally validate. In that case, they might seek external review instead of presenting the output as trustworthy. From this individual perspective, AI tools are valuable when they operate within the user's awareness system. The second factor, closely related to the first, is the individual's ability to use the tool in a way that keeps them within their zone of proximal development, that is, at a level of challenge that fosters learning through interaction. This enables users to activate learning processes not only about the task content but also about the tool itself. Maintaining this balance may prevent overreliance on the AI system and supports a progressively deeper understanding of how to manage the interaction effectively. In this sense, the AI Augmented Crafting dimensions offer an important representation of how individuals engage with AI tools. These dimensions should be integrated into a broader consideration of the personal and contextual mechanisms that shape the diverse outcomes of AI use behaviors.

Taken together, the three studies in this doctoral work highlight the central role of the individual in shaping human–technology interaction, from initial adoption to different forms of technology use. Individual characteristics, such as age, which is increasingly relevant given current demographic trends, emerge as important factors in technology adoption in the workplace. Much less is known, however, about how such characteristics influence different types of technology use behaviors, particularly in relation to AI tools. At present, the debate around technology use is fragmented. Different use behaviors are often studied in isolation, without a shared conceptual foundation, and frequently through a narrow lens, most commonly the organizational point of view. This perspective overlooks both individual agency and the broader ethical implications of everyday technology use. This doctoral work seeks to address that gap by proposing a new construct, called AI Augmented Crafting, and by developing and validating a corresponding measurement to capture how workers use AI in practice. The goal is that this construct will enable future research not only to examine the antecedents of AI use behaviors, but, more importantly, to investigate their consequences. Doing so is essential to inform, guide, and ultimately support more ethical, and potentially extraordinarily ethical, choices by individuals who are now operating in AI-powered work environments where they are directly accountable for the effects of their own use of AI.

Theoretical contributions

This doctoral work have several theoretical implications that contributes to the development of the field of human-technology interactions from both adoption and use behavior point of view. This work clarifies the role of individual characteristic, such that age, in technology adoption in the workplace, and provides a basis for formulating future research questions on this topic. In this regard, it extends the literature on technology adoption that considers workers' age by identifying the antecedents that appear to be shaped by this variable. In doing so, it integrates and refines existing theoretical models of technology adoption (e.g., TAM and UTAUT). At the same time, this dissertation argues that research should move beyond the adoption and pay greater attention to different forms of technology use behavior, which ultimately determine the value created in human–technology interaction. To do so, the dissertation bridges insights from multiple disciplines, including psychology and philosophy, in order to offer more meaningful guidance for the ethical use of technology in the workplace at the individual level. This interdisciplinary move responds to a need, discussed throughout the dissertation, to rethink responsibility for technology use as increasingly distributed rather than exclusively organizational. Also, this work advances theory on technology use behavior by arguing for the importance of studying use behaviors under a broader, unified lens. Such an approach is necessary not only to understand the antecedents of specific behaviors, but, more importantly, to capture their outcomes, that is their consequences for individuals, coworkers, and organizations. In this sense, the analysis in this dissertation shows that the same technology use behavior can generate very different effects for different stakeholders. This observation reinforces the need to ground the discussion in both key ethical principles and a more relativistic ethical stance, one that takes into account both utilitarian considerations (i.e., consequences and harm/benefit) and deontological considerations (i.e., duties and responsibilities).

This work offers an initial integration of these perspectives, which can be further developed and tested in future research. Recognizing the importance of different forms of technology use behavior, especially in an AI-driven context, this dissertation extends job crafting theory by integrating employees' proactive adaptation in the workplace with the new augmentation potential of Artificial Intelligence. In doing so, it introduces the concept of AI Augmented Crafting as a new form of crafting behavior enabled by AI technologies. This theoretical contribution also has a methodological implication: it supports the development of a measurement tool capable of capturing different types of AI use behaviors. Such a tool provides researchers with what is needed to observe, compare, and explain the effects of AI, a powerful technology now directly accessible to every individual more accurately employees across the organization.

Practical recommendations

The findings in this dissertation have important practical implications for organizations and workers across both the adoption and use stages of workplace technology. First, regarding technology adoption, the results suggest that older workers are less likely than younger workers to adopt new technologies. One possible explanation is that older workers may not see new technology as a useful means to help them achieve their work goals (Baltes & Baltes, 1990). This concern may be especially salient at the initial introduction stage of a new tool, when workers are required to change how they perform tasks they already know how to do well (Venkatesh et al., 2012). For older workers in particular, long experience has allowed them to develop effective task knowledge and strategies (Carstensen et al., 1999), so being asked to relearn those tasks through a new digital system may feel efficiency-reducing rather than efficiency-enhancing. These findings suggest that organizations should pay particular attention to supporting adoption across age groups, especially among older workers. Concretely, they should invest in resources that reduce perceived effort and threat (e.g., tailored training, clear communication of benefits, gradual onboarding), so that older workers can engage with new technologies as enablers rather than as risks. Second, different factors appear to matter more for different age groups when it comes to adopting new technology. For example, younger workers may be more influenced by their expectations of how well the technology will improve their performance, whereas older workers may be more influenced by the presence of supportive conditions (e.g., training, assistance) provided by the organization. Therefore, organizations should tailor both the support they offer and the way they communicate about new tools to the needs of different age cohorts, rather than assuming that the same approach will be equally effective for everyone. Third, accelerating adoption should not only increase use, but also ensure ethical, and ideally extraordinary ethical use, while preventing unethical behavior. For traditional technologies, much of this responsibility has rested with organizations, which could design and implement technologies, policies, and practices aimed at minimizing opportunities for harmful or irresponsible use. However, this becomes more complex with emerging AI tools. These tools are often used by individual employees in ways that are decentralized and not always directly monitored or controlled by the organization. In other words, the ethical risk often resides at the individual level and falls under each person's responsibility. Therefore, organizations may not be able to control every instance of technology use, but they can shape the conditions under which employees make choices. This means creating an environment in which workers are able to make informed, responsible decisions. Organizations should invest in clearly communicating core ethical principles and boundaries for acceptable use, and in raising awareness of how different patterns of use can affect different stakeholders (e.g., clients, co-workers, organization). Fourth, this work provides a tool that allows practitioners to assess how workers actively craft their work using AI. This information is valuable on its own, because it helps organizations understand how widely AI is being used, for what purposes, and by whom (e.g., across functions, roles, or departments). Beyond that, the tool also makes it possible to examine the different antecedents and outcomes associated with different use behaviors captured by AI Augmented Crafting. This can inform HR and IT departments in designing policies, practices, and interventions to guide, support, and manage AI use within the organization. Fifth, the AI Augmented Crafting framework can help workers become more aware of their own use behaviors, encouraging them to reflect on the specific actions they take and the higher-order goals they pursue through AI use (i.e., Task Augmentation, Decision-Making Augmentation, Learning Augmentation, and Relational Augmentation). This reflection is valuable not only for recognizing the diverse purposes that employees can pursue through these new tools to craft their work, but also for increasing their awareness of how and why they use AI. In turn, this heightened awareness can enable workers to make more informed, deliberate, and responsible decisions about their technology use.

Limitations and future research

This doctoral work has limitations that should be addressed by future research. Regarding technology adoption, the literature review examined the role of age, offering insight into how age influences antecedents of technology adoption and interpreting these effects through well-established life-span theories. However, the dissertation does not yet offer a full integration between life-span theories and technology adoption theories. Such an integration could better explain why certain variables are shaped by workers' age while others are not. For example, life-span theories can help explain why performance expectancy may matter differently for younger versus older workers, but they are less helpful in explaining why this difference sometimes does not appear in certain contexts or for specific technologies. Future research should therefore work toward a deeper theoretical integration of life-span perspectives and technology adoption models, in order to clarify when and why age affects particular determinants of adoption, and when it does not. Moving to the post-adoption phase, the exploration of different forms of use behavior generated informative findings about ethical use, resulting in an integrative model intended to guide individual technology use. The goal of the second study was to identify and articulate this model based on existing literature. However, the model was not yet operationalized or empirically tested, which remains a limitation. Moreover, while the model accounts for core ethical principles and considers the consequences of different use behaviors for multiple stakeholders, it does not incorporate other potentially relevant aspects. For instance, it does not distinguish between intrinsic motivation to act ethically and more utilitarian or extrinsically driven motivations. Future research should therefore refine and extend this model by integrating such motivational dimensions and then develop measures to operationalize and empirically test the model. Furthermore, by examining the different ways workers use AI to actively craft their work, this dissertation conceptualized, developed, and validated the AI Augmented Crafting. This contributes to both theory and practice by offering a structured way to approach a new phenomenon enabled by AI tools. However, this phenomenon appears to be still in its very early stages. In Study 3, the prevalence of AI use behaviors across the sample was relatively low, suggesting that many workers are not yet engaging with AI in a systematic way. This low base rate may have limited the ability to detect theoretically meaningful links between AI Augmented Crafting and its potential outcomes. Consistent with this, among the AI use behaviors investigated, only Learning Augmentation and Task Augmentation were associated with hypothesized outcomes. No significant relationships were found between the other dimensions (i.e., Decision Making Augmentation, Relational Augmentation) and the outcomes that were tested. There are at least two reasons why this may have happened. First, as noted, usage is still emerging; weak or inconsistent engagement with AI may dampen observable effects. Second, the outcomes examined, while relevant for work crafting more broadly (e.g., job satisfaction), may not be the most proximal outcomes for each specific AI Augmented Crafting dimension. For example, stress may not shift immediately in response to early-stage AI use. By contrast, Decision Making Augmentation might be more directly tied to outcomes such as perceived decision quality or confidence in decisions, outcomes that were not measured here but are theoretically closer to the behavior itself. Future research should continue to validate the AI Augmented Crafting framework in populations where AI use is more widespread and should examine outcomes that are more tightly aligned with each specific augmentation goal. This would help clarify not only whether AI Augmented Crafting matters, but how and for whom it matters. Taken together, this dissertation highlights the importance of individual responsibility and the different ways employees use AI in the workplace, and it offers both insight and a tool to measure these behaviors. However, it does not yet examine how awareness shapes AI Augmented Crafting. It also does not fully account for other factors that may influence the outcomes of these AI use behaviors, such as employees' level of expertise or the dynamics within their teams. Future research should investigate this phenomenon by integrating individual and social/contextual factors into models of AI Augmented Crafting and by testing how these elements jointly affect work outcomes.

REFERENCES

Acemoglu, D., Mühlbach, N. S., & Scott, A. J. (2022). The rise of age-friendly jobs. *The Journal of the Economics of Ageing*, *23*, 100416.

Ajzen, I. (1980). Understanding attitudes and predictiing social behavior. *Englewood Cliffs*.

Aksoy, Y., Basso, H. S., Smith, R. P., & Grasl, T. (2019). Demographic Structure and Macroeconomic Trends. In *American Economic Journal: Macroeconomics* (Vol. 11, Issue 1, pp. 193–222).

Al-Gahtani, S. S. (2008). Testing for the applicability of the tam model in the arabic context: Exploring an extended TAM with three moderating factors. *Information Resources Management Journal*, *21*(4), 1–26. https://doi.org/10.4018/irmj.2008100101

Atzenbeck, C., Nürnberg, P., & Roßner, D. (2021). Synthesising augmentation and automation. *New Review of Hypermedia and Multimedia*, *27*(1–2), 177–203.

Baabdullah, A. (2024). Generative conversational AI agent for managerial practices: The role of IQ dimensions, novelty seeking and ethical concerns. *TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE*, *198*. https://doi.org/10.1016/j.techfore.2023.122951

Baltes, P. B., & Baltes, M. M. (1990). Psychological perspectives on successful aging: The model of selective optimization with compensation. *Successful Aging: Perspectives from the Behavioral Sciences*, *1*(1), 1–34.

Blut, M., Chong, A. Y. L., Tsiga, Z., & Venkatesh, V. (2022). *Meta-analysis of the unified theory of acceptance and use of technology (UTAUT): Challenging its validity and charting a research agenda in the red ocean*.

Bresnahan, T. F., & Trajtenberg, M. (1995). General purpose technologies 'Engines of growth'? *Journal of Econometrics*, *65*(1), 83–108.

Brown, P., Daigneault, A., & Dawson, J. (2019). Age, values, farming objectives, past management decisions, and future intentions in New Zealand agriculture. *Journal of Environmental Management*, *231*, 110–120. https://doi.org/10.1016/j.jenvman.2018.10.018

Brown, S. A., Dennis, A. R., & Venkatesh, V. (2010). Predicting Collaboration Technology Use: Integrating Technology Adoption and Collaboration Research. *Journal of Management Information Systems*, *27*(2), 9–54. https://doi.org/10.2753/MIS0742-1222270201

Bruning, P. F., & Campion, M. A. (2018). A role–resource approach–avoidance model of job crafting: A multimethod integration and extension of job crafting theory. *Academy of Management Journal*, *61*(2), 499–522.

Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Lee Cooke, F., Decker, S., & DeNisi, A. (2023). Human resource management in the age of generative artificial intelligence: Perspectives and research directions on ChatGPT. *Human Resource Management Journal*, *33*(3), 606–659.

Cao, G., Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2021). Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. *Technovation*, *106*, 102312.

Carstensen, L. L., Isaacowitz, D. M., & Charles, S. T. (1999). Taking time seriously: A theory of socioemotional selectivity. *American Psychologist*, *54*(3), 165.

Davis, F. D. (1986). A technology acceptance model for empirically testing new end-user information systems. *Theory and Results/Massachusetts Institute of Technology*.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989a). Technology acceptance model. *J Manag Sci*, *35*(8), 982–1003.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989b). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*(8), 982–1003.

de Pedro, J. M. L. (2024). Social Systems as Moral Agents: A Systems Approach to Moral Agency in Business. *Journal of Business Ethics*, *195*(4), 695–711.

Demerouti, E., Bakker, A. B., Nachreiner, F., & Schaufeli, W. B. (2001). The job demands-resources model of burnout. *Journal of Applied Psychology*, *86*(3), 499.

Economic, D. of. (2024). *World Population Prospects 2024: Summary of Results*. Stylus

Publishing, LLC.

Everton, W. J., Mastrangelo, P. M., & Jolton, J. A. (2005). Personality correlates of employees' personal use of work computers. *CyberPsychology & Behavior*, *8*(2), 143–153.

Fasbender, U., Gerpott, F. H., & Rinker, L. (2023). Getting ready for the future, is it worth it? A dual pathway model of age and technology acceptance at work. *Work, Aging and Retirement*, *9*(4), 358–375.

Fishbein, M., & Ajzen, I. (1977). *Belief, attitude, intention, and behavior: An introduction to theory and research*.

Flanagin, A. J., & Waldeck, J. H. (2004). Technology use and organizational newcomer socialization. *The Journal of Business Communication (1973)*, *41*(2), 137–165.

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., & Rossi, F. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines*, *28*, 689–707.

Gilbert, C. G. (2005). Unbundling the structure of inertia: Resource versus routine rigidity. *Academy of Management Journal*, *48*(5), 741–763.

Green, B. (2021). The contestation of tech ethics: A sociotechnical approach to technology ethics in practice. *Journal of Social Computing*, *2*(3), 209–225.

Griffin, M. A., Neal, A., & Parker, S. K. (2007). A new model of work role performance: Positive behavior in uncertain and interdependent contexts. *Academy of Management Journal*, *50*(2), 327–347.

Handa, K., Tamkin, A., McCain, M., Huang, S., Durmus, E., Heck, S., Mueller, J., Hong, J., Ritchie, S., & Belonax, T. (2025). Which economic tasks are performed with ai? Evidence from millions of claude conversations. *arXiv Preprint arXiv:2503.04761*.

Hillebrand, L., Raisch, S., & Schad, J. (2025). Managing with artificial intelligence: An integrative framework. *Academy of Management Annals*, *19*(1), 343–375.

Hughes, H. P., Clegg, C. W., Bolton, L. E., & Machon, L. C. (2017). Systems scenarios: A tool for facilitating the socio-technical design of work systems. *Ergonomics*, *60*(10), 1319–1335.

Jia, N., Luo, X., Fang, Z., & Liao, C. (2024). When and how artificial intelligence augments employee creativity. *Academy of Management Journal*, *67*(1), 5–32.

Jo, H., & Park, D.-H. (2024). AI in the workplace: Examining the effects of ChatGPT on information support and knowledge acquisition. *International Journal of Human–Computer Interaction*, *40*(23), 8091–8106.

Jones, T. M. (1991). Ethical decision making by individuals in organizations: An issue-contingent model. *Academy of Management Review*, *16*(2), 366–395.

Joshi, P., Kononova, A., & Cotten, S. (2020). Understanding older adults' preferences for and motivations to use traditional and new ICT in light of socioemotional selectivity and selection, optimization, and compensation theories. *International Journal of Communication*, *14*, 20.

Kahneman, D. (2011). Fast and slow thinking. *Allen Lane and Penguin Books, New York*.

Kahneman, D., & Tversky, A. (1972). Subjective probability: A judgment of representativeness. *Cognitive Psychology*, *3*(3), 430–454.

Kallinikos, J., Aaltonen, A., & Marton, A. (2013). The Ambivalent Ontology of Digital Artifacts. *MIS Quarterly*, *37*(2), 357–370. JSTOR.

Kant, I. (1785). Groundwork of the Metaphysics of Morals (1785). *New Haven*.

Katz, D., & Kahn, R. L. (1978). *The social psychology of organizations* (Vol. 2). wiley New York.

Kelly, S., Kaye, S.-A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics*, *77*, 101925.

Khosravi, M., Zare, Z., Mojtabaeian, S. M., & Izadi, R. (2024). Artificial Intelligence and Decision-Making in Healthcare: A Thematic Analysis of a Systematic Review of Reviews. *Health Services Research and Managerial Epidemiology*, *11*, 23333928241234863. https://doi.org/10.1177/23333928241234863

Klonek, F., & Parker, S. (2025). Does AI at Work Increase Stress? Text Mining Social Media About Human–AI Team Processes and AI Control. *Journal of Organizational Behavior*.

Kouchaki, M., & Smith, I. H. (2024). Moral decision-making in organizations. *Annual Review of Organizational Psychology and Organizational Behavior*, *12*.

Lazar, M., Lifshitz, H., Ayoubi, C., & Emuna, H. (2025). Would Archimedes Shout "Eureka" with Algorithms? The Hidden Hand of Algorithmic Design in Idea Generation, the Creation of Ideation Bubbles, and How Experts Can Burst Them. *Academy of Management Journal*.

Li, W., Qin, X., Yam, K. C., Deng, H., Chen, C., Dong, X., Jiang, L., & Tang, W. (2024). Embracing artificial intelligence (AI) with job crafting: Exploring trickle-down effect and employees' outcomes. *Tourism Management*, *104*, 104935.

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, *151*, 90–103.

Man Tang, P., Koopman, J., McClean, S. T., Zhang, J. H., Li, C. H., De Cremer, D., Lu, Y., & Ng, C. T. S. (2022). When conscientious employees meet intelligent machines: An integrative approach inspired by complementarity theory and role theory. *Academy of Management Journal*, *65*(3), 1019–1054.

Maretto, L., Faccio, M., & Battini, D. (2023). The adoption of digital technologies in the manufacturing world and their evaluation: A systematic review of real-life case studies and future research agenda. *Journal of Manufacturing Systems*, *68*, 576–600. https://doi.org/10.1016/j.jmsy.2023.05.009

Maslej, N., Fattorini, L., Perrault, R., Gil, Y., Parli, V., Kariuki, N., Capstick, E., Reuel, A., Brynjolfsson, E., & Etchemendy, J. (2025). Artificial intelligence index report 2025. *arXiv Preprint arXiv:2504.07139*.

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (2006). A proposal for the dartmouth summer research project on artificial intelligence, august 31, 1955. *AI Magazine*, *27*(4), 12–

12.

Mill, J. S. (2015). *On liberty, utilitarianism, and other essays*. Oxford University Press.

Morris, M. G., Venkatesh, V., & Ackerman, P. L. (2005). Gender and age differences in employee decisions about new technology: An extension to the theory of planned behavior. *IEEE Transactions on Engineering Management*, *52*(1), 69–84. https://doi.org/10.1109/TEM.2004.839967

Nord, J. H., Espinosa, S. D., Paliszkiewicz, J., & Madra-Sawicka, M. (2020). Do technology and social media preferences differ with age? A study of the use of social technologies for business purposes in Spain. *Journal of Computer Information Systems*, *60*(2), 101–112. https://doi.org/10.1080/08874417.2018.1423892

Ocampo, L., Acedillo, V., Bacunador, A. M., Balo, C. C., Lagdameo, Y. J., & Tupa, N. S. (2018). A historical review of the development of organizational citizenship behavior (OCB) and its implications for the twenty-first century. *Personnel Review*, *47*(4), 821–862.

Raisch, S., & Fomina, K. (2025). Combining human and artificial intelligence: Hybrid problem-solving in organizations. *Academy of Management Review*, *50*(2), 441–464.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, *46*(1), 192–210.

Rhim, J., Lee, J.-H., Chen, M., & Lim, A. (2021). A deeper look at autonomous vehicle ethics: An integrative ethical decision-making framework to explain moral pluralism. *Frontiers in Robotics and AI*, *8*, 632394.

Roberts, J. A., & Wasieleski, D. M. (2012). Moral reasoning in computer-based task environments: Exploring the interplay between cognitive and technological factors on individuals' propensity to break rules. *Journal of Business Ethics*, *110*(3), 355–376.

Rotolo, A. (2024). *15 Artificial Intelligence and New Paradigms of Human Decision Making: Towards a New Idea of Humanity?*

Salahshour Rad, M., Nilashi, M., & Mohamed Dahlan, H. (2018). Information technology adoption:

A review of the literature and classification. *Universal Access in the Information Society*, *17*(2), 361–390.

Shao, Y., Zope, H., Jiang, Y., Pei, J., Nguyen, D., Brynjolfsson, E., & Yang, D. (2025). Future of Work with AI Agents: Auditing Automation and Augmentation Potential across the US Workforce. *arXiv Preprint arXiv:2506.06576*.

Shareef, M. A., Kumar, V., Kumar, U., & Hasin, A. A. (2009). Theory of planned behavior and reasoned action in predicting technology adoption behavior. In *Handbook of research on contemporary theoretical models in information systems* (pp. 544–562). IGI Global Scientific Publishing.

Silic, M., Barlow, J. B., & Back, A. (2017). A new perspective on neutralization and deterrence: Predicting shadow IT usage. *Information & Management*, *54*(8), 1023–1037.

Sonenshein, S. (2007). The role of construction, intuition, and justification in responding to ethical issues at work: The sensemaking-intuition model. *Academy of Management Review*, *32*(4), 1022–1040.

Tang, P. M., Koopman, J., Mai, K. M., De Cremer, D., Zhang, J. H., Reynders, P., Ng, C. T. S., & Chen, I. (2023). No person is an island: Unpacking the work and after-work consequences of interacting with artificial intelligence. *Journal of Applied Psychology*, *108*(11), 1766.

Tims, M., & Bakker, A. B. (2010). Job crafting: Towards a new model of individual job redesign. *SA Journal of Industrial Psychology*, *36*(2), 1–9.

Tims, M., Twemlow, M., & Fong, C. Y. M. (2022). A state-of-the-art overview of job-crafting research: Current trends and future research directions. *Career Development International*, *27*(1), 54–78.

Trevino, L. K. (1986). Ethical decision making in organizations: A person-situation interactionist model. *Academy of Management Review*, *11*(3), 601–617.

Trist, E. (1981). The Sociotechinical Perspective. *Persoectives on Organization Design and Behavior*, 19–75.

Venkatesh, V. (2022a). Adoption and use of AI tools: A research agenda grounded in UTAUT. *Annals of Operations Research*, *308*(1), 641–652.

Venkatesh, V. (2022b). Adoption and use of AI tools: A research agenda grounded in UTAUT. *Annals of Operations Research*, *308*(1), 641–652.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 157–178.

Wrzesniewski, A., & Dutton, J. E. (2001). Crafting a job: Revisioning employees as active crafters of their work. *Academy of Management Review*, *26*(2), 179–201.

Zhang, F., & Parker, S. K. (2019). Reorienting job crafting research: A hierarchical structure of job crafting concepts and integrative review. *Journal of Organizational Behavior*, *40*(2), 126–146.