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How Technology Shapes Work: ICT Use, Generative AI, and Employee-Centered Technology Implementation as Drivers of Work Design and Well-Being

Doctoral Dissertation

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GENERAL INTRODUCTION

Work is not merely an economic activity. It is a fundamental domain of human experience through which individuals develop competencies, build relationships, and derive meaning from their contributions (Parker et al., 2017). Given the substantial amount of time people spend at work, the design of work, that is, how work is organized, structured, and experienced (Parker, 2014), plays a relevant role in shaping employees' lives. Decades of research have consistently shown that well-designed work fosters motivation, engagement, learning, and well-being, whereas poorly designed work contributes to strain, exhaustion, and diminished satisfaction (Bakker & Demerouti, 2017; Hackman & Oldham, 1976; Humphrey et al., 2007; Parker & Knight, 2024). The consequences of work design extend beyond the individual. For organizations, work design influences productivity, retention, and innovation, with poorly designed work generating costs through absenteeism, turnover, and performance losses (Parker, 2014). At the societal level, work design contributes to population health, labour market participation, and social inclusion, which has led international organizations to place it on contemporary policy agendas (OECD, 2024; World Economic Forum, 2025).

Yet the conditions under which work is designed are not static. They are shaped by the broader contexts in which work takes place, and the technological context is currently undergoing change. The rapid diffusion of digital technologies, from Information and Communication Technologies (ICT) to Artificial Intelligence (AI) and, more recently, Generative Artificial Intelligence (GenAI), is altering how work is organized and experienced across sectors and occupations (Cascio & Montealegre, 2016; Parker & Grote, 2022). Projections from the World Economic Forum (2025) indicate that 39% of workers' core skills are expected to change by 2030, with 86% of employers anticipating that AI and information-processing technologies will reshape their organizations. Similar concerns

have been raised by the OECD (2024), which has called for policies that help individuals, firms, and countries benefit from these transformations while addressing the associated risks, and by the International Labour Organization (2024), which has emphasized the need for a human-centered approach to ensure that the digital transformation of work advances rather than undermines decent work. In this context, understanding how technological change reshapes the design and experience of work has become a central concern in contemporary work and organizational psychology (Parker & Grote, 2022).

Although the importance of technology for work design is increasingly recognized, important problems remain in our understanding of this relationship (Parker & Grote, 2022; Parker et al., 2017). First, the mechanisms through which digital technologies shape employee outcomes remain insufficiently understood. Research has often treated technology as a direct predictor of individual outcomes rather than examining whether it operates through resource-enhancing pathways, demand-generating pathways, or both simultaneously. This is particularly relevant for established digital tools such as ICT, whose widespread use has not been accompanied by a clear understanding of the mechanisms through which they shape employee outcomes (Barley, 2015; Wang et al., 2020). Second, while GenAI has rapidly entered the workplace, largely through employee-driven rather than organizationally mandated adoption (Microsoft & LinkedIn, 2024), its consequences for work design and the psychological factors that drive its use remain insufficiently examined (Hermann et al., 2025). Third, although scholars have increasingly argued that the effects of technology depend not only on the technology itself but on how it is introduced, communicated, and integrated into everyday work (Gagné et al., 2022; Parker et al., 2017), the organizational processes involved in technology implementation have received considerably less empirical attention than the technologies themselves. This

doctoral thesis aims to address these three problems through three empirical studies. The first examines the positive and negative indirect effects of ICT use on employee well-being, operating through job autonomy and workload, and subsequently through work engagement and exhaustion. The second investigates how GenAI use relates to changes in skill variety, job autonomy, job feedback, social support, and role overload, and how attitudes toward GenAI predict its use at work. The third examines how Employee-Centered Technology Implementation (ECTI) relates to changes in those same work characteristics and to job satisfaction.

The first problem addressed in this thesis concerns how ICT relate to work design and employee outcomes. ICT have become pervasive in contemporary work, transforming how employees access information, coordinate with others, and perform tasks (Cascio & Montealegre, 2016). Yet decades of research have produced mixed evidence about whether these technologies ultimately benefit or harm employees. Early accounts emphasized their empowering potential, highlighting gains in flexibility, access to information, and control over work (Malone, 2004; Johns & Gratton, 2013), whereas subsequent research has pointed to their darker side, including constant connectivity, information overload, and the blurring of work and non-work boundaries (Day et al., 2012; Mazmanian et al., 2013). This duality suggests that the consequences of ICT use are not inherent to the technology itself but depend on how it reshapes the characteristics of work (Parker & Grote, 2022).

Despite this recognition, the mechanisms through which ICT shapes the design of work remain insufficiently understood (Barley, 2015; Wang et al., 2020). As a result, the pathways through which these technologies can simultaneously enhance and deplete employees remain unclear (Barley, 2015; Wang et al., 2020). In addition, the role of individual differences such as age has received limited empirical attention, despite evidence

that demographic factors may shape how employees experience digital tools (Coovert & Thompson, 2013; Parker & Grote, 2022). These issues are particularly relevant in light of the aging of the global workforce, as by 2030 one in six people is expected to be 60 years or older (World Health Organization, 2024), meaning that an increasing share of employees interacting with these technologies will belong to older age groups. We aim to tackle these issues in Study 1 of this thesis.

The second problem addressed in this thesis concerns how GenAI relates to work design. Unlike previous waves of workplace technology, which mainly supported structured, repetitive, or analytical tasks, GenAI can operate in creative, analytical, and decision-making domains previously reserved for human judgment (Brynjolfsson et al., 2025; Lee et al., 2025). This expanded scope suggests that GenAI may reshape work design in ways that cannot be straightforwardly extrapolated from research on earlier technologies (Parker & Knight, 2024). Projections from the World Economic Forum (2025) indicate that 86% of employers expect AI and information-processing technologies to transform their organizations by 2030, while existing studies have mainly focused on macro-level outcomes such as workforce transformation and organizational competitiveness (Brynjolfsson et al., 2025), offering limited insight into how GenAI shapes the everyday experience of work.

A further distinctive feature of GenAI is that its adoption is often employee-driven rather than organizationally mandated. Recent evidence indicates that approximately 78% of users are adopting these tools informally, without formal organizational support (Microsoft & LinkedIn, 2024). Although technology acceptance models have long identified individual attitudes as relevant predictors of technology use (Davis, 1989), attitudinal factors have rarely been integrated with work design research to examine how

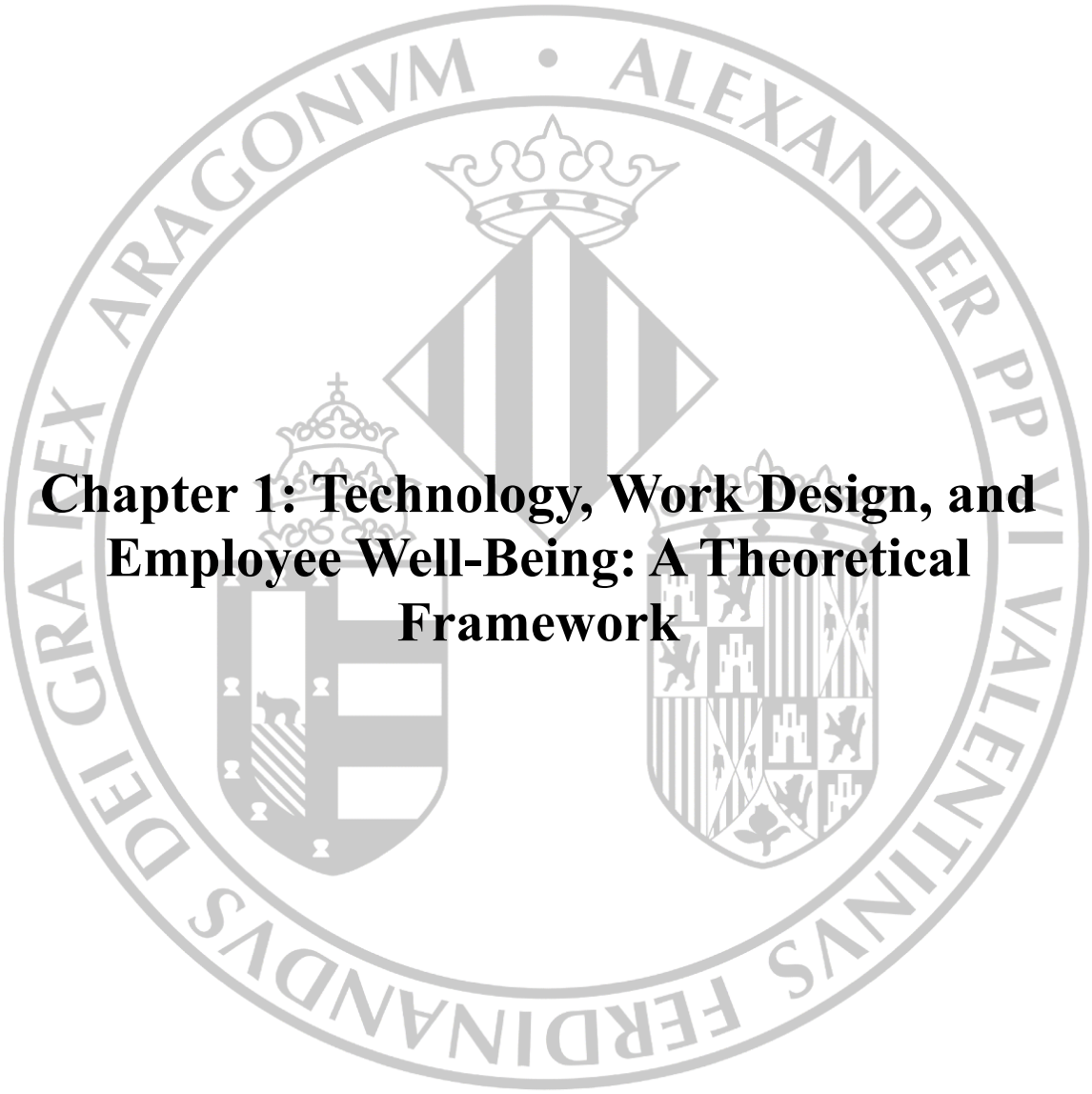
they shape not only adoption but also the ways in which generative tools reshape the organization and experience of work (Lichtenthaler, 2020; Park et al., 2024). In addition, the effects of GenAI are likely to depend on contextual features of the job, as similar tools may operate differently across occupations with varying levels of complexity and discretion (Dierdorff & Morgeson, 2013; Parker et al., 2017). We aim to tackle these issues in Study 2 of this thesis.

The third problem addressed in this thesis concerns how specific approaches to technology implementation relate to work design and employee outcomes. Research on technology and work has paid considerable attention to the consequences of technology use, but considerably less to the question of how technologies are implemented in organizations (Cascio & Montealegre, 2016). Yet emerging evidence suggests that the effects of technology on work are not inevitable or inherent to the technology itself; they also depend on the decisions made during its design and implementation (Gagné et al., 2022; Parker et al., 2017). In this line, sociotechnical systems theory has long emphasized that effective technology use requires the joint optimization of the technical and social subsystems of work (Cherns, 1976; Trist & Bamforth, 1951), a principle that has been recently revived under the Industry 5.0 agenda, which places the worker at the center of technological design and emphasizes that digital transformation should account for human needs alongside technical objectives (Breque et al., 2021).

Despite this growing recognition, there is still limited empirical evidence on how specific organizational approaches to technology implementation relate to work design and employee outcomes. Established work design models have extensively documented the consequences of work characteristics for employee motivation, strain, and satisfaction, but have paid considerably less attention to their organizational antecedents (Parker et al.,

2017). This omission is theoretically and practically relevant. Theoretically, without understanding how implementation practices shape work characteristics, work design models remain incomplete in accounting for the organizational processes that unfold during technological change. Practically, organizations are currently making decisions about how to introduce new technologies with limited evidence on which implementation approaches preserve or enhance the quality of work. We aim to tackle these issues in Study 3 of this thesis.

The dissertation is organized as follows. Chapter 1 presents a theoretical framework on technology, work design, and employee well-being, reviewing the main constructs and theoretical perspectives that ground the three studies. Chapter 2 presents Study 1, which examines the relationships between the use of ICT at work, job autonomy, workload, work engagement, exhaustion, and employee well-being, using cross-sectional data from a large multinational sample of European workers. Chapter 3 presents Study 2, which investigates the relationships between attitudes toward GenAI, GenAI use at work, and five work characteristics (skill variety, job autonomy, social support, job feedback and role overload), in a sample of Spanish employees by means of a three-wave longitudinal design. Chapter 4 presents Study 3, which examines the relationships between ECTI, work characteristics, and job satisfaction, also in a sample of Spanish employees by means of a three-wave longitudinal design. Finally, Chapter 5 discusses and integrates the findings of the three studies, outlines their theoretical and practical implications, addresses the methodological limitations and directions for future research, and presents the main conclusions derived from the dissertation. Chapters 6 and 7 provide a summary of the thesis in English and Spanish, respectively.



Chapter 1: Technology, Work Design, and Employee Well-Being: A Theoretical Framework

1.1 New technologies in the workplace and Work characteristics

The accelerating pace of technological innovation has become a defining force of the twenty-first-century economy, transforming the nature of work, production, and social relations on a global scale (Schwab, 2024). Over the last two decades, digitalization and automation have evolved from specialized applications into the core infrastructure of organizations and societies. International institutions such as the International Labour Organization (ILO), the Organization for Economic Co-operation and Development (OECD), and the World Economic Forum (WEF) have repeatedly underscored the systemic importance of technological change for economic growth, employment, and social inclusion. According to the WEF (2025), nearly 75% of companies worldwide expect to adopt AI technologies by 2027, while more than half foresee significant structural changes in their workforces due to automation and digital tools.

Beyond aggregate indicators of adoption, these developments signal a profound transformation in how work itself is organized and experienced. New technologies increasingly shape task structures, decision-making processes, and the nature of social interactions at work. This unprecedented speed and breadth of technological diffusion marks a qualitative shift compared with earlier waves of computerization, commonly conceptualized as the Fourth Industrial Revolution (Schwab, 2017). As technological innovations emerge and diffuse faster than organizational systems can adapt (Cascio & Montealegre, 2016), employees are increasingly required to coordinate complex information flows, manage digitally mediated tasks, and adjust to continuously evolving work processes. Importantly, these changes do not produce uniform outcomes. As Acemoglu and Restrepo (2019) show, automation can simultaneously displace routine tasks

and generate new, higher-value activities, fundamentally altering the distribution of skills, autonomy, and demands that employees encounter in their daily work.

At the organizational level, technological adoption has restructured how work is coordinated and supervised. Algorithmic management tools now optimize decision-making and resource allocation, shifting forms of control from human supervisors to digital infrastructures (Kellogg et al., 2020; Parent-Rocheleau & Parker, 2022). The expansion of remote and hybrid work arrangements, accelerated by the COVID-19 pandemic, has institutionalized digital communication as the primary mode of organizational interaction, changing how collaboration, supervision, and social coordination unfold within firms (WEF, 2025).

Nevertheless, the effects of digitalization on workers are unevenly distributed. Eurofound (2021) documents strong North–South disparities within the EU, and age and educational differences further compound inequality: older and lower-educated workers face higher risks of displacement, while women remain under-represented in digital and STEM occupations (Gutfleisch & Nennstiel, 2025; OECD, 2023). Beyond material inequalities, technological change alters the lived experience of work itself. Constant connectivity, digital monitoring, and information overload have intensified job demands and blurred the boundaries between work and private life, pressures that Tarafdar et al. (2019) conceptualize as technostress. These dynamics illustrate a dual transformation: technology expands capabilities and opportunities while simultaneously creating new forms of strain and vulnerability for employees.

In summary, the global digital transformation represents both an unprecedented opportunity and a multidimensional challenge for workers and organizations. The central question is not simply whether technologies are adopted, but how their introduction

reshapes the characteristics of work and what this means for employee well-being. This is the question this dissertation sets out to address. The following section traces the historical evolution of workplace technologies, from early digitalization and ICT diffusion to the rise of GenAI, in order to contextualize the mechanisms through which technological progress reshapes jobs, skills, and the design of work.

1.1.1 Early Digitalization and Diffusion of Information and Communication Technologies

The introduction of ICT marked one of the most transformative shifts in the history of modern work. Emerging from mid-twentieth-century advances in computing, electronics, and telecommunications, ICT reshaped not only production processes but also the coordination, communication, and distribution of work. As Cascio and Montealegre (2016) argue, the progression from the industrial to the digital era represents a fundamental discontinuity in how organizations create and manage value. The automation of information processing enabled firms to transcend physical and temporal constraints that had long defined industrial operations. By the late twentieth century, computers had become embedded in virtually all aspects of organizational life, laying the foundations for the data-driven economies and digitally networked workplaces that would dominate the following decades.

The roots of this transformation extend back to the early post-war period, when the first programmable computers were deployed in scientific and military contexts. Early organizational adoption began in the 1950s and 1960s, with mainframe computers used for payroll, inventory, and data analysis (Brynjolfsson & Hitt, 2000). These systems centralized information processing but required highly specialized operators, meaning that technology initially reinforced hierarchical and bureaucratic models of control. At the same

time, early sociotechnical research, most notably Trist and Bamforth's (1951) study of the Longwall coal-mining method, offered an alternative interpretation: technological change was not purely mechanical but socio-organizational, affecting patterns of cooperation, autonomy, and skill utilization. Although their analysis predated digitalization, the sociotechnical perspective anticipated the core principle that would later define the digital revolution, that technology and human systems must evolve jointly to achieve optimal performance and well-being.

The broad diffusion of ICT began during the 1970s and 1980s with the advent of microprocessors and personal computers. As technologies became more accessible, the end-user stage empowered individual workers to interact directly with computers, shifting responsibility for data entry, analysis, and communication from centralized departments to distributed employees. This decentralization paralleled a gradual cultural change in organizations, from administrative hierarchy toward empowered information workers. Brynjolfsson and Hitt (2000) later demonstrated empirically that these ICT investments were strongly correlated with productivity gains, but only when accompanied by complementary organizational changes, flatter structures, skill development, and greater autonomy in decision-making.

The 1990s brought a third wave of ICT evolution, characterized by strategic computing (Cascio & Montealegre, 2016). The integration of computers into competitive strategy was catalyzed by the rapid expansion of the Internet and enterprise resource planning (ERP) systems. Firms began using digital tools not only to automate processes but also to coordinate global operations and generate knowledge-based advantages. The diffusion of electronic communication systems, email, intranets, and digital databases, transformed organizational boundaries and created what Castells (1996) described as the

network society. Information no longer flowed vertically through managerial hierarchies but horizontally across interconnected teams and even across organizational borders. This connectivity revolution enabled virtual collaboration and set the stage for flexible work arrangements that would later become ubiquitous.

ICT adoption also reshaped the very structure of work processes. By digitizing communication and coordination, organizations could operate beyond traditional temporal and spatial limits. Virtual teams became viable, cross-functional collaboration intensified, and remote work, initially a marginal practice, began to emerge as a legitimate organizational model. Cascio and Montealegre (2016) note that these shifts represented more than operational changes: they signified a redefinition of how work was conceived, executed, and managed. Tasks once dependent on physical presence could now be mediated through digital interfaces. This "virtualization" of work allowed firms to draw on global talent pools while reducing transaction costs. Yet, it also introduced new complexities in monitoring performance, maintaining cohesion, and sustaining organizational culture. The balance between flexibility and control became a central management dilemma, one that persists in the age of AI and hybrid work (Parker & Grote, 2022).

The socioeconomic implications of ICT diffusion were equally significant. The automation of routine clerical and administrative functions displaced many traditional middle-skill jobs, while simultaneously increasing demand for analytical, technical, and interpersonal competencies (Autor, Levy, & Murnane, 2003). This polarization of employment patterns marked the beginning of a long-term restructuring of labor markets. According to Brynjolfsson and McAfee (2014), digital technologies act as "general-purpose technologies", meaning that they generate productivity gains across multiple sectors but require systemic adaptation in education, institutions, and management. The initial

productivity paradox, where IT investments seemed to yield limited output growth, gradually resolved as organizations learned to complement technologies with new work systems. Firms that restructured workflows, decentralized authority, and invested in skill upgrading captured the greatest returns from ICT adoption (Brynjolfsson & Hitt, 2000).

Despite its transformative potential, early ICT diffusion also exposed persistent inequalities. Eurofound (2021) shows that digitalisation in the 1980s and 1990s spread unevenly across Europe: technologically advanced economies such as Germany, Sweden, and the Netherlands experienced rapid ICT adoption, while Southern and Eastern European countries lagged behind. This digital divide was not only geographic but also occupational; high-skilled professionals gained new opportunities for autonomy and mobility, while low-skilled workers faced redundancy or precarious employment. Moreover, as information systems extended managerial oversight, concerns emerged regarding surveillance, work intensification, and privacy. These early debates prefigured contemporary discussions about algorithmic control and data ethics. ICT thus introduced both empowerment and constraints, enabling flexible, knowledge-based work but also embedding new forms of control and dependency.

By the turn of the millennium, the digital infrastructure of organizations had become deeply integrated into their strategic and operational cores. The widespread adoption of broadband Internet, mobile devices, and enterprise platforms gave rise to what Cascio and Montealegre (2016) termed ubiquitous computing, the fourth stage of ICT evolution. In this phase, technologies were no longer a tool external to work but a pervasive element of the work environment itself. Information flowed continuously between systems and users, enabling real-time decision-making and blurring the boundaries between work and everyday life. This pervasiveness fundamentally altered employees' experience of time and

space, foreshadowing the 24/7 connectivity and remote collaboration that would define the following decades. As Parker and Grote (2022) later observed, the digitalization of work processes shifted the primary challenge of management from task allocation to the design of meaningful and sustainable work systems within technologically saturated contexts.

In retrospect, the era of early ICT laid the conceptual and infrastructural foundations for the current transformation driven by AI. By digitizing information, automating transactions, and connecting people and systems, ICT established the data ecosystems upon which AI now operates. The expansion of enterprise computing and the Internet created unprecedented volumes of structured data, enabling the development of machine-learning algorithms in the following decades. Moreover, the organizational practices introduced during the ICT era, team-based work, flexible structures, and distributed communication, prepared firms to integrate more advanced intelligent systems. As Eurofound (2021) notes, the digital revolution was not a discrete event but a cumulative process, in which each technological wave builds on the sociotechnical and organizational foundations of the previous one. Understanding this progression is essential for analyzing how AI, and later Generative AI, extend and amplify the transformations first initiated by ICT.

1.1.2 Emergence of Artificial Intelligence in the Workplace

The history of AI in organizational contexts represents a complex trajectory of technological advancement and social adaptation. Emerging in the mid-twentieth century from the intersection of computer science, mathematics, and cognitive psychology, AI was initially conceived as a scientific quest to replicate human reasoning through machines. Over time, it evolved from symbolic logic systems to self-learning algorithms capable of recognizing patterns, predicting outcomes, and, more recently, generating creative content. As Haenlein and Kaplan (2019) note, AI can be broadly defined as a system's ability to

correctly interpret external data, learn from such data, and use that learning to achieve specific goals through flexible adaptation. This definition underscores that AI is not a single technology but a constellation of computational capabilities that extend human cognition. The gradual integration of AI into the workplace has redefined how organizations process information, make decisions, and structure work, culminating in today's era of Generative AI.

1.1.2.1 First wave of AI applications: Expert systems, machine learning, and their initial organizational uses

The origins of AI date back to the 1950s, when pioneering researchers such as Alan Turing, John McCarthy, and Marvin Minsky explored the possibility of simulating human intelligence through symbolic reasoning. This period, often referred to as "classical AI", was dominated by attempts to formalize knowledge and decision-making processes into explicit computational rules. Early systems sought to emulate expert judgment in narrow domains, giving rise to expert systems during the 1970s and 1980s. These programs used rule-based logic to provide diagnostic or prescriptive recommendations, for example, medical diagnostic systems like MYCIN or industrial troubleshooting tools used in manufacturing and finance (Haenlein & Kaplan, 2019). The promise of these systems was to codify professional expertise, making it replicable and scalable across organizations. However, they also revealed a key limitation: their fragility and inability to generalize beyond predefined rules. As computational power, storage, and data availability were still limited, early AI systems were constrained by both technical and organizational barriers.

Despite these constraints, the 1980s witnessed the first significant wave of AI integration into business practice. Rule-based decision-support systems appeared in finance, logistics, and customer service, while robotics gained traction in automotive and

electronics manufacturing. The proliferation of computer-controlled machinery marked an early form of intelligent automation. Brynjolfsson and Hitt (2000) emphasize that such technologies enhanced process efficiency and quality control, yet they often reinforced hierarchical control structures since decision authority remained centralized. These early applications demonstrated AI's potential but also highlighted the dependency on data and computational resources. The overinflated expectations of the 1980s led to the so-called "AI winter", a period of declining research funding and commercial interest during the 1990s (Haenlein & Kaplan, 2019).

The twenty-first century marked a decisive turning point as advances in computing power, data generation, and algorithmic innovation converged. The exponential growth of digital data and connectivity, what Brynjolfsson and McAfee (2014) termed the Second Machine Age, transformed AI from a research niche into an applied organizational capability. Machine-learning techniques, which allow systems to infer patterns from data rather than rely on explicit programming, began to dominate. The availability of large datasets and the rise of cloud computing made it feasible to train models capable of performing complex classification, prediction, and optimization tasks. Firms started embedding AI into core business processes: predictive analytics for marketing and finance, algorithmic scheduling in logistics, and recommendation systems in e-commerce. According to the OECD (2023), by the early 2010s approximately 30% of firms in advanced economies had adopted some form of AI-based data analytics, and by 2023, one in three workers was already using AI tools in their daily activities. AI's re-emergence was not merely technological but organizational, it changed how decisions were made, who made them, and on what informational basis.

The diffusion of AI across industries introduced new possibilities for augmenting human decision-making. In healthcare, algorithms assisted in diagnostic imaging and drug discovery (Alowais et al., 2023); in manufacturing, predictive maintenance systems anticipated equipment failures (Kim et al., 2022); and in human resource management, AI-driven platforms supported recruitment and performance monitoring (Tambe et al., 2019). These applications blurred the boundaries between human and machine intelligence, giving rise to hybrid decision systems in which algorithms complemented rather than replaced human judgment. Early evidence already indicated that the benefits of digital technologies depended not only on their technical capacity but also on how organizations adapted their structures and skills to support them (Brynjolfsson & Hitt, 2000). Subsequent advances in AI reinforced this principle: firms that redesigned workflows and invested in employee upskilling achieved the most substantial productivity gains. As technological transformation evolved, the focus of innovation shifted from the mechanization of routine tasks toward the augmentation of cognitive processes, embedding AI into the strategic and intellectual core of organizational functioning (Cascio & Montealegre, 2016). This evolution also illustrates what Raisch and Krakowski (2021) conceptualize as the automation–augmentation paradox: rather than displacing human intelligence, AI increasingly intertwines with it. Organizations move through recurring cycles in which automation enables new forms of augmentation and vice versa, creating hybrid systems that combine human intuition with algorithmic precision. Together, these developments laid the groundwork for the next major inflection in digital transformation, the emergence of generative AI.

1.1.2.2 Transition toward Generative AI: Technological breakthroughs and distinctive capabilities

The emergence of GenAI represents a qualitative leap in the evolution of workplace technologies. While traditional AI systems were designed to recognize patterns and predict outcomes based on structured data, GenAI systems generate new and contextually meaningful content, such as text, images, code, and designs, by learning probabilistic relationships within vast unstructured datasets. These capabilities are enabled by large language models (LLMs) based on deep learning and transformer architectures (Vaswani et al., 2017), which can process and produce multimodal outputs and engage in natural language interaction. Haenlein and Kaplan (2019) distinguish between analytical, human-inspired, and humanized forms of AI; GenAI approximates the latter two by reproducing aspects of human creativity, reasoning, and communication. This transition from analytical to generative systems expands AI's functional scope from automating information processing to augmenting human cognition and creation.

The diffusion of GenAI has been both rapid and wide-ranging. According to the World Economic Forum (2025), three out of four firms expect to adopt AI technologies, including generative models by 2027, with most anticipating significant changes in job roles and skill requirements. Similarly, the OECD (2023) reports that one-third of workers in member countries already use AI-based tools in their daily activities, ranging from digital assistants to content generators. The release of ChatGPT in late 2022, which surpassed 100 million users in two months, illustrates the unprecedented velocity of technological adoption. Unlike earlier AI waves that required advanced programming skills or specialized infrastructure, GenAI's intuitive interfaces and open-access models have dramatically lowered entry barriers. This democratization of generative tools allows non-

specialists to participate directly in computational creativity, transforming how knowledge work is performed and who performs it.

Employees increasingly collaborate with generative systems to draft reports, analyze data, design visual materials, and develop prototypes. Le Blanc et al. (2024) emphasize that these technologies redistribute cognitive work between humans and algorithms, embedding generative functions into everyday workflows. Rather than displacing human judgment, GenAI typically acts as a copilot, enhancing productivity and innovation through iterative human–machine interaction. This collaborative mode alters traditional notions of expertise: while GenAI expands access to analytical and creative resources, it also introduces new challenges related to validation, authorship, and trust. Knowledge work thus becomes a dynamic dialogue between human intent and algorithmic suggestion, where the boundaries of responsibility are continuously negotiated.

Despite its potential to enhance performance and learning, GenAI also raises profound ethical, managerial, and societal challenges. Algorithmic bias, misinformation, data privacy, and intellectual property disputes have emerged as central concerns across sectors. Governance frameworks such as the OECD's (2019) AI Principles and the European Union's AI Act (European Parliament & Council of the European Union, 2024) reflect increasing awareness of the need for transparency, accountability, and human oversight. Recent analyses by Gmyrek et al. (2023) suggest that the effects of Generative AI on employment are predominantly augmentative rather than substitutive: GenAI tends to transform the composition of tasks within jobs rather than replace them entirely. However, the authors warn that without institutional safeguards, particularly regarding training, regulation, and social dialogue, this transformation could exacerbate inequality and widen

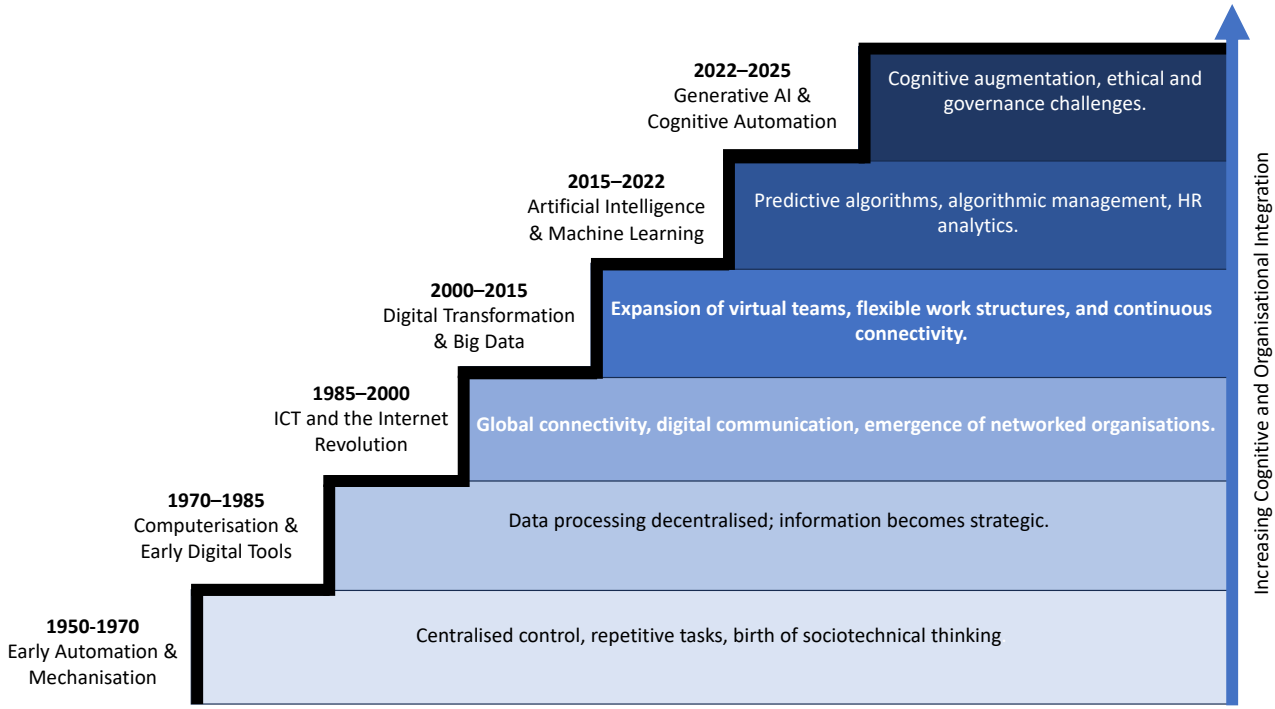
digital divides. The impact of GenAI, therefore, depends less on its technical potential than on how organizations and societies choose to integrate it responsibly.

Taken together, these developments mark a turning point in the trajectory of workplace technologies. Generative AI redefines the relationship between human and machine intelligence by introducing systems that do not merely support decision-making but actively participate in the creation of knowledge, communication, and meaning. This transition from automation to collaboration has far-reaching implications for work design, organizational learning, and employee experience.

In summary, each technological wave has redefined what constitutes a task, a skill, and a role, compelling organizations to reconsider how autonomy, competence, and collaboration are maintained in technologically mediated environments (see Figure 1.1). Understanding these transformations requires theoretical frameworks that can explain how work structures and employee experiences evolve under shifting technological conditions. The following section therefore examines the principal foundations for analyzing this relationship, beginning with the sociotechnical perspective that first articulated the joint optimization of social and technical systems, and continuing with modern frameworks that conceptualize the motivational and structural dimensions of work, the Job Characteristics Model, the Demand–Control model, the Job Demands–Resources approach, and the SMART model that integrates adaptive and proactive work design in the digital era.

Figure 1.1.

Evolution of workplace technologies from early automation to Generative AI (1950–2025)



1.2 Theoretical Foundations to investigate the influence of Technologies on Work Design

Work design refers to the content, structure, and organization of tasks, activities, and relationships that constitute an individual's job (Parker et al., 2017). As a field of research, work design has been concerned with identifying the characteristics of jobs that influence employee motivation, well-being, and performance. Over decades of theoretical development and empirical investigation, scholars have identified a set of core work characteristics that consistently shape how employees experience their work. These include motivational characteristics such as autonomy, skill variety, and feedback, which determine the degree to which work is experienced as meaningful, responsible, and informative; social characteristics such as social support, which capture the relational context in which work

unfolds; and characteristics related to work demands, such as role overload, which reflect the extent to which job requirements exceed employees' available resources (Morgeson & Humphrey, 2006; Humphrey et al., 2007). Meta-analytic evidence confirms that work characteristics are robust predictors of employee engagement, exhaustion, well-being, and job satisfaction across occupational contexts (Humphrey et al., 2007).

Understanding work design is particularly important in contexts of technological change, because technologies does not affect employee well-being directly. Rather, its effects are mediated by the way it reconfigures the characteristics of work itself (Parker & Grote, 2022; Van den Broeck et al., 2025). This perspective positions work design as the central analytical lens through which the relationship between technological change and employee outcomes can be understood and examined.

1.2.1 Sociotechnical theory

The sociotechnical systems (STS) theory stands as one of the most influential frameworks for understanding how technologies shapes the design and experience of work. Emerging in the mid-twentieth century from research conducted at the Tavistock Institute, it challenged the mechanistic assumptions of scientific management by showing that the success of technological systems depends on their alignment with human and social factors (Pasmore et al., 2019). The seminal field study of coal mining revealed that the introduction of the longwall method, an advanced mechanized process, improved efficiency but reduced cohesion and morale among workers. This paradox established the principle of joint optimization, which states that social and technical subsystems must be designed together to achieve both performance and well-being (Trist & Bamforth, 1951). The insight positioned technologies not as a neutral input but as a force that fundamentally alters human roles, relationships, and motivations.

The STS approach soon expanded to a more general theory of organizations as open systems operating within turbulent environments. The integration of social and technical dimensions was seen as crucial for maintaining adaptability under changing conditions (Emery & Trist, 1960). Empirical studies in industries confirmed that productivity gains required redesigning team structures and granting workers autonomy over coordination and feedback mechanisms (Rice, 1958; Sony & Naik, 2020). These early studies demonstrated that technological adoption transforms not only workflows but also the social context of work, making technology a structural antecedent of work design. Later reviews of the evolution of work design theories reaffirmed that sociotechnical systems theory was the first to conceptualize technology as a contextual determinant of work characteristics and human outcomes (Van den Broeck et al., 2025).

Building on these foundations, Cherns (1976, 1987) formalized a set of design principles intended to guide the redesign of socio-technical systems. The most enduring of these principles emphasize that: a) work should be specified only as far as strictly necessary, leaving discretion to those who perform it; b) disturbances should be addressed where they originate, supporting local self-regulation; and c) information should flow first to the points where action is required, enabling learning and adaptation. These principles laid the groundwork for an early model of adaptive, participatory organization, whose influence persists in contemporary frameworks such as agile management and human-centered design (Clegg, 2000; Mumford, 2006).

With the diffusion of ICT and later AI, the STS framework gained renewed relevance as a lens for understanding technologically complex and interdependent work systems. Updated interpretations proposed that digital transformation requires maintaining the core STS principles of distributed control, feedback loops, and flexible boundaries to

ensure resilience and learning (Clegg, 2000; Walker et al., 2008; Baxter & Sommerville, 2011). Research on Industry 4.0 has reinforced this view, showing that the most successful digital transformations occur when new technologies are accompanied by employee empowerment, participatory redesign, and ongoing skill development, rather than focusing solely on technical efficiency (Sony & Naik, 2020). Evidence from AI implementation studies further confirms this pattern: AI enhances satisfaction and collaboration when social and technical subsystems are aligned, but increases stress and resistance when they are not (Yu et al., 2023). These findings demonstrate that the balance between technical capability and social readiness determines whether technology acts as an augmentative or disruptive force on work design.

The enduring relevance of sociotechnical thinking is also visible in contemporary perspectives on human–AI collaboration. Recent frameworks describe how AI can complement rather than replace human cognition, and how the same technologies that automate tasks can also enhance skill variety and autonomy when implemented with human-centered principles, what Raisch and Krakowski (2021) conceptualize as the automation–augmentation paradox. Together, these approaches echo the original sociotechnical emphasis on joint optimization, participation, and adaptability, demonstrating that technological sophistication intensifies rather than diminishes the need for deliberate alignment between human and technical systems.

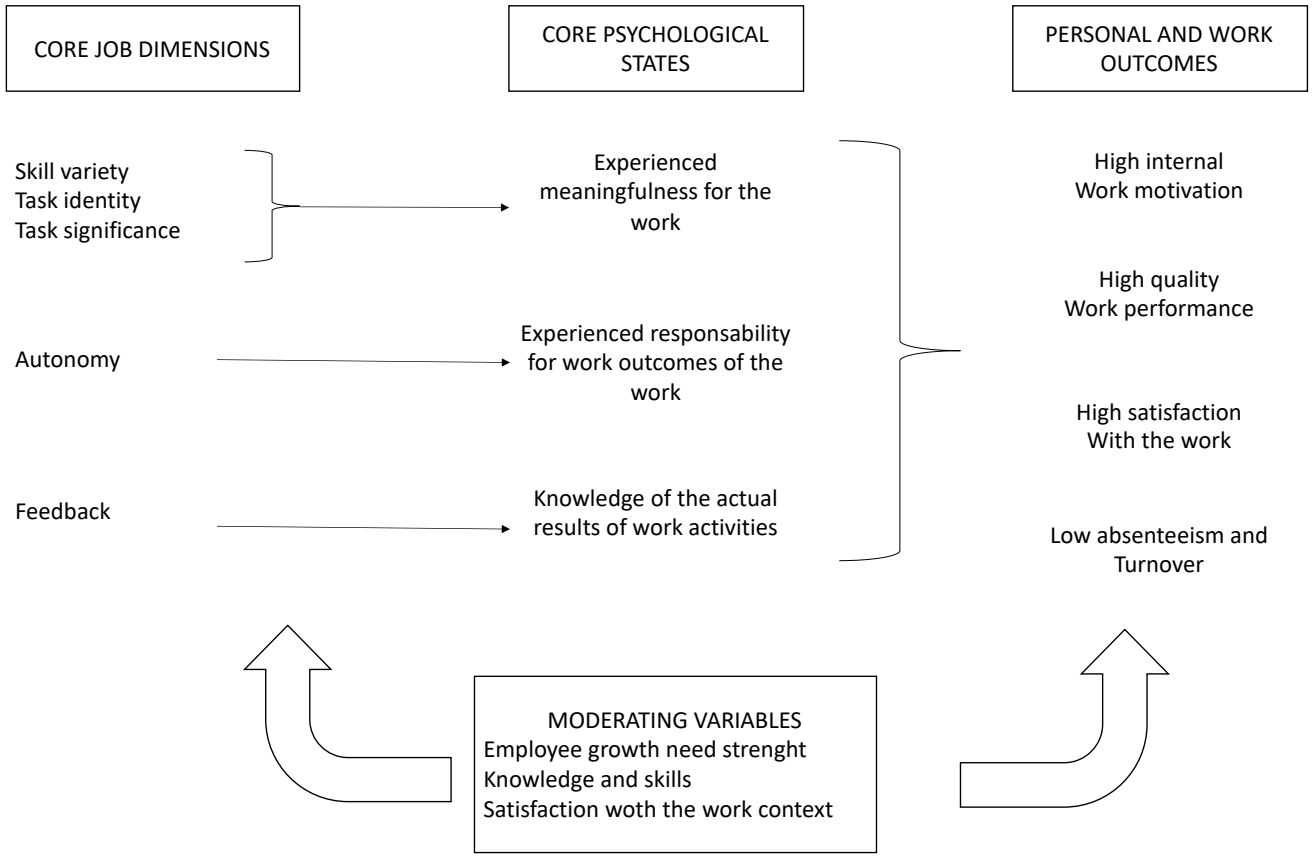
1.2.2 Job Characteristics Model

The Job Characteristics Model (JCM) proposed by Hackman and Oldham (1975) offered a systematic framework to explain how the structural features of work influence employees' motivation and outcomes (see Figure 1.2). Emerging in the 1970s, it reflected a growing dissatisfaction with approaches that either emphasized efficiency and control or

treated job satisfaction as a general outcome without considering the properties of work itself. Earlier traditions such as scientific management (Taylor, 1911) and time–motion studies (Gilbreth, 1917) had focused on maximizing productivity through task specialization and supervision, but these practices often led to monotony and detachment. Later, the motivational perspective advanced by Herzberg (1959) shifted attention to employee morale and intrinsic needs, yet they lacked a comprehensive account of how work design fosters motivation. Hackman and Oldham (1975) sought to address this theoretical gap by identifying specific job characteristics that could elicit positive psychological states and, consequently, enhance motivation, satisfaction, and performance.

Figure 1.2.

Job Characteristics Model (Hackman & Oldham, 1976)



The model built upon earlier empirical findings on task attributes and satisfaction (Hackman & Lawler, 1971) and incorporated insights from sociotechnical systems theory (Trist & Bamforth, 1951; Emery & Trist, 1960), translating two of its core principles into specific job dimensions: the principle of variance control at the source, which informed the centrality of autonomy, and the principle of information for self-regulation, which informed the inclusion of feedback as a key job characteristic.. Hackman and Oldham proposed that five core job dimensions (skill variety, task identity, task significance, autonomy, and feedback) form the basis for meaningful and motivating work. Skill variety, task identity, and task significance collectively determine the experienced meaningfulness of the job by

allowing individuals to apply different competencies, complete whole tasks, and perceive the importance of their contributions. Autonomy produces a sense of responsibility for outcomes by granting discretion over how work is performed, while feedback provides information that helps employees evaluate their effectiveness and adjust behavior accordingly. These dimensions jointly influence three critical psychological states, experienced meaningfulness, experienced responsibility, and knowledge of results, which mediate the relationship between job structure and outcomes such as internal motivation, satisfaction, performance, and reduced turnover (Hackman & Oldham, 1976, 1980; Humphrey et al., 2007).

The JCM also recognized that the motivational impact of job characteristics depends on individual dispositions. Employees with high growth need strength, those who value personal development and self-direction, tend to respond more positively to enriched jobs, whereas those with lower growth needs may prefer greater structure or external guidance. This interaction between job design and personal orientation introduced an early recognition of boundary conditions, suggesting that motivation arises from both environmental and individual factors. The inclusion of growth need strength marked an important conceptual refinement, positioning the JCM as more flexible than previous one-dimensional models of work satisfaction.

Empirical studies during the late 1970s and 1980s provided partial support for the model's propositions. Fried and Ferris (1987), in a meta-analysis of 200 studies, confirmed that the five core dimensions were significantly associated with motivation and satisfaction, with autonomy and feedback consistently showing the strongest relationships with outcomes. However, the strength of these associations varied across occupational and cultural contexts, and the proposed mediating role of psychological states received mixed

support (Johns, 2006). The development of the Job Diagnostic Survey (Hackman & Oldham, 1975) provided a tool to assess job characteristics and their motivational potential, but measurement overlap among dimensions, particularly between autonomy and feedback, raised concerns about discriminant validity (Oldham & Fried, 2016). Moreover, the model's focus on individual jobs with stable task boundaries limited its explanatory power for work organized around teams or flexible structures.

Subsequent research extended the JCM by incorporating additional dimensions reflecting the social and contextual environment of work. Morgeson and Humphrey (2006) proposed the Work Design Questionnaire (WDQ) to include social characteristics such as interdependence, social support, and feedback from others, as well as contextual features like ergonomics, physical demands, and equipment use. Their findings showed that these dimensions predicted well-being and performance beyond the original five characteristics, indicating that the motivational effects of job design are influenced by broader work aspects (Humphrey et al., 2007). These extensions reflected the growing recognition that work is embedded in social, technological, and physical systems rather than existing as isolated sets of tasks.

Despite its limitations, the Job Characteristics Model remains one of the central frameworks in work design research because it provided a clear causal mechanism linking job features to psychological processes and outcomes. It established the conceptual foundation for later integrative approaches, including the Job Demands–Resources model (Demerouti et al., 2001; Bakker & Demerouti, 2007), which expanded the notion of "resources" to encompass autonomy, feedback, and opportunities for growth while incorporating the balancing role of job demands. Similarly, the dimensions identified by Hackman and Oldham are embedded within recent conceptualizations such as the SMART

model (Parker & Knight, 2024), where skill variety, autonomy, and task significance remain central elements of motivating work. These continuities underscore that, although the organization of work has evolved in response to digitalization and automation, the motivational principles articulated in the JCM continue to inform how researchers and organizations conceptualize meaningful and engaging work.

1.2.3 Demand–Control Model

Following the development of the Job Characteristics Model, researchers turned increasing attention to how the structure of work affects not only motivation but also strain and health. The Demand–Control Model (DCM) introduced by Karasek (1979) provided one of the first formal frameworks linking psychosocial work conditions to well-being. Emerging from occupational stress research, the model proposed that the combination of job demands and decision latitude determines whether work produces learning and growth or, conversely, psychological strain and ill health. In contrast to purely motivational theories, the DCM emphasized the regulatory and stress-related functions of work design, reflecting growing concerns about strain and mental health among employees in increasingly complex and demanding jobs.

Karasek (1979) conceptualized job demands as the psychological stressors involved in meeting work requirements, such as workload, time pressure, and conflicting expectations. Decision latitude, often referred to as job control, captured the degree to which workers can influence their tasks and make decisions regarding how to perform them. The model proposed that the effects of job demands on strain depend on the level of control available to the worker. High demands combined with low control led to “high-strain” jobs characterized by exhaustion, anxiety, and health problems. Conversely, high

demands coupled with high control result in “active” jobs that foster learning, motivation, and personal growth. Jobs with both low demands and low control (“passive” jobs) were predicted to lead to skill deterioration and demotivation, while those with low demands and high control (“low-strain” jobs) were expected to produce minimal stress but limited challenge (see Table 1.1).

Table 1.1. The Demands-Control Model

	High demands	Low Demands
High control	“Active jobs”	“Low-strain jobs”
Low control	“High-strain jobs”	“Passive jobs”

Note. Based on Karasek (1979).

This interaction between demands and control offered a parsimonious way to explain why similar levels of workload produce very different outcomes across individuals and occupations. Karasek’s typology highlighted the dual potential of work design: it can generate stress when autonomy is restricted, or it can promote learning when autonomy is high. Later empirical work expanded the model by distinguishing between decision authority and skill discretion as two components of control (Karasek & Theorell, 1990). These refinements clarified that control involves both the ability to make decisions and the opportunity to use and develop skills.

A third dimension, social support, was later incorporated to create the Job Demand–Control–Support (JDCS) model (Johnson & Hall, 1988). The addition of this element recognized that the social environment can buffer or exacerbate the effects of demands and control. High social support from colleagues or supervisors reduces the likelihood that high-strain jobs lead to burnout or ill health, whereas isolation amplifies these risks. This extension aligned the model more closely with sociotechnical perspectives, which

emphasized the role of interdependence and social relations in mitigating work stress (Trist & Bamforth, 1951).

Despite its influence, the DCM has been criticized for several conceptual and empirical limitations. The model's two-dimensional structure oversimplifies the diversity of work experiences by treating all demands as uniformly negative and all forms of control as uniformly positive (De Jonge & Dormann, 2006). Empirical tests have shown inconsistent evidence for the predicted interaction between demands and control, with some studies finding additive rather than multiplicative effects (Van der Doef & Maes, 1999). Moreover, the model assumes that the benefits of control are universal, whereas subsequent research has demonstrated that excessive autonomy without adequate resources can also increase stress (Schaufeli & Taris, 2014). Another limitation concerns its static and individual-level focus: the model does not account for temporal dynamics, team-based interdependencies, or contextual changes such as digital monitoring and algorithmic management, which can simultaneously increase demands and constrain autonomy (Parker & Grote, 2022).

Nevertheless, the Demand–Control Model significantly advanced work design theory by introducing the idea that job structure influences not only motivation but also health outcomes through mechanisms of control and regulation. Its conceptual simplicity facilitated extensive empirical testing across occupations, cultures, and industries, making it a foundational model in occupational health psychology. More importantly, it established autonomy as a pivotal element of job design, linking it to both motivation and strain regulation. This conceptual bridge between motivational and stress-based perspectives directly informed later integrative frameworks, particularly the Job Demands–Resources (JD–R) model (Demerouti et al., 2001; Bakker & Demerouti, 2007).

1.2.4 Job Demands–Resources (JD–R) Model

The Job Demands–Resources (JD–R) model emerged as a response to the conceptual and empirical limitations of earlier frameworks such as the Demand–Control Model. Developed by Demerouti et al. (2001), the JD–R model proposed a broader and more flexible structure to explain how various job characteristics influence employee well-being and performance. Rather than focusing on a fixed set of dimensions, it distinguishes between two overarching categories, job demands and job resources, that can take multiple forms across different occupations and work contexts. This flexibility allowed the model to integrate motivational and health-related perspectives within a single theoretical framework, making it one of the most widely applied approaches in contemporary work and organizational psychology (Bakker & Demerouti, 2007, 2014).

Job demands refer to aspects of work that require sustained physical, cognitive, or emotional effort and are therefore associated with physiological or psychological costs. They include factors such as workload, time pressure, emotional demands, and role conflict. Job resources, in contrast, are aspects of the job that help achieve work goals, reduce the impact of demands, or stimulate learning and development. Typical examples are autonomy, feedback, social support, and opportunities for growth. The model assumes that demands and resources work through two fundamental processes: a health-impairment process and a motivational process (Demerouti et al., 2001). High or chronic demands lead to exhaustion and burnout when not balanced by sufficient resources, whereas resources promote engagement and motivation even in the presence of demanding conditions. These dual pathways account for both negative (health-impairment process) and positive (motivational process) outcomes of work, reflecting the balance between energy depletion and energy restoration.

The health-impairment process describes how excessive demands deplete employees' mental and physical resources, eventually leading to fatigue, strain, and health problems (Bakker & Demerouti, 2007). Empirical studies have consistently shown that high workload, emotional strain, or role ambiguity predict burnout and psychological distress (Lesener et al., 2018). Conversely, the motivational process captures how job resources foster engagement and performance (Bakker & Demerouti, 2017, 2018). Resources such as supportive supervision, performance feedback, and task variety enhance intrinsic motivation, which in turn predicts job satisfaction, commitment, and proactive behavior (Bakker et al., 2004). This dual-process structure not only extended the logic of the Demand–Control Model but also reconciled motivational and strain-based approaches to work design.

A distinctive strength of the JD–R framework lies in its configurational nature: demands and resources are not defined by their content but by their function within a specific job context. For instance, emotional interaction with clients can be enriching for employees in helping professions but draining in high-volume customer service roles. This contextual adaptability explains the model's widespread use in both research and practice (Bakker & Demerouti, 2017). Moreover, empirical evidence supports the idea that resources can buffer the negative effects of demands on strain, consistent with a "buffering hypothesis" already implicit in the Demand–Control model (Van den Broeck et al., 2010).

Since its introduction, the JD–R model has evolved from a descriptive framework into a dynamic theory of well-being at work. Longitudinal studies have confirmed reciprocal relationships between engagement and performance, showing that motivated employees create resourceful environments that sustain their energy over time (Bakker & Xanthopoulou, 2009). The model has also incorporated personal resources, that is, enduring

psychological characteristics such as self-efficacy, optimism, and organization-based self-esteem (Xanthopoulou et al., 2007, 2009). These resources operate as both antecedents and outcomes of work engagement, forming "gain spirals" in which success at work enhances self-beliefs (personal resources) that, in turn, facilitate further engagement. This addition linked the JD–R model to Conservation of Resources theory (Hobfoll, 2001), reinforcing the idea that individuals strive to acquire and protect resources to cope with environmental demands.

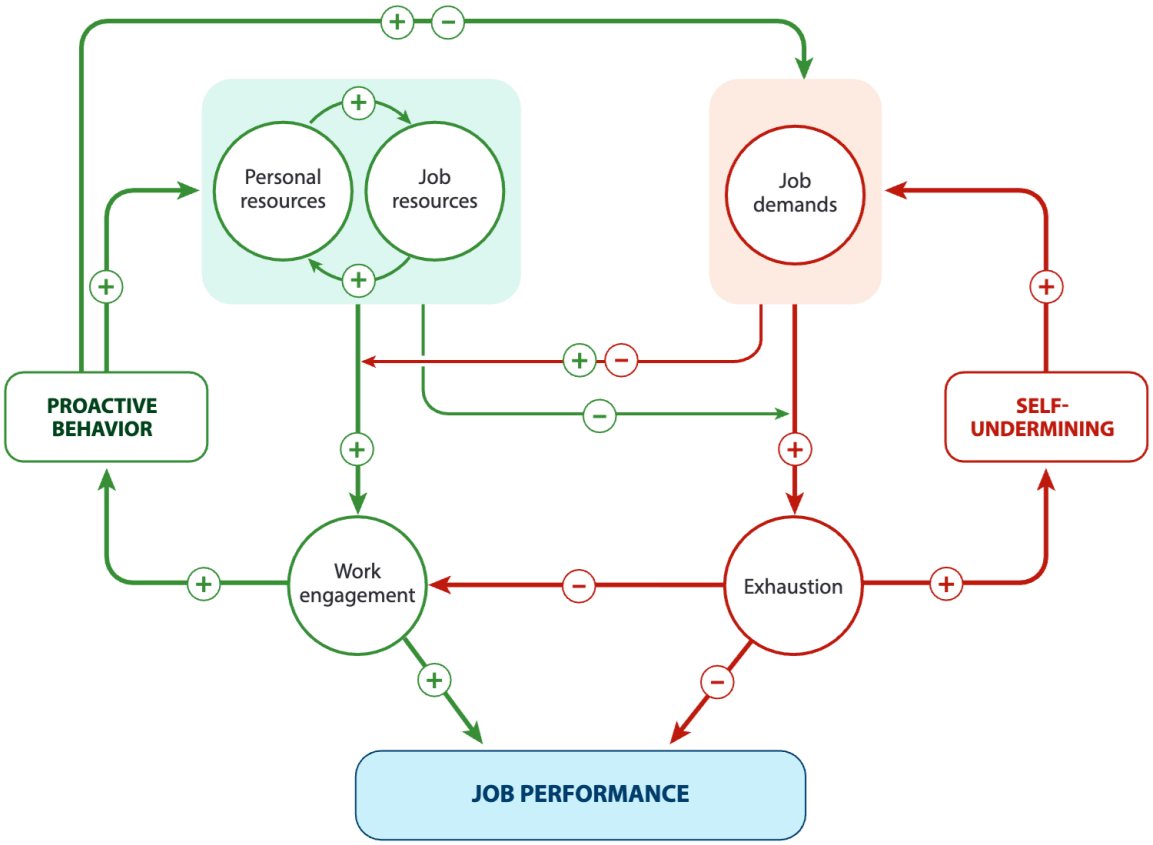
The model also contributed to the conceptualization of work engagement as a positive state of vigor, dedication, and absorption (Schaufeli et al., 2002). Engagement represents the positive counterpart to burnout within the JD–R framework and is predicted by the availability of job and personal resources. This notion expanded the focus of occupational health psychology beyond the prevention of illness toward the promotion of thriving and performance. Meta-analytic reviews have confirmed that engagement mediates the relationship between resources and organizational outcomes such as productivity and innovation (Halbesleben, 2010). The model's flexibility also facilitated its integration with newer concepts such as job crafting, defined as employees' proactive adjustments of their job demands and resources to align work with their strengths and interests (Wrzesniewski & Dutton, 2001; Tims et al., 2013). These developments established the JD–R as a bridge between traditional work design theories and emerging proactive perspectives.

Despite its broad applicability, the JD–R model faces several theoretical challenges. Its flexibility, while advantageous, sometimes leads to conceptual ambiguity, as nearly any job feature can be categorized as a demand or a resource depending on context (Schaufeli & Taris, 2014). The model is also frequently applied cross-sectionally, which limits causal inference and underestimates the temporal and dynamic nature of job experiences (Bakker

& Demerouti, 2017). Furthermore, recent extensions of the JD–R theory emphasize its dynamic and multilevel nature. Bakker et al. (2023) highlight four major innovations: a) the person × situation perspective, recognizing daily fluctuations in demands and resources; b) the multilevel JD–R model, connecting individual, team, and organizational processes; c) the incorporation of proactive behaviors such as job crafting; and d) the work–home resources model, acknowledging cross-domain influences (see Figure 1.3). These refinements underline that job characteristics are embedded within broader organizational and technological ecosystems. In digital contexts, technologies operate as double-edged factors, reducing effort through automation while amplifying cognitive and emotional demands (Parker & Grote, 2022).

Figure 1.3.

The job demands–resources model



Note. Source: Bakker & Demerouti (2017).

Even with these limitations, the JD–R model has become one of the most influential and empirically supported frameworks in contemporary work design. Its conceptual simplicity allows broad application, while its dual-pathway structure captures the complexity of how work influences both health and motivation. The model provides the foundation for later theoretical advancements, such as the SMART model (Parker & Knight, 2024). In this way, the JD–R model occupies a central position in the evolution of work design theory, connecting classical motivational approaches with modern perspectives

that emphasize adaptability, well-being, and the ongoing transformation of work in digital contexts.

1.2.5 The SMART model

Over recent years, research on work design has generated a wide range of constructs and measures to describe work characteristics and their effects on motivation, health, and performance (Parker et al., 2017). Although this expansion advanced the field, it also led to conceptual overlap and inconsistency. Different theoretical perspectives, motivational, social, and strain-related approaches, often described similar job attributes using distinct terminology (Grant et al., 2011). In this context, Parker and Knight (2024) introduced the SMART model of work design to provide a higher-order structure that organizes the many dimensions of work design into a coherent framework. Their aim was not to replace existing models but to integrate and clarify the relationships among them, offering a simplified yet comprehensive structure for understanding how work features influence individual and organizational outcomes.

The SMART model identifies five higher-order factors: Stimulating, Mastery, Autonomous, Relational, and Tolerable work characteristics, each representing a cluster of lower-order dimensions derived from several decades of research (Parker & Knight, 2024). The framework draws on prior models, including the Job Characteristics Model (Hackman & Oldham, 1976), the Job Demands–Resources model (Demerouti et al., 2001), and relational and proactive perspectives (Grant, 2007; Parker et al., 2010). It also synthesizes findings from meta-analyses (Humphrey et al., 2007) and conceptual reviews (Parker et al., 2017) that demonstrated the need for greater integration across motivational, cognitive, and social aspects of work.

Stimulating work characteristics refer to the cognitive and mental complexity of work. These include task variety, skill variety, problem-solving requirements, and information processing demands. Stimulating work promotes meaningfulness and learning by exposing individuals to diverse and challenging activities. It reflects horizontal division of labor, where work complexity arises from the breadth of tasks and relationships rather than from hierarchical control. This factor connects to theories of challenge appraisal and psychological growth (Hackman & Oldham, 1976), emphasizing that work complexity can foster engagement when employees have sufficient competence and support.

Autonomous work characteristics describe the extent to which employees can exercise discretion, influence decisions, and regulate their methods or timing of work. This factor corresponds to vertical division of labor and includes method autonomy, scheduling autonomy, and decision-making autonomy. Autonomy supports the psychological experience of responsibility and self-determination, consistent with Self-Determination Theory (Deci & Ryan, 1985). High levels of autonomy have long been associated with motivation, but the SMART model situates this dimension within a broader structure that recognizes how autonomy interacts with other work features, such as complexity and social interdependence.

Mastery work characteristics capture the cognitive clarity and informational resources that enable employees to perform effectively. These characteristics include role clarity, job feedback, and feedback from others, and they promote challenge appraisal and lower negative affect. Work structured around mastery allows individuals to understand their responsibilities, evaluate progress, and integrate information across tasks. In contrast to stimulating or autonomous aspects that focus on discretion and complexity, mastery emphasizes the informational side of work design that supports learning and competence.

Relational work characteristics reflect the social connections and opportunities to positively influence others that arise from one's work. These include social support, task significance, and beneficiary contact. Relational aspects align with theories of prosocial motivation and the need for relatedness (Grant, 2007; Deci & Ryan, 2000). Work that provides contact with others and a clear understanding of its social impact contributes to a sense of purpose and belonging. In the SMART model, relational characteristics are viewed as integral to work design rather than peripheral, acknowledging that social interaction and meaning are central elements of effective and sustainable work.

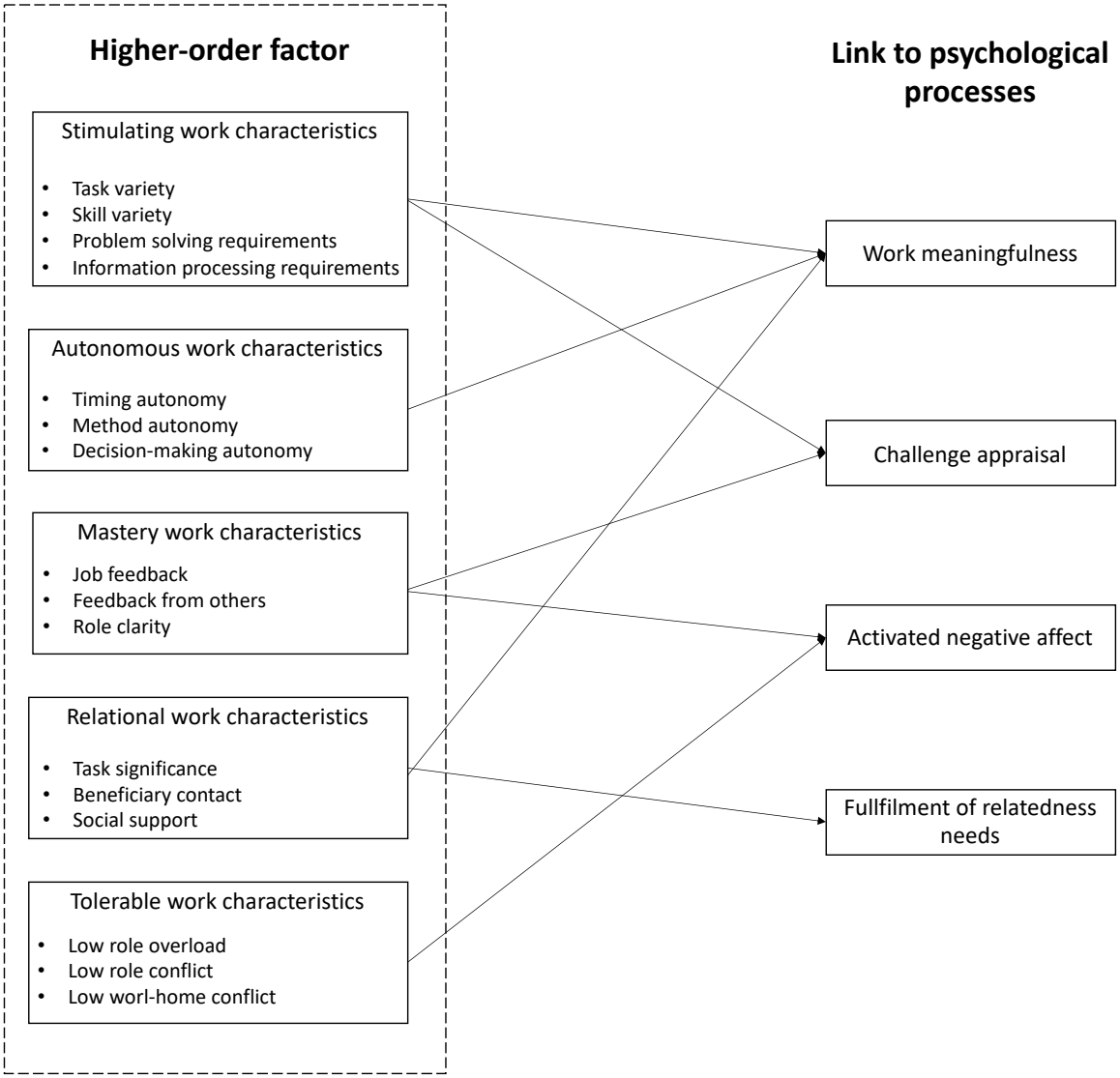
Tolerable work characteristics refer to the absence or low level of hindrance demands that produce strain, such as role overload, role conflict, and work–home conflict. This factor extends traditional motivational models by incorporating aspects of strain and well-being typically addressed in occupational health psychology. By including tolerable work characteristics, the SMART framework connects directly to the health-impairment pathway of the JD–R model (Bakker & Demerouti, 2007) while preserving the motivational focus of work design theory. Tolerable work characteristics thus represent the conditions that allow employees to manage effort and recover energy, contributing to sustainable performance.

Each of these higher-order factors links to specific organizing conditions and psychological processes. Stimulating and relational characteristics are associated with meaningfulness and challenge appraisal; autonomous characteristics with perceived control and responsibility; mastery with learning and competence; and tolerable characteristics with the reduction of negative affect. Together, they form a multidimensional structure that integrates both motivational and strain-related mechanisms (see figure 1.4). Parker and Knight (2024) emphasize that these higher-order dimensions are empirically distinct yet

interdependent, offering a comprehensive view of how work design influences engagement, well-being, and performance.

Figure 1.4.

SMART Model Work Characteristics Proposed by Parker & Knight (2024)



The SMART framework was also motivated by the increasing complexity of contemporary work systems. As digitalization, automation, and AI reshape job structures, many traditional boundaries between task, social, and contextual characteristics have become blurred (Parker & Grote, 2022). Work is now distributed across teams and

technologies, requiring constant adaptation. The SMART model responds to this environment by providing a structure that can accommodate dynamic and technology-mediated work characteristics. For example, automation may simultaneously increase stimulating aspects by adding cognitive demands, reduce autonomy through algorithmic control, and alter relational dynamics through virtual communication. By framing these features within a unified model, SMART helps to identify which aspects of work design contribute to positive adaptation and which create new forms of strain.

A key contribution of the SMART model is conceptual clarity. Earlier frameworks often treated dimensions such as autonomy, skill variety, and task significance as independent predictors, leading to redundancy across studies. The SMART model groups these dimensions into broader, theoretically grounded categories that correspond to distinct psychological mechanisms. This approach facilitates cumulative research and provides a clearer basis for work redesign interventions. It also allows for the integration of new features emerging from digital work, such as data-driven feedback or virtual collaboration, without abandoning the core logic of work design theory.

Despite its integrative value, Parker and Knight (2024) acknowledge that the SMART model is still a conceptual model requiring further empirical validation. The distinctiveness of the five higher-order factors and their generalizability across occupations and cultures remain open questions. Moreover, the model does not specify causal relationships among dimensions, focusing instead on structural organization. Future research is needed to test how these higher-order characteristics evolve over time, particularly in hybrid and algorithmically managed work environments. Nevertheless, the framework provides a parsimonious structure that enables theoretical coherence and practical relevance in a field that has become increasingly complex.

In the broader evolution of work design theory, the SMART model can be viewed as an integrative synthesis of a long process that began with the identification of specific job attributes in the 1970s and gradually expanded to include social, contextual, and technological factors. By organizing diverse work characteristics into a single framework, the SMART model bridges motivational, relational, and strain-based traditions while remaining adaptable to contemporary forms of work. Its focus on stimulation, mastery, autonomy, relationships, and tolerability reflects a comprehensive view of how work design contributes to both performance and well-being. In this sense, the model not only synthesizes past research but also provides a foundation for examining how digital technologies and AI reshape the quality and experience of work.

1.3 Core Constructs and Relationships

1.3.1 Use of ICT at Work as a Driver of Work Design Change

Empirical research has shown that ICT adoption has measurable effects on the characteristics of jobs. In a longitudinal study of service employees, Venkatesh et al. (2010) demonstrated that ICT implementation increased all five work characteristics identified in the Job Characteristics Model, skill variety, task identity, task significance, autonomy, and feedback. Employees reported a broader range of skills required, greater awareness of task interdependence, and more immediate performance feedback. Moreover, ICT systems expanded task identity by linking employees' actions to broader process outcomes, while real-time reporting enhanced feedback. Also, audit trails and digital documentation provided new forms of operational autonomy, allowing employees to make decisions directly in the system rather than through supervisors. Despite these enrichments, the study also found decreases in job satisfaction and performance after implementation, largely due

to contextual barriers such as inadequate training, cultural adjustment, and infrastructural instability.

Early theoretical arguments proposed that ICT adoption would primarily enhance autonomy and flexibility by decentralizing information and enabling employees to access knowledge resources independently (Malone, 2004; Johns & Gratton, 2013). Indeed, digital networks have allowed individuals to make faster, more informed decisions without relying solely on hierarchical supervision. However, empirical evidence reveals that these same systems can simultaneously constrain discretion. Hislop and Axtell (2007) showed that, in telework settings, connectivity often produces new forms of normative control through expectations of constant availability. Algorithmic management has intensified traditional forms of organizational control by embedding managerial oversight into digital infrastructures, where algorithms continuously direct, evaluate, and discipline workers (Kellogg et al., 2020). Leonardi et al. (2010) describe this phenomenon as the connectivity paradox: employees adopt ICTs to increase flexibility yet experience heightened surveillance and reduced control. Rather than uniformly expanding autonomy, ICT redistributes it, shifting decision authority from local supervisors to digital systems and metrics, thereby redefining how employees perceive control over their work.

ICT also transforms the cognitive and learning-related aspects of work. Zuboff (1988) originally distinguished between automation, in which technologies substitutes for human effort, and informating, in which it enhances the availability and use of information for analysis and improvement. Evidence confirms that both processes coexist in modern workplaces, as digital systems simultaneously replace routine tasks and expand employees' access to data and feedback (Brynjolfsson & McAfee, 2014). ICT use amplifies cognitive and temporal demands, as employees must process overlapping streams of digital

information, coordinate multiple communication channels, and respond under increasing time pressure (Barley, 2015). Venkatesh et al. (2010) similarly found that although employees experienced skill enrichment, they also reported stress from learning new systems and adapting to changing workflows. These findings indicate that technologies rarely simplify work; instead, it alters its cognitive texture, demanding continuous adaptation and learning.

Social and relational aspects of work have been equally affected by ICT. Digital communication platforms extend collaboration, allowing geographically dispersed teams to share expertise and maintain situational awareness (Lane et al., 2024). Yet, the nature of social interaction has changed substantially. Classic studies on distributed work (Kiesler & Cummings, 2002; Hinds & Mortensen, 2005; O'Leary & Mortensen, 2010) showed that physical distance and mediated communication reduce opportunities for spontaneous exchange, increasing the risk of miscommunication and weakening group cohesion. Other studies emphasize variability: mobile communication can buffer isolation (Hislop et al., 2015), but platform-based interactions may fragment social identity and collaboration (Lehdonvirta, 2018).

ICT also modifies job demands and strain. Continuous connectivity blurs temporal and spatial boundaries, creating difficulties in managing work–life separation (Baumeister et al., 2021). This "always-on" condition is associated with fatigue and reduced recovery (Eurofound, 2021). Parker and Grote (2022) highlight that ICT operates as both a job resource, enhancing control and efficiency, and a job demand when the speed and quantity of digital interaction exceed adaptive capacity. This duality aligns with the Job Demands–Resources model (Bakker & Demerouti, 2006), since technology can contribute to both the motivational and health-impairment pathways. Venkatesh et al. (2010) also observed that

environmental constraints, such as unreliable infrastructure or insufficient training, amplified ICT-related stressors. Thus, even when ICT enriches work characteristics, contextual factors may determine whether employees experience empowerment or overload.

Taken together, evidence indicates that ICT adoption modifies multiple work characteristics simultaneously rather than influencing them in isolation. It redistributes control, alters the sources of feedback and learning, transforms social coordination, and accelerates work rhythms. The outcomes depend on the interaction between technological affordances, task type, and managerial practices; technology enables but does not determine work experiences (Parker & Grote, 2022). In this sense, ICT adoption represents a process of ongoing sociotechnical adaptation, where each implementation recalibrates the relationship between human capability and digital structure. Understanding technologies as a driver of work design change therefore requires examining both its impact on work characteristics and the contextual conditions in which this influence takes place . The next section extends this reasoning to GenAI, a technology that amplifies many of these relationships by introducing autonomous cognitive functions into the design of work itself.

1.3.2 Use of Generative AI

Building on the earlier discussion about ICT, GenAI introduces a qualitative shift in how technology interacts with work. Whereas ICT primarily transmitted and organized information, GenAI produces it, engaging in text generation, image creation, and problem solving, operations that were previously limited to human cognition. This shift alters the distribution of cognitive work, decision authority, and creativity within organizations. GenAI systems are not merely tools of automation but cognitive collaborators that shape

how knowledge is created, interpreted, and validated. Their introduction redefines the levers of work design, influencing autonomy, skill use, feedback, social relationships, and role demands (Bienefeld & Grote, 2025; Law & Varanasi, 2025; Raisch & Krakowski, 2021; Thénoz et al., 2024). At the same time, employees' awareness that intelligent technologies may alter or replace aspects of their work introduces psychological responses that range from engagement to concern about job relevance, a pattern documented for earlier waves of intelligent automation (Brougham & Haar, 2018) and recently extended to GenAI (Hermann et al., 2025).

GenAI extends the scope of skills required in many occupations. Employees must learn to prompt systems effectively, interpret probabilistic outputs, and critically evaluate AI suggestions, activities that demand meta-cognitive and communicative skills (Bick et al., 2025; Gmyrek et al., 2023). These developments reflect the broader shift from manual or procedural competencies toward reflexive and analytical capabilities (Frank et al., 2019). Empirical studies show that exposure to GenAI often enhances workers' perceived skill variety and satisfaction by enabling new forms of creativity and experimentation (Brynjolfsson et al., 2023; Thénoz et al., 2024).

GenAI also reshapes perceptions of task wholeness and meaning. When humans collaborate with generative systems capable of synthesizing and visualizing complex information, work can approach a form of "AI-supported craftsmanship," where individuals retain authorship and oversight across the full process from idea to output (Thénoz et al., 2024). This experience extends to generative tools the broader logic of decision augmentation, in which intelligent technologies enhance human reflection, learning, and control rather than replacing human judgment (Leyer & Schneider, 2021)

The integration of GenAI also transforms autonomy. In some contexts, GenAI enhances workers' autonomy by offloading repetitive or cognitively demanding tasks, thereby allowing them to focus on higher-value activities such as creativity and strategic decision-making, and to exercise greater discretion over their workflows (Hermann et al., 2025). A field experiment in a customer-service organization found that GenAI support improved both productivity and job satisfaction by simplifying complex queries and freeing agents to focus on relational problem solving (Brynjolfsson et al., 2023). Conversely, algorithmic management and opaque model logic can reduce perceived autonomy, as employees struggle to understand or contest system recommendations (Kellogg et al., 2020; Raisch & Krakowski, 2021). Bienefeld and Grote (2025) emphasize that this duality creates a control–accountability dilemma: humans remain legally and ethically responsible for outcomes that are partially determined by non-transparent algorithms. Human-centered design principles such as explainable AI and participatory system development are therefore essential to maintain agency (Shneiderman, 2020; Amershi et al., 2019; Yu et al., 2023). Under these conditions, autonomy depends not solely on the task itself but on how organizations distribute authority and accountability between humans and intelligent systems.

Additionally, GenAI reconfigures the structure of feedback in work processes. Its interactive interfaces provide continuous and adaptive responses that enable experimentation, self-directed learning, and rapid refinement of ideas (Law & Varanasi, 2025). By offloading repetitive and cognitively demanding elements of feedback processing, GenAI allows workers to focus on interpretation and higher-order reflection, which can strengthen perceptions of mastery and control (Hermann et al., 2025). These adaptive feedback loops resonate with classic work design theories, where learning and

competence satisfaction are central to motivation and engagement. Yet, while AI feedback systems often enhance learning through rapid and data-rich recommendations, such immediacy may also undermine understanding when employees distrust the system or perceive its logic as opaque, reducing learning and performance (Tong et al., 2021).

With respect to demands, delegating cognitive tasks to GenAI reduces routine workload but introduces meta-work: employees must verify, edit, and contextualize AI outputs, while remaining accountable for their accuracy. This oversight responsibility generates new cognitive and emotional demands, often under compressed time frames (Acemoglu & Restrepo, 2019; Brynjolfsson & McAfee, 2014). Bienefeld and Grote (2025) note that the human obligation to supervise autonomous systems can lead to chronic vigilance and "responsibility stress." From a Job Demands–Resources perspective (Bakker & Demerouti, 2006), GenAI functions simultaneously as a job resource, enhancing efficiency, control, and feedback, and as a job demand when the complexity of oversight exceeds available support. Balancing this duality is essential to prevent the transition from empowerment to overload.

Evidence across conceptual and empirical studies suggests that GenAI reshapes multiple work characteristics at once. It enriches work through cognitive augmentation, real-time feedback, and broader task perspectives, yet it can simultaneously fragment tasks, reduce discretion, and heighten responsibility. Outcomes depend on implementation choices, transparency, and the degree of human participation in system design (Parker & Grote, 2022; Bienefeld & Grote, 2025; Thénoz et al., 2024). Understanding Generative AI as a driver of work-design change therefore requires examining not only its technical affordances but also its organizational embedding. The next subsection examines

employees' attitudes toward GenAI, their nature and dimensions, and their role as an antecedent of GenAI use at work.

1.3.3 Attitudes toward Generative Artificial Intelligence

Attitudes toward GenAI represent employees' overall evaluative orientations toward engaging with these technologies in their work. In organizational research, attitudes are understood as enduring evaluative tendencies that integrate cognitive, affective, and ethical components (Ajzen, 2001). Within the context of generative technologies, these attitudes reflect how employees appraise the use of GenAI systems, whether they view them as supportive, empowering, and ethically trustworthy tools that can enhance job performance, or as disruptive and potentially dehumanizing systems that threaten competence, autonomy, and control. This perspective is consistent with technology adoption frameworks such as the Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh & Davis, 2000), which position attitudes as proximal determinants of behavioral intention and actual use. In the case of GenAI, attitudes serve as the psychological gateway through which predispositions towards the technology are translated into patterns of use that can reshape work characteristics.

Contemporary research conceptualizes attitudes toward AI as complex construct, combining positive, negative, and moral components (Park et al., 2024). Positive attitudes encompass curiosity, perceived usefulness, and openness to learning, whereas negative attitudes are characterized by anxiety, fear of replacement, and skepticism toward AI-generated outcomes. Moral concerns, in turn, capture evaluations of fairness, accountability, and the preservation of human values in technological systems. These dimensions coexist and often interact, resulting in ambivalent responses toward generative technologies. For instance, Wang et al. (2025) demonstrated that employees' cognitive

assessments of usefulness and control, together with their affective experiences of fear and their trust in the ethical integrity of GenAI, shape whether their overall attitude is favorable or resistant. Shao et al. (2025) integrated self-efficacy theory and the TAM with perceived AI ethics, showing that individuals who feel confident in their ability to use AI systems and believe that these systems operate responsibly tend to perceive them as more useful and easier to use, thereby fostering more positive attitudes and stronger adoption intentions.

Evidence across studies indicates that these attitudes have an influence on GenAI use. Employees with favorable attitudes toward GenAI tend to explore its capabilities more actively, integrate it into problem-solving routines, and use it to complement their own expertise. Conversely, negative or fear-based attitudes often lead to avoidance, superficial engagement, or passive reliance on the technology. These behavioral differences are particularly relevant to work design. When employees adopt GenAI with curiosity and trust, they are more likely to experience gains in autonomy, skill variety, and feedback through experimentation and self-directed learning (Parker & Grote, 2022; Del Giudice et al., 2023). In contrast, resistance or anxiety toward GenAI may limit opportunities for learning and control, potentially reinforcing perceptions of reduced competence or workload imbalance. Thus, attitudes toward GenAI not only determine whether employees use the technology but also influence how its integration reshapes core work characteristics.

In sum, attitudes toward GenAI function as a central psychological mechanism linking employees' perceptions of technology with its practical use. Positive, trust-based attitudes facilitate exploratory and autonomous use of these tools. Negative or anxiety-driven evaluations, by contrast, constrain experimentation and limit the extent to which employees engage with these tools. Understanding these attitudinal aspects is crucial for explaining variability in how GenAI is adopted, and in turn, how its use shapes work

design. The following subsection examines ECTI as a key organizational approach that shapes how new technologies are introduced and integrated into work, and through this, how employees experience changes in their work characteristics.

1.3.3 Employee-Centered Technology Implementation

ECTI refers to "a human-centered approach in which employee needs and ideas about the implementation process [of new technologies] are considered, and that involves employees in this process by means of, e.g., offering them information, consultation, and training" (González-Romá et al., 2025). Rather than focusing on the technical deployment of digital systems, ECTI captures a set of organizational practices through which employees are informed, involved, and supported during technology implementation. In this sense, ECTI reflects how organizations operationalize human-centered principles in the context of digital transformation.

From a sociotechnical perspective, technology and organization constitute interdependent subsystems whose effectiveness depends on their joint optimization (Trist & Bamforth, 1951; Cherns, 1976). Accordingly, the way technologies are implemented plays a central role in determining whether digital transformation aligns with employees' capabilities and needs. When implementation practices incorporate participation, communication, and training, they can shape key work characteristics that employees experience as they use new technologies at work (Parker & Grote, 2022).

Recent scholarship conceptualizes technology implementation as a design activity rather than a purely technical or managerial process. Research on human-centered design suggests that digital transformation is more effective when technologies are aligned with users' capabilities and work practices throughout the implementation process (Kadir &

Broberg, 2021). This perspective is consistent with broader policy and research agendas, such as the Industry 5.0 framework, which emphasizes the importance of human-centered, sustainable, and inclusive technological development (Breque et al., 2021). Participatory and iterative approaches facilitate this alignment by incorporating user input and adapting systems to evolving work demands, whereas technology-driven approaches may disrupt established routines and reduce system usability (Zink, 2014; Parker & Grote, 2022). From this perspective, implementation practices constitute a key organizational mechanism through which technological change shapes work design.

Complementing this view, Self-Determination Theory (SDT) explains the motivational consequences of implementation choices. According to Gagné et al. (2022), change initiatives foster engagement when they satisfy employees' needs for autonomy, competence, and relatedness. During digital transitions these needs are easily frustrated: automation may reduce discretion, algorithmic management can erode competence, and remote collaboration can weaken social connection. Implementation strategies that counteract these effects, through transparent communication, training, and participation, can sustain intrinsic motivation and well-being. Empirical evidence shows that technology implementations incorporating staff consultation, training, and ongoing support enhance motivation, engagement, and job satisfaction, whereas initiatives focused primarily on compliance or monitoring increase frustration and stress (Jedwab et al., 2023). Implementation orientation therefore acts as a relevant factor that can determine whether GenAI is internalized as a resource or resisted as a threat.

A central element of ECTI lies in the concrete practices through which employees are informed, involved, and supported during technological change. Providing clear information about how and why new technologies are introduced can reduce uncertainty

and facilitate adaptation. Involving employees by considering their questions, concerns, and suggestions allows organizations to better align technological changes with existing work practices. Training and support mechanisms further enable employees to develop the skills required to interact effectively with new systems. Prior research confirms that such practices are associated with more positive employee responses to change (Ullrich et al., 2023), and self-determination theory highlights that supporting employees' needs for autonomy, competence, and relatedness during implementation is linked to higher motivation and well-being (Gagné et al., 2022).

Taken together, ECTI can be understood as a key organizational approach through which the involved technological change can impact the design and experience of work. Building on this perspective, the following section presents the main objectives of this doctoral dissertation.

1.4 Objectives of the doctoral dissertation

1.4.1 Main Objective

The main objective of this thesis is to advance theoretical and empirical understanding of how workplace technologies and their implementation influence work design and employee outcomes. Specifically, the thesis examines the mechanisms through which different aspects related to new technologies at work, namely the ICT use at work, the GenAI use, and ECTI, affect core work characteristics and, in turn, job outcomes (e.g., employee wellbeing, job satisfaction).

Additionally, we divided the main objective into three specific objectives, each tackled by a separate study. These studies are presented in the corresponding chapters of the present doctoral thesis (Study 1: Chapter 2, Study 2: Chapter 3, and Study 3: Chapter 4).

1.4.2 Specific Objectives

The first specific objective is to examine how the use of ICT at work relates to employee well-being through two core work characteristics, job autonomy and workload, and the motivational and health-impairment processes embedded in the JD-R model. Specifically, we examine whether ICT use operates simultaneously as a job resource, by enhancing autonomy, and as a job demand, by increasing workload, thereby activating the motivational and health-impairment pathways proposed by the JD–R model (Bakker & Demerouti, 2014). In addition, we investigate whether these relationships are moderated by employee age, considering that digital fluency and adaptation to ICT may vary across career stages (Parker & Grote, 2022). This objective is addressed in Study 1, using cross-sectional multi-country data from the 2021European Working Conditions Survey.

The second specific objective is to examine how the use of GenAI at work relates to five core work characteristics derived from the SMART model of work design (Parker & Knight, 2024), namely skill variety, job autonomy, job feedback, social support, and role overload. In addition, we examine whether employee attitudes toward GenAI function as an antecedent of its subsequent use at work, and whether the relationships between GenAI use and work characteristics are moderated by occupational skill level. This objective is addressed in Study 2, using a three-wave longitudinal design with a sample of Spanish employees.

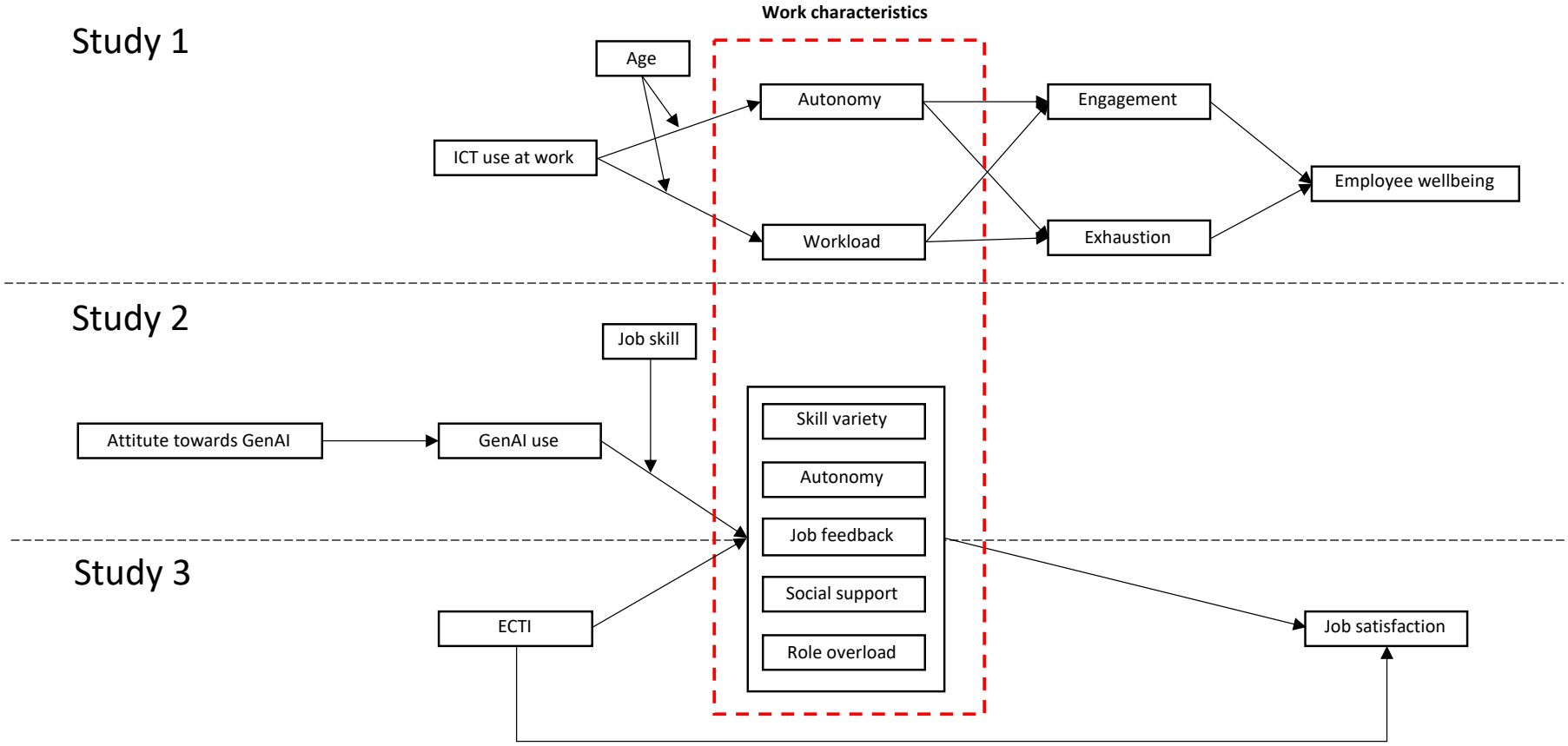
The third specific objective is to examine how ECTI relates to the same five work characteristics (skill variety, job autonomy, job feedback, social support, and role overload) and to job satisfaction. In addition, we examine whether the relationship between ECTI and job satisfaction is mediated by these five work characteristics, thereby testing the mechanisms through which employee-centered implementation practices translate into

employees' evaluations of their work. This objective is addressed in Study 3, using also a three-wave longitudinal design with a sample of Spanish employees.

Figure 1.5 aims to provide a general vision and summary of the research objectives outlined in the three studies of this doctoral thesis. It is important to note that these descriptions are broad in nature. In the forthcoming chapters (2, 3, 4), the specific issues will be defined in greater detail, and the specific research hypotheses will be outlined.

Figure 1.5.

General Overview of the Doctoral Thesis' Studies



Note. ICT: Information and Communication Technologies; GenAI: Generative Artificial Intelligence; ECTI: Employee-Centered Technology Implementation.

Chapter 2: ICT Use at Work as a Double-Edged Sword: A Moderated Mediation Model of Employee Well-Being (Study 1)

2.1 Introduction

The accelerated evolution of ICT (Information and Communication Technology) use at work by means of different devices (e.g., desktop computers, laptops, smartphones, and tablets) and digital technologies (e.g., video-conferencing and geolocation software) has stimulated an unprecedented change in the contemporary labor landscape (Fréour et al., 2021). This technological revolution has significantly altered the essence of work, creating a continuously changing work environment (Cascio & Montealegre, 2016). In 2021, 56% of EU companies reached the basic level of digital intensity (Eurostat, 2021)[1]. According to the World Economic Forum's report on the future of employment in 2023 (World Economic Forum, 2023), it is anticipated that one-quarter of jobs will undergo transformation due to technologies, with 86% of organizations continuing to adopt such technologies. Moreover, it is estimated that the additional value to the economy resulting from the implementation of digital technologies will reach $100 trillion by the year 2025 (World Economic Forum, 2016).

Despite the growing use of ICT in the labor context, a substantial problem persists in understanding the implications that these technologies have for employees (Barley, 2015; Parker & Grote, 2022). Recent research has shown that ICT use can have both positive and negative relationships with certain work characteristics (see Wang et al., 2020 for a review). Considering the empirical evidence and theories about the relationship between work characteristics and well-being (Demerouti et al., 2001; Humphrey et al., 2007), all this suggests that the relationship between ICT use and employee well-being is complex,

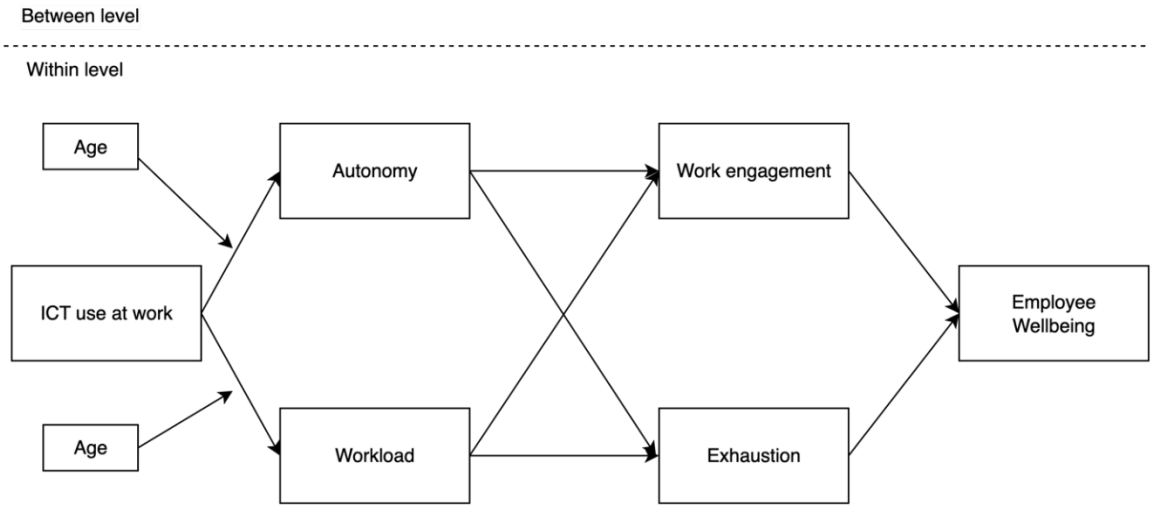
[1] A basic level corresponds to the fulfillment of at least 4 out of 12 criteria for digital technologies, such as the use of IoT (Internet of Things), and enterprises in which over 50% of the workforce utilizes computers with internet access for business purposes.

involving multiple mediators, and has the potential for simultaneous positive and negative indirect effects. Identifying and distinguishing the mediators that transmit the benefits of ICT use for employee well-being from those mediators that potentially trigger its drawbacks is important for theoretical and practical reasons. Theoretically, identifying the mechanisms that explain why two variables are related in different ways helps advance knowledge because it provides a detailed and fine-grained understanding of the investigated relationship (Preacher & Hayes, 2004). Practically, identifying the different mediators involved offers a solid basis to suggest ways to promote the functional impact of ICT use on employee well-being and mitigate its dysfunctional influence. As Parker and Grote (2022, p. 1189) stated, "the more that we can map out how, what, and why technology affects work design, the more we will gain important insights into how to optimize technology's benefits and mitigate its potential dysfunctional effects". Thus, the first goal of this study is to identify some of the mediators that intervene in the positive and negative relationships between ICT use at work and employee well-being.

Furthermore, the relationship between ICT use and employee well-being may depend on boundary conditions (Coovert & Thompson, 2013; Parker & Grote, 2022). Identifying these moderators is important from a theoretical and practical perspective. Theoretically, it will allow us to understand and predict the influence of ICT use on employee well-being under different boundary conditions (Wang et al., 2020). This will also help improve and extend related theoretical models by refining their detail and scope. Practically, identifying moderators suggests potential levers that may be useful to boost the positive impact of ICT use on employee well-being and buffer its negative influence. Therefore, the second goal of this study is to determine whether employee age moderates the positive and negative relationships between ICT use at work and employee well-being.

Our research model (see Figure 2.1) is, to a great extent, based on the Job Demands Resource (JD-R) theory (Bakker & Demerouti, 2007). This model considers two key types of work characteristics: job demands and job resources. Job demands (e.g., workload) are aspects of the job that require constant physical or psychological effort and consume energy. Job resources (e.g., job autonomy) are aspects of the job that facilitate the achievement of work goals and foster personal growth, learning, and development (Demerouti et al., 2001; Bakker & Demerouti, 2007; Bakker et al., 2023). The JD-R model posits that job demands and resources trigger two distinct processes: a health-impairment process and a motivational process, respectively (Bakker & Demerouti, 2007). The health-impairment process indicates that long-term exposure to high job demands leads to job burnout and employee strains, which negatively affect employee well-being. The motivational process points out that job resources can boost employee engagement, which in turn will lead to improved employee well-being (Bakker & Demerouti, 2017, 2018). The original JD-R model (Demerouti et al., 2001) considered these two processes to be independent. However, several studies (e.g., Bakker et al., 2003; Davcheva et al., 2024; González-Romá et al., 2020; Schaufeli & Bakker, 2004) and meta-analyses (Alarcon, 2011; Crawford et al., 2010; Lee & Ashforth, 1996) have provided empirical evidence about the existence of cross-links between the variables involved in the two processes. These cross-links show that job resources are also negatively related to employee exhaustion and strains, whereas job demands are also negatively related to motivational states such as work engagement.

Figure 2.1. The research model



We focused on job autonomy (i.e., the extent to which a job allows freedom, independence, and discretion to schedule work, make decisions, and choose the methods used to perform tasks; Morgeson & Humphrey, 2006) and workload (i.e., the degree to which employees perceive their task demands exceed their capacity; MacDonald, 2003) because they are two of the most important work characteristics within the JD-R model (Bakker et al., 2023). Moreover, previous research has shown that autonomy is strongly and positively related to work motivation and outcomes (Hackman & Oldham, 1976; Humphrey et al., 2007; Parker et al., 2017). In addition, workload is a variable that currently characterizes jobs that use technology (Van Den Broeck et al., 2017) and can have important consequences for employee well-being (Wang et al., 2021). Regarding the psychological states considered, we focused on work engagement (i.e., "a positive, fulfilling, work-related state of mind that is characterized by vigor, dedication, and absorption"; Schaufeli et al., 2002, p.74) and job exhaustion (i.e., a state of physical and emotional fatigue produced by the work one performs (Maslach et al., 1996)), which is generally considered the core dimension of burnout (Halbesleben et al., 2010; Maslach, 1982). We did so because they are two key states involved in the motivational and health-

impairment processes within the JD-R theory, respectively (Bakker & Demerouti, 2007). Finally, we chose employee well-being (i.e., a person's cognitive and affective evaluations of his or her life; Diener, 2002) because it is a relevant employee outcome within the JD-R theory (Bakker et al., 2023) and has been recently highlighted as an ultimate criterion for organizational sciences (Tay et al., 2023).

As potential a moderator of the relationships between ICT use at work, on the one hand, and job autonomy and workload, on the other hand, we considered an individual-level variable (age). We focused on age for two reasons. The first one is related to the aging of the global population. In the year 2030, 1 in 6 people will be 60 years old or older (World Health Organization [WHO], 2017). This is causing and will cause more older people to be in the workforce and, therefore, interacting with ICT. Second, it has been proven that over the years, skills and cognitive capabilities change (Charness, 2020). Thus, there may be differences between age groups in how ICT use at work is related to work characteristics.

Some recent studies have used the JD-R model to examine how ICT use relates to work characteristics and employee outcomes. For example, Leitner and Stöllinger (2022), in a working paper, analyzed public data from European countries and showed that digital technologies are related to several work characteristics and work engagement and exhaustion. Our study differs from Leitner and Stöllinger's (2022) investigation in several ways. First, we included employee well-being as a final outcome, which allowed us to examine the indirect effects on ICT use at work and this variable. The outcome variables in Leitner and Stöllinger's (2022) study were work engagement and exhaustion. Second, we examined the cross-links between the variables included in the motivational and health-impairment processes embedded in the JD-R model. These cross-links were not

investigated in Leitner and Stöllinger's (2022) working paper. Third, we considered the nested structure of data (employees nested within countries) and analyzed data using multilevel modeling methods. Fourth, we investigated a moderator (age) that helped understand to what extent the investigated relationships depend on individual factors. Leitner and Stöllinger's (2022) model did not include any moderator. These differences show that our study goes above and beyond previous studies about the addressed topic and aims to offer more detailed and nuanced knowledge about the relationship between ICT use, work characteristics, and employee well-being.

Our investigation aims to contribute to literature in several ways. First, our study contributes to identifying the mechanisms through which ICT use is linked to employee well-being. The identification of the mediators through which two variables are related "is often an increase in knowledge and an important refinement of the theory" (Spence et al., 2005, p. 846). Second, our investigation helps extend the JD-R model by including ICT use as an antecedent of a specific demand and resource. Third, on a related note, our study also contributes to extending the JD-R model by providing additional empirical evidence about the existence of cross-links between the motivational and health-impairment process. Fourth, we show that the use of ICT at work is a "double-edged sword" that involves both positive and negative indirect relationships with employee well-being. Thus, our study points out that the potential influences of ICT use at work are complex and multifaceted. Fifth, by investigating the moderating role of employee age in the relationship between ICT use at work and the two work characteristics considered (autonomy and workload), we offer a more detailed and nuanced perspective of the investigated phenomenon, showing that the aforementioned individual variable plays an important role.

2.2. Theoretical Background

The JD-R model provides an appropriate theoretical framework to investigate the mediated relationships (indirect "effects") embedded in our research model. Next, we justify the expected relationships and present our research hypotheses.

In this study, ICT use at work refers to the frequency with which employees interact with basic digital tools and technologies (e.g., computers, tablets, smartphones) as part of their job. This operationalization is based on a single item from the EWCS 2021.

2.2.1 The positive indirect effect of ICT use on employee well-being through autonomy and work engagement

We posit that ICT use has a positive indirect effect on employee well-being via the sequential mediation of autonomy and work engagement. First, ICT use at work fosters job autonomy by promoting a more decentralized decision-making structure. This is because ICT facilitates a broader dissemination of information (Fréour et al., 2021; Parker & Grote, 2022). Employees using ICT devices can access necessary resources and information digitally, allowing for greater flexibility in when and where they work (Raghuram et al., 2019). This includes working outside traditional hours, collaborating virtually with teams, and even telecommuting. Finally, ICT empowers employees to organize their work with increased temporal and spatial flexibility (Ninaus et al., 2015), promoting greater autonomy. This aligns with the findings from Kraan et al. (2014) on how computer-based ICT use in a large multinational sample (18,723 workers) increased autonomy in choosing schedule work and methods.

Second, we posit that autonomy is positively related to work engagement. This relationship is grounded in the Self-Determination Theory (SDT), which emphasizes the

role of intrinsic motivation in fostering positive work outcomes. According to the SDT, individuals are more likely to be engaged and motivated when their basic psychological needs for autonomy, competence, and relatedness are satisfied (Deci & Ryan, 2000). In the workplace context, environments that support these needs—particularly autonomy—enhance employees' self-driven motivation and are associated with higher levels of work engagement (Gagné & Deci, 2005). When employees feel control over their work (autonomy), it fuels their intrinsic motivation, leading to greater work engagement (Rahmadani et al., 2019). This aligns with the meta-analysis of Christian et al. (2011), which found that autonomy is an antecedent of work engagement.

Third, we posit that work engagement is positively related to employee well-being. Following the motivational process path of the Job Demands-Resources model, workers with high work engagement experience greater psychological employee well-being due to an increase in positive emotions associated with intrinsic motivation (Schaufeli & Taris, 2014). Furthermore, according to the Self-Determination Theory, when individuals exhibit high levels of engagement, their basic psychological needs for autonomy, competence, and relatedness tend to be satisfied. The fulfilment of these needs is directly associated with the generation of positive emotions and enhanced overall well-being (Van den Broeck et al., 2008). This aligns with the perspective of Bakker and Oerlemans (2011), where work engagement is characterized by high energy, positive emotions, and a sense of accomplishment at work. These positive work experiences, as noted by Culbertson et al. (2012), can contribute to general well-being. A comprehensive meta-analysis conducted by Mazzetti et al. (2023) identified employee well-being as a significant outcome of work engagement.

Based on all the arguments and empirical evidence presented above, we hypothesize the following:

Hypothesis 1: ICT use has a positive indirect effect on employee well-being through autonomy and work engagement, so that ICT use is positively related to autonomy, which in turn is positively related to work engagement, which in turn is positively related to employee well-being.

2.2.2 The negative indirect effect of ICT use on employee well-being through workload and job exhaustion

We posit that ICT use has a negative indirect effect on employee well-being via the sequential mediation of workload and job exhaustion. First, we argue that ICT use at work is positively related to workload based on several reasons. ICT has the capability to accelerate both task speed and volume, leading to an increased perception of workload (Carlson et al., 2017; Day et al., 2012; Zeike et al., 2019). Moreover, ICT may contribute to blurring the boundaries between work and non-work time, facilitating employees taking work home after their regular working time (Barber & Santuzzi, 2015). This can contribute to increasing their perceived workload. Finally, because ICT provide faster communication, ICT use raises expectations for immediate responses from employees, which in turn may increase employees' perceived workload (Scholze et al., 2024). Empirical evidence from quantitative (Chesley, 2014) and qualitative (Towers et al., 2006; Zacher & Rudolph, 2024) studies supports the positive relationship between ICT use and perceived workload.

Second, according to the health-impairment process suggested by the JD-R theory, we posit that workload is positively related to job exhaustion. This theory suggests that high workload leads to increased employee effort. This increased effort stems from the lack of time to efficiently complete tasks. As a result, employees may experience a depletion of

their physical, emotional, or cognitive resources, potentially leading to increased exhaustion (Demerouti et al., 2001). The health-impairment process is well-supported in the literature (Alarcon, 2011; Christian et al., 2011; Crawford et al., 2010; Halbesleben, 2010). For instance, Avanzi et al. (2018) analyzed a sample of 2685 Swiss teachers and found that workload was positively related to exhaustion.

Third, we posit that job exhaustion is negatively related to employee well-being. This hypothesis is based on the theory of Conservation of Resources (COR, Hobfoll, 1989). According to this theory, people seek to obtain, retain, and protect what they value (e.g., material, social, personal, or energetic resources). This theory proposes that the stress experienced by individuals can be understood in relation to potential or actual loss of resources. When workers experience high levels of exhaustion, it indicates a decrease in their personal resources. This situation prevents them from investing in acquiring new resources, creating an imbalance between job demands and available personal resources, which leads to a decrease in psychological well-being (Hobfoll et al., 2018). Furthermore, according to the COR theory, this phenomenon can be intensified due to a "loss spiral", where the inability to cope with additional stressors contributes to a further deterioration of psychological well-being (Hobfoll, 2001). Hakanen & Schaufeli (2012), in their study with three waves of data over seven years, found a negative relationship between emotional exhaustion, depersonalization and employee well-being.

Based on the arguments and empirical evidence presented above, we propose the following hypothesis (Hypothesis 2):

Hypothesis 2: ICT use has a negative indirect effect on employee well-being through workload and exhaustion, so that ICT use is positively related to workload,

which in turn is positively related to exhaustion, which in turn is negatively related to employee well-being.

2.2.3 The positive indirect effect of ICT use on employee well-being through autonomy and exhaustion

This indirect effect (ICT use →Autonomy → Exhaustion → Employee Well-being) is based on the existence of cross-links between the variables involved in the motivational and health-impairment processes embedded within the JD-R theory (see Alarcon, 2011; Bakker et al., 2003; Crawford et al., 2010; Davcheva et al., 2024; González-Romá et al., 2020; Lee & Ashforth, 1996; Schaufeli & Bakker, 2004). In this case, the cross-link involves the negative relationship between work autonomy and job exhaustion. This relationship is based on the following arguments. According to the COR theory, employees that have more resources, such as autonomy, demonstrate lower susceptibility to resource loss and greater potential for resource gain. Therefore, autonomy serves as a resource that allows employees to conserve their resources and energy and prevent the emotional and physical exhaustion (Hobfoll et al., 2018). Previous research with healthcare workers has supported this hypothesis, showing that autonomy is negatively related to stress (Havermans et al., 2017). Additionally, Shoman et al. (2021) conducted a systematic review that indicated that increasing autonomy can serve as a protective factor against exhaustion. Moreover, several studies have reported negative correlations between job resources and burnout (Hakanen, Schaufeli & Ahola, 2008; Schaufeli & Bakker, 2004).

Based on the aforementioned arguments and those outlined in the previous sections, we propose the following hypothesis:

Hypothesis 3: ICT use has a positive indirect effect on employee well-being through autonomy and exhaustion, so that ICT use is positively related to autonomy, which

in turn is negatively related to exhaustion, which in turn is negatively related to employee well-being.

2.2.4 The negative indirect effect of ICT use on employee well-being through workload and engagement

As above, this indirect effect (ICT use → Workload → Engagement → Employee Well-being) is based on the existence of cross-links within the JD-R theory (Alarcon, 2011; Davcheva et al., 2024; González-Romá et al., 2020; Lee & Ashforth, 1996). In this case, the cross-link involves the negative relationship between workload and work engagement. This relationship is based on the following arguments: According to the COR theory, a high workload induces a depletion of personal resources (Hobfoll et al., 2018). This produces a decrease in the resources available to be invested at work, which reduces work engagement (Hakanen et al., 2005). This phenomenon is particularly significant given the first principle of the COR theory: "Resource loss is disproportionately more salient than resource gain" (Hobfoll et al., 2018, p. 106). In this context, resource acquisition becomes progressively more challenging, potentially initiating a cyclical pattern of resource loss, which leads to a decrease in work engagement. A meta-analysis by Nahrgang et al. (2011) revealed a negative association between job demands and work engagement. A subsequent study with teachers in China corroborated this finding, demonstrating that a high level of workload negatively impacts work engagement (Wang, 2024). Considering the arguments presented in this and the previous sections, we formulate the following hypotheses:

Hypothesis 4: ICT use has a negative indirect effect on employee well-being through workload and work engagement, so that ICT use is positively related to workload, which in turn is negatively related to work engagement, which in turn is positively related to employee well-being.

2.2.5 The Moderating Role of Age

We propose that age moderates the relationship between the use of ICT at work and autonomy. This hypothesis is based on research on cognitive aging. The results of this research show decline in memory and the acquisition of new skills after early adulthood as individuals age (McGrew, 2005; Salthouse, 2010). These declines present potential barriers for older workers, affecting their ability to solve new problems, use working memory effectively, and maintain processing speed, all of which are crucial for learning to use new technologies (Beier et al., 2012). Thus, these declines pose challenges for older workers in the development of new skills related to the use of ICT. By contrast, younger workers show greater openness to ambiguity and a greater willingness to experiment with new technologies (Hauk et al., 2018), which can help them to maximize the benefits of using ICT at work. Thus, we posit that the relationship between the use of ICT at work and autonomy is moderated by employee age, so that the relationship is weakened as age increases.

Considering this expected moderator effect of employee age on the relationship between ICT use and job autonomy, on the one hand, and the indirect effects in which the ICT use-autonomy relationship is involved (Hypothesis 1: ICT use → autonomy → work engagement → employee well-being; and Hypothesis 3: ICT use → autonomy → exhaustion → employee well-being), on the other hand, we propose the following hypotheses concerning conditional indirect effects:

> Hypothesis 5: The positive indirect effect of ICT use at work on employee well-being through autonomy and work engagement is moderated by employee age, so that the indirect effect is weaker as age increases.

Hypothesis 6: The positive indirect effect of ICT use at work on employee well-being through autonomy and job exhaustion is moderated by employee age, so that the indirect effect is weaker as age increases.

Second, we posit that age moderates the relationship between ICT use at work and workload. Research suggests that biological and psychological changes associated with aging can make it more challenging for older adults to utilize and adapt to new technologies (Phang et al., 2006; Chen & Chan, 2011). For instance, Saunders et al. (2017) discovered that older users reported feeling more overwhelmed by information generated by ICT than younger users. These authors suggested that this might be related to older users' lowered cognitive skills, which make it harder for them to manage several simultaneous information streams. Given how ICT use generally increases the amount of information flow, older workers may perceive a greater workload from ICT use than their younger counterparts. This is because the former may struggle more than the latter with handling the amount of information associated with ICT use. Thus, we posit that the relationship between the use of ICT at work and workload is moderated by employe age, so that the relationship is enhanced as age increases.

Considering the expected moderator effect of employee age on the relationship between ICT use and workload, on the one hand, and the indirect effects in which the relationship ICT use-workload is involved (Hypothesis 2: ICT use → workload → exhaustion →employee well-being; and Hypothesis 4: ICT use → workload → work engagement → employee well-being) on the other, we propose the following hypotheses concerning conditional indirect effects:

Hypothesis 7: The negative indirect effect of ICT use at work on employee well-being through workload and exhaustion is moderated by employee age, so that the indirect effect is stronger as age increases.

Hypothesis 8: The negative indirect effect of ICT use at work on employee well-being through workload and work engagement is moderated by employee age, so that the indirect effect is stronger as age increases.

2.3 Method

2.3.1 Sample

The individual-level data analyzed come from the seventh European Working Conditions Survey (EWCS) conducted by the European Foundation for the Improvement of Living and Working Conditions in 37 European countries between March and November 2021. The respondents were randomly selected. Random probability sampling using telephone numbers was employed to create nationally representative samples of each country. The survey included questions about work and employment conditions, health, and employee well-being. After removing the self-employed subjects, those with a part-time job, and missing observations, the final sample comprised 7,900 employees. The study sample was composed of roughly equal proportions of men (55.0%) and women (44.9%). The majority of participants (54.0%) were between 35 and 55 years old, 32.6% were younger (under 35 years,) and 13.4% were older (over 55 years). According to educational level, 27.83% had completed upper secondary education, 25.37% held a master's degree or equivalent, and 23.28% had a bachelor's degree or equivalent. According to economic sectors, 15.63% were employed in manufacturing, 11.03% in financial and insurance activities, 9.80% in education, and 8.99% in human health and social work activities. The

sample size varied across countries: the smallest one was collected in Switzerland (N = 79) and the largest one in Germany (N = 457).

2.3.2 Measures

2.3.2.1 Use of ICT at Work

In the EWCS, this variable was measured by asking individuals how often their primary paid job involves the use of technology devices ("How often does your main paid job involve working with computer, laptop, tablet, smartphone?"). The scale response ranges from 1 (never) to 5 (always). This question has been used before to measure ICT use at work (Joling & Kraan, 2008; Barrientos-Marín et al., 2021; Menón et al., 2020; Millán et al., 2021). For instance, Menon et al. (2020) analyzed how the use of ICT at work affects work intensity and work discretion in 15 European countries between 1995 to 2015.

2.3.2.2 Job autonomy

The EWCS measures job autonomy by using the following three questions: "In your main job, are you able to choose or change...: (1) your order of tasks? (2) your methods of work? (3) your speed or rate of work?". The scale response ranges from 1 (never) to 5 (always). This measure has been previously used in empirical studies (e.g., C.-H. Wu et al., 2015; Y.-J. Wu et al., 2021). The reliability coefficients in the study sample (within level) were McDonald's Omega = .74 and Composite Reliability = .74.

2.3.2.3 Workload

The EWCS measures workload by using the following two questions: "Does your job involve working to tight deadlines?" and "Does your job involve working at very high speed?". The scale response ranges from 1 (never) to 5 (always). Previous investigations by Hakanen et al. (2019), Tsen et al. (2023), and Zappalà et al. (2022) have used this scale.

The reliability coefficients at the within level were McDonald's Omega = .64 and Composite Reliability = .64

2.3.2.4 Work engagement

Work engagement was measured with the three items composing the Utrecht Work Engagement Scale (UWES-3) (Schaufeli et al., 2019): 'At work I feel full of energy' (vigor), ' I am enthusiastic about my job (dedication), and 'Time flies when I am working´ (absorption). The items are answered on a Likert scale that ranges from 1 (never) to 5 (always). Hakanen et al. (2019) used the same questions and survey (EWCS) in their study. The reliability coefficients in the study sample (within level) were McDonald's Omega = .70 and Composite Reliability = .70.

2.3.2.5 Job exhaustion

The EWCS measures exhaustion by using two items from the Maslach Burnout Inventory (Schaufeli, 1996): "I feel physically exhausted at the end of the working day" and "I feel emotionally drained by my work". This dimension was selected due to its identification as the core symptom of burnout (Schaufeli et al., 2009). The scale response ranges from 1 (never) to 5 (always). The reliability coefficients at the within level were McDonald's Omega = .59 and Composite Reliability = .59

2.3.2.6 Employee Well-being

The EWCS measures this variable by using the World Health Organization Well-being Index (WHO-5) (World Health Organization (WHO), 1998). This index is a concise, validated self-report questionnaire comprised of five assertions that respondents evaluate based on their subjective well-being over the last two weeks (Topp et al., 2015). The questions are as follows: Over the last two weeks, how often have you been feeling …: (1) "cheerful and in good spirits"; (2) "calm and relaxed"; (3) "active and vigorous"; (4) "fresh

and rested when you woke up"; and (5) "that your daily life has been filled with things that interest you". The response scale ranges from 1 (at no time) to 6 (all of the time). McDonald's Omega within reliability coefficient was .81 and Composite Reliability was .82.

To evaluate the potential impact of common method bias (CMB), we applied both Harman's single-factor test and a confirmatory factor analysis (CFA) comparing a one-factor model with the hypothesized five-factor model, as recommended by Podsakoff et al. (2003) and Hulland et al. (2018). The exploratory factor analysis (EFA) revealed that a single factor accounted for only 22.5% of the total variance, which is well below the commonly accepted threshold of 50% (Harman, 1967). Furthermore, the CFA comparison demonstrated a poor fit for the one-factor model (CFI = .65, TLI = .58, RMSEA = .12, SRMR = .01), whereas the five-factor model showed better fit (CFI = .96, TLI = .95, RMSEA = .04, SRMR = .03).

To assess the constructs' convergent and discriminant validity and *reliability*, we calculated the Average Variance Extracted (AVE), Maximum Shared Squared Variance (MSV), and Average Shared Variance (ASV), McDonald's Omega at the within level (O_W) and Composite Reliability (CRw) at the within level. These results can be found in Table 2.1. All constructs exhibited acceptable CR values (≥ .65), except exhaustion and workload, and satisfied the criteria AVE > MSV and AVE > ASV, supporting discriminant validity (Fornell & Larcker, 1981). Although engagement and exhaustion showed relatively lower ω and AVE values, they still met the minimum requirements for convergent and discriminant validity. In contrast, the well-being construct demonstrated excellent psychometric properties, with ω = .82, CR = .96, and AVE = .83.

Table 2.1.

Reliability, Convergent Validity, and Discriminant Validity Indicators for Each Variable

Variable	$\mathbf{O_w}$	$\mathbf{CR_w}$	AVE	MSV	ASV	AVE > MSV	AVE > ASV
Autonomy	.74	.74	.76	.05	.03	Yes	Yes
Workload	.64	.64	.56	.09	.03	Yes	Yes
Work Engagement	.70	.70	.39	.24	.07	Yes	Yes
Exhaustion	.59	.59	.49	.18	.07	Yes	Yes
Well-being	.81	.82	.83	.24	.10	Yes	Yes

Note. O_w = McDonald's Omega at the within level; CR_w = Composite Reliability at the within level; AVE = Average Variance Extracted; MSV = Maximum Shared Squared Variance; ASV = Average Shared Squared Variance. Following Fornell and Larcker's (1981) criteria, "AVE > MSV" and "AVE > ASV" indicate evidence for discriminant validity when AVE is greater than both MSV and ASV.

2.3.2.7. Age

To measure age, the EWCS asked participants to respond to the following open question: "How old are you?".

2.3.2.9. Control Variables

To ensure the robustness of the model and to avoid potential confounding effects, we included educational level as a control variable. Prior research has shown that educational attainment is closely linked to digital competence and ICT usage patterns (Van Deursen & Van Dijk, 2011), as well as to employee well-being outcomes in the workplace (Solomon et al., 2022). The educational level was measured using a categorical indicator ranging from 1 to 9, reflecting increasing levels of formal education, from incomplete primary education to doctoral studies.

2.3.3 Analysis

Given the nested nature of the analyzed data, we employed multilevel structural equation modeling (ML-SEM) methods (Preacher et al., 2010, 2016) as implemented in Mplus 8.10 (Muthén & Muthén, 2017) to test the study hypotheses. The Intraclass Correlation Coefficient [ICC (1)] calculated for our model's outcome variable (employee well-being) was .059, indicating that 5.9% of its variance is attributed to differences between groups (i.e., countries). As all our hypotheses involved employee-level (Level 1) relationships, we group-mean centered the Level 1 predictors, mediators, and moderator in our model. This process eliminates the between-group variance in these variables and precludes obtaining conflates estimates of individual-level relationships (Preacher et al., 2010, p. 215).

First, we examined the indirect effects implicated in Hypotheses 1, 2, 3, and 4 by fitting a 1/1-1-1-1 model (Preacher et al., 2010) using maximum likelihood estimation techniques. Subsequently, we tested the hypothesized indirect effects by calculating their 95% confidence intervals via the Monte Carlo method (Preacher & Selig, 2012). Second, to examine the moderator and Conditional Indirect Effects (CIEs) implicated in our individual-level hypotheses, we incorporated age as a Level 1 moderator of the "use of ICT at work → autonomy" and "use of ICT at work → workload" relationships. Then, we estimated all the CIEs hypothesized.

2.4. Results

Table 2.2 presents the means, standard deviations (SDs), and correlations among the study variables.

Table 2.2.

Means, Standard Deviation, and Correlations between individual level variables

	M	SD	1	2	3	4	5	6	7	8
1 Age	41.1	11.6	-							
2 ICT use at work	4.13	1.37	.03*	-						
3 Autonomy	3.44	1.01	.04**	.22**	-					
4 Workload	3.40	1.00	-.01	.16**	.00	-				
5 Work Engagement	3.95	0.74	.13**	.02	.20**	.00	-			
6 Exhaustion	2.92	1.14	.00	-.03*	-.15**	.29**	-.23**	-		
7 Employee Well-being	4.25	1.01	- .06**	-.06**	.15**	-.18**	.49**	-.43**	-	
8 Educational level	6.00	1.82	.02	.45**	.16**	.15**	.01	.03*	.08**	-

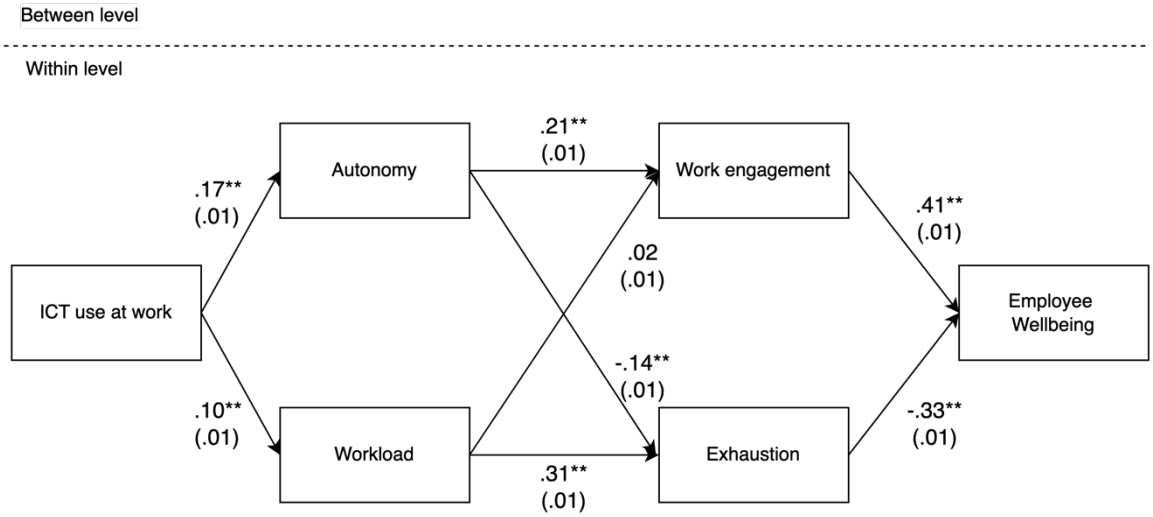
Note. N = 7900. *p < .05; **p < .01.

4.1. Indirect effects of ICT use at work on employee well-being

The Level 1 (i.e., within) model specified to test Hypotheses 1, 2, 3, and 4 is depicted in Figure 2.2. Considering that level-specific indices must be used to assess the fit of multilevel SEM models (González-Romá & Hernández, 2017), we obtained the Standardized Root Mean Square Residual (SRMR)-within provided by Mplus to assess the fit of this model. The value obtained was .05, indicating a good model fit as it was less than .08 (Marsh et al., 2004). The completely standardized parameter estimates for the hypothesized relationships are also shown in Figure 2. The use of ICT at work had a positive relationship with autonomy (.21, $p < .01$). Autonomy was positively associated with work engagement (.22, $p < .01$), and work engagement had a positive relationship with

employee well-being (.42, $p < .01$). Moreover, the use of ICT was positively related to workload (.15, $p < .01$), which in turn had a positive relationship with exhaustion (.31, $p < .01$), and the latter was negatively associated with employee well-being (-.34, $p < .01$). Finally, autonomy was negatively related to exhaustion (-.14, $p < .01$), but workload did not.

Figure 2.2. *Model with the hypothesized indirect effects at the employee level (Level 1).*



Note. ** $p < .01$, two-tailed tests. Bold arrows show the significant relationships involved in the investigated indirect effects. The parameter estimates shown are standardized. Values within parentheses are standard errors.

The indirect effect of ICT use at work on employee well-being through autonomy and work engagement was positive (.015, SE = .001) and statistically significant given the 95% Monte Carlo confidence interval (MCCI) did not include zero 95% MCCI [.012, .017]; see Table 2.3). Consequently, Hypothesis 1 was supported. The indirect effect of ICT use at work on employee well-being through workload and exhaustion was negative (-.011, SE = .001) and statistically significant 95% MCCI [-.013, -.008]. Thus, Hypothesis 2 was supported. The indirect effect of ICT use at work on employee well-being through autonomy and exhaustion was positive (.010, SE = .001) and statistically significant 95% MCCI [.008, .010]. Thus, Hypothesis 3 was supported. Finally, the indirect effect of ICT use at work on employee well-being through workload and work engagement (.001, SE = .001) was non-significant 95% MCCI [.00, .002). Therefore, Hypothesis 4 was not supported.

Table 2.3.

Completely standardized indirect effects of ICT use at work on employee well-being

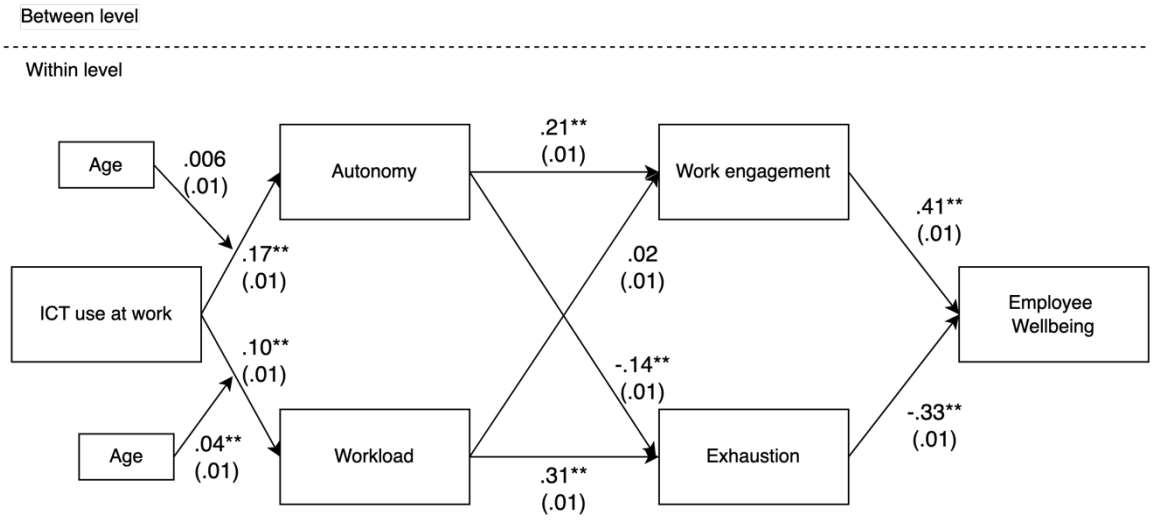
	Indirect Effect		
	IE	SE	95% MCCI
ICT→aut→eng→wb	.015	.002	[.012, .017]
ICT→load→exh→wb	-.011	.001	[-.013, -.008]
ICT→aut→exh→wb	.010	.001	[.008, .010]
ICT→load→eng→wb	.001	.001	[0.00, .002]

Notes. ICT: use of ICT at work, aut: autonomy, load: workload, exh: exhaustion and wb: employee well-being. IE = indirect effect point estimate; SE = standard error; MCCI = Monte Carlo confidence interval.

2.4.2. The Moderator Role of Employee Age

To test Hypotheses 5, 6, 7, and 8, we incorporated employee age into the within-level model shown in Figure 3 as a Level-1 moderator of the relationships between ICT use at work, on the one hand, and autonomy and workload, on the other hand (see Figure 3). The model with the moderator showed a good fit to the data (SRMR-within = .029). Moreover, it had a value for the Akaike Information Criterion (AIC = 169939.61) smaller than the AIC obtained for the model without the moderator (AIC = 169953.0). This indicated that the model using employee age as a moderator (Figure 2.3) provided a better fit to the data than the mediated model without it (Figure 2.2).

Figure 2.3. *Model including employee age as employee level (Level 1) moderator*



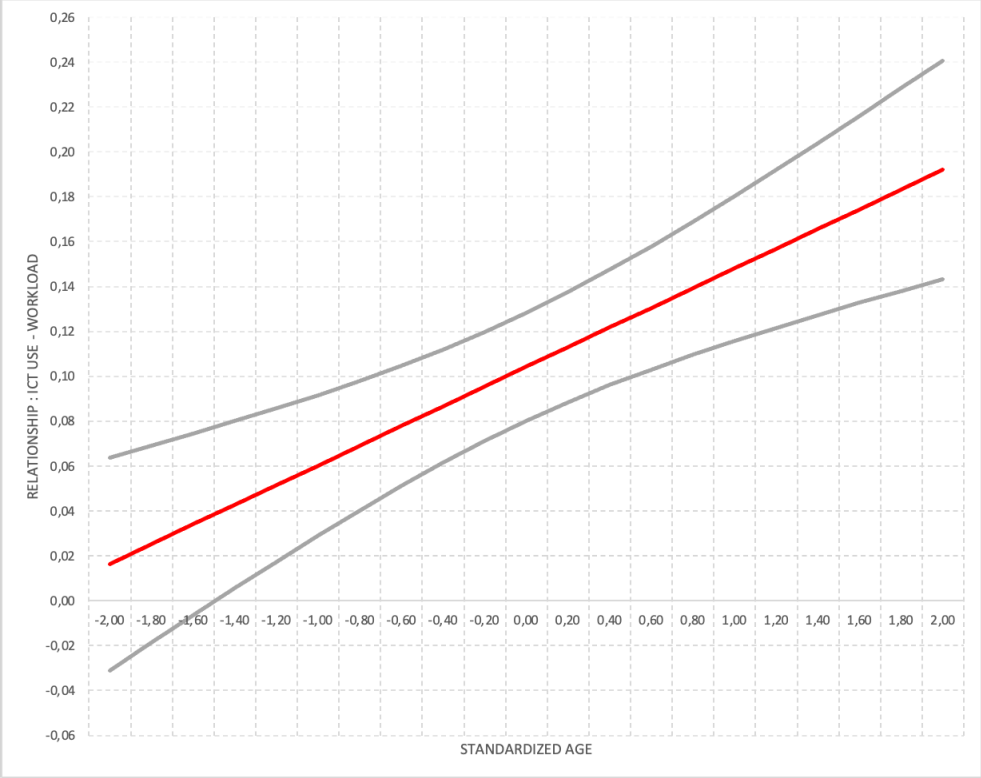
Note. $^{**}p < .01$, two-tailed tests. Bold arrows show the significant relationships involved in the investigated indirect effects. The parameter estimates shown are standardized. Values within parentheses are standard errors.

The results obtained for the parameter estimates revealed that employee age did not moderate the relationship between ICT use at work and autonomy (.006, $p > .05$). This

result implied that the conditional indirect effects involving this non-significant moderation (Hypotheses 5 and 6) were non-significant too.

Employee age did moderate the relationship between ICT use at work and workload (.04, $p < .01$). This moderator role is represented in Figure 2.4. This figure shows, as expected, that as employee age increases, the positive relationship between ICT use at work and workload increases, too.

Figure 2.4. Plot of the moderator role of employee age in the relationship between ICT use at work and workload[2]



Next, we focused on the only indirect effect of ICT use at work on employee well-being involving workload that was statistically significant (ICT use at work → workload → exhaustion→ employee well-being) and tested whether it depended on employee age

[2] This figure shows, as expected, that the positive relationship between ICT use and workload (y-axis) was stronger as age (x-axis) increased.

(Hypothesis 7[3]). To do so, we did several things. First, we computed the index of moderated mediation (Hayes, 2015). The results obtained showed this index was statistically significant (-.004; $p < .05$; 95% MCCI = -.007, -.002). Second, we utilized Mplus to represent the moderator role of employee age in the negative indirect effect of ICT use at work on employee well-being via workload and exhaustion (Figure 2.5). This figure shows, as expected, that this negative indirect effect (y-axis) was stronger as age (x-axis) increased. Third, we computed the CIEs from ICT use at work to employee well-being via workload and exhaustion for different values of the moderator (employee age). The estimated CIEs are presented in Table 2.4. These results show that the indirect effect "ICT use at work → workload→ exhaustion → employee well-being" was statistically significant for all five age values considered. In line with our expectations, the negative indirect effect was stronger as age increased. These findings lend further support to Hypothesis 7.

[3] We did not test whether the indirect effect on ICT use at work on well-being via workload and work engagement was moderated by employee age (Hypothesis 8) because the workload-work engagement relationship and the aforementioned indirect effect were not statistically significant. Thus, Hypothesis 8 was not supported.

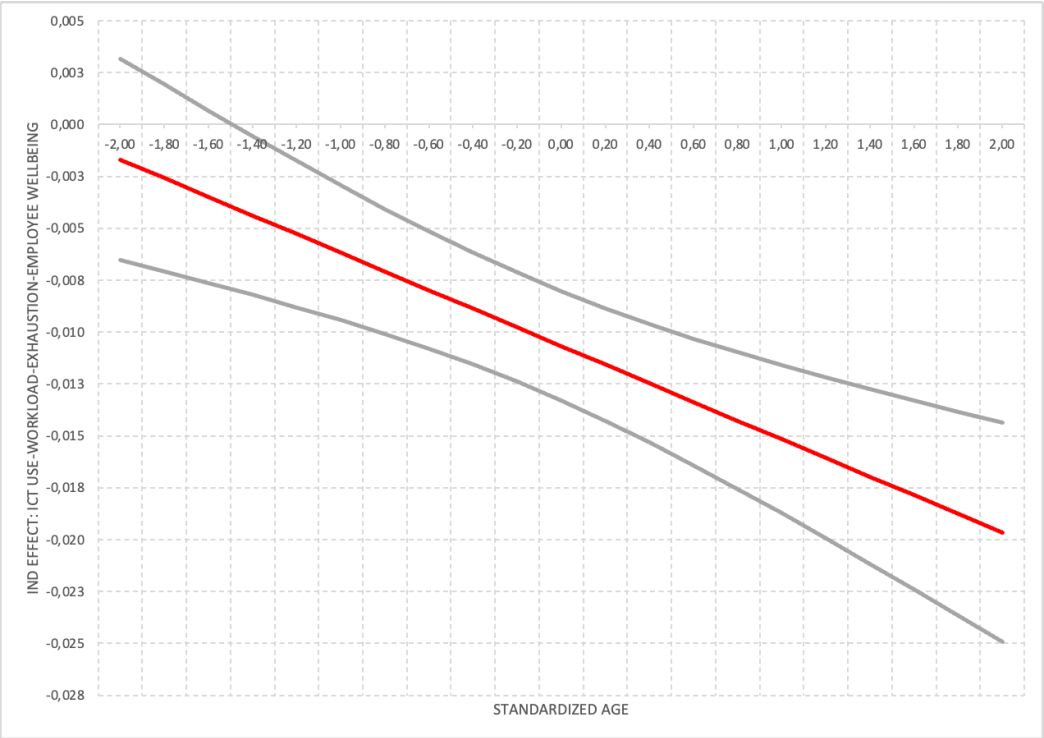
Table 2.4.

Completely standardized indirect effects of ICT use at work on employee well-being through workload and exhaustion for different values of age

Moderator Value (Age)	Indirect Effect		
	IE	SE	95% MCCI
Mean - 2 SD	-.002	.002	[-.001, .001]
Mean - 1 SD	-.006	.001	[-.009, -.004]
Mean	-.011	.001	[-.013, -.008]
Mean + 1 SD	-.015	.002	[-.024, -.017]
Mean + 2 SD	-.020	.003	[-.023, -.017]

Notes. IE = indirect effect point estimate; SE = standard error; MCCI = Monte Carlo confidence interval; SD = standard deviation.

Figure 2.5. *Plot of the conditional indirect effect involved in Hypothesis 7: "ICT use at work →workload→exhaustion→employee well-being" across age standardized values*



Note. Indirect represents the value of the following indirect effect: ICT use at work→workload→exhaustion→employee well-being. Age was standardized. The red line represents the point estimate of the indirect effect across the range of age values. The blue lines define the corresponding 95% confidence interval.

2.5. Discussion

The goal of this study was to examine the complex relationship between ICT use at work and employee well-being. The results obtained showed that, on the one hand, ICT use was positively related to job autonomy, which in turn was positively related to work engagement, which in turn was positively related to employee well-being. Moreover, ICT use at work showed a positive indirect effect on employee well-being via job autonomy and work engagement. On the other hand, ICT use was also positively related to workload,

which in turn was positively related to exhaustion, which in turn was negatively related to employee well-being. Based on these relationships, ICT use at work showed a negative indirect effect on employee well-being via workload and job exhaustion. Additionally, because job autonomy was negatively related to job exhaustion, we identified a second positive indirect effect of ICT use at work on employee well-being via job autonomy and job exhaustion. Finally, we examined age as a moderator. The results obtained showed that age moderated the positive relationship between ICT use and workload, making this relationship stronger as age increases. Similarly, age also moderated the indirect effect of workload on employee well-being via workload and job exhaustion. Next, we elaborate on the theoretical and practical implications of these findings.

2.5.1 Implications for theory and research

This study has several theoretical implications for the understanding of how ICT affects employee well-being. First, responding to the call for understanding the complex relationship between ICT use and employee well-being (Barley, 2015; Parker & Grote, 2022; Wang et al., 2020), this study contributes to theoretical knowledge by demonstrating that ICT use has an indirect relationship with employee well-being through both positive and negative pathways, mediated by key work characteristics. ICT use can foster a job resource: job autonomy. ICT use enables greater flexibility in work scheduling and decision-making, which increases employees' perceived control over their tasks (Raghuram et al., 2019). This autonomy, in turn, fosters work engagement, a psychological state linked to greater motivation, energy, and positive emotions (Schaufeli et al., 2002), which contributes to improved employee well-being. However, ICT use also fosters a job demand: workload, which contributes to job exhaustion (Scholze et al., 2023). These dysfunctional relationships occur when employees feel overwhelmed by the additional volume of tasks

associated with ICT use, leading to higher exhaustion and, consequently, poorer well-being (Van den Broeck et al., 2017). Thus, this study advances our understanding by showing how ICT use can simultaneously promote job autonomy as a resource that enhances employee well-being through engagement, whereas also presenting risks to employee well-being by increasing workload and exhaustion, illustrating the dual-edged nature of ICT in the workplace.

Second, the inclusion of ICT as an antecedent in our research model extends the JD-R theory by showing how a specific technological factor (i.e., ICT use at work) is related to concrete job resources and demands. Specifically, our findings extend the motivation process embedded within the JD-R theory by showing that ICT use at work fosters a job resource (autonomy), which in turn promotes employee motivation (work engagement). This finding is also consistent with the Self-Determination Theory (Deci & Ryan, 2000), which emphasizes that autonomy is a core psychological need. When this need is satisfied, it enhances intrinsic motivation, leading to greater engagement. Our results also extend the health-impairment process proposed by the JD-R theory by showing that ICT use at work fosters a job demand (workload), which in turn promotes employee strain (job exhaustion). This result aligns with the COR theory (Hobfoll et al., 2018), which posits that individuals strive to retain, protect, and build resources, and that stress occurs when these resources are threatened or lost, such as when ICT-related demands exceed one's capacity to manage them. Moreover, the negative relationship observed between job autonomy (resource) and job burnout (strain variable) suggests, along with previous research (Alarcon, 2011; Crawford et al., 2010; Havermans et al., 2017; Shoman et al., 2021), that there are cross-links between the variables involved in the motivational and health impairment processes that the JD-R theory should incorporate.

Finally, our study uncovered a boundary condition (employee age) of the positive direct relationship between ICT use and workload, on the one hand, and the negative indirect relationship between the former variable and employee well-being, on the other hand. These relationships were stronger for older employees. These findings are consistent with previous research that suggests that age-related declines in cognitive resources may make it more difficult for older workers to manage the increased demands associated with ICT use (Phang et al., 2006). The moderation effect of age on the ICT-workload relationship also aligns with the boundary conditions suggested by the JD-R model, which posits that individual characteristics may influence employees' perceptions and responses (Bakker & Demerouti, 2017). Identifying this moderator role of age is relevant for future theoretical development, as it emphasizes the need to consider how demographic factors shape the relationship between technology and employee well-being. While previous research has applied the JD-R framework to investigate how digital technologies relate to employee outcomes (e.g., Leitner & Stöllinger, 2022), our study builds on and extends this line of work by incorporating a key moderator and employee well-being as an ultimate outcome.

2.5.2 Practical Implications

The results of this study have important practical implications. First, as our findings show that ICT use is positively associated with workload and job exhaustion, it is essential for managers and Human Resource professionals to design and implement strategies aimed at mitigating the potentially dysfunctional consequences of ICT use on the aforementioned variables, particularly for older employees who are more vulnerable to these issues when engaging with such technologies. To address this issue, organizations can implement training programs specifically designed to equip older workers with the necessary tools and

skills to use ICT effectively in their jobs. These training sessions should focus not only on teaching employees how to use the technologies efficiently but also helping them understand when it is most appropriate to use them in their daily tasks. By doing so, companies can reduce the risk of job exhaustion and its negative impact on employee well-being (Scholze et al., 2023; Chesley, 2014). Second, another practical implication is related to leveraging the positive influence of ICT use on job autonomy to enhance work engagement and employee well-being. ICT allows employees to have more control over when, where, and how they perform their work, which can lead to greater engagement and employee well-being. By promoting autonomy through ICT use, organizations can foster a more motivated and engaged workforce, which is positively linked to employee well-being (Deci & Ryan, 2000). However, they should do it in an appropriate way that prevents increasing employee workload. For instance, setting clear disconnection times outside work can be helpful in this regard.

2.5.3 Strengths and Limitations

This study has several limitations that should be considered when interpreting the results. First, ICT use was measured using a single item, which may limit the content validity of the measure. However, this limitation is due to the use of a publicly available dataset with predetermined survey questions, and it is not possible to modify or expand these measures. Previous studies that have used the same single-item measures of ICT use (Barrientos-Marín et al., 2021; Menón et al., 2020; Millán et al., 2021) provide empirical evidence supporting its validity. Nevertheless, future studies should replicate these findings by using multi-item scales with broader content coverage. Additionally, future studies should investigate whether different types of ICTs (e.g., communication tools, productivity software) impact work characteristics and employee well-being differently. This would

provide a more nuanced understanding of how specific technologies influence employee outcomes.

Second, the cross-sectional design of this study does not allow us to make causal interpretations of our findings. Longitudinal studies are required to obtain stronger evidence about the causal relationships between ICT use, work characteristics, and their combined relationship on employee well-being. However, the relationships hypothesized in our study have a sound theoretical foundation based on a well-established theory (the JD-R model) in our science.

Third, the indirect effects observed in this study were relatively small, which is common in non-experimental research (Champoux & Peters, 1987). Nonetheless, small effects can hold significant practical importance (Aguinis et al., 2010). In this regard, it is worth saying that a slight increase in employee well-being can significantly enhance their quality of working life. Our findings suggest that improving job autonomy and reducing workload are effective strategies to boost employee well-being. These consequences can be particularly more pronounced among older individuals when addressing the workload associated with ICT use.

Finally, a limitation of the present study concerns the reliability of the workload and exhaustion measures, whose omega values were low (.64 and .59, respectively). Although this may be partly due to the short length of the scales (two items each), it is also possible that the wording and formulation of the items themselves contributed to the lower reliability. Future editions of the EWCS should consider not only increasing the number of items, but also reviewing their quality to ensure greater scale reliability.

This study also has some strengths that we want to highlight. First, we analyzed a large multinational sample. Respondents were randomly selected using probability

sampling, ensuring nationally representative samples across 37 European countries. This design enhances the generalizability of the findings and allows for a comprehensive analysis of the relationships between ICT use and employee well-being across different countries. Second, the use of multilevel structural equation modeling (ML-SEM) allowed us to account for the nested nature of the data, and prevent obtaining parameter estimates conflating within and between components (Preacher et al., 2010).

2.6. Conclusion

Our study contributes to improving our understanding of the complex ways in which ICT use at work is related to employee well-being. Our findings suggest that ICT use fosters employee well-being by enhancing job autonomy and work engagement. However, ICT use also hinders employee well-being by fostering workload and job exhaustion, especially among older workers. Organizations, managers, and HR professionals should carefully consider these results and implement strategies to promote the functional outcomes of ICT use while buffering its dysfunctional ones. By doing so, they will improve the quality of working life for employees in contemporary organizations.[4]

[4] This study was published, and the corresponding reference is as follows: Arriagada-Venegas, M., Ariño-Mateo, E., & González-Romá, V. (2026). ICT Use at Work as a Double-Edged Sword: A Moderated Mediation Model of Employee Well-Being. *The Spanish Journal of Psychology, 29*, e11, 1-14. https://doi.org/10.1017/SJP.2026.10029

Chapter 3: ICT Use at Work as a Double-Edged Sword: A Moderated Mediation Model of Employee Well-Being (Study 2)

3.1. Introduction

The emergence of Generative Artificial Intelligence (GenAI) has triggered a profound transformation in the nature of work, introducing significant changes in what tasks employees perform as well as how they perform those tasks (Hermann et al., 2025; World Economic Forum, 2024). GenAI refers to a class of machine learning technologies capable of generating new content, such as text, images, music, or video, and identifying and replicating patterns from existing data (Brynjolfsson et al., 2025). Organizations and workers are increasingly integrating GenAI into their workflows, which is changing jobs and work roles (Meijer et al., 2021; Gmyrek et al., 2023).

This accelerating use of GenAI not only might affect productivity and efficiency (Brynjolfsson et al., 2025) but also raises critical questions about how these changes shape employees' work design, or "the content and organization of one's work tasks, activities, relationships, and responsibilities" (Parker, 2014, p. 662). Traditionally, automation and digitalization efforts focused on reducing the burden of repetitive manual tasks, thereby increasing efficiency in industries such as manufacturing, logistics, and customer service (Parker & Grote, 2022). From the perspective of work design, the introduction of such technologies led to both job enrichment and job simplification, with the specific impact depending on the factors such as the implementation context and the extent to which employees retained control over their tasks (Bankins et al., 2023; Parker & Grote, 2023). In the case of GenAI, studies suggest that its influence on work characteristics are similarly complex, highlighting the need for a deeper understanding of how employees experience these technological changes (Bankins & Formosa, 2023).

GenAI is especially disruptive in its ability to carry out not only monotonous or routine tasks but also sophisticated knowledge-based work (Brynjolfsson et al., 2025). As

such, GenAI extends automation to creative, analytical, and decision-making domains, which were previously assumed to require human intuition, judgment, and expertise (Lee et al., 2025). For example, in fields such as journalism, translation, marketing, and software development, GenAI tools can now generate text, code, and designs that closely resemble human-created content, prompting discussions about the role of AI as a complement or substitute for human work (Brynjolfsson et al., 2025). Unlike traditional AI systems, such as rule-based expert systems or classifier models designed for specific, well-defined tasks, which primarily affect task execution by reducing routine workload, GenAI employs large transformer models that are inherently versatile (Mayer et al., 2025). This domain-fluidity means GenAI reshapes the cognitive structure of work itself, altering how employees gather information, generate outputs, make decisions, and receive feedback, through mechanisms qualitatively different from prior automation (Lee et al., 2025). These differences suggest that GenAI's influence on work characteristics cannot be straightforwardly extrapolated from prior research on Information and Communication Technology (ICT) or structured AI, and thus warrants dedicated empirical investigation (Parker & Knight, 2024).

The advances and scope of GenAI suggest profound changes in work design are likely. But we do not understand yet what these changes might be (Parker & Knight, 2024). Technology has been identified as a key antecedent of work characteristics (Parker et al., 2017), and prior research has confirmed this link empirically for ICT and earlier forms of AI-driven automation (Arriagada-Venegas et al., 2026; Ninaus et al., 2015; Rahmadani et al., 2019). However, most of these studies assess traditional forms of automation and structured AI applications, such as predictive analytics and process optimization, rather than on the new category of GenAI that operates in more flexible, unstructured, and

creative domains (Lee et al., 2025). In parallel, the literature on AI in organizations has largely centered on macro-level outcomes, including workforce transformation, organizational strategy, and industry competitiveness (Brynjolfsson et al., 2025), offering limited insight into the influence of GenAI usage on work characteristics. While these perspectives are valuable, they do not fully capture the impact of GenAI on employees' work design.

The first goal of this study is to examine the influence of GenAI usage at work on key work characteristics. This research question is particularly timely and distinctive because GenAI represents a novel form of workplace technology. Moreover, unlike traditional technologies implemented top-down from top management decisions to lower-base employees (e.g., industrial robots), generative AI tools are predominantly adopted informally by employees themselves. A recent study involving a sample of 31,000 employees from thirty-one contries showed of 78% of GenAI users started using it on their own (Microsoft & Linkedin, 2024)

We specifically examine how GenAI affects five specific work characteristics: skill variety, job autonomy, job feedback, social support, and role overload. We selected these five work characteristics because they represent each one of the five dimensions considered in the SMART model of work design (Parker & Knight, 2024): Stimulating (skill variety); Mastery (job feedback); Autonomous (job autonomy); Relational (social support); and Tolerable (role overload). Our focus on one characteristic from each dimension of the SMART model ensures a balanced analysis covering key aspects of work.

Our second goal is to investigate the moderating role of occupational skill level in the relationship between GenAI use and work characteristics. Occupational skill level captures the complexity and range of tasks and duties to be performed in an occupation

(International Labour Organization, 2012). Although theoretical frameworks have emphasized the importance of the occupational context in shaping work design, research on technology and work characteristics has rarely systematically included this factor (Parker et al., 2017). This omission is notable given that occupational variables, such as occupational skill level, account for a meaningful proportion of variance in the perception of work characteristics (Dierdorff & Morgeson, 2013). By incorporating occupational skill level as a moderator, we aim to test whether the impact of GenAI on work characteristics differs across varying levels of required occupational skill levels. This is theoretically relevant because occupational skill level reflects the complexity, discretion, and problem-solving required in a job. These aspects likely shape how GenAI is adopted and used: in higher-skill roles, employees may have greater autonomy to apply GenAI in ways that support their work processes, while in lower-skill roles, its use may be more constrained or standardized. As a result, the effects of GenAI on work characteristics may vary depending on the skill requirements of the job.

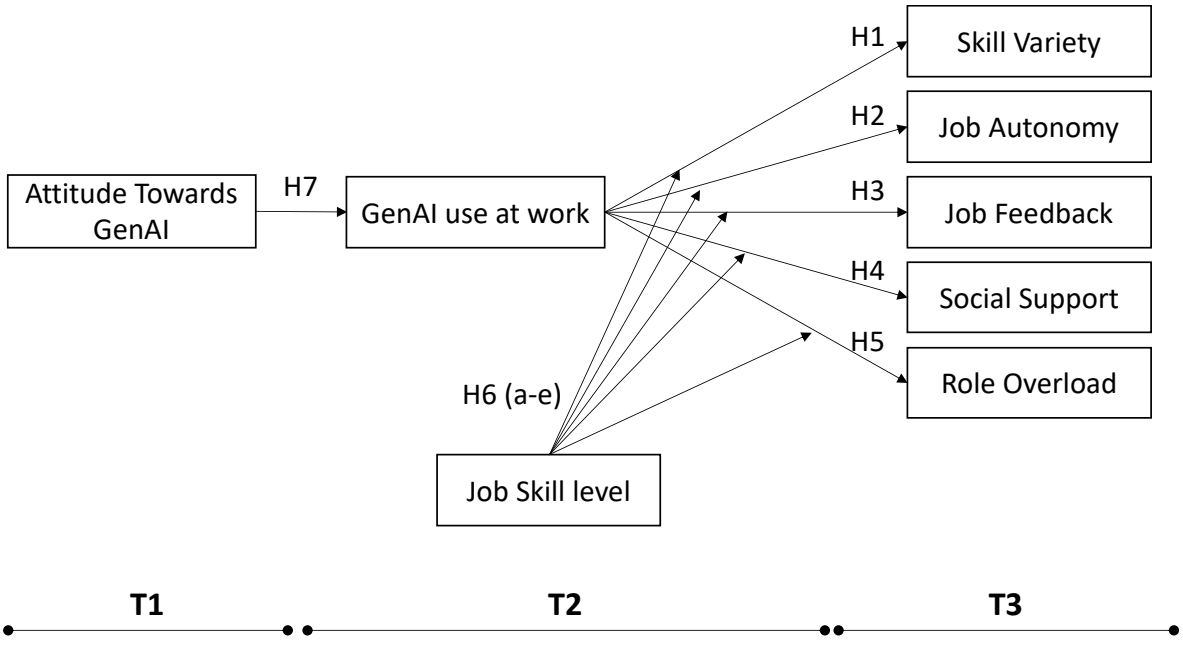
Finally, if GenAI use at work influences work characteristics, it will be important to ascertain its antecedents. Thus, our third goal is to examine attitudes toward GenAI as a potential antecedent of GenAI use. This focus is grounded on the Technology Acceptance Model (TAM; Davis, 1989), which has consistently demonstrated that attitudes toward a technology are among the strongest predictors of its actual use.-This focus is particularly relevant given that GenAI adoption in organizations is often informal and employee-driven rather than mandated by top-down policies (Microsoft & LinkedIn, 2024). Understanding what drives employees to engage with GenAI is essential, as the presence of technology alone does not guarantee its effective integration into work processes. This choice is grounded in the growing evidence that employees are continuously exposed to

contradictory information about artificial intelligence, ranging from promises of increased productivity and innovation to concerns about job loss, ethical risks, and reduced job autonomy (Wang et al., 2025). Examining attitudes as an antecedent thus provides a valuable insight into the factors that facilitate or hinder the use of GenAI in contemporary workplaces.

Altogether, we propose a model in which GenAI use influences five key work characteristics, with this influence being moderated by occupational skill level, and with individual attitudes towards GenAI as an antecedent of GenAI use at work (see Figure 1). We tested this model using a longitudinal research design, collecting survey data across three waves spaced 1.5 months, from a sample of employees whose demographic characteristics were similar to those of the Spanish working population.

Figure 3.1.

The Research Model



Our study contributes to literature in several ways. First, building on Parker et al.'s (2017) framework, which identifies technology as a key antecedent of work characteristics,

we extend work design theory by providing longitudinal evidence of how GenAI, a new and conceptually distinct form of technology, shapes five key work characteristics organized around the SMART model (Parker & Knight, 2024). This goes beyond simply applying existing theory to a new context: by focusing on GenAI's unique capacity to operate in creative, analytical, and decision-making domains previously reserved for human judgment, we offer theoretically grounded predictions about how this technology reshapes core elements of work design. Second, our research further contributes to knowledge by investigating whether the influence of GenAI use on work design is context-dependent, shaped by occupational skill level. This approach not only offers a more nuanced understanding of how GenAI interact with occupational features (Parker, 2017; Dierdorff & Morgeson, 2013), but it also potentially helps to explain why some researchers suggest that GenAI can enhance skill variety, autonomy, and feedback by supporting cognitive tasks whereas others raise concerns about potential deskilling, reduced control, and increased performance pressure (Bick et al., 2025). Third, our research also contributes to the technology adoption literature by identifying attitudes toward GenAI as a key predictor of its use. Drawing from both the technology acceptance and work design perspectives, we clarify one of the individual-level variables that encourages GenAI use in daily work practices. Finally, this study offers practical recommendations for organizations seeking to implement GenAI in ways that support rather than disrupt well-being and productivity. By identifying which work characteristics are most affected for which occupations, organizations can better tailor their job design, human resource practices, training programs, and digital transformation strategies to foster responsible and effective GenAI integration.

3.2. Theoretical Background

We adopted a work design perspective to provide a structured framework for analyzing how technologies shape work characteristics, or important aspects of work that influence employee well-being, motivation, and performance (Parker & Grote, 2022). Within this tradition, the SMART model has recently emerged as a comprehensive and integrative framework that organizes work characteristics into five higher-order categories (Parker & Knight, 2024): Stimulating, Mastery, Autonomous, Relational, and Tolerable. As well as demonstrating the higher-order structure of this model, and the predictive value of these dimensions for job satisfaction in their empirical tests (Parker & Knight, 2024), the SMART model is grounded in decades of research demonstrating that these overarching work design dimensions are consistently linked to a range of important work outcomes such as organizational commitment, job performance, and well-being (Humphrey et al., 2007; Parker et al., 2001).

More specifically, stimulating work characteristics refer to "work having a high degree of mental complexity and variety as a result of the nature and organization of one's work tasks, responsibilities, and relationships" (Parker & Knight, 2024, p. 269). We focus on skill variety as an exemplar work characteristic in this category, defined as the degree to which the job requires the worker to use a wide range of skills. Mastery work characteristics reflect "the coordination and integration of effort via information" (Parker & Knight, 2024, p. 270). We focus on job feedback as a key type of mastery, defined as the extent to which the job gives information about worker performance. Autonomous work characteristics "refer to perceiving a high degree of autonomy, control, and influence over one's work tasks, activities, relationships, and responsibilities" (Parker & Knight, 2024, p.

269). We focus here on decision-making autonomy, or the extent to which the job offers freedom to make decisions at work. Relational work characteristics refer to "the social processes that facilitate the integration of people's efforts" (Parker & Knight, 2024, p. 270). We focus here on social support, or "the degree to which a job provides opportunities for advice and assistance from others" (Morgeson & Humphrey, 2006, p. 1324). Finally, tolerable work characteristics refers to a low score on "quantitative demands that reflect working in a highly intensified way" (Parker & Knight, 2024, p. 272). We focus here on a role overload, with role overload referring to employees' perceptions that they have excessive responsibilities relative to their time and capability constraints.

3.2.1 GenAI Use and Its Relationships with Work Characteristics

We posit that GenAI use at work is positively related to stimulating, mastery, autonomy, and relational aspects of work, but negatively related to tolerable work.

Focusing on *skill variety*, we argue that GenAI use can increase this aspect by motivating workers to acquire new cognitive and technical skills. These skills include, for instance, prompt engineering, AI oversight, data validation, and contextual decision-making, which are essential for effective interaction with AI technologies (Lozie et al., 2024; World Economic Forum, 2024). Moreover, automating routine and repetitive tasks through GenAI facilitates workers' engagement in higher-order cognitive tasks, enabling them to undertake more strategic, analytical, and creative roles that require new skills. Thus, GenAI use encourages workers to diversify their skill sets and adapt to new technological demands, thus increasing the breadth of their professional abilities (Bankins & Formosa, 2023; Wilson & Daugherty; Jarrahi, 2019). Also, the utilization of GenAI exposes employees to a wider range of tasks that are intellectually stimulating and require adaptive problem-solving. These changes encourage continuous learning and development,

supporting a positive association between GenAI use and skill variety (World Economic Forum, 2024). Based on these arguments, we posit the following:

Hypothesis 1: GenAI use at work is positively related to skill variety.

Focusing now on *job autonomy*, the integration of GenAI into the workplace has been associated with a potential enhancement of worker autonomy, particularly regarding decision-making processes and the allocation of cognitive resources (Hermann et al., 2025). A way in which GenAI fosters job autonomy is by functioning as a decision-support system that provides workers with information and insights that would otherwise be inaccessible, enabling them to make more informed and reasoned decisions (Tursunbayeva & Renkema, 2023). This increased access to relevant data contributes to a sense of control over one's work, allowing individuals to rely on enhanced situational awareness without surrendering their decision-making authority.

Moreover, GenAI contributes to autonomy by automating routine or repetitive tasks, allowing workers to redirect their attention to more complex and meaningful activities. As noted by Wilson and Daugherty (2018), AI systems can serve to amplify human capabilities, supporting individuals in ways that allow them to focus on the strategic, interpersonal, and creative elements of their work. From this perspective, GenAI becomes a tool that enhances rather than replaces human agency. For example, generative AI can assist by generating drafts, synthesizing data, or suggesting options, while the worker retains responsibility for judgment and final decision-making (Mayer et al., 2025). This shift from execution to oversight can strengthen autonomy, especially when workers are encouraged to apply critical thinking and domain expertise in evaluating AI-generated content. Therefore, we hypothesize the following:

Hypothesis 2: GenAI use at work is positively related to job autonomy.

Regarding *job feedback*, GenAI can enhance it by providing real-time, data-driven performance indicators that inform employees about the effectiveness and efficiency of their work. GenAI-powered systems, such as large language models and machine learning algorithms, can analyze work outputs and detect patterns, offering immediate and personalized recommendations (Bohren et al., 2024; Lozie et al., 2024). For example, GenAI can assess written reports for clarity and coherence, providing actionable feedback, or track productivity metrics to identify areas for improvement (Bankins & Farmosa, 2023). Additionally, GenAI enables the scalable distribution of feedback across teams, reducing managerial workload while ensuring consistent performance evaluations (Lee et al., 2025). Thus, we posit the following hypothesis:

Hypothesis 3: GenAI use at work is positively related to job feedback.

With respect to *social support*, this work characteristic tends to increase in work contexts that promote collaboration, communication, and mutual help (Parker & Knight, 2024). The integration of GenAI into work processes may influence these conditions by reshaping task structures in ways that encourage more frequent interpersonal interactions. One way in which this may occur is by reducing the time spent on repetitive or administrative tasks, allowing employees to focus more on activities that involve teamwork and shared problem solving. Empirical evidence shows that when GenAI handles routine processes, workers report more availability for collaborative engagement. For instance, Lozie et al. (2024) found that the use of GenAI enabled employees to participate more in cooperative tasks, leading to greater interaction with colleagues. Another argument to consider is the need to interpret and refine GenAI-generated outputs. These outputs, such as summaries, drafts, or suggestions, often require discussion and joint evaluation. As a result,

the job becomes more socially embedded, as workers consult with one another to ensure accuracy or relevance.

Furthermore, the adoption of GenAI introduces new tools and practices, often demanding new learning. When employees face unfamiliar systems, they tend to ask for help from colleagues, reinforcing peer-based support structures. Gagné et al. (2022) emphasize that technologies that increase task novelty and complexity lead to increased informal learning and support among coworkers. This process aligns with work design that promotes the development of social support through interaction and shared learning. Finally, practical experiences from early adopters indicate that GenAI use is frequently explored and optimized through teamwork. According to the World Economic Forum (2024), employees play an active role in testing and adapting GenAI tools, frequently doing so in collaboration with peers. Based on the arguments and empirical evidence presented above, we hypothesize the following:

Hypothesis 4: GenAI use at work is positively related to social support.

Finally, a lack of *role overload* is a core tolerable work characteristic (Parker & Knight, 2024). In the context of GenAI, role overload presents a paradox. On the one hand, GenAI can reduce perceived workload by automating repetitive or administrative tasks, enabling employees to focus on higher-value activities and improving overall task efficiency (Bohren et al., 2024; Lozie et al., 2024). On the other hand, GenAI may intensify work demands. Employees must monitor, validate, and refine AI-generated outputs, which adds cognitive and temporal demands (Tankelevitch et al., 2024). The accelerated pace of AI-driven work cycles can further compound this burden, as employees must rapidly process and act on AI outputs (World Economic Forum, 2024). Furthermore, GenAI can generate large volumes of output that appear polished but lack substance, requiring

employees to invest additional time and effort in reviewing, correcting, and validating the content, a phenomenon recently termed “workslop” (Niederhoffer et al., 2025). This can paradoxically increase rather than reduce perceived role overload. Based on these ideas and empirical evidence, we hypothesize the following:

Hypothesis 5. GenAI use at work is positively related to role overload (that is, negatively predictive of tolerable work).

3.2.2 Occupational Skill Level as a Moderator Between GenAI Use and Work Characteristics

While GenAI is likely to influence work characteristics, these effects may not be same across different jobs. The extent to which employees experience changes in work characteristics triggered by GenAI use might depend on the level of occupational skill required (occupational skill level). Theories of skill-biased technological change (SBTC) suggest that new technologies, including ICTs, tend to produce more favorable outcomes for high-skilled jobs compared to low-skilled ones (Autor et al., 2003; Parker et al., 2017). One explanation is that technological advancements increase the demand for high-skilled labor, motivating organizations to improve the working conditions and task flexibility of these roles to attract and retain talent (Goos et al., 2009). As a result, high-skill occupations may be more likely to benefit from technological change in terms of how jobs are structured and experienced. Prior evidence supports this notion, showing that work design features such as job autonomy and task complexity tend to be more prevalent in high-skilled roles using ICTs than in comparable low-skilled roles (Eurofound, 2015; Green, 2009). Thus, it is reasonable to expect that GenAI may reinforce or amplify existing differences in work characteristics depending on occupational skill level. We now turn to this potential moderator.

3.2.2.1 Skill variety

We posit that the influence of GenAI use on skill variety is moderated by occupational skill level. In high-skill jobs, workers typically perform non-routine tasks that involve cognitive flexibility, decision-making, and adaptation (elements that GenAI tends to support and enhance rather than substitute). These employees are more likely to engage in AI supervision, prompt engineering, contextual interpretation, and integration of AI-generated outputs into complex workflows (Wilson & Daugherty, 2018; Jia et al., 2024). As such, GenAI can act as a stimulus for acquiring new technical and analytical skills, leading to enriched job content and greater perceived skill variety (Lozie et al., 2024). Moreover, empirical findings suggest that investments in digital technologies, including AI, are positively associated with job creation for high-skilled workers, reinforcing the notion that these jobs are more amenable to skill expansion through technological augmentation (Balsmeier & Woerter, 2019). In contrast, low-skill jobs are typically characterized by standardized and procedural tasks that allow for limited discretion. In these contexts, the introduction of GenAI often leads to task substitution and greater workflow rigidity, which inherently offer fewer opportunities for learning and skill development, thus limiting the extent to which GenAI can enhance these aspects.

Altogether, we propose that in high-skill jobs, the utilization of GenAI often leads to the expansion enriching of jobs and continuous upskilling, whereas in low-skill jobs, the potential of GenAI to enhance skill variety may be more limited as these jobs typically involve more standardized tasks and fewer opportunities for expanding the scope of work. We propose:

Hypothesis 6a: Occupational skill level moderates the positive relationship between GenAI use and perceived skill variety, such that this positive relationship increases at higher levels of occupational skill.

3.2.2.2 Autonomy

We propose that occupational skill level moderates the relationship between the use of GenAI and perceived autonomy. Employees with a high skill level occupation are more likely to effectively engage with new technologies, interpret outputs critically, and integrate them into their work processes in ways that support independent decision-making. Supporting this, Jia et al. (2024) found that employees with high skill level occupations that were engaged with AI-enabled workflows reported greater task ownership, which is associated with perceived autonomy Conversely, in occupations with a low skill level, the benefits of GenAI use at work for discretionary decision-making may be more limited, as employees may struggle to adapt GenAI outputs to their specific contexts. This suggests that the extent to which GenAI enhances autonomy depends in part on the skill demands of the occupation. Some empirical evidence seems to support these ideas. Research shows that AI use tends to enhance autonomy in high-skill roles but reduce it in low-skill ones due to increased task standardization (Glering & Kirchner, 2025; OECD, 2023). Moreover, the effective use of Gen AI seems to rely on employees possessing adequate job-specific skills to integrate AI as a supportive tool rather than experiencing it as a limitation (Holm & Lorenz, 2022; Zirar et al., 2023). Based on these arguments, we hypothesize:

Hypothesis 6.b: Occupational skill level moderates the positive relationship between GenAI use and job autonomy, such that this positive relationship increases as occupational skill level increases.

3.2.2.3 Job feedback

We propose that occupational skill level moderates the positive relationship between GenAI use at work and job feedback. GenAI changes how feedback is given, often replacing traditional feedback from people or tasks with real-time information generated by the system. Chuang et al. (2025) suggest that AI technologies may serve as job resources by enhancing access to information and supporting task-related decisions, which could influence how employees receive feedback about their performance. In this context, occupational skill level becomes crucial for decoding, validating, and applying GenAI-generated feedback effectively. According to Zirar et al. (2023), effectively working alongside AI requires employees to develop a combination of technical, human, and conceptual skills. Without these abilities, they may struggle to process AI-generated feedback, which could lead to confusion. Thus, employees in high skill level occupations are more likely to interpret GenAI-generated feedback as useful and actionable, whereas those in low skill level occupations may struggle to benefit from such systems. Therefore, we hypothesized:

Hypothesis 6.c: Occupational skill level moderates the positive relationship between GenAI use and perceived job feedback, such that this positive relationship increases as occupational skill level increases.

3.2.2.4 Social support

We propose that occupational skill level moderates the positive relationship between GenAI use at work and social support. The use of GenAI in the workplace can reconfigure task structures by reducing manual or repetitive work, providing employees with greater flexibility in how they allocate their time and attention. When tasks are simplified through automation, employees may have more time and mental capacity to engage in social interactions. However, the degree to which this potential is realized may depend on

employees' occupational skill level. Those with occupation with a high skill level tend to adapt more quickly to AI-mediated workflows, allowing them to take advantage of time-saving features and redirect those gains toward socially supportive behaviors, such as mentoring, coordinating, or being more available to colleagues (Chuang et al., 2025; Jia et al., 2024). In contrast, employees with jobs with lower skill levels may need more time to understand and manage GenAI systems, which could reduce or delay these benefits due to the added effort (Zirar et al., 2023; Holm & Lorenz, 2022). As a result, the opportunities for social support that GenAI may create, such as being more available to assist coworkers or collaborate with them, are more likely to be realized by employees with high skill level occupations because the latter allows them to efficiently integrate Gen AI in their workflows. Thus, we hypothesize the following:

> Hypothesis 6.d: Occupational skill level moderates the positive relationship between GenAI use and perceived social support, such that this positive relationship increases as occupational skill level increases.

3.2.2.5 Role overload

We propose that occupational skill level moderates the positive relationship between GenAI use and perceived role overload. According to the Conservation of Resources (COR) theory, employees strive to preserve key personal resources, such as time, energy, and competence, to manage demands and avoid strain (Hobfoll et al., 2018). GenAI introduces new work demands (e.g., supervising AI outputs, learning prompts, faster turnaround expectations), which can become overwhelming if employees lack the resources to handle them. Occupational skill level plays a critical role in this context, as it is related to the set of resources that are available to employees for managing GenAI-related demands. Employees in high-skill-level jobs are better equipped with the technical and cognitive

resources needed to integrate GenAI efficiently into their workflows. This allows them to maintain control over tasks, reduce unnecessary effort, and ultimately conserve resources, lowering the likelihood of overload. In contrast, employees in low-skill-level jobs often lack the capabilities to manage GenAI effectively, requiring more time and energy to complete tasks and increasing their vulnerability to role overload. Thus, we hypothesize the following:

> Hypothesis 6.e: Occupational skill level moderates the positive relationship between generative AI use and role overload, such that this positive relationship increases as occupational skill level decreases.

3.2.3 Attitude towards GenAI as an Antecedent

Employee attitudes toward GenAI can influence their actual use of this technology in the workplace (Lichtenthaler, 2020; Park et al., 2023). The existing research on AI in workplaces suggests that attitudes can either encourage or discourage the effective use of AI (Guingrich & Graziano, 2024; Suseno et al., 2023). A useful theoretical perspective for understanding the relationship between attitudes towards GenAI and GenAI use is provided by the Technology Acceptance Model (TAM) proposed by Davis (1989). According to this model, employees with positive attitudes toward GenAI are generally more open and willing to embrace and fully integrate the technology into their daily workflows. They perceive GenAI as beneficial and accessible, which leads them to actively explore and utilize its features, resulting in significant improvements in their job experiences (Taşgıt et al., 2023). Conversely, employees with negative attitudes toward AI typically resist fully adopting the technology, leading to limited or superficial use (Kaya et al., 2024). This resistance reduces the potential benefits of GenAI use. Thus, employee attitude toward

GenAI is a crucial antecedent, influencing its effective adoption and use at work. Based on these arguments, we propose the following hypothesis:

Hypothesis 7: Attitude towards GenAI is positively related to GenAI use at work.

3.3. Method

3.3.1. Procedure and Sample

Data were collected through an online panel managed by a market research company. Panel members were invited to participate in the study on the condition that they were older than 18 years and not self-employed. Data were collected at three time points separated by 1.5 months: Time 1 (T1) December 2024, Time 2 (T2) February 2025, Time 3 (T3) final of March 2025. While there is no universally accepted optimal time lag between data collection waves, recent guidelines suggest shorter intervals, particularly in organizational psychology research, where longer intervals have been the norm (Dormann & Griffin, 2015). Research on work characteristics and well-being variables has employed a wide range of time lags, from weeks to years (Decius et al., 2023; Demerouti et al., 2009). Additionally, the application of artificial intelligence is expected to exhibit high temporal variability, necessitating shorter intervals between measurement points to accurately capture potential changes. At T1, 804 participants answered the questionnaire. This sample mirrored the characteristics of the working population employed in Spain regarding sex, age, region of residence, and economic sector. At T2, 653 participants responded (81.2% response rate), and, finally, at T3, 554 participants answered the questionnaire (68.9% response rate based on the initial sample of 804 participants). To ensure the quality of the data, we included two attention control items (e.g., “To estimate your level of attention, please now select the option “Strongly disagree.”). All participants answered both questions

correctly. Thus, our final longitudinal sample consisted of 554 employees. They were between 22 and 65 years old (M = 46.2, SD = 9.9), and 58.8% were male. Their organizations operated in a variety of business sectors, such as wholesale and retail trade (12.3%), manufacturing (11.9%), health and social services (10.5%), public administration (8.1%), education (7.6%), and accommodation and food service activities (7.0%), among others.

3.3.2 Attrition analysis

To test for sample attrition bias in our study, we conducted a response-nonresponse analysis. We compared the group of participants who responded at all three time points (N3 = 554) with these two groups: those who only responded at T1 (N1 = 151) and those who responded at T1 and T2 (N2 = 99). We compared them on gender (with a chi-square test), age, job tenure, and the variable measured at Time 1: attitude toward GenAI (using ANOVA). We found a significant relationship between the distribution of the participants in these three groups and gender, $\chi^2(2, N = 804) = 9.80$, $p = .007$, with women being more inclined to exit the study across waves. However, the strength of this association was small, as indicated by a phi coefficient of $\varphi = .11$. Additionally, we found significant differences in age, $F(2, 801) = 10.79$, $p < .001$, $\eta^2 = .024$, and job tenure, $F(2, 801) = 9.40$, $p < .001$, $\eta^2 = .022$, indicating that younger and less experienced participants were more likely to discontinue their participation. However, the η^2 values were small, suggesting a small practical influence. No significant differences were found between the three groups in attitude toward GenAI, $F(2, 801) = 1.76$, $p = .172$.

We also compared the final sample (N = 554) with those who only responded at T1 and T2 (N = 99) on the frequency of GenAI use measured at Time 2. An independent-samples t-test revealed a significant difference between the two groups, $t(651) = –2.10$, $p =$

.036, with the final sample reporting higher GenAI use (M = 2.35, SD = 1.43) than those who left after T2 (M = 2.02, SD = 1.37). However, the small effect size (Cohen's d = –0.23) suggested that the attrition bias in this variable was minimal.

3.3.3 Measures

All the scales that were originally developed in English were translated into Spanish using a double-translation and reconciliation procedure (International Test Commission, 2018), involving two independent translators and a third person for reconciliation.

3.3.3.1. Attitude towards GenAI (T1)

Attitude towards GenAI was measured with a 4-item scale (e.g., "I believe that AI will improve my life'') developed by Grassini (2023). Additionally, a minor modification was made to the original instrument, replacing the term *artificial intelligence* with *generative artificial intelligence*. Participants answered on a response scale from 1 (Strongly Disagree) to 6 (Strongly Agree). McDonald's Omega reliability coefficient was .93.

3.3.3.2 Use of GenAI at work

At the beginning of the section containing questions about GenAI, a definition was provided to ensure that workers understood what was meant by GenAI. The definition was as follows:

"Generative artificial intelligence (AI) is a technology that can create new things, such as text, images, or music, based on existing information. For example, it can write a report or create an image by simply providing it with simple instructions. This technology learns from large amounts of data and then uses that learning to generate useful content. Some applications that use generative AI include ChatGPT, Claude, Gemini, and Copilot."

Use of GenAI at work was measured at T1 (to control for stability effects) and T2 by a one item ("How often do you use any generative artificial intelligence (such as ChatGPT, Claude, Gemini, Copilot) when performing your work?"). Participants answered on a scale from 1 (Never) to 6 (Constantly). Test-retest reliability was .79. To support the construct validity of this single-item measure, we examined its correlation with trust in AI. This variable which was measured with three items elaborated by Müller et al. (2024) and Shin (2021): I completely trust the Generative AI, I heavily rely on the Generative AI, I feel comfortable relying on the Generative AI. These three items were answered by suing a 7-point Likert scale ranging from fully disagree to fully agree. Its omega reliability coefficient .94. As expected, use of GenAI at T1 was positively and significantly correlated with trust in GenAI at T1 ($r = .51$, $p < .001$).

3.3.3.3 *Work characteristics*

We selected one variable to represent each dimension of the SMART model (Parker & Knight, 2024). This decision was guided by two key considerations: theoretical relevance and parsimony. Specifically, within each dimension, we chose the variable that was most likely to be influenced by the use of generative AI, based on prior literature and conceptual alignment. Additionally, selecting a single representative variable per dimension allowed us to reduce model complexity while still capturing the core aspects of each SMART domain. Thus, representing stimulating work characteristics, we selected skill variety; for autonomy work characteristics, decision-making autonomy; for mastery work characteristics, job feedback; for relational work characteristics, social support; and for tolerable work characteristics, role overload.

Skill variety (e.g., "The job requires me to use a number of complex or high-level skills.''), decision-making autonomy (e.g., "The job allows me to make a lot of decisions

on my own.''), job feedback (e.g., "The job itself provides feedback on my performance.'') and social support (e.g., "I have the opportunity to develop close friendships in my job.'') were measured with 3-item scales. Items were selected from Morgeson and Humphrey's (2006) work design questionnaire. Role overload was measure with a 3-item scale (e.g., "I never seem to have enough time to get everything done'') from Cammann et al. (1983). McDonald's Omega coefficients ranged from .84 to .93 (see Table 1). These scales were responded to on a 6-point Likert scale (1. Strongly Disagree, 6. Strongly Agree) and measured at T2 (to control for stability effects) and T3.

3.3.3.4 Occupational skill level

Occupational skill level was measured based on participants' self-reported occupation and the International Standard Classification of Occupations (ISCO-08) from the International Labour Organization (ILO, 2012). First, participants selected one of ten major occupational groups in which they could be included according to their current job. Second, this variable was then recoded into a occupational skill level variable using the ILO's skill level classification. Specifically, Elementary Occupations were assigned to skill level 1; Plant and Machine Operators and Assemblers, Craft and Related Trades Workers, Skilled Agricultural, Forestry and Fishery Workers, Service and Sales Workers, and Clerical Support Workers were coded as skill level 2; Technicians and Associate Professionals were coded as level 3; and Professionals as level 4. Managers were coded as level 4, except for Hospitality, Retail and Other Services Managers, who were coded as level 3, in accordance with the ISCO-08 guidelines. The resulting variable was an ordinal variable that ranged from 1 (low skill) to 4 (high skill).

To examine the convergent and discriminant validity of the study measures, we performed a confirmatory factor analysis (CFA) at T1, using Maximum Likelihood as the

estimation method. The proposed seven-factor model, in which items were specified to load on their respective latent factors and factors were free to covary, provided a good fit to the data ($\chi^2(132) = 536.12$, $p < .001$; CFI = .96; RMSEA = .06; SRMR = .04). All factor loadings were statistically significant ($p < .001$) and exceeded .68. This model was then tested against two alternative specifications: a one-factor model, where all items were specified to load on a single underlying latent variable ($\chi^2(152) = 6194.85$, $p < .001$; CFI = .39; RMSEA = .22; SRMR = .17), and a three-factor model (attitudes toward GenAI, GenAI, work design) ($\chi^2(150) = 3612$, $p < .001$; CFI = .65; RMSEA = .17; SRMR = .11). The proposed seven-factor model outperformed both the one-factor model ($\Delta\chi^2(20) = 5658.38$, $p < .001$; ΔCFI = .57; $|\Delta$RMSEA$|$ = .16; $|\Delta$SRMR$|$ = .13) and the three-factor model ($\Delta\chi^2(18) = 3076$, $p < .001$; $|\Delta$CFI$|$ = .31; $|\Delta$RMSEA$|$ = .11; $|\Delta$SRMR$|$ = .07). These findings provided evidence of the convergent and discriminant validity of the scales employed in this study.

To assess potential multicollinearity concerns, we computed variance inflation factors (VIF) for the mean-centered predictors following Kalnins (2018). All VIF values were consistently below 1.20 across all equations in the model, well within acceptable thresholds, indicating that multicollinearity did not pose a concern in the present study.

3.3.4 Analysis

We examined our hypotheses using path analysis as implemented in Mplus 8 (Muthén & Muthén, 2017), applying the Maximum Likelihood estimation method. All hypotheses were tested simultaneously in a single model. Attitude toward GenAI at T1 was included as a predictor of GenAI use at work at T2 (Hypothesis 7), controlling for GenAI use at T1 (i.e., stability effect, see Figure 2). Then, direct paths were specified from GenAI use at T2 to work characteristics at Time 3 (T3) (Hypotheses 1 to 5), controlling for work

characteristics at T2 (i.e., stability effects). Finally, to test Hypotheses 6a to 6e, the model incorporated the moderating role of occupational skill level in the relationship between GenAI use at T2 and: (a) skill variety, (b) autonomy, (c) job feedback, (d) social support, and (e) role overload at T3 (controlling for work characteristics at T2). Indirect effects of attitudes toward GenAI on work characteristics through GenAI use were not tested because the focus of the study was on identifying a hypothetical antecedent of GenAI use and its consequences for work design.

3.4 Results

Descriptive statistics and correlations among the study variables are shown in Table 3.1.

Table 3.1.

Descriptive Statistics and Correlations Among the Study Variables

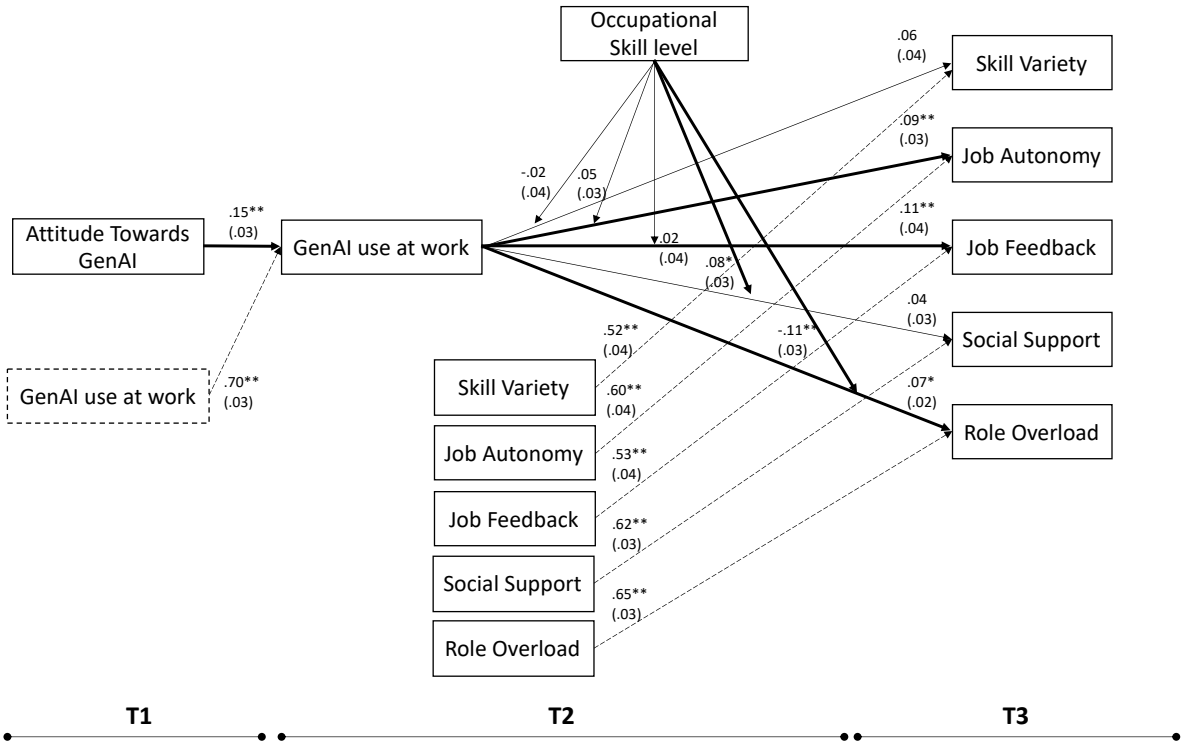
Variable	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Age	44.8	10.7	-															
2. Experience	20.5	10.4	.88**	-														
3. OSL	2.65	0.81	.04	.04	-													
4. ATT(T1)	3.92	1.25	-.10**	-.14**	.23**	(.93)												
5. GAI(T1)	2.22	1.41	-.20**	-.20**	.29**	.56**	-											
6. GAI(T2)	2.35	1.43	-.17**	-.18**	.28**	.56**	.79**	-										
7. SV(T2)	4.94	0.88	.10*	.13**	.20**	.10**	.06	.08	(.90)									
8. SV(T3)	5.02	0.87	.09*	.15**	.19**	.13**	.09*	.09*	.56**	(.90)								
9. Aut(T2)	4.61	1.06	.10**	.08*	.31**	.16**	.17**	.19**	.56**	.32**	(.89)							
10. Aut(T3)	4.63	1.09	.13**	.14**	.34**	.20**	.23**	.20**	.44**	.56**	.64**	(.90)						
11. Feed(T2)	4.45	1.05	.09*	.09*	.20**	.14**	.17**	.17**	.43**	.25**	.64**	.45**	(.88)					
12. Feed(T3)	4.48	1.10	.07	.07	.21**	.16**	.19**	.20**	.25**	.40**	.37**	.57**	.57**	(.89)				
13. SS (T2)	4.52	0.94	.03	.00	.14**	.12**	.11**	.12**	.35**	.17**	.41**	.27**	.44**	.22**	(.84)			
14. SS (T3)	4.55	0.98	.00	-.05	.13**	.18**	.16**	.12**	.17**	.25**	.26**	.36**	.29**	.38**	.61**	(.84)		
15. RO (T2)	2.30	1.43	-.02	-.03	.07	.05	.08*	.06	.14**	.14**	.09*	.09*	.05	-.01	.09*	-.01	(.88)	
16. RO (T3)	2.41	1.46	-.11*	-.07	.00	.03	.06	.10*	.10*	.21**	-.01	.09*	-.05	.00	-.02	.05	.65**	(.89)

Note. N(T1) = 804; N(T2) = 648; N(T3) = 554. * p < .05, ** p < .01. Entries in brackets in the main diagonal are Omega reliability coefficients. OSL = occupational skill level; ATT = Attitudes toward GenAI; GAI = Generative AI use at work; SV = Skill Variety; Aut = Job autonomy; Feed = Job Feedback; SS = Social Support; RO = Role overload.; (T1) = Time 1; (T2) = Time 2; (T3) = Time 3.

The model, including all the hypothesized relationships and controlling for the aforementioned stability or autoregressive "effects," showed a good fit to data ($\chi^2(37) = 73.60$, $p < .001$; RMSEA = .039; CFI = .99; TLI = .97; SRMR = .035; see Figure 2). The results showed a significant positive relationship between attitude toward GenAI at T1 and GenAI use at T2 (Hypothesis 7, $\beta = .15$, $p < .01$). Furthermore, GenAI use at work T2 was significantly related to job autonomy at T3 (Hypothesis 2, $\beta = .07$, $p < .01$), job feedback at T3 (Hypothesis 3, $\beta = .09$, $p < .01$), and role overload at T3 (Hypothesis 5, $\beta = .06$, $p < .05$). These resulted supported hypotheses 2, 3 and 5**.** However, GenAI use at T2 was not significantly related to skill variety at T3 (Hypothesis 1, $\beta = .03$, $p > .05$) and social support at T3 (Hypothesis 4, $\beta = .03$, $p > .05$). Thus, Hypotheses 1 and 4 were not supported.

Figure 3.2.

Standardized Path Estimates for the model including occupational skill level as a moderator



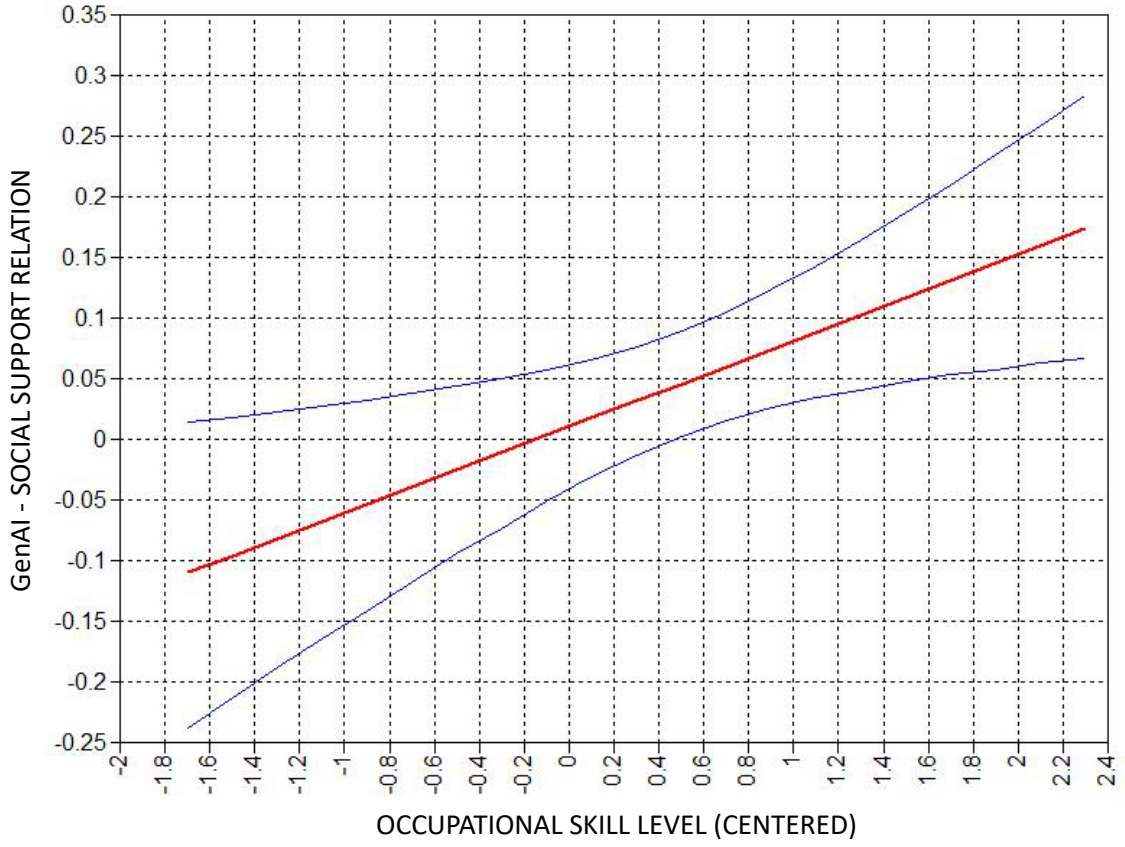
Note. The standardized path estimates are shown in bold. (Standard errors within brackets). *p ≤ .0; **p ≤ .01.

Regarding the moderator hypotheses (H6a-6e), we found support for the moderator role of occupational skill level in the relationships between GenAI use at work at T2 and two work characteristics: social support at T3 (Hypothesis 6d, β = .07, p < .05) and role overload at T3 (Hypothesis 6e, β = –.11, p < .05). The moderator role of occupational skill level in the other investigated relationships was not significant (GenAI use-skill variety: β = .00, p > .05; GenAI use-job autonomy: β = .03, p > .05; GenAI use-job feedback: β = –.01, p > .05). Thus, Hypotheses 6a, 6b, and 6c, were not supported

To further interpret these moderation effects, Table 2 reports the conditional direct "effects" of GenAI use on social support and role overload across different values of occupational skill level. Focusing on the GenAI-social support relationship, the results indicate that the influence of GenAI on social support became (increasingly) positive as at higher levels of occupational skill level. The GenAI → social support influence was statistically significant (and positive) only for high values of occupational skill level (+1SD and +2SD). Figure 3 shows how the GenAI-social support relationship varied across values of occupational skill level. The relationship became positive and stronger as occupational skill level increased, being statistically significant for employees above the mean of occupational skill level. These results support Hypothesis 6d.

Figure 3.3.

Moderator effect of occupational skill level on the relationship between GenAI use at work and social support



Focusing on the GenAI-role overload relationship, the values reported in Table 2 showed that the influence of GenAI use on role overload became (increasingly) positive as occupational skill level decreased. The GenAI → role overload influence was statistically significant (and positive) only for mean and low values of occupational skill level (-1SD and -2SD). Figure 4 shows how the GenAI-role overload relationship varied across values of occupational skill level. The relationship became positive and stronger as occupational skill level decreased, being statistically significant for employees at or below the mean of occupational skill level. In other words, for employees in lower-skill occupations, GenAI use tended to be associated with higher perceived role overload. These results support Hypothesis 6e.

Figure 3.4.

Moderator effect of occupational skill level on the relationship between GenAI use at work and role overload

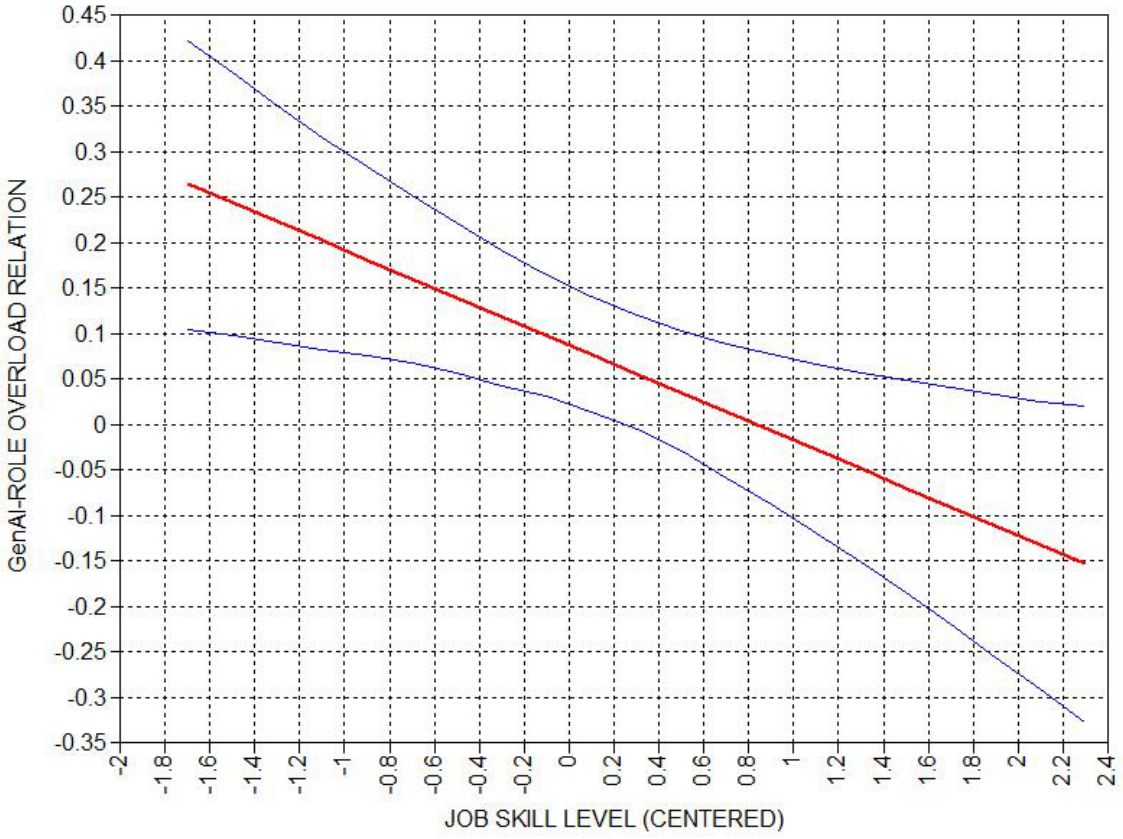


Table 3.2.

The influence of GenAI use at work on social support and role overload for different values of occupational skill level

	Moderator value (Occupational skill level)	Estimate	SE	Bootstrapped 95% CI
Social support	Mean - 2 SD	-.11	.07	[-.25; .01]
	Mean - 1 SD	-.05	.04	[-.14; .03]
	Mean	.01	.03	[-.04; .06]
	Mean + 1 SD	.07*	.03	[.02; .12]
	Mean + 2 SD	.13*	.04	[.05; 21]
Role overload	Mean - 2 SD	.27*	.08	[.11; .43]
	Mean - 1 SD	.18*	.05	[.07; .28]
	Mean	.09*	.03	[.02; .15]
	Mean + 1 SD	-.01	.04	[-.08; .08]
	Mean + 2 SD	-.10	.07	[-.23; .04]

Notes. SE = standard error.

3.5 Discussion

This study examined the impact of GenAI use at work on five core work characteristics. Using three-wave panel data, we found that employee attitude toward GenAI was positively associated with GenAI use at work. Furthermore, GenAI use was positively associated with job autonomy, job feedback, and role overload. No significant relationship was found with skill variety and social support. Additionally, occupational skill level moderated the relationship between GenAI use at work and two work characteristics:

social support and role overload. The positive relationship between GenAI use and social support was statistically significant for above-average levels of occupational skill, with stronger relationships as occupational skill level increased. In contrast, the positive relationship between GenAI and role overload was statistically significant only for low values of occupational skill levels, with stronger relationships as occupational skill level decreased, suggesting that less skilled jobs are more vulnerable to overload when using GenAI. These findings have important theoretical and practical implications that we discuss next.

3.5.1. Theoretical Implications

First, the study findings contribute to extending work design theory and research by identifying an antecedent of three key work characteristics: GenAI use at work. This contribution is especially relevant because, despite the recognition that technology is a key antecedent of work characteristics (Parker et al., 2017), empirical research examining the specific influence of GenAI on work design remains scarce (Parker & Knight, 2024). Our findings begin to fill this gap by providing longitudinal evidence of how employee-driven GenAI adoption shapes perceived work characteristics. In doing so, this study extends existing work design models by incorporating GenAI as a new and conceptually distinct form of technology, one whose influence on work design was theoretically anticipated but had not yet been empirically examined. Our findings reveal that GenAI use at work enhances decision-making autonomy and job feedback, and it does so irrespective of occupational skill level. These findings are consistent with previous research showing that GenAI supports employee autonomy by providing real-time access to relevant information and decision-support tools that enhance control over task execution (Chuang et al., 2025). Rather than replacing decision-making, GenAI seems to enable employees to make more

informed, reasoned decisions by offering synthesized data, suggestions, or insights, while leaving the final judgment in the hands of the worker (Bankins & Formosa, 2023). This reallocation of cognitive load allows employees to redirect their focus toward more strategic, creative, or interpersonal elements of their work (Wilson & Daugherty, 2018), thereby strengthening their sense of agency.

Regarding job feedback, GenAI systems enhance how employees receive input about their performance by offering immediate, tailored, and data-driven insights. These systems can evaluate outputs, such as documents or productivity indicators, and generate specific, actionable feedback to guide improvement (Bohren et al., 2024; Lozie et al., 2024). In doing so, GenAI complements traditional feedback sources like supervisors or peer evaluation. Moreover, its scalability allows organizations to deliver consistent performance feedback and recommendations across entire teams, thereby reducing supervisory burdens and increasing feedback frequency and precision (Lee et al., 2025). Altogether, these mechanisms help employees continuously adjust and refine their performance, reinforcing their mastery over tasks and contributing to sustained learning at work.

Second, our study provides initial evidence about the role of occupational skill level as a boundary condition in the relationship between GenAI use and work characteristics. This knowledge has "a pivotal role in the theoretical development of the organizational sciences … because [it allows] us to understand the conditions under which relationships between variables change in strength and direction" (Aguinis & Gottfredson, 2010, p. 784). The interaction "effects" found revealed that occupational skill level moderates the relationship between GenAI use and both social support and role overload. Interestingly, these two variables reflect socially related aspects of work, as they are shaped not only by the job

itself but also by the broader social environment and interpersonal dynamics at work. In the case of social support, its social-related aspect is clear because it refers to building good relationships with others. The social-related aspect of role overload resides in that it depends, to some extent, on organizational members' expectations and demands. This pattern of observed interaction "effects" suggests that occupational skill level helps employees to take advantage of Gen AI use when social-related aspects of their work are involved. Specifically, a high occupational skill level may allow employees to integrate Gen AI in their work more efficiently, saving time that can be devoted socially supportive behaviors (Chuang et al., 2025; Jia et al., 2024). On the downside, our findings showed that for people in low-skill occupations, GenAI use is related to role overload. This result is congruent with previous research showing that AI adoption can exacerbate work demands (Humlum & Vestergaard, 2024). This relationship may be explained by the fact that, although GenAI can increase task efficiency, it also raises expectations for productivity and responsiveness. Employees must often supervise and refine AI-generated outputs, which adds new layers of cognitive and time demands (Brachman et al., 2024; World Economic Forum, 2024). These pressures can intensify especially when organizational standards increase in response to AI capabilities (Chuang et al., 2025). Moreover, research on ICT use shows that even supportive technologies can heighten perceived workload due to increased pace and interruptions (Arriagada-Venegas et al., 2025; Chesley, 2014; Towers et al., 2006; Zacher & Rudolph, 2024), reinforcing the idea that the adoption of digital tools like GenAI can inadvertently lead to resource strain. In contrast, prior studies suggest that high occupational skill levels facilitate more effective adaptation to AI technologies, enabling employees to better manage workload pressures and conserve resources (Johansson et al., 2017; Verma & Singh, 2022). This interpretation aligns with the skill-biased technological

change perspective, which posits that new technologies tend to generate more favorable outcomes for high-skilled occupations, while amplifying challenges for low-skilled occupations (Autor et al., 2003; Parker et al., 2017). According to this view, the differential capacity to integrate GenAI effectively may reflect broader patterns of technological complementarity, where GenAI augments high-skill occupations but adds strain in low-skill contexts.

This pattern of results highlights that GenAI's impact on work characteristics is multifaceted, as it benefits employees by fostering their perceived job autonomy and job feedback and hinders them by increasing their perceived role overload. These results align with the dual nature of AI integration identified in organizational studies (Brynjolfsson et al., 2025; Liu & Li, 2025), showing the simultaneous benefits and drawbacks that AI brings to the workplace. We found that occupational skill level did not moderate the relationship between GenAI use and skill variety, job autonomy, or job feedback. These three work characteristics, often categorized as task-related may not have shown significant moderation "effects" because GenAI systems tend to offer similar cognitive and informational support across different job types, regardless of their complexity or required skill level (Chuang et al., 2025; Liu & Li, 2025). For example, features such as task automation and real-time feedback may be universally accessible, thus reducing the relevance of occupational skill level in shaping how these work characteristics are experienced. Future studies should replicate these findings.

Third, our findings show that employee attitude toward GenAI is a relevant antecedent influencing its use in organizational settings. This finding aligns with the Technology Acceptance Model (Davis et al., 1989), which posits that attitude toward technology is positively related to its actual use through behavioral intention to use

technology. Positive attitudes significantly increase the likelihood of GenAI adoption and integration (Lichtenthaler, 2020; Park et al., 2023; Sartori & Bocca, 2023). In contrast, negative attitudes toward GenAI may result in resistance or minimal use, restricting its potential contribution to organizational functioning (Kaya et al., 2024; Suseno et al., 2023). Our study provides sound empirical evidence of this relationship in the specific context of GenAI, a technology whose use is often initiated by employees themselves. This highlights the need to better understand psychological antecedents of GenAI use, beyond technical or organizational factors. By identifying attitude toward GenAI as a key antecedent of GenAI use at work, our study underscores the importance of psychological variables in this regard.

Finally, although we hypothesized that GenAI use would enhance perceived skill variety by encouraging workers to develop new competencies such as prompt engineering, AI supervision, and contextual problem-solving (Lozie et al., 2024; World Economic Forum, 2024), our findings did not support this association. A likely explanation lies in the standardization of work routines that often accompanies the introduction of such technologies. While GenAI is capable of supporting a wide array of tasks, employees may engage with it in repetitive and procedural ways, such as generating summaries, correcting language, or formatting content, which make different activities feel structurally similar. This usage pattern may create an illusion of uniformity in task execution, thereby reducing the perceived diversity of skills involved. As Leonardi (2011) argues, the effects of technology on work depend less on its technical potential and more on how users perceive and enact its affordances. Once GenAI becomes integrated into daily workflows, it may turn “ready-to-hand,” used habitually without prompting conscious awareness of variation. Similarly, Howard and Rose (2019) suggest that unless accompanied by deliberate job redesign, automation technologies tend to reinforce existing task structures rather than

expanding them. In this context, GenAI may streamline work processes without enriching employees' perceived skill sets, offering a plausible explanation for the null influence observed in this study. More broadly, this finding aligns with evidence suggesting that bottom-up, employee-initiated processes do not always reliably produce changes in all work characteristics (Holman et al., 2010, 2024), highlighting the importance of examining which specific characteristics are more or less susceptible to employee-driven GenAI use.

3.5.2. Practical Implications

Our findings have several practical implications for both employees and organizations. First, our findings indicate that GenAI use at work is positively associated with autonomy and job feedback, suggesting that this technology can support the redesign of smarter jobs by enhancing control and providing timely, relevant information (Chuang et al., 2025; Parker & Knight, 2024). Second, however, GenAI use is also positively related to role overload, consistent with research showing that AI adoption may increase cognitive demands (Tankelevitch et al., 2024). Importantly, this relationship was only significant at lower levels of occupational skill, suggesting that employees in low-skill occupations are less equipped to manage the additional demands that GenAI imposes. Organizations should therefore take targeted action for these employees, such as providing structured training in prompt formulation and output validation, establishing realistic expectations about GenAI-assisted task completion times during the adoption period, and creating spaces for employees to share strategies for managing AI-related workload, for instance through peer learning groups or dedicated coaching sessions. Implementing GenAI in a way that promotes autonomy and feedback, while also supporting skill acquisition, should be a key priority for responsible and equitable technology deployment (Parker et al., 2017). Third, our results demonstrate that positive employee attitudes are a key antecedent of GenAI use,

directly influencing the degree and effectiveness of technology adoption (Lichtenthaler, 2020; Park et al., 2023). Given this, organizations should prioritize communication strategies and support mechanisms that build favorable perceptions of GenAI among workers. Transparent messaging about the benefits, limitations, and intended use of GenAI can reduce uncertainty and resistance, fostering openness and willingness to engage with the technology (Sartori & Bocca, 2023; Suseno et al., 2023). Furthermore, providing hands-on support, training, and forums for employee feedback helps address concerns and improve user confidence (Guingrich & Graziano, 2024). Such initiatives are crucial because employees with positive attitudes tend to explore and utilize GenAI features more deeply, resulting in meaningful improvements in job experiences, whereas negative attitudes often lead to superficial or reluctant use, limiting potential benefits (Taşgıt et al., 2023; Kaya et al., 2024). To ensure effective adoption, organizations should consider developing employee-centered implementation strategies that include clear communication, active consultation, and structured training opportunities tailored to their needs and concerns (Ullrich et al., 2023).

3.5.3. Limitations, Strengths, and Future Research

Although we adopted a longitudinal research design and focused on real workers, our study has limitations that must be considered when interpreting the study results. First, we focused on a selected set of work characteristics, which, although important, do not capture the full range of work characteristics potentially influenced by GenAI use at work. Investigating other variables, such as information processing requirements, role clarity, and task significance, can shed more light on the influence of GenAI on work design and should be included in future investigations (Bienefeld & Grote, 2025; Lee et al., 2025). Second, we only investigated one moderator (occupational skill level) of the relationship between

GenAI use and work characteristics. Although we found out that this moderator plays a relevant role in the relationships between GenAI and social support and role overload, future studies should consider other potential moderators, such as task complexity and organizational support for technology use. Task complexity may shape how employees interact with GenAI, as more complex tasks could provide greater opportunities to benefit from its functionalities (Brynjolfsson et al., 2025; Parker & Grote, 2022). Organizational support, can also influence whether GenAI enhances or undermines work characteristics, by shaping employees' ability and motivation to engage with the technology (Venkatesh et al., 2012; Suseno et al., 2023). Finally, our operationalization of GenAI use at work was based on a single-item measure. However, concrete and specific single-item measures (as ours) seem to have the same predictive validity as multiple-item measures (Bergkvist & Rossiter, 2007). Similarly, recent research has shown that single-item measures can have good psychometric properties (Mathews et al., 2022). Related to this, our GenAI measure showed good psychometric properties. Its test-retest reliability coefficient was .79, and generally it showed the expected relationships with the considered antecedent (attitude toward GenAI) and consequences (work characteristics). Furthermore, construct validity was supported by a positive and significant correlation with trust in AI, a theoretically related construct ($r = .51$, $p < .001$). These results supported the reliability and validity of our single-item measure.

Our study also has strengths. First, we implemented a longitudinal research design and an analytical strategy (controlling for stability "effects") that allowed us to examine how GenAI use at work is related to *change* in perceived work characteristics over time. This longitudinal approach offers and more accurate view of the examined relationships than cross-sectional research. Second, the fact that the study sample mirrored the

characteristics of the working population employed in Spain regarding several demographic variables (i.e., sex, age, region of residence, and economic sector) suggests that our findings are not limited to a specific occupation or region in the Spanish context. However, future studies should investigate whether similar relationships are observed in other countries.

Regarding future research, we need studies that examine if the nature and function of the tasks for which employees use GenAI (e.g., writing communications, performing administrative tasks, searching for information, coding software; Bick et al., 2025) shape how GenAI influences work characteristics. Our study shows that how frequently employees use GenAI impacts on several work characteristics. Future studies could examine whether this influence depends on the task type for which GenAI is used. Additionally, future investigations should also examine the role of top-down organizational strategies, such as differential planned access to GenAI tools and training, in shaping the relationship between GenAI use and work characteristics. Such processes may amplify existing inequalities across occupational skill levels, contributing to a digital divide in how employees experience the benefits and burdens of GenAI adoption at work (Neufeld et al., 2025)

Finally, ethical and social concerns associated with GenAI implementation and use warrant deeper inquiry to ensure responsible and equitable integration of this technology in the workplace (Bankins & Formosa, 2023; Suseno et al., 2023). Future research could investigate whether ethically guided implementation practices influence core work characteristics. Recent frameworks for evaluating AI in organizational settings (Van de Poel, 2016; Hosseini et al., 2024) emphasize principles such as transparency, fairness, and

the preservation of worker agency. Investigating how these principles affect employees' perceptions of work characteristics represents a promising avenue for future research.

3.6. Conclusion

We identified some of the antecedents and consequences of GenAI use at work and uncovered a moderator impacting on some of the relationships between GenAI use and perceived work characteristics. Our study contributes to a nascent area of research in our discipline and offers relevant knowledge to extend work design theories and improve the quality of jobs in a context of rapid technological change. Producing knowledge based on sound research designs is crucial because "the more that we can map out how, what, and why technology affects work design, the more we will gain important insights into how to optimize technology's benefits' and mitigate its potential dysfunctional effects" (Parker & Grote, 2022, p. 1189).

Chapter 4: The impact of employee-centered technology implementation on work characteristics and job satisfaction (Study 3)

4.1. Introduction

Technological transformation is reshaping the global labor landscape at an unprecedented speed. Innovations such as artificial intelligence (AI), autonomous systems, and digital information processing are expected to affect the majority of organizations across sectors. According to the Future of Jobs Report 2025 (WEF, 2025), 86% of employers anticipate that AI and information-processing technologies will transform their businesses by 2030, a greater proportion than for any other emerging technology. This shift is driven by exponential advancements in computing power, increasing access to large-scale data, and global investments estimated at nearly $1 billion per day (WEF, 2025). These technologies are not merely enhancing how work is done, they are fundamentally altering the nature of work itself, and how tasks are performed and coordinated (Cascio & Montealegre, 2016).

Although much of the debate has centered on task automation and job loss, the focus on employment numbers does not consider the deeper and more complex ways in which technology transforms the nature of work itself. Scholars have called for a shift from macro-level projections of job loss to examining how new technologies influence the specific work characteristics (Parker et al., 2025). Technological change not only affects job availability but also job design, altering fundamental aspects of work. However, these effects are not determined solely by the technology itself (e.g., AI, robots). A growing body of research indicates that several organizational, social, and human factors such as implementation strategy, leadership, and employee participation, play a decisive role in shaping how digital transformations unfold (Blanka et al., 2022; Brosnan et al., 2023; Kane, 2019). Specifically, how organizations implement new technologies may significantly influence whether these transformations lead to more motivating and

sustainable work designs (Mehmood, 2024; Kohnke, 2017). Recent evidence from the American Job Quality Study further underscores this point: employees who report greater influence over technology adoption are more than twice as likely to experience high job satisfaction compared to those with no influence (Gallup, 2025). This highlights how worker voice in technology decisions is not only a matter of fairness but also a determinant of well-being, reinforcing the importance of implementation strategies when it comes to shaping the quality of work. Emerging evidence suggests that the effects of technology on work design are not inevitable or inherent to the technology itself. Instead, they also depend on the decisions made during the design and implementation phases. Findings from diverse academic disciplines show that managerial and stakeholder choices at these stages are central in determining how technology ultimately impacts workers and their work (Gagné et al., 2022; Parker et al., 2017).

Despite increasing recognition that technology alone does not determine how work is transformed, there is still limited theoretical understanding and sound empirical evidence regarding the influence of the organizational strategy of technology implementation on work characteristics. This knowledge gap is problematic for both theory and practice. From a theoretical perspective, existing work design models such as the Job Characteristic Model (Hackman & Oldham, 1976), the SMART model (Parker & Knight, 2024), and the Job Demands-Resources model (Bakker & Demerouti, 2017) have extensively documented the consequences of work characteristics for employee motivation, strain, performance, and well-being, but have paid considerably less attention to their organizational antecedents. Without understanding how implementation strategies shape work characteristics, these models remain theoretically incomplete, as they are unable to account for the organizational processes that shape work characteristics in times of new technologies. From a practical

perspective, organizations are currently making high-stakes decisions about how to introduce new technologies with limited evidence about which implementation practices preserve or enhance job quality. Without this knowledge, managers risk designing transformation processes that inadvertently undermine work characteristics known to sustain employee satisfaction, with significant costs for both individuals and organizations. This challenge is particularly relevant for human resource management (HRM), as HR functions are increasingly expected to support the introduction of new technologies while protecting employee well-being. Although HRM research has long examined how employee-oriented practices shape work outcomes (Boxall & Macky, 2009), clarifying how such practices operate during the implementation of new technologies is a research challenge.

To address this gap, we examine the impact of an Employee-Centered Technology Implementation (ECTI) strategy on key work characteristics. ECTI refers to "a human-centered approach in which employee needs and ideas about the implementation process of new technologies are considered, and that involves employees in this process by means of, e.g., offering them information, consultation, and training" (González-Romá et al., 2025). We focused on ECTI because it is aligned with the human-centric approach that characterizes Industry 5.0 both in theory and practice (Breque et al., 2021). Unlike the efficiency-driven logic of Industry 4.0, Industry 5.0 emphasizes placing the worker at the center of technological design, highlighting that digital transformation should be developed in ways that account for human needs alongside technical objectives. ECTI operationalizes this principle by translating human-centric needs and demands into concrete implementation practices (e.g., informing employees about upcoming changes, considering their input, and addressing their training needs). This makes ECTI not only conceptually

congruent with current perspectives on human-centered digitalization, but also a practical and actionable construct that organizations can deliberately design and assess.

Our study is grounded in sociotechnical systems theory (Clegg, 2000; Emery & Trist, 1973), which posits that work outcomes depend on the joint optimization of the technical and social subsystems. From this perspective, implementation strategies are not neutral technical decisions but active forces that shape the interaction between technology and the social conditions of work, determining how jobs are ultimately experienced by employees.

While work design theory has emphasized the importance of contextual factors in shaping the motivational potential of jobs (Parker & Grote, 2022), empirical research has rarely examined how specific technology implementation practices affect work design and its outcomes. As Parker et al. (2017) note, advancing work design research requires identifying and testing its antecedents, an effort that this study seeks to address by positioning the implementation strategy of new technologies as a proximal antecedent of work characteristics. Implementation strategies involve practices (e.g., providing information on how and why technology will be introduced, clarifying its impact on employees' roles, and considering their questions and training needs) that represent actionable elements of implementation. Overlooking them may decrease motivation and disrupt performance (Gagné et al., 2022; Kirkendall et al., 2013), whereas involving employees and ensuring transparent communication increases the likelihood of aligning technological change with workers' needs to create sustainable work environments (Ullrich et al., 2023). Although literature on both organizational change and work design address the consequences of technological innovation, these two fields have often evolved in parallel. Research on organizational change tends to focus on macro-level outcomes, such as

implementation success, resistance, or productivity gains (Brosnan et al., 2023; Ullrich et al., 2023), while work design studies center on how structural features of work shape employee experience and well-being (Parker & Knight, 2024). By focusing on ECTI, this study helps to bridge these perspectives, connecting change management processes to the design of work itself and shedding light on how employees' experiences are shaped during technological transformation.

Our study examines whether ECTI influences five key work characteristics. We adopted the SMART model of work design (Parker & Knight, 2024) as a guiding framework to select the examined five core work characteristics: skill variety, job autonomy, job feedback, social support, and role overload. Supported by robust theoretical and empirical evidence as key determinants of employee motivation and well-being (Humphrey et al., 2007; Parker & Knight, 2024), these characteristics are theoretically expected to be influenced by ECTI, as explained in the next section. These characteristics are particularly likely to change when tasks are restructured, autonomy is redistributed, feedback mechanisms are altered, interpersonal collaboration is reshaped, and workload demands are modified (Kadir & Broberg, 2021; Parker & Grote, 2022). They serve as diagnostic indicators of how employees' work changes following technological implementation, allowing for a theoretically grounded yet practice oriented examination of how organizational strategies shape work design during the implementation stage. Furthermore, we include job satisfaction as a core outcome to assess the broader implications of implementation strategies for employee well-being. Job satisfaction is one of the most widely studied and reliable indicators of overall work experience (Judge et al., 2002), and previous research has shown that work characteristics are significant antecedents of job satisfaction (Humphrey et al., 2007). Therefore, including job

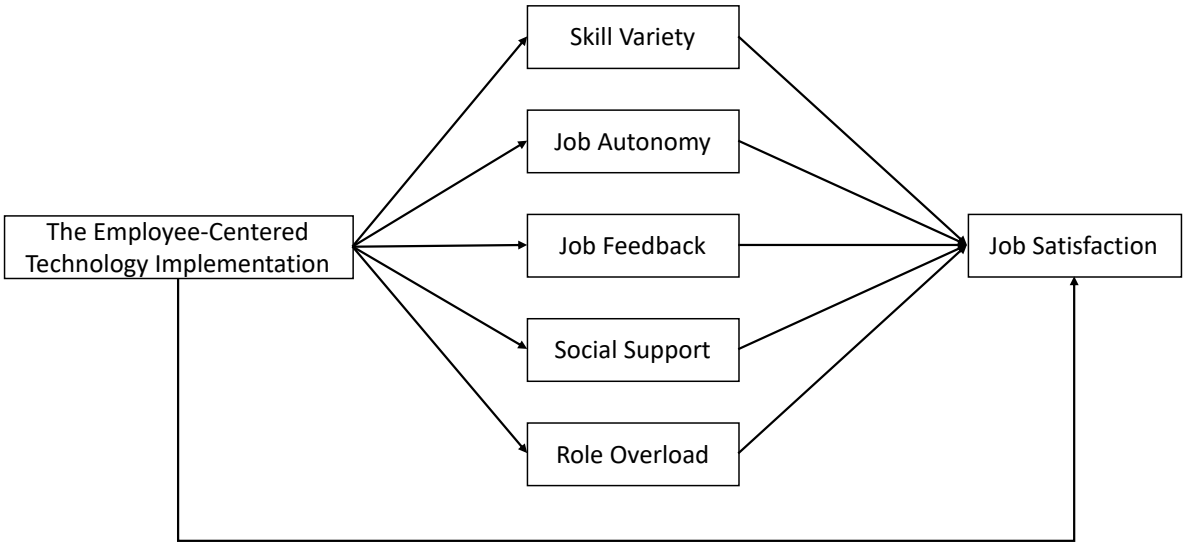
satisfaction allows us to examine whether the effects of the implementation strategy on work characteristics also translate into broader evaluative judgments about the job.

Thus, the goal of this study is to test a model that examines the direct impact of ECTI on five key work characteristics (skill variety, job autonomy, job feedback, social support, and role overload) and its indirect impact on job satisfaction (see Figure 1). We tested this model using a longitudinal design with survey data collected at three time points separated by 1.5 months between successive measurements. This design allowed us to assess temporal precedence and examine the indirect pathways through which ECTI may affect job satisfaction via changes in work characteristics.

With this study we aim to contribute to literature in several meaningful ways. First, we advance work design research by investigating how ECTI is associated with core work characteristics. Despite increasing recognition of the importance of organizational implementation strategies, empirical studies linking these processes to how employees experience their work remain limited. By identifying specific pathways through which ECTI relates to work design we contribute to extending work design theory by identifying a relevant antecedent of key work characteristics. Second, we identify the mechanisms through which ECTI influences job satisfaction by examining five work characteristics as mediators. Although prior research has documented the relevance of work characteristics for employee well-being (Humphrey et al., 2007), the specific mechanisms linking implementation strategies to job satisfaction remain unclear in the context of new technologies. By testing these indirect effects, we clarify how ECTI shapes employee outcomes through changes in work characteristics. Third, we provide sound empirical evidence on the influence of ECTI on changes in work characteristics and job satisfaction using a three-wave longitudinal design. This design allows us to investigate the

relationships by controlling for stability or autoregression effects and assuming temporal precedence between the involved variables, offering stronger empirical evidence than traditional cross-sectional and time-lagged studies. Finally, our findings offer practical insights for organizations. By showing how ECTI influences work characteristics and subsequent job satisfaction, our results can inform evidence-based practices for introducing technology in ways that enhance job quality.

Figure 4.1
The Research Model



4.2. Theorical background

3.2.1 ECTI and Work Characteristics

According to sociotechnical systems theory, organizational decisions about how new technologies are implemented can shape work design and the experiences of employees. Drawing on sociotechnical systems theory, work design is seen as the result of the interaction between technical and social subsystems (Clegg, 2000). From this perspective, the implementation of technology is not a neutral or purely technical process, but rather a form of work redesign that can either enhance or constrain key aspects such as autonomy and skill variety. As Parker and Grote (2022) argue, the way technologies are

integrated into work systems, particularly whether organizations choose between employee-centered and technocentric strategies, determines the extent to which employees retain control over their work. Generally, employee-centered strategies allow for a better alignment between employee demands and new technology characteristics, increasing the likelihood that employees will maintain influence over their work.

ECTI can enhance employees' experience of skill variety (i.e., the degree to which the job requires the worker to use a wide range of skills; Morgeson & Humphrey, 2006), encouraging engagement with a broader range of tools, tasks, and processes. When organizations follow an ECTI strategy, workers are more likely to acquire new competencies and take on a wider set of responsibilities (Mehmood, 2024). This increases the opportunities to apply diverse skills in daily activities, contributing to a richer and more varied job profile. Implementation strategies that attend to both the technical and social dimensions of work, such as how tasks are redesigned and how roles evolve, help ensure that technological change becomes a source of task enrichment rather than restriction. As Parker and Grote (2022) argue, when employees are positioned as active contributors in the technological transformation, their involvement fosters learning and adaptation across different work domains. This alignment between implementation efforts and the structure of work allows for the expansion of skill sets and reduces the risk of task simplification.

Empirical findings support this reasoning. Mehmood (2024) shows that employees who are informed and included in implementation processes are more likely to master and integrate new technologies into their routines. Similarly, Peeters et al. (2025) highlight the importance of anticipating how innovations will reshape core work characteristics like skill variety to ensure meaningful, human-centered integration. Based on these arguments, we propose the following hypothesis:

Hypothesis 1: ECTI will be positively related to subsequent skill variety.

Job autonomy refers to the degree to which a job allows individuals freedom, independence, and discretion to make decisions to execute their work (Morgeson & Humphrey, 2006). This characteristic becomes particularly salient in contexts of new technologies, where new tools can alter work processes, responsibilities, and decision-making structures. The way technologies are introduced into organizations, specifically, ECTI, shapes whether autonomy is preserved or diminished. Informing employees about upcoming changes and considering their input reduces uncertainty, making decision-making control more likely to be maintained (Parker & Grote, 2022). This involvement fosters psychological ownership (Barki & Hartwick, 1994) and a greater capacity to adapt work methods to new demands.

Furthermore, ECTI facilitates a closer alignment between technological functionalities and actual job requirements, allowing workers to preserve their decisions. Models of supervised and assured autonomy, as discussed in recent research on human-centered AI, illustrate how implementation strategies that embed structures for human intervention and oversight allow employees to retain control even in digitally mediated environments (Schmager et al., 2025). Similarly, Kadir and Broberg (2021) emphasize that implementation strategies must align technological changes with the characteristics and demands of the work system. When employees are engaged early, digital tools are more likely to support rather than undermine autonomy. This involvement ensures that workers remain active agents in their roles, rather than passive recipients of externally imposed changes. Accordingly, we formulate the following hypothesis:

Hypothesis 2: ECTI will be positively related to subsequent job autonomy.

Job feedback refers to the degree to which employees receive clear and useful information about their performance (Morgeson & Humphrey, 2006). As organizations adopt new technologies, ECTI becomes a key determinant of the extent to which employees experience feedback on their work. ECTI can enhance job feedback by illuminating the logic behind digital feedback systems, allowing employees to understand how data is collected and how performance information is generated. When employees are informed about the functioning and purpose of new systems, the feedback they receive from their work is more likely to be perceived as relevant, constructive, and trustworthy, shaping how feedback from the job is interpreted and valued (Colquitt, 2001; Wright & Kim, 2004).

Empirical research suggests that when employees are informed and included in the process, digital tools are more likely to be integrated in ways that preserve or enhance core work characteristics, including job feedback (Mutschler et al., 2007; Peeters et al., 2025). Moreover, evidence from participatory organizational practices indicates that implementation strategies designed around knowledge integration and user input contribute to more effective feedback loops by aligning digital processes with daily work routines (Mehmood, 2024). Thus, we propose the following hypothesis:

Hypothesis 3: ECTI will be positively related to job feedback.

Social support (i.e., the degree to which a job provides opportunities for advice and assistance from others; Morgeson & Humphrey, 2006) can be promoted by ECTI by facilitating collaboration, open dialogue, and collective sensemaking. When employees take part in shaping the implementation process, they are more likely to develop a shared understanding of its implications and to view their colleagues as sources of support rather than competition (Nielsen & Randall, 2012). In such contexts, not only does ECTI work as an implementation strategy but also as a social mechanism that deepens interpersonal

connections and encourages mutual support. Rather than imposing top-down approaches, ECTI helps maintain essential work characteristics such as social support, by informing employees, considering their input, and addressing their needs, fostering a more supportive and cohesive work environment (Parker et al., 2017; Parker & Grote, 2022). Therefore, implementation strategies that foster employee voice may not only facilitate smoother technological adoption but also help cultivate environments in which social support can thrive. Consequently, we suggest the following hypothesis:

Hypothesis 4: ECTI will be positively related to subsequent social support.

We posit that ECTI is negatively related to perceived role overload (i.e., the extent to which employees perceive that the amount of work they are required to perform is excessive; Cammann et al., 1983). Poorly managed implementation processes can increase workload by generating additional tasks and requiring employees to invest extra effort in adapting to new systems (Rasool et al., 2022; Ragu-Nathan et al., 2008). When employees are not adequately informed or prepared, they may need to expend additional time and effort to learn and integrate new technologies into their work, increasing perceptions of overload. In contrast, ECTI can reduce this risk by facilitating a smoother implementation process. By informing employees about how new technologies will affect their work and addressing their training needs, ECTI helps employees anticipate changes and adapt more efficiently to them, reducing the additional effort required. Furthermore, by considering employees' input, ECTI contributes to a better alignment between new technologies and existing work demands, reducing the likelihood of workloads that exceed employees' available resources (Kadir & Broberg, 2021; Rasool et al., 2022). Thus, we propose the following hypothesis:

Hypothesis 5: ECTI will be negatively related to subsequent role overload.

4.2.2 ECTI and Job Satisfaction

ECTI can play a critical role in fostering job satisfaction by creating implementation conditions that support the fulfillment of employees' basic psychological needs. According to self-determination theory, the satisfaction of autonomy, competence, and relatedness needs is a fundamental driver of positive work attitudes, including job satisfaction (Deci & Ryan, 2000; Gagné & Deci, 2005). First, ECTI may enhance employees' sense of autonomy by providing timely and relevant information about technological changes and considering employees' input during the implementation process. Prior research has shown that high-quality communication during organizational change reduces uncertainty and enables employees to better understand and anticipate upcoming changes (Allen et al., 2007), which can contribute to a greater sense of control and autonomy over their work situation. Second, ECTI can support employees' sense of competence by facilitating their adaptation to new technologies. When employees are informed about how their work will change and their training needs are considered, they are better prepared to deal with new work requirements, which can enhance their sense of competence to perform effectively (Oreg et al., 2011). Third, ECTI may strengthen employees' sense of relatedness by signaling that their concerns and perspectives are acknowledged during the implementation process. When employees perceive that the organization considers their input and addresses their needs, they are more likely to experience a sense of belonging and interpersonal connection with colleagues and the organization (Atouba et al., 2019; Van den Broeck et al., 2016). In line with self-determination theory, the fulfillment of these basic psychological needs is expected to promote more positive valuations of the work environment, leading to higher levels of job satisfaction. Thus, we propose the following hypothesis:

Hypothesis 6: ECTI will be directly and positively related to subsequent job satisfaction.

4.2.3 The Indirect Effect of ECTI on Job Satisfaction via Work Characteristics

Considering the hypothesized relationships between ECTI and the work examined characteristics (Hypotheses 1-5) on the one hand, and the existing work design theories and cumulated empirical evidence about the relationship between work characteristics and job satisfaction on the other hand, we also posit indirect effects of ECTI on the latter via work characteristics.

4.2.3.1 The Indirect Effect of ECTI on Job Satisfaction via Skill Variety

According to work design theory, skill variety is a core motivational dimension of jobs (Morgeson & Humphrey, 2006). Jobs that allow individuals to draw on diverse abilities and perform varying tasks are more likely to be perceived as interesting, stimulating, and personally rewarding. The SMART model (Parker & Knight, 2024) emphasizes that when workers engage in activities that demand different skills, they experience a stronger sense of capability and connection to their roles, which contributes to higher satisfaction. Meta-analytic evidence indicates that skill variety is positively associated with job satisfaction across different occupational contexts (Humphrey et al., 2007). This relationship shows that jobs requiring a broader range of skills tend to be valued more positively by employees. Thus, based on Hypothesis 1 (on the relationship between ECTI and skill variety) and the ideas presented above, we propose:

> Hypothesis 7: There is a positive indirect effect of ECTI on job satisfaction via skill variety, such that ECTI is positively related to skill variety, which in turn is positively related to job satisfaction.

4.2.3.2 The Indirect Effect of ECTI on Job Satisfaction via Job Autonomy.

Job autonomy is a core motivational dimension of work design that fosters responsibility, ownership, and personal impact (Hackman & Oldham, 1976; Parker & Knight, 2024), which are essential psychological mechanisms underlying job satisfaction. Meta-analytic evidence shows that autonomy is positively associated with job satisfaction across a wide range of occupations and contexts (Humphrey et al., 2007). This relationship is typically explained by the fact that autonomy allows employees to align their work with their preferences and exercise control over their tasks, which contributes to more positive appraisals of their jobs. Therefore, based on Hypothesis 2 (on the relationship between ECTI and job autonomy) and the ideas presented above, we propose:

> Hypothesis 8: There is a positive indirect effect of ECTI on job satisfaction via job autonomy, such that ECTI is positively related to job autonomy which in turn is positively related to job satisfaction.

4.2.3.3 The Indirect Effect of ECTI on Job Satisfaction via Job Feedback

Job feedback is a central element in work design theories (Hackman & Oldham, 1976; Morgeson & Humphrey, 2006). Employees who receive clear and relevant information about their performance are better able to interpret their work outcomes, which is reflected in more positive appraisals of their jobs. Meta-analytic findings indicate that job feedback is associated with higher levels of job satisfaction across a wide range of work contexts (Humphrey et al., 2007). Thus, considering Hypothesis 3 (on the relationship between ECTI and job feedback) and the ideas presented above, we propose:

> Hypothesis 9: There is a positive indirect effect of ECTI on job satisfaction via job feedback, such that ECTI is positively related to job feedback, which in turn is positively related to job satisfaction.

4.2.3.4 The Indirect Effect of ECTI on Job Satisfaction via Social Support

Social support, such as receiving help, advice, or encouragement, can significantly shape how employees appraise their jobs. When individuals feel they can rely on coworkers and supervisors for assistance, they are more likely to interpret their work environment as fair, collaborative, and psychologically safe, conditions that foster greater job satisfaction (Harris et al.,2007). This theoretical reasoning is supported by meta-analytic evidence showing that social support is positively associated with job satisfaction (Humphrey et al., 2007). Thus, employees who experience supportive interactions with others in their work environment tend to perceive their jobs more positively. Therefore, considering Hypothesis 4 (on the relationship between ECTI and social support) and the ideas presented above, we propose:

> Hypothesis 10: There is a positive indirect effect of ECTI on job satisfaction via social support, such that ECTI is positively related to social support, which in turn is positively related to job satisfaction.

4.2.3.5 The Indirect Effect of ECTI on Job Satisfaction via Role Overload

Experiencing role overload can undermine job satisfaction by depleting personal resources such as energy, time, and attention. According to conservation of resources theory, individuals strive to obtain, retain, and protect valued resources, and when these are threatened or lost, psychological strain and dissatisfaction tend to follow (Hobfoll, 1989). In line with this reasoning, the SMART model of work design emphasizes that excessive workload disrupts core psychological mechanisms, such as the experience of task accomplishment or competence, that sustain satisfaction (Parker & Knight, 2024). Supporting this theoretical perspective, empirical studies show that role overload is negatively related to job satisfaction (Pearson, 2008). Thus, considering Hypothesis 5 (on

the relationship between ECTI and role overload) and the ideas presented above, we propose:

Hypothesis 11: There is a positive indirect effect of ECTI on job satisfaction via role overload, such that ECTI is negatively related to role overload which in turn is negatively related to job satisfaction.

4.3. Method

4.3.1 Procedure and Sample

The sample was obtained from an online panel administered by a professional market research company. Eligibility criteria required participants to be over 18 years of age and employed by an organization (i.e., not self-employed). Although the sample was not a random sample drawn from the Spanish working population, its composition very closely reflected the distribution of key demographic and occupational characteristics (e.g., gender, age, region, and industry sectors) in the Spanish working population. The research followed a three-wave longitudinal design, with measurements collected at 1.5-month intervals: Time 1 (T1) in late December 2024, Time 2 (T2) in early February 2025, and Time 3 (T3) in late March 2025. Although there is no single standard regarding the optimal time lag between measurement points, the 1.5-month interval adopted in this study represents a balanced compromise between the long lags that have traditionally dominated organizational research (e.g., six months or more) and very short intervals (e.g., one to two weeks) that may be insufficient to capture meaningful change in work characteristics (Dormann & Griffin, 2015).

At baseline (T1), 804 employees participated in the survey. Of these, 653 completed it at T2 (81.2% response rate), and 554 responded at T3 (68.9% of the initial sample). To

ensure data quality, two attention-check items were included (e.g., “To estimate your level of attention, please now select the option ‘Strongly disagree’”). All participants in the final sample passed these checks, resulting in a longitudinal dataset of 554 employees. Participants were between 22 and 65 years old (M = 46.2, SD = 9.9), and 58.8% were men. They were employed across diverse business sectors, including wholesale and retail trade (12.3%), manufacturing (11.9%), health and social services (10.5%), public administration (8.1%), education (7.6%), and accommodation and food service activities (7.0%), among others. Regarding hierarchical position, 39% of the participants worked as operators or base-level employees, 12% as supervisors, 37% as middle managers, 8% as managers, and 4% as senior executives. In terms of education, the largest groups had completed university (25%), vocational training (21.7%), and high school (17%).

Attrition analysis

To assess the presence of attrition bias across waves, we conducted a response–nonresponse analysis. We compared three groups of participants based on their responses across the three waves of data collection: those who only responded at T1 (N = 151), those who only responded at both T1 and T2 (N = 99), and those who completed all three waves (T1, T2, and T3; N = 554). To evaluate potential attrition bias, we first compared the three groups on demographic and study-related variables measured at Time 1. A chi-square test revealed a significant association between group membership and gender, $\chi^2(2, N = 804) = 9.80$, $p = .007$, with women being more likely to drop out across waves. However, no significant differences were found in educational level or in participants’ initial perceptions of ECTI. A series of one-way ANOVAs showed no significant difference across the three groups in ECTI, $F(2, 801) = 2.44$, $p = .087$, $\eta^2 = .006$; skill variety, $F(2, 801) = 1.83$, $p = .161$, $\eta^2 = .005$; autonomy, $F(2, 801) = 0.07$, $p = .932$, $\eta^2 = .000$; job feedback, $F(2, 801) =$

0.40, p = .668, η^2 = .001; social support, F(2, 801) = 0.19, p = .825, η^2 = .000; role overload, F(2, 801) = 1.53, p = .216, η^2 = .004 and job satisfaction, F(2, 801) = 0.67, p = .514, η^2 = .002. Taken together, these results suggest that although gender was associated with dropout, participants who discontinued their participation did not differ meaningfully from those who completed all waves in terms of education, age, ECTI, work characteristics, and job satisfaction.

4.3.2. Measures

4.3.2.1. Employee-centered technology implementation

ECTI was measured with a 7-item scale developed and validated by González-Romá et al. (2025) [5]. Items were preceded by the following stem: "Below you will find some statements about the implementation of new technologies (for example, robots, Artificial Intelligence, digitalization, automation) in your company. Please tell us to what extent you agree or disagree with these statements. Before my company implemented new technologies …". Example items are: "Employees were informed about how new technologies would be implemented"; "The ideas of the employees about the implementation plan were considered", "The employees' training needs related to working with new technologies were considered". Participants answered on a 6-point Likert scale ranging from 1 (Strongly disagree) to 6 (Strongly agree). McDonald's Omega reliability coefficient was .97.

4.3.2.2. Work characteristics

[5] Given that this hidden study is under review (second round) in a scientific journal, we provide a summary of the development and validation process of the ECTI scale in the Appendix.

The five work characteristics investigated (skill variety, decision-making autonomy, job feedback, social support, and role overload) were measured with three items each. For the four first variables, items were taken from Morgeson and Humphrey's (2006) Work Design Questionnaire. Example items include: "The job requires me to utilize a variety of different skills in order to complete the work" (skill variety); "The job gives me a chance to use my personal initiative or judgment in carrying out the work" (autonomy); "The work activities themselves provide direct and clear information about the effectiveness (e.g., quality and quantity) of my job performance" (job feedback); and "I have the chance in my job to get to know other people" (social support). Role overload was measured with three items from the Michigan Organizational Assessment Questionnaire (Cammann et al., 1983), such as "The amount of work I have to do (or that I am asked to do) is excessive." All responses were recorded on a 6-point scale ranging from 1 (Strongly disagree) to 6 (Strongly agree). Reliability was satisfactory, with McDonald's Omega coefficients ranging from .84 to .93 (see Table 1).

4.3.2.3. Job Satisfaction

Job satisfaction was measured with González-Romá et al.'s (2018) 3-item scale, which asks employees to indicate their degree of satisfaction with the job they perform, their pay, and their opportunities for professional development. Responses were given on a 6-point scale ranging from 1 (Very dissatisfied) to 6 (Very satisfied). McDonald's Omega reliability coefficient was .79.

To assess the discriminant and convergent validity, we conducted a confirmatory factor analysis (CFA) at T1 using Maximum Likelihood estimation. The hypothesized seven-factor model, in which each item loaded on its corresponding latent factor and all factors were allowed to covary, showed a good fit to the data ($\chi^2(231) = 1114.00$, $p < .001$; CFI =

.94; RMSEA = .07; SRMR = .04). All factor loadings were statistically significant ($p < .001$) and higher than .63. We compared this model against two alternative models: a one-factor model in which all the items loaded on the same underlying latent variable ($\chi^2(252) = 7926.00$, $p < .001$; CFI = .49; RMSEA = .20; SRMR = .20), and a three-factor model (ECTI, work design, and job satisfaction) in which all the work characteristics considered loaded on the same latent variable (work design) ($\chi^2(249) = 4270.00$, $p < .001$; CFI = .73; RMSEA = .14; SRMR = .10). The fit of the hypothesized seven-factor model was better than the fit of the one-factor model ($\Delta\chi^2(21) = 6812$, $p < .001$; ΔCFI = .45; ΔRMSEA = -.13; ΔSRMR = -.16) and the three-factor model ($\Delta\chi^2(18) = 3156$, $p < .001$; ΔCFI = .21; ΔRMSEA = -.07; ΔSRMR = -.06). These results supported the convergent and discriminant validity of the scales used.

4.3.3 Analysis

We tested our hypotheses using path analysis in Mplus 8 (Muthén & Muthén, 2017), applying the Maximum Likelihood estimation method. Specifically, ECTI at Time 1 (T1) was included as a predictor of work characteristics at Time 2 (T2) (Hypotheses 1–5), controlling for work characteristics at T1 (i.e., stability or autoregression effects). In addition, ECTI at T1 was included as a predictor of job satisfaction at Time 3 (T3) (Hypothesis 6), controlling for job satisfaction at T2 (i.e., stability effect). This model specification allowed us to test the indirect effects of ECTI on job satisfaction via work characteristics (Hypotheses 7–11). Indirect effects were evaluated by computing 95% bias-corrected bootstrap confidence intervals (MacKinnon et al., 2004; Williams & MacKinnon, 2008) with 5,000 bootstrapped samples.

4.4. Results

Table 4.1 provides descriptive statistics and correlations among the study variables.

Table 4.1

Descriptive Statistics and Correlations Among the Study Variables

Variable	M	SD	1	4	5	7	8	10	11	13	14	16	17	20	21
1. T1ECTI	3.44	1.44	(.97)												
4. SV(T1)	4.97	.90	.15**	(.90)											
5. SV(T2)	4.94	.88	.06	.56**	(.88)										
7. Aut(T1)	4.58	1.12	.27**	.54**	.39**	(.90)									
8. Aut(T2)	4.61	1.06	.23**	.34**	.56**	.64**	(.88)								
10. Feed(T1)	4.44	1.09	.31**	.45**	.30**	.64**	.45**	(.85)							
11. Feed(T2)	4.45	1.05	.32**	.28**	.43**	.41**	.64**	.53**	(.84)						
13. SS(T1)	4.50	1.00	.33**	.35**	.19**	.41**	.28**	.42**	.32**	(.82)					
14. SS(T2)	4.52	.94	.27**	.22**	.35**	.30**	.41**	.28**	.44**	.62**	(.80)				
16. RO(T1)	3.60	1.22	.06	.16**	.10*	.10**	.04	.04	.03	.07*	0.04	(.86)			
17. RO(T2)	3.66	1.23	.01	.09*	.14**	.09*	.09*	.00	.05	.00	0.09*	.65**	(.90)		
20. Jsat(T2)	4.18	1.05	.38**	.15**	.13**	.31**	.36**	.36**	.40**	.29**	.33**	-.10*	-.13**	(.81)	
21. Jsat(T3)	4.19	1.06	.39**	.08	.06	.28**	.34**	.30**	.35**	.29**	.28**	-.17**	-.19**	.77**	(.81)

Note. N(T1) = 804 ; N(T2) = 648 ; N(T3) = 554. * p < .05, ** p < .01. Entries in brackets in the main diagonal are Omega reliability coefficients. ECTI = Employee-Centered Technology Implementation; SV = Skill Variety; Aut = Job autonomy; Feed = Job Feedback; SS = Social Support; RO = Role overload. Jsat = Job satisfaction; (T1) = Time 1; (T2) = Time 2; (T3) = Time 3.

The hypothesized model, which included all the hypothesized relationships as well as the involved stability effects, showed an acceptable fit to the data ($\chi^2(30) = 106.42$, $p < .01$; RMSEA = .062; CFI = .97; SRMR = .067). Figure 4.2 presents the standardized path estimates for the model.

The results showed that ECTI was positively and significantly related to job autonomy (.09, $p < .01$), job feedback (.21, $p < .01$), social support (.10, $p < .01$), and job satisfaction (β = .09, $p < .01$). In contrast, the paths from ECTI to skill variety (–.02, $p > .05$) and role overload (–.01, $p > .05$) were not statistically significant. Therefore, Hypotheses 2, 3, 4, and 6 were supported, but Hypotheses 1 and 5 were not.

Before examining the indirect effects, we first report the relationships between work characteristics at T2 and job satisfaction at T3, controlling for job satisfaction at T2. Results showed that job autonomy (β = .08, $p < .05$) and role overload (β = -.09, $p < .01$) were significantly related to job satisfaction in the expected directions. Unexpectedly, skill variety was negatively related to job satisfaction (β = -.07, $p < .01$). Job feedback (β = .01, $p > .05$) and social support (β = .05, $p > .05$) were not significantly related to job satisfaction.

Hypotheses 7 to 11 evaluated the indirect effects of ECTI on job satisfaction via the five work characteristics. Results for the standardized indirect effects are displayed in Table 4.2. Hypothesis 8, which proposed a positive indirect effect through job autonomy, was supported (Indirect Effect (IE) = .01, 95% CI [.001, .022]). Although statistically significant, the indirect effect through job autonomy was small in magnitude (IE = .01). This value indicates that for every unit increase in ECTI, job satisfaction increases by .01 standard deviation units through the mediating role of job autonomy, after controlling for stability or autoregression effects. Hypothesis 7 was not supported, as the indirect effect via skill variety was not statistically

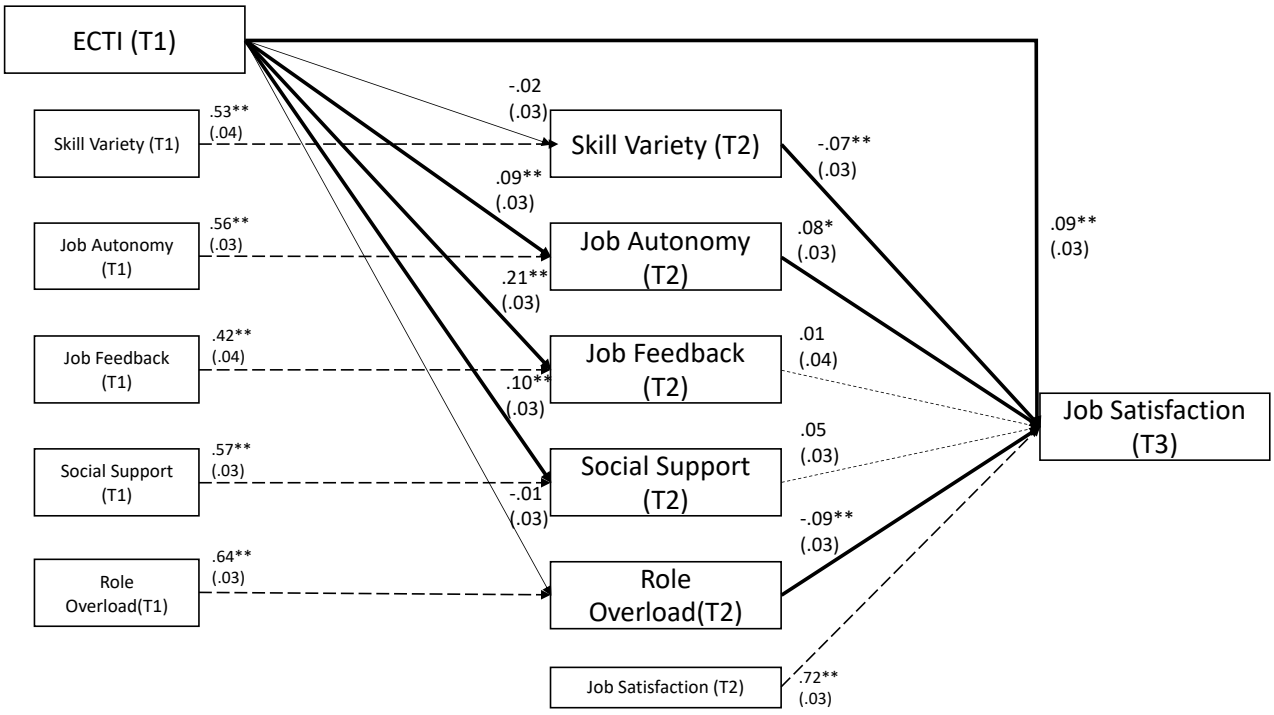
significant (IE = .00, 95% CI [–.002, .008]). Similarly, Hypotheses 9, 10, and 11, which proposed mediation through job feedback (IE =.00, 95% CI [–.012, .017]), social support (IE = .00, 95% CI [–.001, .015]), and role overload (IE =.00, 95% CI [–.005, .008]), were not supported.

Table 4.2
Standardized Indirect Effects

Indirect effects	Estimate	Bootstrapped (95% CI)
ECTI → Skill Variety → Job Satisfaction	.00	-.002; .008
ECTI → Job Autonomy → Job Satisfaction	**.01**	.001; .022
ECTI → Job Feedback → Job Satisfaction	.00	-.012; .017
ECTI → Social Support → Job Satisfaction	.00	-.001; .015
ECTI → Role Overload → Job Satisfaction	.00	-.005; .008

Note. Statistically significant indirect effects are in bold.

Figure 4.2.
Standardized Path Estimates for the model including work characteristics as a mediator



Note. Note. Standardized path estimates are reported, with standard errors in parentheses. Dashed lines represent autoregressive effects, and bold coefficients indicate statistically significant effects (*p ≤ .05; **p ≤ .01).

4.5. Discussion

The aim of this study was to examine whether ECTI influenced five key work characteristics and job satisfaction. The results showed that ECTI was positively related to job autonomy, job feedback, and social support, whereas its relationships with skill variety and role overload were not statistically significant. Moreover, ECTI was positively related to job satisfaction, both directly and indirectly via job autonomy. Overall, these findings provide sound empirical support for ECTI's impact on work characteristics and suggest that job autonomy mediates the indirect effect of ECTI on job satisfaction.

4.5.1. Theoretical Implications

This study provides several theoretical contributions. First, it advances work design research by identifying ECTI as an organizational antecedent of core work characteristics. The work design literature has extensively documented the structural dimensions of jobs and their consequences for employee motivation and well-being (Hackman & Oldham, 1976; Morgeson & Humphrey, 2006; Parker & Knight, 2024) but has rarely considered the organizational processes that shape these characteristics when new technologies are implemented (Parker et al., 2017). Our findings show that when organizations adopt ECTI by informing employees about the coming changes, considering their concerns, and addressing their training needs, employees report higher levels of autonomy, job feedback, and social support, as well as greater job satisfaction. This highlights that work characteristics are not determined by technology itself, but by how technology is introduced and implemented.

Second, our findings contribute to sociotechnical systems theory (Emery & Trist, 1973; Clegg, 2000) by showing that ECTI is positively related to key work characteristics, namely job autonomy, job feedback, and social support. While technical features of new technologies often attract the most attention, our results empirically demonstrate that the way they are introduced into the organization's social system can foster job autonomy, social support, and job satisfaction. This resonates with prior research emphasizing that inclusive and human-centered approaches sustain job quality during digital transitions (Kadir & Broberg, 2021; Peeters et al., 2025). By showing that ECTI plays a role in shaping work characteristics, the study reinforces the sociotechnical view that technology and social practices (e.g., informing, consulting, and training employees) must be jointly considered to understand how work design is shaped.

Third, this study suggests that ECTI can help satisfy employees' basic psychological needs for autonomy, competence, and relatedness, thereby promoting more positive appraisals of

their jobs. From a self-determination perspective (Deci & Ryan, 2000), the direct relationship between ECTI and job satisfaction supports this interpretation, positioning ECTI as a proximal organizational antecedent that shapes need satisfaction when new technologies are implemented. This contributes to a more nuanced understanding of how implementation processes influence employee well-being.

Finally, this study provides insights into how ECTI operates in relation to work characteristics. Our findings suggest that ECTI functions primarily as a resource-enhancing strategy, fostering job autonomy, job feedback, and social support, but not reducing role overload. From a conservation of resources perspective (Hobfoll, 1989), this pattern indicates that ECTI may be more effective at generating resources than at preventing resource depletion, a distinction that future research should explicitly consider.

We observed an unexpected negative relationship between skill variety and job satisfaction. Although work design theory (Hackman & Oldham, 1976; Parker & Knight, 2024) proposes a positive relationship between skill variety and job satisfaction and meta-analytical correlations support this association (Humphrey et al., 2007), our results showed the opposite pattern. One possible interpretation is that during periods of technological implementation, greater skill variety may function more as a demand than as a resource. When new technologies reshape task structures, employees may experience increased variety not as enrichment but as pressure to adapt, potentially generating cognitive overload and uncertainty about role expectations (Rasool et al., 2022). However, given that we did not measure the mechanisms underlying this relationship, this interpretation remains speculative and future research should examine the conditions under which skill variety enhances or undermines job satisfaction.

4.5.2. Practical implications

This study also provides important practical implications. First, the findings demonstrate that the way in which new technologies are implemented is as important as the technologies themselves. ECTI were positively associated with autonomy, job feedback, and social support, which, particularly in the case of job autonomy, contributed to job satisfaction. This underscores prior research showing that ECTI facilitates successful adoption and protects core aspects of work design (Parker & Grote, 2022; Mehmood, 2024). Managers should, therefore, design implementation processes that include clear communication, adequate training, and opportunities for employee participation when implementing new technologies. These practices may be particularly effective because they can support employees' basic psychological needs for autonomy, competence, and relatedness, which are essential for maintaining job satisfaction during the implementation of new technologies.

Second, the positive effects on job feedback, social support, and job autonomy highlight the importance of designing implementation processes that strengthen communication and collaboration in ways that are aligned with Industry 5.0 principles. When employees are actively involved in technological transitions and feedback mechanisms are transparent, they are more likely to interpret feedback as constructive and to perceive colleagues as supportive, fostering more inclusive and human-centered work environments (Nielsen & Randall, 2012; Peeters et al., 2025). Managers can, therefore, enhance both individual learning and collective adjustment by creating collaborative spaces, explaining how technology-generated feedback works, and appointing change "champions" to facilitate peer support.

Finally, the findings also have broader implications for managers and policymakers. For managers, the results emphasize the need to embed participation, early communication, and training into implementation processes to safeguard job quality (Mehmood, 2024; Ullrich et al.,

2023), positioning technology implementation as a relevant domain of HRM action. HR departments can play a leading role by designing structured communication plans, identifying training needs early in the implementation process, and creating channels for employees to provide input on how new technologies will affect their work. For policymakers, the study highlights the importance of promoting responsible digitalization policies that encourage inclusive and human-centered approaches to the introduction of new technologies, echoing calls to align technological adoption with employee well-being (Peeters et al., 2025; Brosnan et al., 2023).

4.5.3. Limitations, Strengths, and Future Directions

This study is not without limitations, which at the same time open promising avenues for future research. First, the data were collected exclusively from employees in Spain. Although this provides valuable insights into how technological implementation unfolds in this context, the findings cannot be generalized to other cultural or institutional settings. As Parker and Grote (2022) argue, work design processes are shaped by broader contextual influences, suggesting that future studies should replicate this research in different countries to examine whether the effects of ECTI on work design and satisfaction hold across contexts.

Second, although the three-wave longitudinal design allowed us to capture temporal precedence, the relatively short interval of 1.5 months between waves may not be sufficient to observe long-term dynamics. Certain relationships, such as those involving skill variety or role overload, may evolve differently over extended periods. Future research would benefit from longer follow-up intervals that capture delayed or cumulative effects of implementation strategies on work characteristics and satisfaction, as recommended in organizational psychology for studying dynamic processes (Dormann & Griffin, 2015).

Third, the model examined in this study focused on five work characteristics representing different dimensions of the SMART model. While this selection was theoretically grounded and parsimonious, it did not cover other important aspects of work design, such as task identity, task significance, or interdependence. Future research should broaden the set of work characteristics included in the model to provide a more comprehensive understanding of how ECTI shapes work design. A final limitation concerns the magnitude of the effect size of the observed indirect effect, which was small. This is largely attributable to the strong autoregressive effects observed. When prior levels of the outcome variables are controlled for, the variance available for predictors to explain is necessarily reduced, attenuating the observed effect sizes.

Despite these limitations, our study also has strengths. First, its three-wave longitudinal design provides solid empirical evidence about the temporal precedence in the relationships between ECTI, work characteristics, and job satisfaction, offering stronger support than cross-sectional and two-wave designs. Second, by controlling for stability or autoregression effects, our study shows how ECTI is related to changes in work characteristics and job satisfaction over time. Third, the inclusion of ECTI as a predictor of work characteristics and satisfaction represents a novel contribution, positioning this construct as a critical yet previously underexplored mechanism in the study of how new technologies shape work design.

4.6. Conclusion

Our study shows that the way new technologies are introduced into organizations shapes how employees experience their work. ECTI was positively related to job autonomy, job feedback, social support, and job satisfaction, highlighting that employee-centered implementation practices can influence key aspects of work design and employee well-being.

These findings offer both theoretical insights and practical guidance for organizations seeking to introduce new technologies in ways that enhance job quality.

Chapter 5: General Discussion

This chapter provides an integrated synthesis of the main findings from the three studies presented in this doctoral dissertation. The chapter begins by summarizing the main results of each study. It then discusses the theoretical and practical implications derived from the three studies as a whole, followed by a consideration of their limitations, strengths, and directions for future research. The chapter closes with the overall conclusions of the dissertation.

5.1 Summary of Main Results

5.1.1 Study 1

Study 1 examined how ICT use at work relates to employee well-being through two core work characteristics, job autonomy and workload, in a large multinational European sample. Grounded in the Job Demands–Resources model, the study proposed that ICT simultaneously operates as a resource and as a demand, shaping well-being through the motivational and health-impairment processes embedded within the JD-R model. The results confirmed this dual role. ICT use was positively related to job autonomy, which was positively associated with work engagement and well-being, and negatively associated with exhaustion. In parallel, ICT use was positively related to workload, which increased exhaustion and indirectly reduced well-being. The cross-link between workload and work engagement was not significant, indicating that workload operates exclusively through the health-impairment pathway, increasing exhaustion and reducing well-being, rather than affecting motivational processes.

Regarding the moderating role of age, the results showed that age did not moderate the ICT–autonomy relationship, but it did moderate the ICT–workload relationship, which was stronger for older employees. As a result, the negative indirect effect of ICT use on well-being through workload and exhaustion was also stronger among older workers. Together, these findings show that ICT does not influence well-being uniformly but operates as a contextual

factor whose consequences depend on the work characteristics it shapes and on the individuals who use it.

5.1.2 Study 2

Study 2 examined how the use of GenAI at work relates to five core work characteristics derived from the SMART model, namely skill variety, job autonomy, job feedback, social support, and role overload, and whether these associations differ depending on employees' occupational skill level. The study also tested whether employee attitudes toward GenAI act as an antecedent of its use. Using a three-wave longitudinal design, the results showed that positive attitudes toward GenAI were positively related to subsequent GenAI use at work. In turn, GenAI use was positively related to job autonomy, job feedback, and role overload, but not to skill variety or social support.

Occupational skill level moderated two of these relationships. The GenAI–social support relationship was statistically significant and positive only for employees in high-skill occupations, indicating that the social benefits of GenAI use emerge specifically in more complex jobs. The GenAI–role overload relationship was statistically significant and positive for employees in low-skill occupations, indicating that the demands associated with GenAI use concentrate in less complex jobs. Together, these findings show that GenAI simultaneously enhances certain work resources and introduces new demands, and that the quality of employees' experience with GenAI depends on the skill requirements of their job.

5.1.3 Study 3

Study 3 examined how ECTI relates to five work characteristics (skill variety, job autonomy, job feedback, social support, and role overload) and job satisfaction. Using a three-wave longitudinal design, the study tested both direct and indirect pathways from ECTI to job

satisfaction through work characteristics. The results showed that ECTI was positively related to job autonomy, job feedback, and social support, but not to skill variety or role overload. ECTI was also positively and directly related to job satisfaction.

Regarding the indirect pathways, only one was supported: ECTI was positively related to job satisfaction through job autonomy. The indirect effects through skill variety, job feedback, social support, and role overload were not statistically significant. This pattern indicates that although ECTI shapes several aspects of work design, job autonomy is the mechanism that most clearly translates it into employees' subsequent job satisfaction.

5.2 Theoretical Implications

Taken together, the three studies in this doctoral dissertation offer four integrative contributions to the literature on technology and work design. These contributions emerge when the findings are considered jointly rather than in isolation, and they refine current understanding of how technology relates to the design and experience of work. Next, we explain these contributions in more detail.

The first integrative contribution concerns the extension of the antecedents of work design models by identifying three distinct technological factors that shape work characteristics. Established work design models have extensively documented the consequences of work characteristics for employee motivation, strain, performance, and well-being, but considerably less attention has been paid to their antecedents (Parker et al., 2017). This imbalance is particularly relevant in contexts of rapid technological change, where new tools and organizational practices are reshaping the conditions under which work is performed (Parker & Grote, 2022).

The three studies in this thesis address this imbalance by showing that three conceptually distinct forms of technology-related factors function as relevant antecedents of core work characteristics. Study 1 shows that ICT use at work is related to both job autonomy and workload, thereby acting as an antecedent of both resource-type and demand-type characteristics. Study 2 shows that GenAI, a qualitatively different and more recent form of technology capable of operating in creative and cognitive domains (Brynjolfsson et al., 2025), is related to job autonomy, job feedback, and role overload. Study 3 shows that ECTI, which is not a technology itself but an organizational approach to introducing new technologies, is related to job autonomy, job feedback, and social support. Jointly, these findings demonstrate that the relevant antecedents of work characteristics in the digital era include not only the technologies that employees use, but also ECTI as an organizational approach to introducing those technologies.

This positioning is theoretically consequential for two reasons. First, it aligns with the sociotechnical tradition (Cherns, 1976; Trist & Bamforth, 1951), which first conceptualized technology as a structural antecedent of work design rather than as a neutral input (Pasmore et al., 2019; Van den Broeck et al., 2025), and with more recent theorizing that treats technology as a contextual determinant of the motivational and strain-related features of work (Cascio & Montealegre, 2016; Parker & Grote, 2022). The present thesis provides empirical support for this view across three different technology-related aspects, reinforcing the argument that technology is not peripheral to work design but one of its shaping forces. Second, by showing that technology-related antecedents encompass both individual behaviors (ICT use, GenAI use) and organizational practices as perceived by employees (ECTI), the thesis expands the antecedent side of work design models in a way that is responsive to contemporary workplaces, where technological change unfolds through both employee behavior and organizational decisions. This

expanded view responds to Parker et al.'s (2017) call for a more complete mapping of work design antecedents and contributes to a work design theory better equipped to explain how work is being reshaped in the digital era.

Additionally, across the three studies, job autonomy emerged as the work characteristic most consistently related to technology. In Study 1, job autonomy was a central mechanism linking ICT use to employee well-being through work engagement and exhaustion. In Study 2, GenAI use was positively related to job autonomy over time. In Study 3, job autonomy was the only work characteristic that significantly mediated the relationship between ECTI and job satisfaction, despite testing five alternative mediators. This recurring pattern suggests that, although the SMART model (Parker & Knight, 2024) conceptualizes autonomy as one dimension among several others, autonomy may occupy a particularly central position when the antecedent under examination is technology. Theoretical accounts of technology and work design could therefore benefit from treating autonomy not only as one of the different outcomes of new technologies at work, but as a core mechanism through which different forms of technology influence employee well-being and job satisfaction.

The second integrative contribution concerns the dual nature of technology as both a resource and a demand within the work system. Across the three studies, technology consistently emerged as a double-edged factor rather than as an inherently beneficial or detrimental force, an idea that reinforces long-standing calls for more nuanced theorizing on new technologies at work (Barley, 2015; Parker & Grote, 2022; Wang et al., 2020).

The three studies provide converging but differentiated evidence for this dual pattern. Study 1 showed that ICT simultaneously enhances job autonomy and increases workload, activating both the motivational and the health-impairment processes of the Job Demands–

Resources model (Bakker & Demerouti, 2017; Demerouti et al., 2001). Study 2 extended this dual pattern to GenAI, showing that its use is positively related to job autonomy and job feedback but also to role overload, consistent with recent evidence that AI adoption generates simultaneous gains and strains (Brynjolfsson et al., 2025; Humlum & Vestergaard, 2024; Liu & Li, 2025). Study 3 showed a somewhat different pattern: ECTI operates primarily through the resource-enhancing side, increasing job autonomy, job feedback, and social support without reducing role overload. This asymmetry echoes evidence that human-centered implementation approaches tend to generate resources rather than remove demands (Gagné et al., 2022; Kadir & Broberg, 2021), suggesting that the balance between resource- and demand-generating pathways depends on the specific form of technology-related factor under consideration.

Taken together, these findings refine the Job Demands–Resources model (Bakker & Demerouti, 2017) and the SMART model (Parker & Knight, 2024) in two ways. First, they show that technology is not uniformly a resource or a demand, but a structural feature that can activate both pathways simultaneously, with the relative weight of each pathway shaped by the form of technology considered. Second, the evidence from study 1 suggests the existence of cross-links between the motivational and health-impairment processes, as resources influence strain-related variables and demands affect work engagement and motivational states (Bakker & Demerouti, 2007; Crawford et al., 2010; González-Romá et al., 2020; Havermans et al., 2017). The cross-link between workload and work engagement, by contrast, was not significant. Recognizing that a single form of technology can simultaneously enable and constrain employees advances a more realistic theoretical account of technology-enabled work, one that moves beyond the search for uniformly positive or negative influences and toward a framework that distinguishes the specific work characteristics through which each pathway operates.

The third integrative contribution concerns the contextual nature of the relationship between technology and work design. The first and second study, taken together, show that the influence of technology on work characteristics is not universal but depends on individual and occupational conditions, an insight that responds to repeated calls for more contingent theorizing on technology and work (Coovert & Thompson, 2013; Parker & Grote, 2022; Wang et al., 2020).

Each study contributes a different layer of evidence on this point. Study 1 identified employee age as a relevant boundary condition, showing that the positive relationship between ICT use and workload, and the corresponding indirect effect on well-being through exhaustion, were stronger for older employees. This finding is consistent with evidence that age-related changes in cognitive resources may accentuate the demands associated with digital tools (Charness, 2020; Phang et al., 2006), and it aligns with the argument within the Job Demands–Resources model that individual characteristics shape how employees perceive and respond to their work environment (Bakker & Demerouti, 2017). Study 2 identified occupational skill level as a boundary condition, showing that the positive relationship between GenAI use and social support concentrates in high-skill occupations, whereas the positive relationship between GenAI use and role overload concentrates in low-skill occupations. This pattern is consistent with the skill-biased technological change perspective, which argues that digital technologies amplify advantages for high-skill workers while generating additional pressures for low-skill workers (Autor et al., 2003; Parker et al., 2017), and extends it to the specific case of GenAI (Johansson et al., 2017; Verma & Singh, 2022).

Jointly, these results advance work design theory in two ways. First, they identify two distinct types of boundary conditions that operate: person-related characteristics (such as age) and job-related characteristics (such as occupational skill level) suggesting that future theorizing

on technology and work design needs to account for moderators of disntinct types. Second, the convergence between studies reinforces the idea that universal claims about whether technology benefits or harms employees are theoretically and empirically unwarranted (Dierdorff & Morgeson, 2013; Parker et al., 2017). This contextual view aligns with broader calls in organizational psychology to identify the conditions under which relationships between variables change in strength and direction, which has been described as central to theoretical development in the field (Aguinis & Gottfredson, 2010).

5.3 Practical Implications

In addition to the theoretical implications discussed above, the three studies of this doctoral thesis offer practical implications for organizations, managers, human resource professionals, and policy makers dealing with the adoption and use of new technologies at work. As the findings show, the relationship between technology and work design is not predetermined: it depends on which technologies employees use, how organizations implement them, and on individual and occupational conditions. This opens a space for deliberate action, where decisions made within and beyond the workplace can shape whether the use of new technologies enhances or erodes the quality of work. Aligned with the human-centered principles that characterize the Industry 5.0 agenda (Breque et al., 2021), the following practical implications integrate findings from the three studies and are organized around four areas in which evidence-based decisions can make a meaningful difference.

The first practical implication concerns how organizations implement new technologies. As Study 3 shows, when organizations adopt ECTI, employees report higher job autonomy, job feedback, and social support, as well as higher job satisfaction, with job autonomy operating as a mechanism that links ECTI to job satisfaction. This indicates that the organizational practices

used to implement new technologies can shape work characteristics in their own right (Gagné et al., 2022; Parker & Grote, 2022), and that organizations have a meaningful margin of action in shaping the conditions under which employees experience new technologies at work.

For organizations and managers, this means embedding participation, transparent communication, and structured training into every phase of technology implementation, rather than treating these elements as optional add-ons. Concretely, this involves informing employees in advance about the rationale and scope of new technologies, opening channels through which their input and concerns can be heard and considered, providing training that addresses both the technical and the work-related dimensions of the new tools, and appointing change "champions" who can facilitate adaptation and peer support during the transition (Mehmood, 2024; Nielsen & Randall, 2021; Ullrich et al., 2023). For policy makers, the findings reinforce the relevance of promoting responsible digitalization policies that encourage inclusive and human-centered approaches to the implementation of new technologies, in line with the Industry 5.0 agenda (Breque et al., 2021; Brosnan et al., 2023; Peeters et al., 2025). National and regional digital strategies can incorporate criteria of employee participation and training quality as part of the standards for the implementation of new technologies, particularly in sectors undergoing rapid digital change.

The second practical implication concerns the dual nature of technology as both a resource and a demand within the work system. As the three studies suggest, the use of new technologies at work can simultaneously enrich and strain employees, which means that organizations should monitor and act on both sides of this balance rather than focusing exclusively on the expected benefits. For organizations and managers, this means recognizing that promoting the resource-enhancing effects of technology is not enough on its own: the

demand-generating side must also be deliberately managed. Concretely, this includes handling the role overload associated with the use of new technologies at work, setting realistic expectations about the time needed to adapt to new tools and to validate AI-generated outputs, and establishing clear boundaries that prevent technology use from intensifying work demands beyond what employees can sustain (Scholze et al., 2023; Tankelevitch et al., 2024). For example, setting clear disconnection times outside working hours can help prevent ICT use from blurring the boundaries between work and non-work life and inflating perceived workload (Barber & Santuzzi, 2015). For human resource professionals, the findings reinforce the relevance of incorporating indicators of demand-related strain into routine workforce assessments. Job redesign initiatives that focus exclusively on enriching motivational characteristics, such as autonomy or feedback, may overlook the parallel growth of demands that can erode the very benefits they aim to create.

The third practical implication concerns the contextual nature of the relationship between technology and work design. The same technology can have different consequences for employees depending on individual and occupational conditions, which means that one-size-fits-all approaches to technology use at work are unlikely to deliver consistent benefits across the workforce.

For organizations and managers, this implies tailoring the use of technology to the specific characteristics of employees and jobs rather than assuming uniform effects. In the case of older employees, who appear more vulnerable to the workload increases associated with ICT use, this includes providing targeted training that addresses not only the technical aspects of digital tools but also strategies for managing the cognitive demands they generate (Charness, 2020), as well as designing workflows that prevent constant connectivity from intensifying

perceived workload. In the case of employees in lower-skill occupations, who appear more vulnerable to the role overload associated with GenAI use, this includes providing structured training in prompt formulation and output validation, setting realistic expectations about GenAI-assisted task completion times during the adoption period, and creating spaces for peer learning where employees can share strategies for managing AI-related demands (Tankelevitch et al., 2024).

For policy makers, these findings highlight the relevance of digital inclusion policies that account for demographic and occupational diversity in the workforce. Given that older workers aged 55 to 64 are projected to represent close to one quarter of the global labour force by 2030 (International Labour Organization, 2023), national digital strategies can incorporate measures that protect older employees and workers in lower-skill occupations from being disproportionately burdened by the demands associated with the use of new technologies at work.

The fourth practical implication concerns the role of employee attitudes in shaping how new technologies enter and operate in the workplace. As Study 2 shows, attitudes toward GenAI are positively related to its subsequent use at work, indicating that the adoption of new technologies depends not only on their availability but also on the cognitive and affective evaluations that employees develop toward them. This is particularly relevant for technologies whose adoption is largely employee-driven rather than organizationally mandated, where individual willingness to engage becomes decisive (Microsoft & LinkedIn, 2024).

For organizations and managers, this implies that promoting the adoption of new technologies cannot rely on availability alone: organizations need to actively cultivate the conditions under which positive attitudes can develop. Concretely, this includes communicating

transparently about the rationale, benefits, limitations, and intended use of new technologies, addressing employee concerns and uncertainties through open dialogue, and providing hands-on support that helps employees build confidence in their interactions with the technology (Guingrich & Graziano, 2024; Sartori & Bocca, 2023; Suseno et al., 2023). This is particularly important in a context where employees are continuously exposed to contradictory information about emerging technologies, ranging from promises of productivity gains to concerns about job loss and ethical risks (Wang et al., 2025), which can shape attitudes in ways that are not always grounded in the actual conditions of their work.

For human resource professionals, the relevance of attitudes underscores the value of incorporating attitudinal assessments into the planning and evaluation of technology adoption initiatives, and designing internal communication and training programs that explicitly target perceived usefulness, trust, and openness toward emerging tools (Lichtenthaler, 2020; Park et al., 2024).

5.4 Limitations and Strengths

As with any empirical research, the three studies presented in this thesis have limitations that should be considered when interpreting their findings. First, the temporal scope and contextual reach of our research designs present some limitations. Study 1 used a cross-sectional design, which does not allow causal inferences regarding the relationships between ICT use, work characteristics, and employee well-being. This limitation was partially addressed in Studies 2 and 3 through a three-wave longitudinal design, which allowed us to examine temporal precedence between the study variables. Nevertheless, the three waves in Studies 2 and 3 spanned a limited time lag, so certain relationships, such as those involving skill variety or role overload, may unfold differently when observed over longer follow-up periods. In terms of

contextual reach, Studies 2 and 3 were conducted with samples of employees working in Spain, and although their composition closely mirrored the distribution of key demographic and occupational characteristics of the Spanish working population, the findings may not generalize to other cultural, institutional, or economic contexts. Study 1, although based on a multinational European sample, remains limited to the European context and does not speak to how ICT use relates to work characteristics and well-being in regions such as North America, Asia, Latin America, or Africa.

Second, the measurement of some key constructs presents limitations that should be acknowledged. In Study 1, ICT use was measured with a single item, and the workload and exhaustion scales, each composed of only two items, showed relatively low reliability. These constraints reflect the use of a publicly available dataset with predetermined survey questions, which did not allow the incorporation of multi-item measures with broader content coverage. In Study 2, GenAI use was also operationalized with a single item, which may not capture the intensity and variety of ways in which employees use GenAI across different work tasks.

Third, the theoretical scope of the three studies presents some limitations. Studies 2 and 3 focused on five work characteristics representing each of the five dimensions of the SMART model (Parker & Knight, 2024), while Study 1 focused on two work characteristics that operate as a resource and a demand, respectively. Although these selections allowed for a balanced and parsimonious examination of work design, they do not cover the full range of work characteristics potentially related to the use of new technologies, such as information processing requirements, role clarity, or task significance (Bienefeld & Grote, 2025; Lee et al., 2025). Additionally, the three studies examined a limited set of boundary conditions. Study 1 considered age as a moderator, and Study 2 considered occupational skill level, but other individual-level

moderators, such as technological self-efficacy (Andrei & Parker, 2022), and organizational-level moderators, such as leadership styles or organizational support for technology use, were not considered.

The three studies also present several strengths worth acknowledging. First, from a methodological standpoint, Studies 2 and 3 employed three-wave longitudinal designs with autoregression controls, allowing for the examination of how the studied predictors relate to change over time in the outcome variables, offering stronger causal inference than cross-sectional designs. Second, Study 1 relied on multilevel structural equation modeling to appropriately handle the nested structure of a large multinational dataset spanning 37 European countries. Third, Study 2 and 3 drew on a sample that mirrored the characteristics of the working population employed in Spain across several demographic variables, enhancing the generalizability of its findings within the Spanish context. Finally, the three studies collectively advance the examination of underexplored constructs and relationships, including the dual role of ICT, the attitudinal antecedents of GenAI use, and ECTI as an organizational predictor of work characteristics.

5.5 Future Research Directions

The findings of this doctoral thesis as a whole raise new questions that can be addressed in future research in order to expand our understanding of how technology relates to work design and employee outcomes. A first line of future research concerns the temporal dynamics through which technology relates to work design. Future studies could replicate the cross-sectional findings from Study 1 with longitudinal data to assess how the relationships between ICT use, work characteristics, and well-being unfold over time. Future studies could also adopt longer follow-up intervals to capture delayed and cumulative effects of GenAI use and ECTI on work

characteristics and employee outcomes (Dormann & Griffin, 2015), and complement these with within-person designs that track how individual employees' experiences of technology evolve across time.

A second line of future research concerns the measurement of technology use and work characteristics. Future studies could use multi-item scales with broader content coverage to operationalize ICT and GenAI use, and differentiate between types of technologies (e.g., communication tools, productivity software, or specific GenAI applications), given that different technologies may relate to work characteristics and employee outcomes in different ways (Bienefeld & Grote, 2025; Lee et al., 2025).

A third line of future research concerns the contextual generalization of the findings. Future studies could replicate the studies presented in this thesis in other countries and regions, particularly in cultural contexts that differ from the European and Spanish settings considered here. Comparative studies across countries would allow researchers to assess whether the relationships between ICT use, GenAI use, ECTI, and work characteristics hold across different institutional and cultural conditions, or whether they are shaped by contextual factors such as digital infrastructure, labor regulations, or collective norms around work and technology. Future research could also examine specific industries and workforce segments that may be particularly affected by the use of new technologies, such as healthcare (Jedwab et al., 2023; Tursunbayeva & Renkema, 2023) or manufacturing (Kim et al., 2022), to examine whether sector-specific conditions shape the relationships identified in this thesis.

Finally, future studies could incorporate additional work characteristics, particularly those related to information processing, role clarity, or task significance, which may be also relevant for the use of new technologies at work (Bienefeld & Grote, 2025; Lee et al., 2025). Future

research could also examine additional moderators of the relationships between technology use and work characteristics, both at the individual level (e.g., technological self-efficacy) and at the organizational level (e.g., leadership styles, organizational support for technology use), given that these contextual factors may shape how employees experience and engage with new technologies (Andrei & Parker, 2022; Parent-Rocheleau & Parker, 2022; Parker & Grote, 2022).

5.6 Final Conclusions

1. Technology is a relevant antecedent of work characteristics. The three studies of this thesis show that ICT, GenAI, and ECTI are related to core work characteristics, supporting the view that the antecedents of work design in the digital era include not only the technologies that employees use, but also the organizational approaches through which those technologies are implemented.

2. Technology operates as both a resource and a demand. Across the three studies, technology consistently enhances some work characteristics while introducing new demands, supporting the dual nature of technology as a feature of work that can simultaneously enrich and strain employees.

3. ICT use relates to employee well-being through two distinct pathways. ICT fosters well-being by enhancing job autonomy and work engagement, and hinders well-being by increasing workload and job exhaustion.

4. GenAI use is positively related to job autonomy, job feedback, and role overload, but not to skill variety or social support. These findings indicate that GenAI simultaneously enhances work resources and introduces new demands on employees.

5. Employee attitudes are a relevant antecedent of GenAI use at work. Positive attitudes toward GenAI predict its subsequent use, highlighting that individual-level cognitive and affective evaluations shape how emerging technologies enter the workplace.

6. ECTI is positively related to job autonomy, job feedback, and social support, and to job satisfaction. These findings show that employee-centered implementation approaches can shape several core work characteristics and contribute to employees' overall evaluation of their work.

7. Job autonomy emerged as a recurring mechanism linking technology to employee outcomes. Across the three studies, job autonomy consistently appeared as the work characteristic most strongly related to technology and as a key mediator translating technology-related antecedents into employee well-being and job satisfaction.

8. The relationship between technology and work design is contextually dependent. Individual characteristics, such as employee age, and occupational conditions, such as occupational skill level, moderate how technology relates to work characteristics and employee outcomes, indicating that universal claims about whether technology benefits or harms employees are empirically unwarranted.

To conclude, this doctoral thesis aimed to contribute to scientific and practical knowledge about how technology shapes the design and experience of work. This objective was guided by the growing recognition that contemporary workplaces are being reshaped by the use of new technologies at an unprecedented pace (Parker & Grote, 2022), and by the call within work design theory to identify the antecedents that shape work characteristics in the digital era (Parker et al., 2017). With this thesis, we aimed to respond to this call by examining how three conceptually distinct technology-related aspects, ICT use at work, GenAI use at work, and ECTI,

relate to core work characteristics and employee outcomes. Taken together, the three studies offer empirical evidence that the relationship between technology and work design is neither inevitable nor uniform: it depends on which technologies are used, how they are introduced, and on individual and occupational conditions. This opens a space for deliberate action, in which decisions made by employees, organizations, and policy makers can shape whether the use of new technologies enhances or erodes the quality of work. In a labor landscape that is being reshaped by the diffusion of new technologies, understanding how technology relates to work design is not only a theoretical endeavor, but a practical and ethical imperative for building sustainable and humanly meaningful work in the digital era.



Chapter 6: Resumen

En este capítulo se resumen los principales aspectos de la tesis doctoral. El capítulo comienza con una introducción al tema central de la tesis, seguida de la descripción de sus objetivos. A continuación se presenta la metodología empleada, un resumen integrado de los tres estudios realizados para alcanzar los objetivos planteados, con sus principales resultados e implicaciones, y las limitaciones generales junto con las direcciones futuras de investigación. Finalmente, se exponen las conclusiones que pueden derivarse de la tesis.

6.1 Introducción

Esta tesis doctoral aborda una pregunta central para el mundo laboral contemporáneo: la relación entre las nuevas tecnologías presentes en el lugar de trabajo y el diseño del trabajo. La interrogante importa porque las tecnologías digitales se han convertido en un componente estructural de la práctica laboral y porque está cambiando con rapidez. Las tecnologías de la información y la comunicación (TIC) constituyen ya una infraestructura cotidiana en una parte sustancial de los puestos de trabajo (Cascio y Montealegre, 2016; Parker y Grote, 2022), y en los últimos años se ha añadido la inteligencia artificial generativa (IAGen), un conjunto de sistemas capaces de producir contenido en formato texto, imagen, audio o código a partir de instrucciones del usuario. La velocidad con la que estas tecnologías penetran en las organizaciones plantea preguntas urgentes sobre cómo configuran las tareas, los roles y las relaciones que componen el trabajo, y sobre las consecuencias que tienen para el bienestar y la satisfacción de los empleados.

El diseño del trabajo, entendido como el estudio de las características que configuran las tareas, los roles y las relaciones laborales (Parker, 2014), constituye el marco disciplinar desde el que esta tesis aborda dicha cuestión. La literatura sobre diseño del trabajo ha documentado de forma extensa las consecuencias que tienen las características del trabajo sobre la motivación, tensión laboral, el desempeño y el bienestar de los empleados. Sin embargo, los antecedentes de

estas características han recibido mucha menos atención (Parker et al., 2017). Este desequilibrio resulta especialmente limitante en un contexto en el que la tecnología introduce cambios rápidos en las condiciones bajo las cuales se realiza el trabajo, ya que dificulta tanto el avance teórico como la formulación de orientaciones aplicadas para las organizaciones y los responsables de políticas públicas. Para contribuir a abordar este desequilibrio, esta tesis examina tres aspectos relacionados con la tecnología que pueden operar como antecedentes del diseño del trabajo: el uso de TIC en el trabajo, el uso de IAGen en el trabajo y la implementación de tecnologías centrada en los empleados (Employee-Centered Technology Implementation, ECTI).

6.1.1 Antecedentes del diseño del trabajo en la era digital

La tesis se apoya en varios marcos teóricos que han contribuido históricamente al estudio del diseño del trabajo. La teoría sociotécnica (Sociotechnical Theory; Trist y Bamforth, 1951; Cherns, 1976) ofrece la base conceptual para tratar la tecnología como un componente estructural del sistema de trabajo, y no como un factor neutro. Sobre esta base, el Modelo de Características del Trabajo (Job Characteristics Model; Hackman y Oldham, 1976) y el Modelo Demanda-Control (Demand-Control Model; Karasek, 1979) establecieron las primeras taxonomías de características del trabajo y los procesos psicológicos a través de los cuales estas se vinculan con el bienestar y el desempeño. El Modelo de Demandas y Recursos Laborales (Job Demands–Resources model, JD-R; Bakker y Demerouti, 2017) amplió esta tradición distinguiendo entre dos categorías generales de características, las demandas y los recursos, y entre dos procesos psicológicos paralelos: el proceso motivacional, en el que los recursos laborales fomentan estados motivacionales positivos como el “work engagement”, y el proceso de deterioro de la salud, en el que las demandas laborales agotan los recursos psicológicos y pueden producir agotamiento. Más recientemente, el modelo SMART (SMART model; Parker y

Knight, 2024) ha propuesto cinco dimensiones integradoras del diseño del trabajo (estimulantes, autonomía, dominio, relacionales y tolerables), con la pretensión de organizar la abundancia de características que la literatura ha ido acumulando.

Estos marcos coinciden en que las características del trabajo importan, pero ofrecen menos orientaciones sobre qué las configura. La revisión de Parker et al. (2017) identificó, entre otros, los factores tecnológicos como una categoría de antecedentes del diseño del trabajo cuyo estudio sistemático seguía siendo limitado. Tomando esta revisión como punto de partida, la tesis examina dos modalidades de uso de tecnología y una práctica organizativa asociada a su introducción. El uso de TIC en el trabajo se entiende como la frecuencia con la que los empleados utilizan dispositivos digitales (ordenador, portátil, tableta o teléfono inteligente) en el desempeño de sus tareas. El uso de IAGen en el trabajo se entiende como la frecuencia con la que los empleados utilizan sistemas como ChatGPT, Claude, Gemini o Copilot para realizar su trabajo. La ECTI es un enfoque centrado en las personas, en el que se consideran las necesidades e ideas de los empleados sobre el proceso de implementación [de nuevas tecnologías], y que involucra a los empleados en este proceso mediante, por ejemplo, la provisión de información, consulta y formación (González-Romá et al., 2025). Estos tres aspectos plantean preguntas teóricas diferentes y se abordan en los tres estudios empíricos de la tesis.

6.1.2 El uso de TIC en el trabajo y el bienestar de los empleados

Las TIC han sido objeto de una literatura abundante, pero su papel como antecedente del diseño del trabajo presenta un panorama mixto. Por una parte, las TIC se han descrito como recursos que pueden incrementar la autonomía laboral, al permitir a los empleados elegir cuándo, dónde y cómo realizar sus tareas, y al facilitar el acceso a información relevante para la toma de decisiones (Cascio y Montealegre, 2016). Por otra parte, las TIC se han descrito como demandas

que pueden incrementar la carga de trabajo, al acelerar el ritmo de las tareas, al ampliar el volumen de información que el empleado debe procesar y al difuminar las fronteras entre la vida laboral y la vida personal (Day et al., 2012; Mazmanian et al., 2013). Esta dualidad sugiere que las TIC pueden activar simultáneamente los dos procesos psicológicos centrales del modelo JD-R: el proceso motivacional, a través de la autonomía, y el proceso de deterioro de la salud, a través de la carga de trabajo.

Una segunda pregunta que la literatura previa ha planteado es si la relación entre el uso de TIC y las características del trabajo es uniforme entre los empleados, o si depende de variables individuales. La edad del empleado constituye un candidato razonable para esta moderación, ya que la fluidez digital y los procesos de adaptación a las TIC pueden variar a lo largo de la trayectoria profesional (Parker y Grote, 2022). El primer estudio de la tesis examina ambas cuestiones: si el uso de TIC en el trabajo se relaciona con el bienestar de los empleados a través de la autonomía y de la carga de trabajo, y si estas relaciones están moderadas por la edad.

6.1.3 El uso de IAGen en el trabajo y las características del trabajo

La IAGen representa una novedad sustancial respecto a las TIC. Aunque comparte con ellas la condición de tecnología digital, sus capacidades difieren cualitativamente: la IAGen produce contenido nuevo en lugar de simplemente facilitar el acceso o el procesamiento de información existente (Tankelevitch et al., 2024). Esta diferencia implica que sus consecuencias para el diseño del trabajo no son necesariamente reducibles a las que se conocen para las TIC, y requiere una investigación específica. El segundo estudio de la tesis examina cómo el uso de IAGen en el trabajo se relaciona con cinco características centrales del trabajo derivadas del modelo SMART: la variedad de habilidades (dimensión estimulante), la autonomía (dimensión de autonomía), la

retroalimentación del puesto (dimensión de dominio), el apoyo social (dimensión relacional) y la sobrecarga de rol (dimensión tolerable).

Además, el estudio aborda dos asuntos adicionales. La primera se refiere a los antecedentes del propio uso de IAGen en el trabajo. A diferencia de muchas tecnologías cuya adopción se decide centralizadamente, la IAGen es accesible a los empleados de forma directa, lo que sugiere que sus actitudes individuales pueden contribuir a configurar su uso posterior. El estudio examina si la actitud hacia la IAGen opera como antecedente del uso. El segundo se refiere a la posible heterogeneidad de las relaciones entre el uso de IAGen y las características del trabajo en función de las características del puesto. La perspectiva del cambio técnico sesgado por habilidades (Autor et al., 2003) sugiere que las consecuencias de las tecnologías digitales pueden diferir entre ocupaciones de distinta cualificación. El estudio examina si el nivel de cualificación ocupacional modera las cinco relaciones entre el uso de IAGen y las características del trabajo.

6.1.4 La implementación de tecnologías centrada en los empleados y la satisfacción laboral

El tercer tema abordado en la tesis desplaza el foco desde las tecnologías mismas hacia las prácticas organizativas a través de las cuales se introducen. Las nuevas tecnologías no llegan al lugar de trabajo de forma neutra: la manera en la que las organizaciones las implementan determina, en parte, qué consecuencias tienen para los empleados. La agenda Industria 5.0 (Breque et al., 2021) ha articulado una visión de la transición digital centrada en las personas, que reclama incorporar a los empleados en los procesos de adopción de tecnología en lugar de tratarlos como meros receptores pasivos. La ECTI operacionaliza este principio como una práctica organizativa concreta: una aproximación a la introducción de nuevas tecnologías que incorpora la información previa, la consulta, la consideración de la opinión de los empleados, la

atención a sus necesidades de formación y el apoyo durante la transición (González-Romá et al., 2025).

Aunque la propuesta de la ECTI tiene un sustento teórico sólido, la evidencia empírica sobre cómo se relaciona con las características del trabajo y con resultados laborales como la satisfacción laboral todavía es limitada. El tercer estudio de la tesis examina si la ECTI se relaciona con las cinco características del trabajo derivadas del modelo SMART y con la satisfacción laboral, y si esta relación está mediada por dichas características. Esta especificación permite identificar los mecanismos a través de los cuales las prácticas de implementación centradas en los empleados se traducen en la evaluación que estos hacen de su trabajo.

6.2 Objetivos de la Tesis

6.2.1 Objetivo general

Teniendo en cuenta la revisión de la literatura sobre la tecnología en el lugar de trabajo y los vacíos identificados, la presente tesis doctoral tiene como objetivo general avanzar en el conocimiento teórico y empírico sobre cómo las tecnologías presentes en el lugar de trabajo y los procesos organizativos asociados a su implementación se relacionan con el diseño del trabajo y con resultados relevantes para los empleados. De manera específica, la tesis examina los mecanismos a través de los cuales tres aspectos relacionados con las nuevas tecnologías en el trabajo (el uso de TIC, el uso de IAGen y la ECTI) se relacionan con características centrales del trabajo y, a su vez, con resultados laborales como el bienestar de los empleados y la satisfacción laboral.

6.2.2 Objetivos específicos

A su vez, este objetivo general se divide en tres objetivos específicos abordados en los tres estudios de la tesis.

Objetivo 1: Investigar cómo el uso de TIC en el trabajo se relaciona con el bienestar de los empleados a través de dos características centrales del trabajo, la autonomía y la carga de trabajo, así como con los procesos motivacional y de deterioro de la salud propuestos por el modelo JD-R. De forma específica, se examina si el uso de TIC opera simultáneamente como recurso laboral, al incrementar la autonomía, y como demanda laboral, al incrementar la carga de trabajo, activando así ambos procesos. Además, se investiga si estas relaciones están moderadas por la edad del empleado.

Objetivo 2: Investigar cómo el uso de IAGen en el trabajo se relaciona con cinco características centrales del trabajo derivadas del modelo SMART: la variedad de habilidades, autonomía, retroalimentación del puesto, apoyo social y sobrecarga de rol. Además, se examina si la actitud hacia la IAGen opera como antecedente del uso posterior de IAGen en el trabajo, y si las relaciones entre el uso de IAGen y las cinco características del trabajo están moderadas por el nivel de cualificación ocupacional.

Objetivo 3: Examinar cómo la ECTI se relaciona con las mismas cinco características del trabajo (variedad de habilidades, autonomía, retroalimentación del puesto, apoyo social y sobrecarga de rol) y con la satisfacción laboral. Además, se examina el papel mediador de las cinco características del trabajo en la relación entre la ECTI y la satisfacción laboral, centrando así la atención en los mecanismos a través de los cuales las prácticas de implementación centradas en los empleados se traducen en la evaluación que estos hacen de su trabajo.

6.3 Metodología

Los datos utilizados en esta tesis proceden de dos fuentes diferentes. Para el Estudio 1 se utilizaron datos individuales procedentes de la séptima edición de la European Working Conditions Survey (EWCS, 2021), llevada a cabo por la European Foundation for the

Improvement of Living and Working Conditions (Eurofound) en 37 países europeos entre marzo y noviembre de 2021. La muestra analítica final estuvo compuesta por 7.900 empleados, tras excluir a las personas trabajadoras por cuenta propia, a los empleados con contrato a tiempo parcial y a las observaciones con datos perdidos. Para los Estudios 2 y 3 se recogieron datos primarios mediante un panel en línea gestionado por una empresa de investigación de mercados. Los criterios de elegibilidad exigieron que los participantes fueran mayores de 18 años y que no trabajaran por cuenta propia. Los datos se recogieron en tres momentos temporales separados por intervalos de 1,5 meses entre diciembre de 2024 y marzo de 2025 (T1, T2 y T3), con una muestra inicial de 804 participantes en T1 y una muestra longitudinal final de 554 empleados que respondieron a las tres olas y superaron dos ítems de control de atención. Para ambos estudios se realizó un "attrition análisis" que mostró que la muestra final no se vio afectada por sesgos sustanciales relacionados con las variables de interés. En cuanto a las medidas, en los tres estudios se emplearon escalas validadas en la literatura previa, traducidas al castellano cuando fue necesario mediante un procedimiento de doble traducción y reconciliación (International Test Commission, 2018). Todas las medidas mostraron una fiabilidad satisfactoria, con coeficientes Omega de McDonald superiores a 0,84 en los Estudios 2 y 3, y los análisis factoriales confirmatorios respaldaron la validez convergente y discriminante de las escalas utilizadas. En el Estudio 1, dada la estructura anidada de los datos (empleados anidados en países), se empleó modelización de ecuaciones estructurales multinivel implementada en Mplus 8.10 con estimación de máxima verosimilitud, con las variables de nivel 1 centradas en la media del grupo y los efectos indirectos estimados mediante intervalos de confianza del 95% por el método de Monte Carlo. En los Estudios 2 y 3 se realizó un path analysis en Mplus 8, con estimación de

máxima verosimilitud, y los efectos indirectos del Estudio 3 se evaluaron mediante intervalos de confianza del 95% obtenidos por bootstrapping, con 5.000 muestras.

6.4 Resumen de los Estudios, Resultados e Implicaciones

El Estudio 1 aborda el primer objetivo de la tesis. En este estudio se investiga si el uso de TIC en el trabajo se relaciona con el bienestar de los empleados a través de la autonomía y de la carga de trabajo, activando los procesos motivacional y de deterioro de la salud del modelo JD-R, y si estas relaciones están moderadas por la edad del empleado. Basándose en la teoría sociotécnica y en el modelo JD-R, se planteó que el uso de TIC podría operar como un "double-edged sword": por una parte, como recurso laboral que incrementa la autonomía y, a través de ella, fomenta el "work engagement" y reduce el agotamiento; por otra, como demanda laboral que incrementa la carga de trabajo y, a través de ella, fomenta el agotamiento. Adicionalmente, basándose en la literatura sobre adaptación digital a lo largo de la trayectoria profesional, se planteó que la edad podría moderar tanto la relación entre el uso de TIC y la autonomía como la relación entre el uso de TIC y la carga de trabajo.

Los resultados del modelo multinivel especificado en una muestra de 7.900 empleados procedentes de 37 países europeos respaldaron la propuesta del "double-edged sword". El uso de TIC en el trabajo se relacionó positivamente tanto con la autonomía como con la carga de trabajo. A su vez, la autonomía se relacionó positivamente con el "work engagement" y negativamente con el agotamiento, mientras que la carga de trabajo se relacionó positivamente con el agotamiento. El "work engagement" se relacionó positivamente con el bienestar y el agotamiento se relacionó negativamente con él. Tres de los cuatro efectos indirectos hipotetizados resultaron estadísticamente significativos: el uso de TIC se relacionó positivamente con el bienestar a través de la autonomía y el "work engagement" (proceso motivacional),

negativamente a través de la carga de trabajo y el agotamiento (proceso de deterioro de la salud) y, de forma adicional, positivamente a través de la autonomía y el agotamiento. En cuanto al papel moderador de la edad, los resultados mostraron que la edad no moderó la relación entre el uso de TIC y la autonomía, pero sí moderó la relación entre el uso de TIC y la carga de trabajo, que fue más fuerte para los empleados de mayor edad. En consecuencia, el efecto indirecto negativo del uso de TIC sobre el bienestar a través de la carga de trabajo y el agotamiento también fue más fuerte entre los trabajadores de mayor edad.

Este estudio contribuye a la literatura sobre tecnología y diseño del trabajo al documentar empíricamente la dualidad de las TIC como recurso y como demanda dentro del sistema de trabajo, y al integrar este patrón con los dos procesos psicológicos del modelo JD-R. Asimismo, el estudio identificó la edad como una condición de borde relevante, contribuyendo a la perspectiva más amplia de que la relación entre tecnología y diseño del trabajo es contextualmente dependiente y no uniforme entre los empleados. Desde un punto de vista práctico, los resultados sugieren que las organizaciones deben monitorizar y gestionar de manera deliberada tanto la vertiente de los recursos como la vertiente de las demandas asociadas al uso de las TIC, en lugar de centrar la atención exclusivamente en los beneficios esperados, y que las intervenciones organizativas asociadas al uso de las TIC (formación, soporte, rediseño de flujos de trabajo) deben adaptarse al perfil etario de los empleados. Este estudio se publicó en The Spanish Journal of Psychology (Arriagada-Venegas, Ariño-Mateo y González-Romá, 2026).

El Estudio 2 aborda el segundo objetivo de la tesis. En este estudio se investiga cómo el uso de IAGen en el trabajo se relaciona con cinco características centrales del trabajo derivadas del modelo SMART (variedad de habilidades, autonomía decisional, retroalimentación del puesto, apoyo social y sobrecarga de rol), si la actitud hacia la IAGen opera como antecedente de IAGen

en el trabajo, y si el nivel de cualificación ocupacional modera las relaciones entre el uso de IAGen y las cinco características del trabajo. Basándose en el modelo SMART y en la literatura emergente sobre IAGen en el lugar de trabajo, se planteó que el uso de IAGen podría incrementar la autonomía, la retroalimentación del puesto y la variedad de habilidades, al ampliar el rango de tareas que el empleado puede abordar de forma independiente y al facilitar respuestas inmediatas sobre el avance de la tarea, así como el apoyo social, al funcionar como una fuente complementaria de asistencia. Al mismo tiempo, basándose en Tankelevitch et al. (2024), se planteó que el uso de IAGen podría incrementar la sobrecarga de rol, dado que su uso productivo requiere competencias de formulación de instrucciones, evaluación crítica de las respuestas y verificación de la información, que se añaden a las demandas habituales del puesto. Adicionalmente, basándose en la perspectiva del cambio técnico sesgado por habilidades (Autor et al., 2003), se planteó que el nivel de cualificación ocupacional podría moderar estas relaciones, con beneficios concentrados en las ocupaciones de mayor cualificación y demandas concentradas en las ocupaciones de menor cualificación.

Los resultados en una muestra longitudinal de 554 empleados de España mostraron que la actitud hacia la IAGen en T1 se relacionó positivamente con el uso de IAGen en T2. A su vez, el uso de IAGen en T2 se relacionó positivamente con tres de las cinco características del trabajo medidas en T3: la autonomía, la retroalimentación del puesto y la sobrecarga de rol. Las relaciones con la variedad de habilidades y con el apoyo social no resultaron significativas en el modelo principal. En cuanto al papel moderador del nivel de cualificación ocupacional, los resultados mostraron dos relaciones moderadas significativas. En primer lugar, la relación entre el uso de IAGen y el apoyo social fue positiva y significativa únicamente para los valores altos de cualificación ocupacional, lo que indica que los beneficios sociales del uso de IAGen emergen

específicamente en ocupaciones de mayor cualificación. En segundo lugar, la relación entre el uso de IAGen y la sobrecarga de rol fue positiva y significativa únicamente para los valores bajos y medios de cualificación ocupacional, lo que indica que las demandas asociadas al uso de IAGen se concentran en ocupaciones de menor cualificación.

Este estudio contribuye a la literatura sobre tecnología y diseño del trabajo al ofrecer evidencia longitudinal sobre cómo el uso de IAGen en el trabajo se relaciona con un conjunto amplio de características centrales del trabajo, integradas en el modelo SMART. El estudio identifica una dualidad similar a la documentada para las TIC en el Estudio 1, el uso de IAGen se vincula simultáneamente con recursos (autonomía decisional, retroalimentación del puesto) y con demandas (sobrecarga de rol). Adicionalmente, el estudio amplía la comprensión de los antecedentes del uso de IAGen al mostrar que las actitudes individuales contribuyen a configurar su uso posterior, lo que resulta especialmente relevante para tecnologías cuya adopción es impulsada por los propios empleados. Finalmente, los resultados de moderación respaldan que la relación entre el uso de IAGen y las características del trabajo no es uniforme entre las ocupaciones, sino que está condicionada por la cualificación, en línea con la perspectiva del cambio técnico sesgado por habilidades. Desde un punto de vista práctico, este estudio sugiere que las organizaciones deben cultivar actitudes positivas hacia la IAGen mediante comunicación transparente, atención a las inquietudes de los empleados y apoyo durante el aprendizaje, y que la formación y los flujos de trabajo asociados al uso de IAGen deben adaptarse al perfil ocupacional de los empleados, con una atención particular a la prevención de la sobrecarga de rol en ocupaciones de menor cualificación.

El Estudio 3 aborda el tercer objetivo de la tesis. En este estudio se investiga si ECTI se relaciona con las cinco características del trabajo derivadas del modelo SMART (variedad de

habilidades, autonomía decisional, retroalimentación del puesto, apoyo social y sobrecarga de rol) y con la satisfacción laboral, y si la relación entre ECTI y satisfacción laboral está mediada por las cinco características del trabajo. Basándose en la agenda Industria 5.0 y en la teoría sociotécnica, se planteó que ECTI podría operar como un antecedente organizativo del diseño del trabajo, ya que la información previa, la consulta y la consideración de la opinión de los empleados durante la introducción de nuevas tecnologías podrían favorecer la apropiación de las tareas tecnológicamente mediadas y reducir la incertidumbre asociada al cambio. De forma específica, se planteó que ECTI podría incrementar la autonomía decisional, la retroalimentación del puesto, el apoyo social y la variedad de habilidades, así como reducir la sobrecarga de rol, y que estos cambios en las características del trabajo podrían mediar la relación entre ECTI y la satisfacción laboral posterior.

Los resultados en la misma muestra longitudinal de 554 empleados mostraron que la ECTI en T1 se relacionó positivamente con tres características del trabajo medidas en T2: autonomía, retroalimentación del puesto y apoyo social. Las relaciones de ECTI con la variedad de habilidades y con la sobrecarga de rol no resultaron significativas. Además, ECTI en T1 se relacionó positivamente con satisfacción laboral en T3, controlando satisfacción laboral en T2. En cuanto a las relaciones entre las características del trabajo en T2 y satisfacción laboral en T3, autonomía se relacionó positivamente con satisfacción laboral, y sobrecarga de rol se relacionó negativamente con ella. De forma inesperada, la variedad de habilidades se relacionó negativamente con satisfacción laboral. Las relaciones de la retroalimentación del puesto y del apoyo social con la satisfacción laboral no resultaron significativas. De los cinco efectos indirectos examinados, únicamente el que vincula la ECTI con la satisfacción laboral a través de autonomía resultó estadísticamente significativo.

Este estudio contribuye a la literatura sobre tecnología y diseño del trabajo al identificar ECTI como un antecedente organizativo de varias características centrales del trabajo, y al documentar la autonomía como mecanismo a través del cual las prácticas de implementación centradas en los empleados se traducen en la satisfacción laboral posterior. El estudio muestra una asimetría relevante: ECTI opera principalmente por la vía del incremento de los recursos (autonomía decisional, retroalimentación del puesto, apoyo social), sin reducir las demandas (sobrecarga de rol). Asimismo, el patrón de mediación, en el que la autonomía es la única característica que media significativamente la relación entre la ECTI y la satisfacción laboral, refuerza la idea de que la autonomía ocupa una posición especialmente central cuando el antecedente examinado es de naturaleza tecnológica u organizativa-tecnológica. Desde un punto de vista práctico, el estudio sugiere que las organizaciones que introducen nuevas tecnologías deben incorporar de manera deliberada la información previa, la consulta, la consideración de la opinión de los empleados, la atención a sus necesidades de formación y el apoyo durante la transición, ya que estas prácticas se relacionan con un mayor margen de decisión, con una mayor retroalimentación y con un mayor apoyo social percibidos, así como con una mayor satisfacción laboral posterior. No obstante, los resultados también sugieren que la ECTI por sí sola puede no ser suficiente para reducir las demandas asociadas al uso de tecnología, lo que indica que su implementación debería complementarse con medidas adicionales orientadas específicamente a la prevención de la sobrecarga.

6.5 Limitaciones e Investigaciones Futuras

Cabe reconocer algunas limitaciones de esta tesis doctoral y proporcionar algunas direcciones para la investigación futura. Primero, el Estudio 1 utiliza un diseño transversal, que no permite realizar inferencias causales sobre las relaciones examinadas. Los Estudios 2 y 3

emplean diseños longitudinales de tres olas con intervalos de 1,5 meses, lo que atenúa esta limitación, pero deja abierta la cuestión de cómo se desarrollan las relaciones examinadas en horizontes temporales más amplios. Recomendamos que la investigación futura adopte horizontes temporales más amplios y, en el caso del Estudio 1, que se utilicen datos longitudinales para examinar la dinámica entre el uso de TIC, las características del trabajo y el bienestar a lo largo del tiempo.

Segundo, la medición del uso de TIC y del uso de IAGen se basa en ítems únicos, lo que limita la captura de la intensidad y la variedad de las formas concretas de uso. Las investigaciones futuras pueden emplear medidas multi-ítem que distingan entre tipos específicos de tecnologías y entre modalidades de uso (búsqueda de información, redacción asistida, generación de código, etc.), lo que permitiría comprender con mayor matiz cómo cada tipo de uso se relaciona con las características del trabajo.

Tercero, los Estudios 2 y 3 se llevaron a cabo en España, lo que restringe la generalización de los hallazgos a otros contextos culturales e institucionales. Las investigaciones futuras pueden replicar los estudios en otros países y sectores industriales, así como integrar variables institucionales (por ejemplo, regulación laboral) en el modelo. Esta integración resulta especialmente pertinente para la IAGen, cuya regulación y difusión presentan importantes diferencias entre regiones.

Cuarto, el conjunto de características del trabajo examinadas, aunque representativo del modelo SMART y del marco JD-R, no abarca todas las posibles características potencialmente relevantes. Las investigaciones futuras pueden incorporar características adicionales (como el procesamiento de información, la claridad de rol o la significatividad de la tarea), así como moderadores tanto individuales (como la autoeficacia tecnológica) como organizativos (como los

estilos de liderazgo o el apoyo organizativo al uso de tecnología). Asimismo, la integración de antecedentes a distintos niveles, individuales y organizativos, puede contribuir a una comprensión más completa de cómo la tecnología configura el diseño del trabajo en la era digital.

6.6 Conclusiones

Para cerrar este capítulo, se resumen las conclusiones más destacadas que pueden derivarse de esta tesis doctoral.

1. Las nuevas tecnologías presentes en el lugar de trabajo (TIC, IAGen) y las prácticas organizativas asociadas a su implementación (ECTI) constituyen antecedentes relevantes de las características del trabajo. Los tres estudios respaldan empíricamente la idea de que los antecedentes del diseño del trabajo en la era digital incluyen tanto las tecnologías que los empleados utilizan como las aproximaciones organizativas mediante las cuales esas tecnologías se introducen.

2. La tecnología no es uniformemente beneficiosa ni perjudicial para los empleados. El Estudio 1 documenta que las TIC operan simultáneamente como recurso (a través de la autonomía) y como demanda (a través de la carga de trabajo), activando los procesos motivacional y de deterioro de la salud del modelo JD-R. El Estudio 2 documenta una dualidad similar para la IAGen, cuyo uso se vincula simultáneamente con la autonomía decisional, la retroalimentación del puesto y la sobrecarga de rol. El Estudio 3 muestra una asimetría relevante para la ECTI, que opera principalmente por la vía del incremento de los recursos sin reducir las demandas.

3. La autonomía emerge como el mecanismo más consistente a través del cual la tecnología se vincula con resultados relevantes para los empleados. En el Estudio 1, la autonomía actúa

como mecanismo central que vincula el uso de TIC con el bienestar. En el Estudio 2, el uso de IAGen se relaciona positivamente con la autonomía a lo largo del tiempo. En el Estudio 3, la autonomía es la única característica del trabajo que media significativamente la relación entre la ECTI y la satisfacción laboral. Este patrón sugiere que, aunque el modelo SMART conceptualiza la autonomía como una más entre cinco dimensiones, esta puede ocupar una posición especialmente central cuando el antecedente examinado es la tecnología.

4. La relación entre la tecnología y el diseño del trabajo es contextualmente dependiente. Las características individuales y ocupacionales moderan cómo la tecnología se relaciona con las características del trabajo y con los resultados de los empleados. La edad modera la relación entre el uso de TIC y la carga de trabajo, que es más fuerte para los empleados de mayor edad (Estudio 1). El nivel de cualificación ocupacional modera las relaciones entre el uso de IAGen y el apoyo social, así como entre el uso de IAGen y la sobrecarga de rol, con beneficios sociales concentrados en ocupaciones de alta cualificación y demandas concentradas en ocupaciones de baja cualificación (Estudio 2).

5. Las actitudes de los empleados constituyen un antecedente relevante del uso de la IAGen en el trabajo. La actitud hacia la IAGen en T1 se relaciona positivamente con el uso de IAGen en T2 (Estudio 2). Este hallazgo resulta especialmente relevante para tecnologías cuya adopción es impulsada por los propios empleados, y no exclusivamente decidida por la organización.

6. Las prácticas organizativas de implementación importan. La ECTI se relaciona positivamente con autonomía, retroalimentación del puesto, apoyo social y satisfacción laboral posterior (Estudio 3). Las organizaciones que incorporan la información previa, la consulta, la consideración de la opinión de los empleados y el apoyo durante la transición ofrecen, en consecuencia, condiciones de trabajo evaluadas más positivamente por los empleados.

7. Las afirmaciones universales sobre si la tecnología beneficia o perjudica a los empleados resultan empíricamente injustificadas. El patrón general que emerge de los tres estudios es que la tecnología configura el diseño del trabajo de forma heterogénea, y que dicha heterogeneidad depende del tipo de tecnología, de cómo se introduce en la organización y de las características individuales y ocupacionales de los empleados. Esta evidencia abre margen para la acción deliberada por parte de empleados, organizaciones y responsables de políticas públicas.

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