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Crafting the AI-Integrated Workplace
An Online Job Crafting Training Based on Human-Task-AI Fit and JD-R

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Crafting the AI-Integrated Workplace: An Online Job Crafting Training Based on Human-Task-AI Fit and JD-R

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Abstract

Purpose: As AI technologies become increasingly embedded in the workplace, employees need new strategies to adapt. This study developed a brief online job crafting training to help employees proactively shape their work in response to AI integration. The training is grounded in the Human-Task-AI fit theory and the Job Demands-Resources model, encouraging workers to align AI tools with their tasks and rebalance their job demands and resources.

Design/Methodology: A quasi-experimental design was employed, with an intervention group (who underwent self-training) and a control group (who received no training). Participants (N = 61 final, from an initial 131) were surveyed before and after 2 weeks. The training included three self-paced modules (improving fit, seeking resources, and optimizing demands) with videos, exercises, and SMART goal setting. Key outcomes measured included job crafting behaviors (seeking resources and optimizing demands), Human-Task-AI fit, adaptivity, proactivity, innovativeness, and AI usage. Data were analyzed using mixed-effects models and mediation analysis.

Findings: The intervention had significant positive effects on employees’ work adaptation to AI. Compared to the control group, trained participants reported increased frequency of AI use, greater Task-AI fit (i.e., better alignment of AI with their tasks), and more job demand optimization behavior. There was no direct change in seeking resources or in adaptive, proactive, and innovative behavior. However, mediation analyses revealed that the training improved proactivity and innovativeness indirectly: trainees who optimized job demands and improved Task-AI fit subsequently became more proactive and innovative. Leader support for AI serves as a boundary condition for the intervention’s effectiveness.

Implications: This research shows that a short, low-cost online intervention can partially equip employees to cope with AI-related changes by crafting their own jobs. Organizations should complement technical AI deployments with employee-focused programs that foster active adaptation. By learning to realign tasks and reduce AI-related strain, employees not only use AI more but also develop a more proactive and innovative mindset. This bottom-up approach can help turn AI implementations into opportunities for enhanced performance and employee growth rather than sources of stress.

Originality/Value: This study is among the first to operationalize job crafting training specifically for AI-integrated work environments. It combines a new theoretical framework (integrating Human-Task-AI fit with JD-R) with empirical testing, offering promising preliminary insights into how employees can be empowered to make AI a meaningful job resource. The findings contribute to both theory and practice by demonstrating tangible ways to support the workforce during digital transformation.

Executive summary

The rapid rise of Artificial Intelligence (AI) is changing the way we work at a fast pace. Many jobs and routines are affected, and employees are expected to adapt quickly. This study responds to that urgent need by introducing and testing the first empirical job crafting intervention tailored for AI-integrated workplaces. The results show that even a brief online self-training can empower employees to take charge of their evolving relationship with AI, turning uncertainty into opportunity.

Traditional technology acceptance models fail to address the AI's unique characteristics. In particular, AI is dynamic of nature, continuously evolves, has the dual potential of providing both opportunities and challenges, and has a personalized impact on employees. In AI-integrated workplaces, employees face new demands (e.g., technostress and uncertainty), while simultaneously encountering opportunities for enhanced efficiency and meaningful work. Moreover, the manifestation of new demands and resources depends highly on the context and employee-level characteristics. Solely top-down AI integration approaches would fall short in recognizing, identifying, and anticipating these detailed work design- and employee-level factors, entailing the risk of unbalanced jobs and work environments. This study argued that employees themselves must actively shape how AI effectively integrates into their daily work as a complementary and proactive response to top-down approaches.

The intervention builds on an integration of two complementary theories: 1) Human-Task-AI fit theory explains when AI functions effectively by examining alignment between task requirements, AI capabilities, and individual skills. 2) The Job Demands-Resources (JD-R) model reveals how this alignment affects employee well-being and performance. Together, these theories show that AI's impact depends on whether it serves as a job resource (supporting work) or a demand (burdening employees), which varies by individual and context.

The study developed a 14-day online self-training with three modules, each combining educational videos, practical exercises, and SMART goal setting. Module 1 focused on improving Human-Task-AI fit by helping employees identify where AI could add value to their specific tasks. Module 2 taught strategies for seeking resources like knowledge, peer support, and learning opportunities. Module 3 addressed optimizing demands by simplifying or optimizing AI-related work processes. The intervention emphasized concrete, immediate application through daily goal implementation and reflection.

Using a quasi-experimental design, 61 participants (28 experimental, 33 control) from various sectors completed pre- and post-intervention surveys. The experimental group underwent training, while the control group continued with their normal work. Mixed-effects models were used to analyze changes in job crafting behaviors, Human-Task-AI fit, behavioral competencies (adaptivity, proactivity, innovativeness), and AI usage patterns.

The results show strong effects on three primary outcomes: AI usage frequency (*d* = 1.08), optimizing demands behavior (*d* = .87), and Task-AI fit (*d* = .81). These strong effects suggest that the training fundamentally changed how employees experience and adapt to AI integration.

Although the intervention focused on improving the two main job crafting dimensions (i.e., seeking resources and optimizing demands), differential effectiveness across both dimensions was observed. While demand optimization improved significantly, seeking resources behavior remained unchanged. This suggests that optimizing job demands may be more immediately actionable than developing resource-seeking capabilities and insights. Resource-seeking may require a more elaborate understanding of the employees' personal characteristics and contextual factors, which might take a longer than fourteen days to develop or different training approaches. Going on, Task-AI fit (alignment between AI functionalities and task requirements) emerged as more responsive to intervention than Human-AI fit (alignment between AI and individual capabilities). This finding suggests employees may need to first master task-level adaptation before progressing to deeper personal alignment with AI systems.

One of the study's core contributions lies in identifying how the intervention works through dual mediation pathways. Both optimizing demands and improved Task-AI fit independently mediated the intervention's effects on proactivity, innovativeness, and AI usage variety. This means the training enhances these competencies not directly, but by first improving employees' ability to streamline demanding work and align AI with their tasks. These parallel pathways suggest successful AI adaptation requires both practical work reorganization and improved task-technology alignment.

This research advances theory in three ways. First, it empirically shows the effectiveness of integrating Human-Task-AI fit and the JD-R theory, showing how technical alignment translates into behavioral and performance outcomes. Second, it provides the first empirical support that job crafting principles can be successfully applied to AI contexts via structured interventions. Third, it identifies specific mediating mechanisms, which goes beyond simply showing that interventions work and explains both why and how they are effective.

The findings challenge purely technocentric approaches to AI integration by demonstrating that employee agency and bottom-up interventions produce substantial improvements in AI utilization and work outcomes. As a result, job crafting can be positioned as a critical capability in the AI era.

Organizations should complement technical AI deployments with employee-focused programs that develop job crafting capabilities. Rather than expecting workers to adapt automatically and reactively, companies can provide structured support for employees to proactively shape their AI-work relationships. The intervention's online, self-paced format makes it scalable and cost-effective.

Key recommendations include: prioritizing task-AI alignment over abstract AI training, focusing initial efforts on demand optimization strategies, and recognizing that different employees will benefit from different types of support based on their AI experience levels.

The strong mediation findings suggest that even small improvements in job crafting behaviors can roll out into broader competency development.

While promising, the study faced limitations, including substantial differential attrition (65.5% experimental vs. 31.9% control dropout), a brief follow-up period that prevented assessment of long-term sustainability, and potential self-selection bias. Future research should examine whether effects persist over months rather than weeks, test the intervention across diverse organizational contexts, and explore why seeking resources behaviors proved resistant to change.

This study demonstrates that employees can be systematically empowered to shape their AI-integrated work through a brief, targeted intervention. By learning to optimize demanding tasks and improve task-AI alignment, workers not only use AI more frequently but also become more proactive and innovative. These findings offer a more positive perspective that the AI transformation of work need not be a source of stress and displacement, but rather an opportunity for employees to craft more engaging and productive working lives. The key lies not in the technology itself, but in giving workers the tools and agency to make AI work for them.

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1. Introduction

Artificial Intelligence (AI) is the next disruptive technology that is fundamentally changing the workplace. Deranty and Corbin (2024) describe AI in the context of workplaces as data-driven computational methods that replicate human labor within established economic systems. This technology can perform various business-critical tasks, from collecting and processing data to predicting business outcomes and managing customer demands. The integration of AI spans various sectors, such as accounting, software engineering, legal services, healthcare, manufacturing, and hospitality (Babashahi et al., 2024a; Deranty & Corbin, 2024; J. Li et al., 2019). Organizations implement AI primarily to enhance productivity through process automation and optimization, while simultaneously reducing costs by improving efficiency and minimizing errors (Toorajipour et al., 2021). This widespread implementation of AI is driven by a capitalistic imperative to increase profits and maintain economic competitiveness, which in turn accelerates AI-technological developments (Deranty & Corbin, 2024). This reciprocal relationship between AI exploitation and development suggests a continued and possibly accelerated integration of AI in the workplace, which would fundamentally transform workplaces and how work is performed for a substantial portion of the workforce across sectors. However, meeting actual AI-related goals and reaching desired outcomes appears to be a great challenge for organizations.

A significant problem that explains why AI-related goals are not met is that organizations do not possess the right balance between technical-, human-, and organizational resources (Mikalef & Gupta, 2021). AI's complexity and capabilities are often underestimated leading to unaligned and unjustified implementation efforts and goals. Moreover, work design and human factors such as the employees' skills, adoption behavior, and well-being are often neglected even though these factors are of crucial importance (Demerouti, 2022; Mikalef & Gupta, 2021; Parker & Grote, 2022a). AI technologies are complex and dynamic of nature, and their capability to mimic humanlike work results in a change in tasks and responsibilities for employees. These changes can be particularly demanding for employees. Poorly managed AI integrations often manifest in unbalanced jobs, increased techno-stress, job insecurity, cognitive overload, and resistance to change, ultimately affecting employee well-being and performance (Chuang et al., 2025; Demerouti, 2022; Deranty & Corbin, 2024; Tan et al., 2024). Furthermore, organizations suffer from lost implementation costs, missed competitive opportunities, decreased productivity, and, importantly, decreased well-being among their workforce. This shows that successful AI implementation needs more than just good technology. Instead, organizations must carefully balance technical capabilities with optimized work design and attention to human factors.

Traditional approaches to technology integration are not suited to deal with AI's unique characteristics and implementation challenges. Well-known technology acceptance models, such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), assume that successful technology integration primarily depends on the humans who have to adopt and adapt to the new technology (Davis, 1989; Venkatesh &

Davis, 2000). However, these models fall short in the context of AI integration for several reasons. First, regarding the nature of technology, these models assume technology to be static and deterministic, requiring only one-time user acceptance. In contrast, AI systems are dynamic, continuously learning, and evolving their capabilities and behaviors based on context and usage patterns. Second, concerning employees' influence, their technocentric approach positions employees as passive recipients who can only adapt and respond to technology integration as it is presented to them. Third, related to AI's dual potential, these models do not account for AI's capacity to function as both opportunity and burden, which varies significantly across individuals, tasks, and contexts. Therefore, AI integration requires a new approach in which employees can get involved and shape how AI is exploited because merely traditional top-down implementation approaches cannot address the detailed- and context specific challenges that emerge at the employee level.

The limitations of traditional models in the AI era require a shift towards sociotechnical work design approaches that recognize the interdepend relationship between human and technical systems (Parker & Grote, 2022a). The current study draws on complementary theoretical perspectives that together explain how employees can influence AI's impacts on their work. The Human-Task-AI fit derives from the Task-Technology fit theory (Goodhue & Thompson, 1995), and refers to the alignment between task characteristics, individual abilities, and the AI system’s functionalities. The Job Demands-Resources (JD-R) model explains how this alignment affects employee well-being and performance by determining whether AI functions as a job resource that supports work or a job demand that burdens employees (Bakker et al., 2003; Demerouti et al., 2001). Together, these theories reveal that AI's impact heavily depends on whether employees can optimize both their Human-Task-AI fit and their balance of job demands and resources. Such processes require active employee agency rather than passive technology acceptance.

This need for employee agency points directly to job crafting as a valuable solution. Job crafting, as conceptualized by Tims and Bakker (2010) using the JD-R model, is described as employees' proactive behavior to align job demands and resources with their personal strengths and needs. The strategy offers a theoretical approach for employee-driven AI adaptation. In AI-integrated workplaces, employees can craft their jobs by seeking resources (such as training, peer support, and time to adjust) and optimizing demands (by simplifying or streamlining AI-related work processes) to enhance their Human-Task-AI fit and maintain optimal work experiences. However, while emerging research shows that employees naturally engage in some AI-related job crafting behaviors (Perez et al., 2022), these efforts are often reactive, inconsistent, and may not effectively optimize both fit and demands-resources balance. No comprehensive intervention exists that systematically trains and empowers employees to craft their jobs in AI contexts, representing a critical gap in both theory and practice.

The current study addresses this gap by developing and testing the first empirical job crafting intervention that is designed for AI-integrated workplaces. The intervention combines Human-Task-AI fit theory with the JD-R model to develop a systematic approach that trains employees to proactively optimize their AI-work relationships. By learning to enhance their

Human-Task-AI fit and balance their AI-related demands and resources, employees should develop the key behavioral competencies essential for thriving in the AI era: adaptivity (flexibly adjusting to AI-driven changes), proactivity (taking initiative to shape AI integration), and innovativeness (discovering novel ways to leverage AI capabilities). This approach represents a fundamental shift from technocentric implementation strategies to employee-driven work design, in which job crafting becomes a critical bottom-up strategy that complements top-down AI integration efforts.

This study makes three key contributions to understanding employee-driven AI adaptation. First, it demonstrates why traditional technology acceptance models fall short in addressing AI's dynamic and context-dependent nature, necessitating a sociotechnical work design approach. Second, it theoretically integrates Human-Task-AI fit theory with the Job Demands-Resources model to explain how AI can simultaneously function as both opportunity and challenge for employees. Third, and most importantly, it develops a concrete job crafting intervention that empowers employees to proactively optimize their Human-Task-AI fit and demands-resources balance, ultimately fostering the behavioral competencies (adaptivity, proactivity, and innovativeness) essential for thriving in AI-integrated workplaces. By doing so, this research provides both theoretical insights and practical tools for transforming AI from a potential burden into a meaningful job resource.

This lead to the following main research question:

"Does an online self-training on job crafting, that focuses on:

- *helping employees in improving their balance in job demands and resources,*
- *improving their Human-Task-AI fit,*

increase employee behavioral competencies and improve effective employment of AI in an organization?"

The main research question is supported by four sub questions:

- *To what extent does the training increase job-crafting behaviors: (a) seeking resources and (b) optimizing demands?*
- *To what extent does the training increase Human-Task-AI fit: (a) Task-AI fit and (b) Human-AI fit?*
- *To what extent does the training increase effective AI use (a) frequency and (b) variety of applications?*
- *Does the training improve (a) proactivity, (b) innovativeness, and (c) adaptivity?*

2. Theoretical background

2.1 AI in the workplace

As organizations are employing AI to support work, perform human-like tasks, and improve efficiency, employees will face changes in their work environment and job content. Aspects such as decision-making, work processes, and information-processing will be affected by the AI's capacity to process large amounts of data and information. For employees, the nature of such aspects will shift from intuitive, linear, and routine-based to data-driven, analytic, and complex (Asfahani, 2022) entailing increased cognitive demands. Moreover, new roles and tasks arise such as monitoring AI-tools, interpreting outputs, and aligning with IT-teams, which may enhance skill variety (a resource) but also introduce uncertainty about role boundaries (a demand). Due to these increases in task-depth and novel tasks, employees will need to enhance their technical literacy, critical thinking, and collaboration across disciplines (Richthofen et al., 2022). This illustrates that resources such as learning opportunities and peer support become more essential. In a study on the potential impact of AI on occupations, it was found that areas that require abilities in conceptualization, quantitative reasoning, and comprehension are most prone to the impact of AI (Martínez-Plumed et al., 2021). Furthermore, whereas previous waves of technological developments impacted primarily high-skilled workers positively and middle- to low-skilled workers negatively, the way in which current AI developments may impact either type of worker is still unknown. The social- and economic context of each type of work play an essential role in these outcomes as well (Deranty & Corbin, 2024; Martínez-Plumed et al., 2021). Lastly, work environments may change when managers use AI to schedule, monitor, and evaluate employees and their work which may change the employees' experience of autonomy and control either positively or negatively (Deranty & Corbin, 2024; Parker & Grote, 2022a). Taken together, these changes manifest as both challenges and opportunities for employees, operating directly and indirectly through shifts in job demands and resources.

The following sections present complementary theories to understand better how AI can manifest as opportunities or challenges for employees. Moreover, they support the need for an employee-focused, bottom-up work design perspective, such that employees can benefit from AI at work.

2.2 Understanding AI integration: From technology acceptance to work design

While several frameworks exist to understand human-technology interactions, many fall short in addressing the unique challenges of AI integration.

2.2.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Davis (1989), is among the most well-known models in the field of technology-acceptance (Tang & Chen, 2011). The model proposes that technology usage is determined by the user's intention to use, which in turn is influenced by two core beliefs. These variables are; perceived usefulness, the perception of the user on how likely the usage will increase one's performance; and perceived ease of use, which is the degree to which the user expects the usage to be effortless. According to TAM, those two constructs mediate the influence of external variables on the user's intention to use technology. Furthermore, perceived ease of use also influences perceived usefulness as a system that seems easy to work with, is believed to deliver more yields (Davis, 1989).

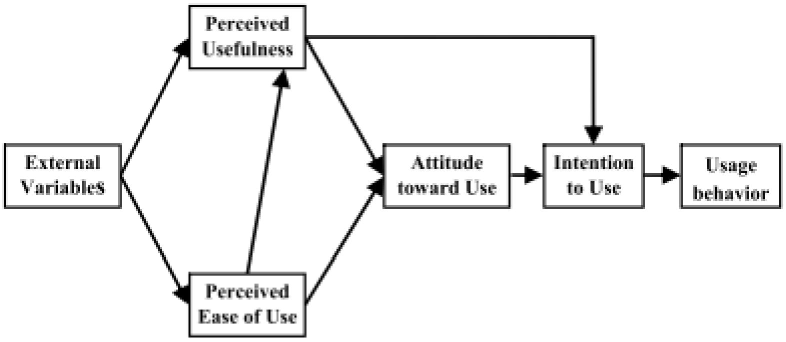

Figure 1: The Technology Acceptance Model (TAM) (Davis, 1989)

2.2.2 The Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), represents the consolidation of eight prominent technology acceptance models into one framework. The model proposes that technology usage behavior is directly influenced by behavioral intention and facilitating conditions. Behavioral intention is determined by three key constructs which are: performance expectancy, defined as the degree to which an individual believes that using the system will help to enhance job performance; effort expectancy, which represents the degree of ease to use the system; and social influence, which is the degree to which an individual perceives that important others believe they should use the new system. A distinctive feature of UTAUT is its incorporation of four moderating variables (gender, age, experience, and voluntariness of use) that influence the strength of the relationships between the core constructs and behavioral intention. According to UTAUT, these moderating effects create complex interaction patterns, such as performance expectancy being more salient for men and younger workers, while effort expectancy has stronger effects for women and older users, particularly in early stages of experience (Venkatesh et al., 2003).

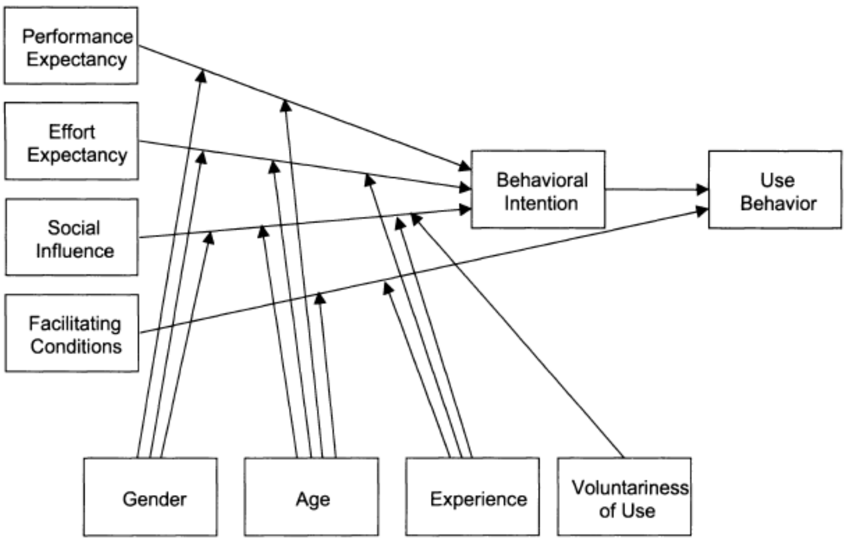

Figure 2: The Unified Theory of Acceptance and Use of Technology (UTAUT) Model (Venkantesh, 2003)

2.2.3 Social-Technical Systems (STS) approach instead of technocentric

The two models mentioned above are valuable models that focus on the acceptance of new technologies. However, both models seem to have a technocentric approach to technology implementation, in which people alone are adapting to new technology. This perspective might be too narrow since it implies technology to be considered neutral, deterministic, static and unflexible after implementation. However, AI systems learn, evolve, and change their behavior based on usage patterns, requiring continuous mutual adaptation rather than one-time user acceptance. As already discussed, this dynamic nature of AI provokes fundamental changes in work (environments) which employees will need to deal with (Deranty & Corbin, 2024). Moreover, AI at work can trigger psychological processes which can impact employee well-being and organizational outcomes (Demerouti, 2022; Tan et al., 2024; van Emmerik et al., 2009; Verma & Singh, 2022). Even well-functioning AI can fail due to employee perspectives and resistance (Rastogi & Pandita, 2025), emphasizing that successful AI integration requires more than just user acceptance.

An alternative and more holistic approach than technocentric ones is that of the social-technical systems (STS) theory. The fundamental idea of this theory is that organizations consist of mutually dependent subsystems; the technical subsystem (technology, hardware, systems), and the social subsystem (work design and employees with their relationships, abilities, and needs). So, to optimize an organization as a system entirely, instead of optimizing work design to the technology (or the other way around), the focus is to find the best fit between both systems by treating them as one integrated system (Trist, 1981). Parker and Grote (2022) build upon this theory and use it as an active principle for technology implementation. Using one of Kranzberg's laws that technology is neither good or bad, nor neutral (Kranzberg, 1986), they explain that the same technology can have different outcomes depending on work design. Furthermore, Parker and Grote (2022) argue that organizations should not passively wait for potential outcomes or problems, but proactively design work and anticipate the outcomes for optimal human-AI collaboration. By emphasizing proactive design and mutual adaptation, this sociotechnical perspective establishes important principles for creating technology implementations that enhance rather than burden the work experience (Parker & Grote, 2022a).

As response to Parker and Grote's sociotechnical perspective on AI, Demerouti (2022) provides a complementary lens through the Job Demands-Resources theory. Demerouti argues that digitalization can contribute to stimulating and "healthy" jobs when certain key conditions are fulfilled, including supportive technology design, employee autonomy, balanced job demands and resources, and adequate protection of employment conditions. This perspective emphasizes that successful AI integration requires proactive work design (as advocated by Parker & Grote) and careful attention to the balance between what AI demands from employees versus what it offers them.

2.3 Human-Task-AI fit and JD-R

As described above, the integration of AI technology at work requires a holistic view in which the effects of the technology are not deterministic but rather dependent on the whole organizational system that it is integrated into. Many environmental, organizational, and human factors need to be reconsidered to optimize AI utilization. In this section, two theoretical perspectives are used to argue for a concrete bottom-up approach to increase effective and engaging AI-usage.

2.3.1 Human-Task-AI fit

The fit between humans, their tasks, and AI technology is crucial for employees to work with AI successfully. Goodhue and Thompson (1995) introduced the Technology-to-Performance Chain (TPC), which is a theoretical model that proposes how technology has a positive impact on individual performance only if the technology is 1) utilized, and 2) fits the tasks it aims to support. It bases on the concept of Task-technology-fit (TTF) which refers to how effectively a technology supports an individual in accomplishing their set of tasks. TTF specifically highlights the alignment between task characteristics, the technology's functionalities and the users' individual abilities (Goodhue & Thompson, 1995). The TPC combines TTF with utilization of the technology and describes how TTF increases individual performance both directly and indirectly via increased usage (utilization); if the technology does not fit the task (low TTF), its utilization will not lead to any extra added value. Furthermore, technology with a good fit must be utilized for it to increase performance since it is impossible to benefit from the technology if it is not used. Moreover, a good fit leads, via precursors of utilization, to actual utilization, which eventually enhances individual performance.

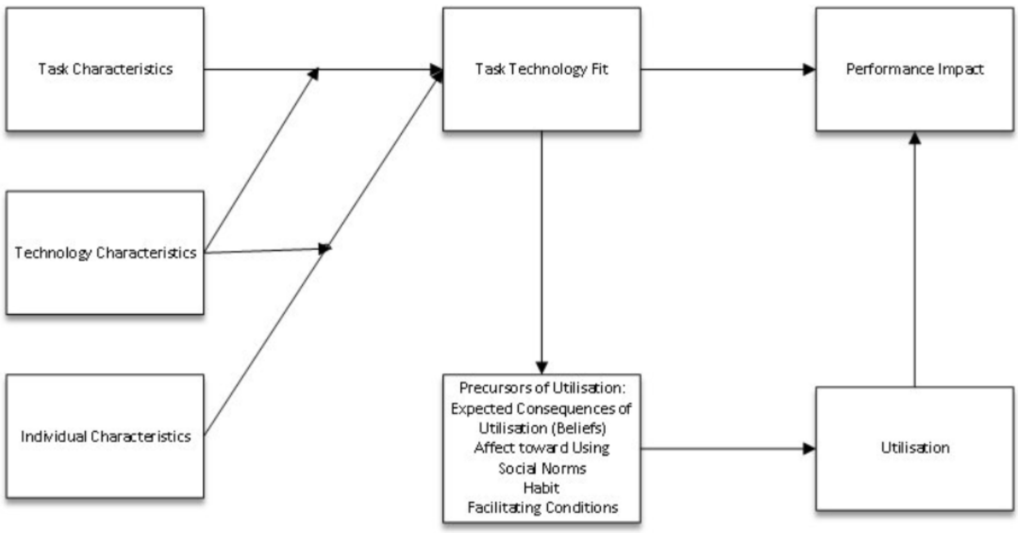

Figure 3: The Technology to Performance Chain(Goodhue & Thompson, 1995)

In line with the TPC and TTF theory, it is expected that the fit between 1) employees facing AI-workplace integrations, 2) their tasks, and 3) the AI systems' functionalities, is crucial for successful AI adaptation and effective utilization.

2.3.2 The Job Demands-Resources model

The Job Demands-Resources (JD-R) model aims to explain the impact of job characteristics on employee well-being. It is based on the assumption that job stress-related risk factors within any occupation can be categorized into two general categories, which are job demands and job resources (Bakker et al., 2003; Demerouti et al., 2001). Job demands are described as aspects of work (whether physical, mental, social, or organizational) that demand ongoing effort and expertise at a physical and/or psychological cost (Demerouti et al., 2001). Furthermore, job resources are aspects of work (whether physical, mental, social, or organizational) that facilitate goal achievement, mitigate job-related strain and the consequent physiological or psychological burden, and promote personal growth, -learning, and -development (Demerouti et al., 2001).

Consequently, the JD-R model forms the basis for three psychological processes. First, the health impairment process occurs when an individual's mental and physical resources get exhausted by chronic job demands or a disbalanced job with relatively too many job demands. As a result, the individual's energy may deplete (i.e., exhaustion) and/or health problems may arise (Demerouti et al., 2001). Second, a motivational process can manifest when the individual retrieves sufficient resources to perform one's job. By fostering personal need fulfillment, learning and development, and dedication to complete tasks successfully, job resources can enhance motivation, leading to engagement and increased performance (Bakker & Demerouti, 2007). Lastly, job resources may buffer the effect of job demands on strain. Examples of such buffer effects are job resources that prevent the manifestation of stressors, change the perception of stressors, influence the response to stressors, and reduce negative health consequences (Kahn & Byosiere, 1992). A crucial realization is that the manifestations of the described processes vary among individuals, with personality characteristics and personal resources playing a crucial moderating role. For example, personal characteristics, such as overcommitment, can amplify the negative impacts of demands, whereas self-efficacy and motivation can buffer such impacts.

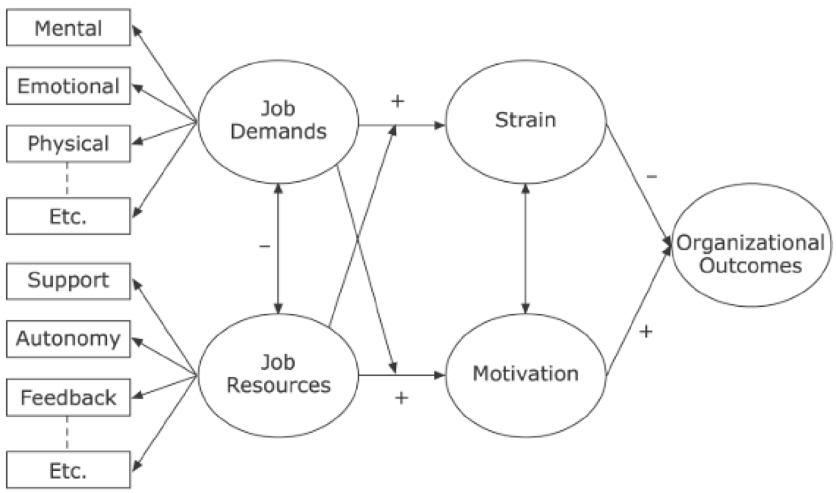

Figure 4: The JD-R model (Demerouti et al. 2001)

2.4 AI Through the lens of Human-Task-AI fit and JD-R

2.4.1 The dynamic interplay

While Human-Task-AI fit and the JD-R model each offer valuable insights, their integration reveals a more complete picture of AI's workplace impact. The effects of AI at work depend on the human, the AI, and inherently, the task. To understand these relationships, both theories serve as complementary lenses: 1) Human-Task-AI fit determines if AI itself functions as a job resource or demand; a high fit enables AI to support work, while a poor fit makes AI a burden. 2) AI fundamentally changes work, creating new demands (e.g., technostress, dealing with uncertainty, adapting to change) and requiring new resources (e.g., support, training, time, autonomy). The JD-R model helps to explain how both processes affect employee well-being and performance through engagement and exhaustion.

These mechanisms are dynamic over time. Initial poor fit may improve due to employees' learning, development, and adaptation. Moreover, environmental- or work characteristics may change, improving fit as well. Due to the improved fit, AI could shift from a demand to a resource. Similarly, AI-related work factors that initially manifested as demands may transform into resources. For example, skill gaps that create uncertainty can evolve into enriched job content as employees develop new competencies. Conversely, both mechanisms can deteriorate as well: for example, good fit may decrease due to evolving AI capabilities, while manageable AI-related changes can become overwhelming when work pressure intensifies.

This interplay shows why static acceptance models fall short, as they cannot capture the evolving dual role of AI as both demand and resource. Therefore, a dynamic, employee-driven approach is needed (job crafting), which enables workers to actively rebalance demands and resources and restore Human-Task-AI fit. The following sections examine how these theoretical mechanisms manifest in practice, first exploring specific demands and resources, then addressing the crucial role of employee agency.

2.4.2 AI as demands and resources

The dual nature of AI in the workplace becomes evident when examining empirical findings through the JD-R lens. Chuang et al. (2025) performed one of the first large empirical studies demonstrating what they term 'the dual impact of AI', which is its simultaneous function as both job demands and resources.

On the one hand, they found that AI-technostress can serve as a demand that decreases job satisfaction via exhaustion. Technostress is the negative psychological effect that is induced by the introduction of new technologies. It results from employees' efforts to deal with evolving AI-technologies and the associated changing demands (Ayyagari et al., 2011; Chuang et al., 2025; Tarafdar et al., 2007). Technostress consists of five factors which are: T-overload, the increased work pressure; T-invasion, which fades the boundaries of work-life balance; T-complexity, technology being too complicated; T-insecurity, the fear of job displacement; T-uncertainty, resulting from ongoing evolvement of technologies, which requires continued learning. Technostress as a job demand requires employees' energy and effort to deal with, and overcome such stressors at the risk of exhaustion that results in negative work outcomes such as decreased job satisfaction and increased work-family conflict (Chuang et al., 2025).

Other studies describe similar mechanisms that align with the idea of AI technostress serving as job demand. Van Emmerik et al. (2009) demonstrate how employees face substantial workload increases when they must change routines and simultaneously acquire new knowledge, increasing T-overload, T-complexity, and T-uncertainty. Furthermore, as AI increases the efficiency and quality of processes and outcomes, employees may feel pressured to improve their own performance (Kang et al., 2023), which can relate to T-overload. Besides, the higher complexity of the new tasks increases the employees' cognitive and mental load (Demerouti, 2022), which reinforces T-uncertainty and T-overload.

Beyond immediate workload concerns, AI can trigger concerns about one's professional career as well. Integrating AI into traditionally human roles triggers concerns about responsibilities, tasks, and potential job displacement (Deranty & Corbin, 2024; Kang et al., 2023; Tan et al., 2024), relating to T-insecurity. As the relevance of skills gets redefined, employees may worry about their ability to unlearn existing skills and learn new ones (Vrontis et al., 2022) reinforcing T-uncertainty. As a result, these concerns may disrupt career planning, which can induce uncertainty, breaking the positive cycle of career satisfaction and self-esteem (Brougham & Haar, 2018). Similarly, Tan et al. (2024) demonstrate how workplace anxiety, stemming from job-related nervousness and concerns, diminishes employees' perceived job security and career opportunities. Subsequently, these negative perceptions contribute to undesired work outcomes such as job dissatisfaction, burnout and turnover intentions (Tan et al., 2024).

On the other hand, Chuang et al. (2025) found that AI-efficacy can serve as a job resource by supporting employees in their work. With its two dimensions of usefulness and reliability, AI-efficacy can lead to decreased exhaustion, increased productivity, and increased job satisfaction through enhanced work engagement. This occurs by enabling employees to complete tasks more efficiently, expand learning opportunities, strengthen their trust in and adoption of AI, and improve their work-life balance (Chuang et al., 2025). Similarly, studies in Spain and Taiwan have shown that both organizations and employees perceive AI as a complementary instrument that supports and enhances employees' professional capabilities (Rivera Hernáez et al., 2019; Wang & Lu, 2025). Furthermore, work can become more meaningful as boring or routine-based tasks can now be performed by AI, leaving employees more time to focus on difficult, creative, or strategic tasks (Grover et al., 2022; Verma & Singh, 2022). Other supporting job resources may include training and education, social support, constructive feedback, autonomy, and opportunities for personal growth and flexibility (Bakker & Demerouti, 2007; Demerouti, 2022). Such resources can help employees to deal with AI-induced demands and foster well-being (e.g., motivation and engagement) and performance.

Lastly, Chuang et al. (2025) revealed that the specific characteristics and capabilities of different AI technologies can influence how they function as job resources or demands. The study found that the effects of AI on work outcomes (e.g., productivity and satisfaction) are mediated by psychological processes (engagement and exhaustion) and can vary depending on the type of AI technology implemented.

The findings above show that the effects of AI on work outcomes (e.g., productivity and satisfaction) are mediated by psychological processes (engagement and exhaustion) and differ between types of AI. To conclude, the empirical evidence presents a nuanced picture: AI simultaneously creates burdens (demands) and opportunities (resources), which depends on technology type, individual differences, and organizational support. These outcomes indicate that a one-size-fits-all approach to AI-integration would fall short.

2.4.3 The need for employee agency

The heterogeneous and dynamic nature of AI's workplace effects, as demonstrated above, reveals a crucial limitation of merely top-down implementation approaches. Since the same technology can serve as either demand or resource depending on individual- and contextual differences, standardized solutions will fall short. This raises the need for employee agency in shaping their AI-integrated work environment. Demerouti (2022) explicitly pleads for employee-control in technology integration, arguing that digitalization can only contribute to healthy jobs when employees keep autonomy over how technology is incorporated into their work. This aligns with the sociotechnical systems approach, which emphasizes mutual adaption instead of one-sided adjustment.

Employee agency becomes important for four reasons: 1) Considering Human-Task-AI fit, employees have the best position to identify misalignments and necessary adjustments. They have intimate knowledge of their task requirements and personal capabilities (Nielsen, 2013), something that external designers or managers cannot fully anticipate. 2) The dual nature of AI as a demand and resource requires personalized strategies to deal with AI-integrated work environments, because optimal AI integration differs from person to person (Cheng et al., 2023; Chuang et al., 2025). For example, while some may need to take things slower to prevent overload, others may benefit from deeper understanding and advanced usage to increase their performance. 3) The dynamic nature of AI developments and integration require continuous adaptation (Dell' et al., 2023). As both AI capabilities and work demands evolve, employees need the flexibility to continuously adjust and recalibrate their relationship with the AI technology rather than depending on static, periodic top down interventions. 4) by giving employees autonomy, their openness and adaptivity to the AI-induced changes may increase (Demerouti, 2022).

This need for agency points directly to job crafting. Rather than passively experiencing the effects of AI integrations, employees must be able to proactively shape their job environment, with the aim to enhance their personal Human-Task-AI fit and optimize their personal balance of demands resources in evolving AI-integrated workplaces. The next section explores how job crafting provides a theoretical and practical framework for such employee-driven adaptation.

2.5 Job crafting as employee-driven adaptation

As described above, AI alters job demands, resources, and fit in ways that are heterogeneous and dynamic. Existing acceptance models fall short because they cannot capture these changes or support employees in actively adapting. This study therefore turns to job crafting as the core solution, because it provides employees with proactive strategies to re-shape their tasks, resources, and relational boundaries in response to AI.

AI-induced workplace changes be understood and viewed through the lenses of sociotechnical systems, the Job Demands-Resources model, and Human-Task-AI fit. These lenses together inform the conceptualization of job crafting in this study. The sociotechnical perspective emphasizes that technology and work must be designed in mutual adaptation (rather than in a technocentric way). Job crafting provides a bottom-up mechanism for such continuous adaptation (Demerouti, 2022). Going on, the JD-R model highlights that AI systems can disrupt the employees' balance between job demands and resources. Employees can directly influence this balance through job crafting, as elaborated on below. Finally, Human-Task-AI fit emphasizes that the AI's value depends on the alignment between human abilities, task requirements, and AI functionalities. Job crafting is a way for employees to actively restore and improve this fit. Together, these theories frame job crafting not as an isolated behavior but as a theoretically grounded response to the challenges and opportunities of AI at work.

2.5.1 Job crafting

Job crafting was first conceptualized by Wrzesniewski and Dutton (2001), who illustrated that employees can proactively revise and craft their jobs by committing changes in their cognitive, task, or relational boundaries to create meaning and identity. This conceptualization was revised by Tims & Bakker (2010), who used the Job Demands-Resources (JD-R) model as a theoretical foundation to redefine job crafting as the behavior of employees to make changes in their work to align job demands and resources with their personal strengths and needs. As a result, job crafting from a JD-R perspective has a tangible connection to job redesign, which provides great implications for practice in the context of a changing work environment (Demerouti, 2014).

2.5.2 Core job crafting dimensions

Job crafting in light of the JD-R model was found to consist of three core dimensions: Seeking resources, optimizing demands, and seeking challenges (Demerouti & Peeters, 2018; Petrou et al., 2012). Seeking resources is behavior that manifests in actions such as asking advice from team members or leaders, asking for feedback on personal performance, or pursuing learning opportunities (Petrou et al., 2012). Optimizing demands refers to simplifying one's job and improving work processes for increased efficiency (Demerouti & Peeters, 2018). Seeking challenges involves taking on tasks and situations that foster skill development and learning, which in turn helps sustain motivation and prevent boredom (Demerouti, 2014). Given the goal of this study (to enhance efficient adaptation to AI-induced changes at work) the primary emphasis of the job crafting intervention will be on seeking resources and optimizing demands.

2.5.3 Job Crafting and AI

Job crafting in the AI-context is an emerging topic in the academic field. Xu and Li (2002) theoretically explored how AI could change work characteristics, and argued that employees should proactively adapt to those changes. Employees could do this by redefining tasks and focusing on what is not in the AI's capabilities (Xu & Li, 2020). Going on, Afiouni et al. (2022) theoretically built a model that explains how employees can reobtain control by sequentially 1) changing tasks, 2) crafting their skills, 3) entering or reestablishing relationships, and 4) adjusting cognitively. They introduced the term "human-in-control", to emphasize the importance of the role of employees during AI integration. Furthermore, they advocated for targeted training to empower employees in effective job crafting, the stimulation of autonomy, and the creation of trust in AI (Afiouni & Pinsonneault, 2022). Although theoretically substantiated, their model of sequential job crafting has not been validated by empirical research yet. Perez et al. (2022) were among the firsts to empirically study employee job crafting as a response to AI technologies. They investigated how learning algorithms shaped job characteristics, influenced autonomy and the meaning of work, and how constructs changed over time. Their findings show that employees reacted to AI by altering their tasks and relationship boundaries. Additionally, the employees reframed how they perceived their jobs. These job crafting efforts were considered as attempts of employees to restore their levels of autonomy (which were initially decreased by AI) and to adjust their work experience (Perez et al., 2022). In a more deepening empirical research (Cheng et al., 2023), it was found that personal differences determine the nature and outcomes of the employees' job crafting activities. On the one hand, employees with an internal locus of control perceive AI integrations as challenges that may positively affect themselves and their jobs. Such employees are likely to respond more openly, confidently and proactively to overcome the opposed challenges and benefit from them (i.e., promotion-focused job crafting). On the other hand, employees with an external locus of control tend to perceive AI integration as a threat to which they cannot exert any influence. Because of their hindrance appraisal of AI, the employees may feel pressured and incapable, whilst their proactive behavior gets inhibited. Furthermore, hindrance appraisal stimulates behavior to prevent any negative outcomes such as losses and risks (i.e., prevention-focused job crafting) (Cheng et al., 2023). Besides the individual aspects of job crafting in the AI-context, Li et al. (2024) investigated social aspects that influence employee AI job crafting. They found that employees imitate their leader's AI job crafting efforts, if leaders were perceived genuine and performance-focused, which led to more engagement and openness to use the AI (W. Li et al., 2024).

2.5.4 Being successful in the era of AI: Three behavioral competencies

The dynamic relationship between AI integration and -development indicates continuously changing workplaces. Therefore, employees need to realign their tasks and abilities, on an ongoing basis. For employees to sustain performance, well-being and effective AI-use, three behavioral competencies are particularly important: adaptivity, proactivity, and innovativeness. These competencies are directly linked to the demands and opportunities that AI entails. Adaptivity enables employees to cope with, and adjust to new and dynamic technologies, tasks and processes. Furthermore, proactivity allows employees to take initiative in shaping their AI-integrated work environment. Lastly, innovativeness helps them in finding new or better ways to work or create value with AI.

Adaptivity

Grover et al. (2022) and Popa et al. (2024) argue the necessity for employees to become more adaptive in the new era of AI at work. Adaptivity is the degree to which employees adapt to changes in work. Specifically, individual task adaptivity reflects how well an employee can cope with, react to, and/or approve and assist changes that affect their personal role. Examples of individual adaptive behavior are adjusting to new equipment, procedures, or processes in core tasks (Griffin et al., 2007). Adaptivity can be linked with job crafting as job crafting is a means for employees to flexibly alter or realize conditions that help them modify and align new roles and tasks to their preference in order to adapt to workplace changes (Petrou et al., 2012). In particular, a positive relationship between adaptive performance and job crafting was found when focusing on the dimension of seeking job resources (Vakola et al., 2023). The retrieved resources support employees in dealing with change and uncertainty as well as adjusting to new environments (Robinson & Griffiths, 2005; Terry et al. 1996). Additionally, Gordon et al. (2018) have particularly shown that their job crafting intervention enhanced adaptivity. Similar findings were also found in an AI context, where AI-awareness and job crafting were studied. Job crafting was positively related to how well employees were able to adapt to changes at work (Mo et al., 2024). Furthermore, it is expected that an increased Human-Task-AI fit allows employees to remain adaptable to change. Fit enables employees to feel confident and prepared during demanding and dynamic situations (Jundt et al., 2015).

Proactivity

Proactivity enables employees to engage in AI and initiate work- and process optimization (Qin et al., 2024). Furthermore, employees must use their proactivity to regain control over their dynamically changing work and improve their work environment, which is crucial for protecting and enhancing their well-being and successfulness in working with AI (Grant & Parker, 2009; Parker & Grote, 2022b). Griffin et al. (2007) describe proactivity among employees as taking self-directed measures to anticipate future challenges and/or opportunities by initiating or influencing changes in work. Narrowing it down to the individual level, individual task proactivity is aimed at changing one's individual work environment, work role, or oneself (Griffin et al., 2007). Van den Heuvel et al. (2015) found that a job crafting intervention helps employees to proactively change their work environment. Moreover, the positive effects of the intervention, such as autonomy and self-efficacy, may form a positive spiral with proactive behavior (Demerouti et al., 2019; van den Heuvel et al., 2015). Besides, it is expected that Human-Task-AI fit plays an important role. Erdogan and Bauer (2005) have shown that employees with a good fit between their job characteristics, tasks, knowledge and skills can better understand which proactive initiatives will be feasible, effective, and in line with their own- and organizational goals. Furthermore, they have more possibilities to utilize the right resources and knowledge to let their initiatives be successful (Erdogan & Bauer, 2005). It is therefore expected that employees with a high Human-Task-AI fit are more likely to initiate changes as a response to future opportunities and/or challenges.

Innovativeness

Innovative behavior can help employees to find unique ways in which they can benefit from AI (Verma & Singh, 2022). Furthermore, they may think of new solutions to create added value to the organization or find new roles (Babashahi et al., 2024b; Verma & Singh, 2022). As a result of their innovative strategies, employees remain valuable which decreases potential fear of getting replaced (Verma & Singh, 2022). Furthermore, because AI will replace them in performing repetitive tasks, employees are left with more time to perform creative and innovative tasks (Grover et al., 2022). Individual innovation is the employee-level dimension of workplace innovation and refers to the employee's creative and innovative capacity to think of novel ways to interact with their work environment. Individual workplace innovation can manifest in developing original ideas, making decisions, or improving the work environment (McMurray et al., 2023). Ok and Lim (2022) have shown that job crafting can increase perceptions of fit, leading to enhanced work engagement and motivation. In turn, enhanced engagement and motivation were found to improve employees' innovativeness (Ok & Lim, 2022).

Taken together, these competencies demonstrate that job crafting is not only a strategy for coping with AI-induced changes, but also a proactive and creative approach for shaping how such changes manifest in increased work quality. Through adaptivity, employees can adjust to immediate disruptions. Through proactivity, they can steer the AI integration process and regain control. Lastly, through innovativeness, employees can think of new or better ways of how to improve their work environment and performance (e.g., finding ways to transform potential resource losses into new meaningful opportunities). In this way, job crafting empowers employees not only to sustain but also to enhance the quality of their work in AI-integrated environments, leading to increased well-being, performance, and effective use of AI systems.

2.5.5 Need for training/intervention

While the theoretical foundation demonstrates the potential of job crafting for AI adaptation, translating this into practice requires systematic support. The emerging research on AI job crafting reveals that some natural engagement in job crafting behavior was found among employees that were confronted with AI integration (Perez et al., 2022). However, those efforts are often reactive, inconsistent, and may not optimize both Human-Task-AI fit and demands-resources balance effectively. Moreover, individual differences in locus of control and AI appraisal suggest that without guidance, some employees may engage in prevention-focused rather than promotion-focused crafting strategies (Cheng et al., 2023). Mo et al. (2024) explicitly argue that organizations should support employees in developing promotion-focused job crafting strategies to maximize the benefits of AI integration.

The need for as systematic intervention becomes particularly clear when considering the three identified competencies crucial for success in the AI-era. Job crafting (seeking resources and optimizing demands) and improved Human-Task-AI fit can serve as underlying mechanisms through which employees develop adaptivity (by flexibly modifying work arrangements), proactivity (by taking initiative in shaping their AI-integrated environment), and innovativeness (by discovering novel ways to leverage AI). However, these practices and competencies require active training rather than hoping they emerge spontaneously.

Furthermore, job crafting in the AI context demands specific knowledge about AI's capabilities, limitations, and integrations strategies that employees may not possess without targeted support (e.g., learning how to improve fit, and identifying what resources and demands to manage).

Therefore, a structured job crafting intervention that is tailored to the AI workplace context is needed. A training that empowers employees to systematically enhance their Human-Task-AI fit, optimize their demand-resources balance, and develop the behavioral competencies necessary for thriving in AI-integrated workplaces. The following section examines how such an intervention can be designed and implemented.

2.6 The job crafting intervention

Although self-initiation is a crucial aspect for job crafting, employees can be stimulated and trained to craft their jobs through an intervention. Van den Heuvel et al. (2015) developed such an intervention to familiarize employees with job crafting and the JD-R model, and to stimulate goal setting. Also, the intervention provides a framework for recording and reflecting on personal job crafting behaviors. Several JD-R based job crafting interventions were successfully designed and tested in different contexts such as remote work during the COVID-19 pandemic, and increasing employee well-being among a Dutch police department (Demerouti, 2023; van den Heuvel et al., 2015). Because AI-integration has its own characteristics and implications for the workplace, the current study follows the framework of Demerouti and Peeters' (2012) job crafting intervention with the aim to refine it to an AI-workplace context. Their intervention design consists of a preparation phase in which insights are gained with regards to the employees' needs. The next phase is a workshop with the aim to create awareness and teach employees how they can change their work. The workshop consists of education on the JD-R model, and guidance in identifying job demands and resources. Furthermore, the workshop includes the creation of a Personal Crafting Plan (PCP) that will function as the tangible and personal red thread that enhances the employee's ownership and sustained behavioral change (Demerouti et al., 2019). Then, the action period starts in which the employees will convert their new knowledge into concrete behavior. They continue with their regular work, whilst increasing their resources and optimizing their demands in line with the goals in their PCP. Furthermore, logging and self-reflection assignments will help the employee to learn from their processes in attaining their goals. Lastly, a global reflection session will focus on the successes, problems and learning opportunities for all employees. Furthermore, the employees will be encouraged to continue their job crafting behaviors in the future (Demerouti et al., 2019).

This study's intervention will thus consist of three training modules: 1) Human-Task-AI-fit, in which employees observe their fit and identify new opportunities to bring AI in the mix, 2) Seeking resources, in which employees learn about seeking resources and get inspired by several examples of resources, 3) Optimizing demands, in which employees learn to identify aspects in their situation that are demanding but prone to improvement. Each module is consoled with assignments, PCP elements, a two-day practice period, and logging and reflection exercises, in line with the job crafting intervention of Demerouti and Peeters (2012). Finally, the employees will receive a closing session in which they will refresh their memory about the three modules, and get inspired by several job crafting efforts from others.

2.7 Organizational influence: Leader AI-symbolization

This study's job crafting intervention is an organizational means to support and empower employees to start crafting their jobs. While job crafting is employee driven behavior, various organizational factors may influence how employees engage in job crafting and respond to these supportive initiatives. Among these factors, leadership plays a particularly important role.

Leader AI-symbolization refers to leaders who demonstrate their acceptance and support towards AI by performing AI-related actions and/or showing aspects that illustrate their affinity for AI. Especially, when employees perceive their leader's AI-symbolization as genuine, their openness to change increases which results in enhanced job crafting behavior (He et al., 2023). Similarly, in later research it was found that servant leadership stimulates promotion-focused job crafting, where employees were seeking ways to improve and benefit from the AI-induced changes, rather than merely trying to prevent negative outcomes (Mo et al., 2024). Furthermore, Li et al. (2024) demonstrated that employees are more likely to imitate their leader's AI job crafting efforts when these are perceived as genuine and performance-focused, leading to increased engagement and openness to AI use.

Therefore, leader AI-symbolization is expected to moderate the effectiveness of the AI job crafting intervention. When leaders demonstrate genuine AI engagement, the intervention's impact on job crafting behavior, Human-Task-AI fit and three behavioral competencies (adaptivity, proactivity, and innovativeness) should be stronger compared to contexts where leader AI-symbolization is low.

2.8 Hypotheses and research model

Accumulating the theoretical background above has led to the formulation of the following hypotheses.

H1: The experimental group demonstrates more job crafting behavior post-intervention as compared to the pre-intervention.

H2: The experimental group reports a higher Human-Task-AI fit post-intervention as compared to pre-intervention.

H3: The experimental group demonstrates higher adaptivity post-intervention as compared to pre-intervention.

H4: The experimental group demonstrates higher proactivity post-intervention as compared to pre-intervention.

H5: The experimental group demonstrates higher innovativeness post-intervention as compared to pre-intervention.

H6: The experimental group demonstrates higher usage of AI post-intervention as compared to pre-intervention.

H7: The positive effect of the intervention on job crafting behavior will be stronger when leader AI symbolization is high compared to when it is low.

H8: Human-Task-AI Fit mediates the effects of the intervention on adaptivity (8a), proactivity (8b), innovativeness (8c), and AI-use (8d)

H9: Job crafting behavior mediates the effects of the intervention on adaptivity (9a), proactivity (9b), innovativeness (9c), and AI-use (9d)

Leading to the following theoretical model:

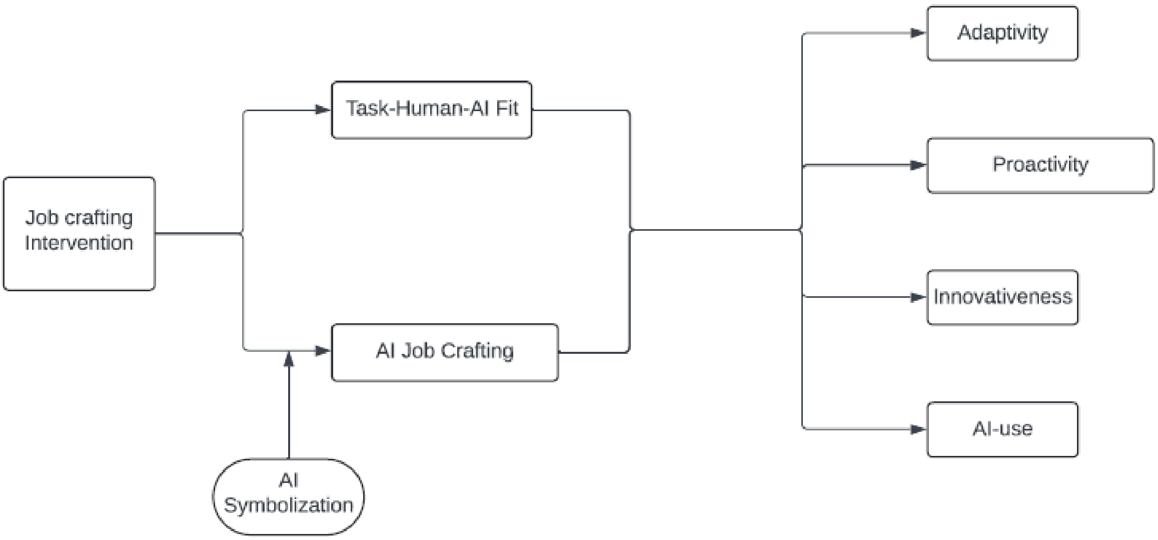

Figure 5: Theoretical model

3. Research methodology

3.1 Participants and procedure

In line with the job crafting intervention of Van den Heuvel et al. (2015), this intervention study follows a quasi-experimental study design with a pre-measure, a training/intervention period, and a post-measure. An experimental group will receive the training and completes the pre- and post-measure to test the effectiveness of the training. Furthermore, a control group was created who completed the pre- and post-measure without receiving the training, in order to control for external influences or natural changes over time. Participants from the control group got the opportunity to do the training afterwards (i.e., in a second training round), after which they completed the post measure for a second time. In this way, these participants serve both as control and experimental group members, providing additional data to assess the effectiveness of the training and maximize power under the same recruitment costs(Hart et al., 2008).

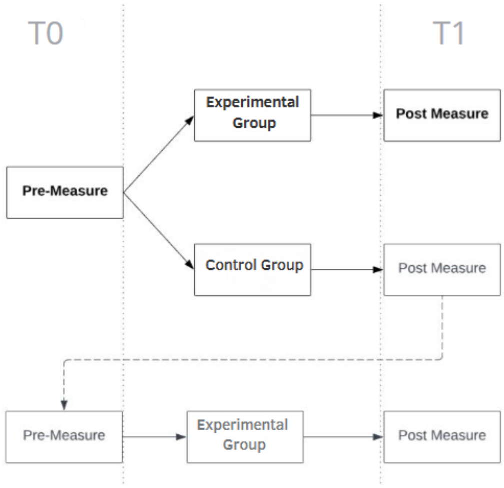

Figure 6: Experimental Design

At Veneta, participants for the experimental group (*N*=39) were collected from three departments: Human Resources, Sales Inside, and the Project Management Office (PMO). Because the control group ended up with only eight participants from other departments, fifteen participants from the experimental group were transferred to the control group, making the initial sizes of the control- and experimental group 23 and 24 respectively. Furthermore, an online registration form was opened through which external professionals could apply to the training as well. This effort was done to increase the group sizes. Initially, the online registration form was distributed via LinkedIn and students of the TU/e's Master's course 1JM11. This online registration resulted in 140 extra participants, who were individually randomized to either the control or intervention condition (1:1 allocation) using a Python script (NumPy random number generator, sampling without replacement). A fixed random seed was set to allow reproducibility. Over the two weeks after the intervention kick-off, another 48 people registered themselves. These participants were all assigned to the experimental group because the drop-out rate in the experimental group appeared to be higher than that of the control group during the first training round. The final groups of which participants completed the pre-measure consisted of $N_{control}$=49 and $N_{experimental}$=82.

All participants were asked to evaluate and complete the informed consent form in which they were informed that their data would be treated as confidential. The Eindhoven University of Technology's ethical committee evaluated the data processing procedure of this study and approved of its confidentiality.

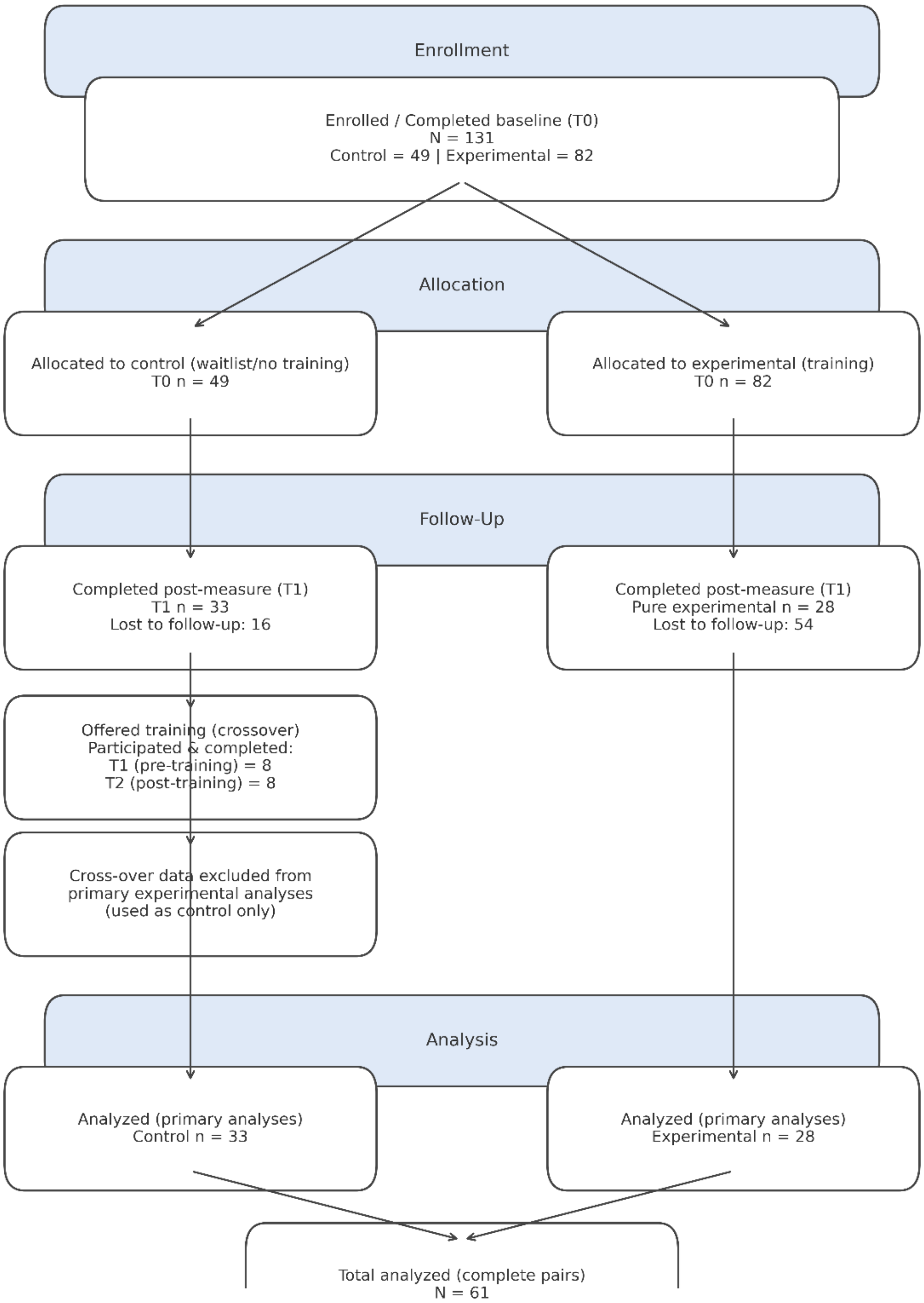

Figure 7: CONSORT Flow diagram

Tabel 1: Demographics final sample

	Control group (n=33)	Experimental group (n=28)	Total sample (n=61)

Age (years)	38.73 (12.61)	32.14 (12.16)	35.70 (12.74)
Educational level			
Highschool	2 (6.1%)	2 (7.1%)	4 (6.6%)
Vocational education	0 (0.0%)	8 (28.6%)	8 (13.1%)
Bachelor's degree	8 (24.2%)	11 (39.3%)	19 (31.1%)
Master's degree	23 (69.7%)	5 (17.9%)	28 (45.9%)
PhD / Doctorate	0 (0.0%)	2 (7.1%)	2 (3.3%)
Other	0 (0.0%)	0 (0.0%)	—
Gender			
Male	17 (51.5%)	19 (67.9%)	36 (59.0%)
Female	15 (45.5%)	9 (32.1%)	24 (39.3%)
Non-binary	1 (3.0%)	0 (0.0%)	1 (1.6%)
Organizational tenure (years)			
0-1	8 (24.2%)	13 (46.4%)	21 (34.4%)
2-3	12 (36.4%)	6 (21.4%)	18 (29.5%)
4-5	4 (12.1%)	0 (0.0%)	4 (6.6%)
5+	9 (27.3%)	9 (32.1%)	18 (29.5%)
Overall work experience (years)			
0-2	5 (15.2%)	5 (17.9%)	10 (16.4%)
3-5	3 (9.1%)	6 (21.4%)	9 (14.8%)
5-10	10 (30.3%)	6 (21.4%)	16 (26.2%)
10+	15 (45.5%)	11 (39.3%)	26 (42.6%)
Perceived AI experience			
Beginner	8 (24.2%)	8 (28.6%)	16 (26.2%)
Incidental user	14 (42.4%)	6 (21.4%)	20 (32.8%)
Regular user	10 (30.3%)	14 (50.0%)	24 (39.3%)
Advanced user	1 (3.0%)	0 (0.0%)	1 (1.6%)

3.2 Intervention design

The intervention followed the structure of an online self-training. Demerouti (2023) demonstrated that such an approach can stimulate job crafting behavior. This study aimed to develop an online self-training in line with Demerouti's model. In between the pre- and post-measure, three modules were covered. Each module consisted of an informational video and one or more exercises to practice the newly learned materials. Each module concluded with setting one or more SMART-goals (i.e., Specific, Measurable, Acceptable, Realistic, and Time-bound), through which the participants translated the lessons or actions into their work. Those goals were reflected on by the participant at the start of the next module. A specified overview of all events:

Kickoff – (Day 1)
On Day 1, both the experimental and control group watched an introductory video about AI and completed the pre-measure survey. Next, only the experimental group continued with a second video in which the researcher introduced the project, explained its purpose, discussed the potential benefits of participating in the intervention, and briefly outlined the training structure.

Module 1 – Fit (Days 2–4)
Participants started with the video *What is fit?*, which introduced the idea of aligning AI tools with both their tasks and personal preferences or strengths. After this video, participants completed assignments to explore their own beliefs about AI and reflect on these. They then mapped their current tasks to identify where AI might offer added value. Based on these insights, participants formulated SMART goals to translate intentions into concrete actions. For example, if someone intended to seek peer support, the SMART goal would specify who they would ask, when, and what they hoped to gain. On Day 4, participants reflected briefly on their actions and goals by indicating whether they had worked on their goals, how successful they had been, and what they had learned.

Module 2 – Seeking Resources (Days 4–6)
This module began with a video about which introduced the concept of job resources within the context of AI, supported by relevant theory and practical examples. Participants then chose at least one resource they wanted to increase or obtain, and again translated this into a SMART goal. They worked on their goal and later reflected on their progress, success, and insights gained.

Module 3 – Optimizing Demands (Days 6–8)
In the third module, participants watched the video Demands at work, which explained the concept of job demands in an AI-context and how these can be optimized, for example by rearranging tasks. Based on this, they formulated a SMART goal aimed at optimizing their own demanding tasks or AI-related challenges. On Day 8, they again reflected on their efforts and outcomes.

Wrap-up and post-measure (Day 14)
On Day 14, participants from the experimental group watched a wrap-up video summarizing the main lessons from the training and encouraging them to continue job crafting as they explore AI in their work. Afterwards, both the experimental and control group completed the post-measure survey. Finally, the control group was given the opportunity to follow the training as well, whereas the experimental group received a document with future-advice and a summary of a working paper on collaborating with generative AI at work, consisting of relevant insights and prompt-techniques for employees (Dell'acqua et al., 2025).

3.3 Measures

To measure the key constructs in this study, validated multi-item scales from existing literature were used, unless stated otherwise. All items were measured on a 5-point Likert scale ranging from [1 = strongly disagree to 5 = strongly agree] which provides optimal balance between response discrimination and participant cognitive burden while maintaining sufficient variance for statistical analyses (Lozano et al., 2008). Measures were provided in Dutch and English. Where needed, items were translated to from English to Dutch or from Dutch to English. The translation process consisted of a hybrid approach where the researcher translates both manually and with the support of ChatGPT-4o and ChatGPT-o1 (i.e., ChatGPT's reasoning model). Existing literature on the translation-quality of ChatGPT shows that GPT-4o effectively interprets implicit meanings, produces grammatically correct translations, and preserves both tone and style (Sun, 2024). Furthermore, the translated items will be reviewed by a second researcher. In this section, all scales will be described and specific notions will be mentioned if needed. For a clear overview of the Cronbach's Alpha's, see Table's 1 and 2.

Job crafting

Seeking Resources. Job crafting behaviors aimed at acquiring new resources were measured with five items adapted from Petrou et al. (2012). Participants rated how frequently they perform each behavior. An example item is *"I ask others for feedback about my performance."* The original Seeking Resources scale consisted of five items. However, reliability analysis showed that item 1 had a corrected item-total correlation of .055 and negatively correlated with several other items. When reviewing the item on its content "*I make sure that I can decide myself how to do my work"*, the item seemed to measure decision autonomy rather than seeking external resources. After removing this item, Cronbach's alpha increased to .592 and .603 for the pre- and post-measure respectively. Furthermore, item 2 had a corrected item-total correlation of .275. After inspecting the item, "*I make sure I have enough variety in my work"*, the item seemed to potentially differ from the other items in terms of meaning (i.e., "variety in work" may not be as clear of a resource, since it may also be classified as a challenge). Furthermore, both item 1 and 2 were not found in the scale of Petrou et al. (2012), indicating a copying error. Therefore, combining both statistical and theoretical considerations, item 1 and 2 were excluded from the scale. The remaining 3 items provided a scale reliability of .680 and .728 for the pre- and post-measure respectively.

Optimizing Demands. The strategy of optimizing demands was assessed with five items from Demerouti and Peeters (2018). This scale captures proactive behaviors that simplify or improve work processes. A sample item is *"I improve work processes or procedures to make my job easier."* Cronbach's alpha's for the pre- and post-measure were .891 and .824 respectively.

Human-Task-AI fit

Human-Task-AI fit was measured in two parts. The first scale that was used to measure this construct was *"Human-AI fit".* This measure, drawn from Wu and Chen (2017) and Yu and Yu

(2010), evaluates how effectively the AI system complements employees' skills and abilities. Eight items were rated on a scale from (1) "strongly disagree" to (5) "strongly agree," including *"Working with the AI system helps me achieve my task requirements."* Cronbach's alpha's for the pre- and post-measure were .915 and .902 respectively.

A second scale *"Task-AI fit"* was drawn from Jarupathirun and Zahedi (2007) that measures how well the AI system's functionalities align with the demands of the employees' specific tasks. The employees were asked to finish the sentence "In helping me to perform the assigned task(s), the functionalities of the AI are/will be: .. " for 8 items of which each item represents some type of perception that the AI's functionalities can be evaluated on. For example, adequacy was evaluated from (1) "very inadequate" to (5) "very adequate". Cronbach's alpha's for the pre- and post-measure were .843 and .837 respectively.

Behavioral competencies

Three dimensions of employee competencies were measured, each of which is critical for adapting to AI-related workplace changes.

- **Adaptivity.** Three items from Griffin et al. (2007) will evaluate how well individuals cope with changes in their core tasks. An example item is *"I adapt well to changes in my core tasks."* Cronbach's alpha's for the pre- and post-measure were .678 and .668 respectively. However, a detailed item analysis showed that item 3 *"I learn new skills that help me adapt to changes in my core tasks"* had corrected item-total correlation of .303 and exclusion of the item would improve Cronbach's alpha's for the pre- and post-measure to .789 and .687. According to Raykov (2008), deleting could harm the instrument's content validity. Therefore, item deletion should only be considered if Cronbach's alpha increased by at least .10. The Cronbach's alpha's increase by .111 and .019 in the pre- and post-measure respectively. Furthermore, when comparing item 3 to the other two items in the scale *"I adapt well to changes in core tasks* " and *"I cope with changes to the way I have to do my core tasks"*, items 1 and 2 seem to measure the degree of adaptiveness, whereas item 3 seems to measure a proactive antecedent (learning new capabilities). Such proactive learning behavior has been differentiated from adaptivity (Ahmad et al., 2020)(Ahmad et al., 2020). Moreover, this study measured "proactivity" as a construct as well. Considering the arguments above, item 3 was deleted from the scale.
- **Proactivity.** Another three items from Griffin et al. (2007) gauge self-directed change behaviors, such as *"I come up with ideas to improve the way in which my core tasks can be done."* Cronbach's alpha's for the pre- and post-measure were .824 and .836 respectively.
- **Innovativeness.** To measure individual-level innovation, five items from McMurray et al. (2023) were used. A sample statement is *"I am constantly thinking of new ideas to improve my workplace."* Cronbach's alpha's for the pre- and post-measure were .724 and .822 respectively.

AI-use

To measure the employees' AI-use, this research has come up with two self-created items that ask the employees.

- **Frequency AI use.**The first item was created to indicate the frequency of participants AI-use per week: "*My weekly use of AI is approximately:"* had six multiple choice options(a:0 times, b:1-2 times, c:2-5 times, d:5-10 times, e:10-15 times, f:15+ times) with an average of 3.42 at T0 indicating that the average participant used AI between 2 to 10 times.
- **Types of use.** The second item measured the number of different types of tasks the participants used AI for: *"Fill in the blank: I use AI for … different kinds of tasks"* had eleven multiple choice options (a-j:1-10 or k:10+).

Leader AI-Symbolization

Leader AI-symbolization was measured via a seven-item scale adapted from He et al. (2023), itself based on Desai and Kouchaki's (2017) moral symbolization framework. Participants evaluated statements such as *"My supervisor shares recent news on AI with me"*. Cronbach's alpha's for the pre- and post-measure were .804 and .779 respectively.

Tabel 2:Cronbach's alpha of main variables of conceptual model

Variable	T0	T1	Number of items
Seeking Resources	.680	.728	3
Optimizing Demands	.891	.824	5
Task-AI fit	.915	.902	8
Human-AI fit	.843	.837	7
Adaptivity	.789	.688	2
Proactivity	.824	.836	3
Innovativeness	.724	.822	5
Leader AI-Symbolization	.804	.779	6

Additionally, several other constructs were included in the measure as well.

Human-AI teaming

To capture the quality of collaboration between employees and the AI system, a 12-item scale was employed (Christopoulou, 2024). Items focus on perceived synergy, division of tasks, and team-like dynamics. An example item is *"We can achieve more together than I or the AI system can alone."* The reliability analysis showed that items 6-8 were negatively correlated to the other items and had a low corrected item-total correlations (item-6=.042, item-7=.095, item-8=.088). Deleting those three items from the scale increased Cronbach's alpha's from .680 to .812, and from .638 to .800, for the pre- and post-measure respectively.

Attitudes towards AI

General attitudes toward AI were measured via four newly developed items. An example statement is *"I believe that AI will improve my work."* Cronbach's alpha in the pre- and post-measure were .704 and .714 respectively.

AI Evaluation

Additionally, participants' evaluations of AI were gathered using five semantic differentials adapted from Berretta et al. (2023). These items prompted respondents to rate the AI system on dimensions such as "very harmful – very beneficial" and "very bad – very good." Cronbach's alphas for the pre- and post- measure were .860 and .858 respectively.

Well-being when work with AI

Three items adapted from Berretta et al. (2023) assessed employees' comfort, enjoyment, and perceived benefit when collaborating with the AI. A sample item is *"I feel comfortable working with the AI system."* Cronbach's alphas for the pre- and post- measure were .713 and .767 respectively.

Work Engagement

To measure employees' engagement at work, the UWES-3 (Schaufeli et al., 2019) was used. This ultra-short scale comprises three items reflecting vigor, dedication, and absorption. An example item is *"At my work, I feel bursting with energy."* Cronbach's alphas for the pre- and post- measure were .823 and .769 respectively.

Exhaustion

Eight items of the Exhaustion dimension from the Oldenburg Burnout Inventory (Demerouti & Bakker, 2008) were used to measure the participant's exhaustion levels. Example items include *"After my work, I regularly feel worn out and weary".* Cronbach's alphas for the pre- and post- measure were .816 and .786 respectively.

Perceived performance

Four items from Kuvaas (2006) were used to assess the extent to which employees exceed acceptable performance levels or invest extra effort in their tasks. Participants rated their performance from (1) "never" to (5) "always." A sample statement is *"I often perform better than can be expected from me."* Cronbach's alphas for the pre- and post- measure were .606 and .667 respectively.

Psychological Needs

The **Interface Autonomy** scale proposed by Peters, Calvo, and Ryan (2018) evaluates psychological needs in the context of AI usage. The subscale is rated on a five-point Likert scale, with negatively worded items being reverse-scored. For example, *"The technology provides me with useful options and choices."* (*Cronbach's alpha: pre-measure*=.761; *post-measure*=.766).

Job Autonomy. Job autonomy will be assessed using three items. An example item is *"I can decide myself how I execute my work."* Cronbach's alphas for the pre- and post- measure were .796 and .699 respectively.

Workload. Four items measured the employees' perceived workload, including time pressure and volume of tasks. A representative item is *"I have to work under time pressure."* Cronbach's alphas for the pre- and post- measure were .823 and .769 respectively.

Tabel 3: Cronbach's alpha of additional variables of interest

Variable	T0	T1	Number of items
Human-AI Teaming	.812	.800	9
General Attitudes	.704	.714	4
AI Evaluation	.860	.858	5
Well-being	.713	.767	3
Workload	.823	.769	4
Job Autonomy	.796	.699	3
Engagement	.813	.774	3
Exhaustion	.816	.786	8
Performance	.606	.667	4
Interface Autonomy	.761	.766	5

3.4 Data analysis

3.4.1 Data preparation

The first stage of data preparation was organizing and combining the measurement results. For the experimental group, three pre-measure datasets existed (Veneta Sales Inside, Veneta Rest, and External participants), who were combined with the experimental post-measure dataset to form one dataset for the experimental group. A dummy variable was created to indicate whether a case originated from the pre- or post-measure (e.g., Timepoint = 'Pre'). Specifically, the dataset could consist of two rows (pre and post) per participant who completed the intervention and both measures, or one row (pre-measure data only) per participant who dropped out during the intervention. In a similar vein, the pre- and post-measure dataset from the control group were consolidated into one control dataset. Then, items that contained written text, such as "Industry Type", were checked for hidden white spaces or incorrect values. Furthermore, several items required reverse coding to ensure consistent directionality. Specifically, items from the Human-AI Teaming scale (items 6, 7, 8), Exhaustion scale (items 3, 5, 7, 8), Interface Competence scale (items 3, 4, 5), Interface Autonomy scale (items 3, 4, 5), and Task Competence scale (items 3, 4) were reverse coded using the formula: new value = 6 - original value. Additionally, the AI Symbolization scale required value rectification as response options were incorrectly coded as 4-8 instead of 1-5, corrected using the formula: new value = original value - 3. Lastly, scale scores were calculated by combining and averaging the corporate items into new construct variables scores (e.g., the 5 items measuring demands-optimization were averaged into a single variable 'Optimizing_Demands _Score'.)

3.4.2 Sample characteristics

Baseline equivalence between control and experimental groups was assessed using independent samples t-tests for all primary outcome variables, secondary constructs, demographic variables, and AI-related measures. Levene's test (1960) was conducted prior to each t-test to assess homogeneity of variances, with Welch's correction applied when equal variances could not be assumed. Effect sizes were calculated using Cohen's d, with values of 0.2, 0.5, and 0.8 representing small, medium, and large effects respectively.

Analysis of the complete raw sample (N = 131) showed excellent randomization success, with only 1 out of 26 tested variables showing significant baseline differences (3.8%). Specifically, Educational level showed a significant difference between groups (Control: M = 3.57, SD = 0.79; Experimental: M = 3.19, SD = 1.03*; t(129)* = 2.16*, p* = .032), with the control group having slightly higher educational levels. Importantly, no significant differences were found in any primary outcomes (0/8 variables) or secondary constructs (0/12 variables), confirming successful randomization for the main study variables.

Dropout analysis was conducted by comparing baseline variables (T0) between participants who dropped out and participants who completed all modules including the post-measure. Before conducting the independent t-test, Levene's test was performed to indicate whether homogeneity of variances between the dropout and completion groups was met and to determine whether the assumption of equal variances could be retained in the t-test analysis. This analysis revealed completion rates of 68.1% for the control group (33 completers out of 49 enrolled) and 34.5% for the experimental group (28 completers out of 84 enrolled, including crossovers). In the control group, one variable (Proactivity, *M_completers* = 3.83, *M_dropouts* = 4.11*, p(t_test)* = .023) showed systematic differences between completers and dropouts, indicating that participants who completed the study had slightly higher baseline proactivity levels. No systematic dropout patterns were detected in the experimental group.

3.4.3 Excluding crossover participants from the experimental sample

Participants from the control group had the opportunity to take part as an experimental participant after they finished the control group phase. A total of 8 participants completed this crossover design. During sensitivity analyses, it appeared that both direct and indirect intervention effects regarding Task-AI fit became insignificant when the crossover participants were part of the experimental sample as well, as opposed to when they were excluded and Task-AI fit effects appeared significant.

Carry over analyses (mixed model on crossover participants only, with covariate "Period") indicated that crossover participants showed significant carry-over effects for Optimizing demands (B≈0.38, p≈.046). Thus, the intervention effect size of optimizing demands could be overestimated when crossover participants were included in the experimental sample. However, both when crossover participants were included or excluded, Optimizing demands had significant effects.

To examine differences between crossover participants (experimental phase) with pure experimental participants, and regarding the small group size for the crossover participants, Cohen's d was analyzed between both groups. Cohen's d's for Performance and Interface autonomy were .59 and .64 respectively, indicating moderate differences between these groups.

Taking into consideration the potential for research awareness effects, survey familiarity, and demonstrated carry-over effects, crossover participants were excluded from the experimental data for all primary analyses. Only their control data was used, following similar approaches in existing intervention studies with crossover designs. Primary analyses employed the optimal sampling strategy, with consistency validated through comparison with alternative approaches (see Results). Model assumptions were verified through residual diagnostics for significant effects.

3.4.4 Data quality investigation final sample

After cleaning and organizing the final samples, the control and experimental group consisted of 33 and 28 complete observations respectively. With these samples, further data quality was evaluated.

Missing value patterns were systematically analyzed across all variables. The percentage of missing data was calculated for each variable, with particular attention to construct scores versus demographic variables. The final matched datasets showed overall missing data rates of 6.77% for the control group and 7.49% for the experimental group. Specifically, missing data in demographic variables (30-57%) primarily reflected the study design, as these characteristics were only collected at baseline and not repeated in post-intervention measurements. More importantly, no missing values were found in any construct scores across both measurement timepoints, ensuring complete data availability for all primary and secondary outcome measures.

Final baseline equivalence testing was conducted on the matched analysis sample to ensure that the participant matching and crossover exclusion process preserved randomization. Among the final samples significant baseline differences were found for Age and Educational level. However, no significant differences were detected in any primary outcome variables, confirming that randomization was largely preserved for the main study variables despite the sample reduction. More elaborate discussion on these results will be presented in the results section.

Lastly, multicollinearity among construct scores was assessed using Pearson correlation analysis. Correlations exceeding $r = .80$ were considered as potentially problematic, as they may indicate that constructs are measuring similar underlying concepts. In the experimental group, one problematic correlation was identified between Task-AI fit and Human-AI Fit scores (r = .848), exceeding the .80 threshold. No concerning correlations were found in the control group (*maximum* r = .698). However, when analyzing the combined dataset, the maximum correlation was r = .780, suggesting that multicollinearity concerns were limited to the experimental subsample. Therefore, it was decided that the potential multicollinearity was reported for transparency without further combining the scales.

Overall, data quality was deemed acceptable for hypothesis testing, with successful randomization largely preserved, minimal missing data in key variables, and complete construct score data. The final analysis sample provided a clean dataset suitable for rigorous hypothesis testing.

3.4.5 Analytical strategy: Confirmatory vs. Exploratory approach

To maintain scientific rigor and control Type I error rates, all analyses were organized into two distinct analytical streams: confirmatory theory-driven analyses and exploratory post-hoc investigations. This separation was implemented to distinguish between pre-specified theoretical hypotheses and additional insights from measured constructs that were not central to the theoretical model.

Confirmatory analyses tested the pre-specified theoretical hypotheses (H1-H9) using only the constructs directly derived from the literature review and conceptual model. These analyses focused on: (1) job crafting behaviors (Seeking Resources, Optimizing Demands), (2) Human-Task-AI fit (Task-AI fit, Human-AI fit), (3) behavioral competencies (Adaptivity, Proactivity, Innovativeness), and (4) AI usage (Frequency AI use, Types of Use). As these represented a priori theoretical predictions, no multiple testing corrections were applied to confirmatory analyses.

Exploratory analyses examined additional constructs that were measured but not central to the theoretical framework, including well-being outcomes (Well-being, Performance, Engagement, Exhaustion), AI attitudes (General Attitudes, Evaluation, Human-AI Teaming), work environment factors (Workload, Autonomy, Interface Autonomy, Task Competence), and leadership variables (AI Symbolization). Given the post-hoc nature of these analyses and the increased risk of Type I errors from multiple testing (i.e., the probability of getting at least one false positive across the multiple exploratory outcomes), Bonferroni corrections were applied to maintain family-wise error rates at $\alpha = 0.05$ (Sedgwick, 2012)(Sedgwick, 2012).

This analytical separation serves two purposes. First, it ensures that theoretical conclusions rest on confirmatory evidence. Second, it enables the discovery of additional patterns that can guide future research, creating a balance between scientific rigor and exploratory investigation.

3.4.6. Statistical procedures

All analyses were conducted using RStudio version 2025.05.1-513 with the following key packages: lme4 and lmerTest for mixed-effects modeling, emmeans for post-hoc comparisons, dplyr for data manipulation, and here for reproducible file management.

3.4.6.1 Main intervention effects

Confirmatory main intervention effects: Primary analyses employed Linear Mixed-Effects Models (LMM) using the lmer() function from the lme4 package, with REML = FALSE to enable model comparisons. For each theory-driven outcome variable, the model specification was: outcome ~ Group × Time + (1|ID), where the Group × Time interaction term represents the intervention effect. Random intercepts for participants (1|ID) account for individual differences and within-person correlations across measurement occasions. Moreover, the LMM approach is better suited to handle differences in dropout rates between groups and accommodates the exclusion of crossover participants from the experimental sample, as it can flexibly model unbalanced data structures and nested observations. Effect sizes were quantified using Cohen's d approximation, calculated as the interaction estimate divided by the model's residual standard deviation, providing standardized effect size estimates appropriate for intervention research.

Prior to conducting main analyses, data preparation ensured complete pairs of observations per participant, with participants having incomplete data excluded from respective analyses. Sample sizes were verified to meet minimum requirements for mixed-effects modeling, with analyses proceeded only when at least 20 participants with complete data were available per outcome.

Exploratory main intervention effects: Exploratory main effects analyses followed identical LMM procedures as confirmatory analyses but applied Bonferroni correction as discussed earlier. With 13 exploratory outcome variables tested, the corrected significance threshold was set at $\alpha = 0.05/13 = 0.0038$. Both corrected and uncorrected results are reported to distinguish robust findings that survive multiple testing correction from nominal effects.

3.4.6.2 Indirect effects

Confirmatory mediation analyses: Mediation analyses were conducted to examine the theoretical mechanisms through which the intervention influences the outcome variables (behavioral competencies and AI usage). Four key mediators were examined based on theoretical expectations and empirical evidence: Seeking Resources Score, Optimizing Demands Score, Task-AI fit Score, and Human-AI Fit Score. These mediators were tested against five theoretically relevant outcome variables: Adaptivity, Proactivity, Innovativeness, Frequency AI use, and Types of Use.

For each mediator-outcome combination, three mixed-effects models were estimated using the lmerTest package: (1) the total effect model examining the direct intervention effect on the outcome (c-path: outcome ~ Group × Time + (1|ID)), (2) the mediator model testing intervention effects on the proposed mediator (a-path: mediator ~ Group × Time + (1|ID)), and (3) the full mediation model including both intervention and mediator effects (b-path and c'-path: outcome ~ mediator + Group × Time + (1|ID)). All models included random intercepts for participants to account for repeated measures dependencies.

Bootstrap confidence intervals for indirect effects were calculated using 1000 resamples with person-level resampling procedures. This approach preserves the natural pairing of pre- and post-intervention measurements within individuals, preventing artificial combinations of baseline and follow-up data from different participants (Falk et al., 2024)(Falk et al., 2024). The bootstrap procedure involved resampling participants (not individual observations), refitting all three mediation models for each bootstrap sample, and calculating the indirect effect (a-path × b-path) for each resample.

Mediation was considered statistically significant when 95% bootstrap confidence intervals for the indirect effect excluded zero (Falk et al., 2024)(Falk et al., 2024). Additionally, marginal mediation evidence was identified when individual pathway coefficients showed statistical trends ($p < .10$) or when bootstrap p-values approached conventional significance levels, providing preliminary support for potential mediating mechanisms. Given the theory-driven selection of mediator-outcome combinations based on the literature review, no multiple testing corrections were applied to confirmatory mediation analyses.

Exploratory mediation analyses: Exploratory mediation analyses examined the same four confirmed mediators against eleven additional outcome variables beyond the theoretical model: Well-being, Performance, Engagement, Exhaustion, General Attitudes, Evaluation, Human-AI Teaming, Workload, Autonomy, Interface Autonomy, and Task Competence. These analyses followed identical multilevel mediation procedures as confirmatory analyses but applied Bonferroni correction for the 44 tested pathways (4 mediators × 11 outcomes), setting the corrected significance threshold at $\alpha = 0.05/44 = 0.0011$. Both corrected and uncorrected findings are reported to distinguish robust effects from those requiring replication.

3.4.6.3 Covariates and moderating effects

Mixed-effects modeling was employed to examine theoretically motivated moderation hypotheses, particularly the role of leader AI symbolization in influencing intervention effectiveness (H7). Additionally, baseline AI experience, work experience, time at organization, and age were examined as potential moderators to understand individual differences in intervention responsiveness.

Confirmatory moderation analyses focused on the pre-specified H7 hypothesis that leader AI symbolization moderates intervention effects on job crafting behaviors (Seeking Resources and Optimizing Demands). For these theory-driven tests, no multiple testing correction was applied.

Exploratory moderation analyses examined all five potential moderators against all theory-driven outcomes (job crafting dimensions, Human-Task-AI fit dimensions, and behavioral competencies), resulting in comprehensive moderation testing. Again, given the exploratory nature and multiple comparisons, Bonferroni correction was applied to the full set of tested interactions.

For each moderation analysis, three nested models were systematically compared using likelihood ratio tests with REML = FALSE. All moderators were centered at their baseline (pre-intervention) grand mean to reduce multicollinearity and facilitate interpretation. The base model included only the Group × Time interaction (outcome ~ Group × Time + (1|ID)), the covariate model added the centered baseline moderator as a main effect (outcome ~ Group × Time + moderator_centered + (1|ID)), and the full moderation model incorporated the three-way interaction (outcome ~ Group × Time × moderator_centered + (1|ID)).

Model fit comparisons using Akaike Information Criterion (AIC) supplemented significance testing, with AIC improvements indicating whether moderator inclusion enhanced predictive accuracy. This comprehensive approach ensured that both statistical significance and practical model improvement were considered when evaluating moderation effects.

Robustness checks and assumption testing

To ensure robustness of findings, supplementary analyses were conducted comparing the optimal sampling strategy against alternative approaches: 1) all participants included 2) pure participants only, for a subset of primary outcomes. Additionally, assumption checking was performed through model diagnostics, examining residual normality and homoscedasticity for statistically significant effects. These robustness checks validated the primary analytical approach and confirmed consistency of results across different methodological choices. All analysis scripts were organized into a reproducible pipeline with clear separation between confirmatory and exploratory analyses, ensuring transparent distinction between theory-driven findings and post-hoc discoveries.

4. Results

4.1 Baseline Equivalences and Descriptive statistics

A total of 61 participants provided matched pre–post data (*control n* = 33*; intervention n* = 28*).* At baseline, groups differed on age *(*control*: M* = 38.73*, SD* = 12.61*;* intervention*: M* = 32.14*, SD* = 12.16*; t(59)* = 2.07*, p* = .043) and educational level *(*control*: M* = 3.58*, SD* = 0.79*;* intervention*: M* = 2.89*, SD* = 1.03*; t(59)* = 2.92*, p* = .005*).* No baseline differences emerged for any primary outcome (0/8 tests), supporting comparability on the main study constructs (Appendix 1). Table 4 reports descriptive statistics by group and time. Values are mean (SD) unless otherwise noted; for non-normal distributions we report median [IQR]. Two competency measures (adaptivity, proactivity) showed ceiling effects across both groups (Mdn ≈ 4.00), which we address in the limitations. Extended descriptives for secondary outcomes are provided in Appendix 2.

Tabel 4: Descriptive Statistics for Primary Outcome Variables by Group and Time

Variable	Control Group (n = 33)		Experimental Group (n = 28)	
	Pre-intervention	Post-intervention	Pre-intervention	Post-intervention
Job Crafting Behaviors				
Seeking Resources	3.20 (0.67)	3.28 (0.70)	3.13 (0.70)	3.33 [1.33]*
Optimizing Demands	3.60 (0.64)	3.51 (0.51)	3.59 (0.64)	3.78 (0.63)
Human-Task-AI fit				
Task-AI fit	3.67 (0.56)	3.60 (0.58)	3.69 [0.78]*	3.92 (0.52)
Human-AI fit	3.56 (0.57)	3.53 (0.45)	3.60 (0.65)	3.78 (0.65)
Behavioral Competencies				
Adaptivity	4.00 [0.50]*	4.00 [0.00]*	4.00 [0.50]*	4.00 [0.50]*

Proactivity	4.00 [0.33]*	4.00 [0.33]*	4.00 [0.33]*	4.00 [0.33]*
Innovativeness	3.57 (0.70)	3.56 (0.58)	3.60 (0.61)	3.53 (0.65)
AI Usage				
Frequency of AI Use	3.00 [2.00]*	3.00 [3.00]*	3.50 [2.25]*	4.00 [2.00]*
Types of AI Use	3.00 [2.00]*	4.00 [2.00]*	3.00 [2.25]*	3.50 [3.00]*

Values are mean (SD); * median [IQR] for non-normal distributions (Shapiro–Wilk). Control *n* = 33; Intervention *n* = 28."

4.2 Main effect analyses

Table 5 presents the main intervention effects. Three of nine theory-driven outcomes reached statistical significance. The intervention had the strongest effect on AI usage frequency (*B* = 0.623*, SE* = 0.209*, p* = .004*, d* = 1.08)*,* representing a large effect size. Significant effects also emerged for optimizing demands (*B* = 0.277*, p* = .020*, d* = 0.87) and task-AI fit (*B* = 0.314*, p* = .030*, d* = 0.81), both demonstrating large effect sizes (Schäfer & Schwarz, 2019)(Schäfer & Schwarz, 2019). Regarding the hypotheses on the intervention outcomes, H1 (job crafting) received partial support, with optimizing demands increasing significantly but seeking resources showing no change (*p* = .986). H2 (Human-Task-AI fit) was also partially supported, with Task-AI fit improving significantly while human-AI fit did not reach significance (*p* = .142). Hypotheses 3-5 regarding behavioral competencies were not supported, with none of the three competency measures reaching significance (*all p's* > .11).

Tabel 5: Main Intervention Effects (Linear Mixed Models)

Outcome Variable	B	SE	t	p	Cohen's d	95% CI
Frequency of AI use	0.623	0.209	2.98	.004**	1.083	[0.213, 1.033]
Optimizing demands	0.277	0.115	2.41	.020*	0.870	[0.050, 0.503]
Task-AI fit	0.314	0.141	2.23	.030*	0.809	[0.038, 0.590]
Adaptivity	0.102	0.064	1.60	.112	0.254	[-0.023, 0.228]
Human-AI fit	0.090	0.061	1.48	.142	0.242	[-0.030, 0.210]
Types of AI use	0.293	0.264	1.11	.268	0.159	[-0.227, 0.813]
Innovativeness	0.034	0.063	0.54	.591	0.086	[-0.090, 0.158]
Proactivity	0.006	0.060	0.10	.917	0.017	[-0.112, 0.124]

Seeking resources	0.001	0.072	0.02	.986	0.003	[-0.140, 0.143]

Note: N = 61. B = unstandardized Group × Time coefficient (fixed effect); SE = standard error; d = interaction_estimate / residual_sd; CI =confidence interval. *p < .05. **p < .01.

4.3 Mediation analyses

Confirmatory mediation analyses (Table 5) provided partial support for H8 and H9. Six of the twenty pre-specified pathways showed significant indirect effects (four full, one partial, one additional full), and two pathways showed marginal evidence. Specifically, Optimizing Demands significantly mediated the intervention's effects on Proactivity, Innovativeness (full mediation), and Frequency of AI use (partial mediation), and showed marginal mediation for Types of Use. Task-AI fit significantly mediated effects on Proactivity, Innovativeness, and Types of Use (full mediation), and showed marginal mediation for Frequency of AI use. No indirect effects were found via Seeking Resources or Human-AI Fit.

Tabel 6: Confirmatory Mediation Analysis Results (Linear Mixed Models)

Mediator	Outcome	a-path	p(a)	b-path	p(b)	Indirect (95% CI)	bootstrap p	Type
Optimizing Demands	Proactivity	0.277	.020	0.458	<.001	0.127 [0.023, 0.242]	.014	Full
	Innovativeness	0.277	.020	0.307	.001	0.085 [0.011, 0.197]	.022	Full
	Frequency AI use	0.277	.020	0.504	.010	0.139 [0.013, 0.338]	.026	Partial
	Types of Use	0.277	.020	0.596	.098	0.165 [-0.014, 0.462]	.090	Marginal
Task–AI fit	Proactivity	0.314	.030	0.212	.009	0.067 [0.004, 0.144]	.030	Full
	Innovativeness	0.314	.030	0.203	.012	0.064 [0.001, 0.160]	.046	Full
	Types of Use	0.314	.030	1.028	.001	0.323 [0.031, 0.795]	.020	Full

	Frequency AI use	0.314	.030	0.385	.024	0.121 [-0.021, 0.367]	.112	Marginal

Note. N = 61. Bootstrap confidence intervals based on 1,000 resamples at the participant level. A-path = intervention (Group × Time) → mediator; B-path = mediator → outcome (controlling for the intervention). Full = significant indirect effect and non-significant direct effect (c'); Partial = significant indirect effect and significant direct effect; Marginal = .05 ≤ p_indirect < .10 or both a- and b-path p-values < .10.

4.4 Moderation analyses

H7 predicted that leader AI symbolization would moderate intervention effects on job crafting. As shown in Table 6, the three-way interaction was marginally significant for optimizing demands (*B* = .221*, p* = .073) but non-significant for seeking resources (*B* = .046*, p* = .764)*,* providing limited support for H7.

Tabel 7: Moderation analysis (Linear Mixed Models)

Outcome	Moderator	Three-way B	SE	p	Model Comparison p
Seeking_Resources_Score	AI_Symbolization	0.046	0.125	.764	.258
Optimizing_Demands_Score	AI_Symbolization	0.221	0.121	.073	.327

Notes: B_3way = unstandardized coefficient for the Group × Time × Moderator interaction from linear mixed-effects models (random intercepts for participants); moderators were baseline-centered.. SE = standard error. *p < .05.

To better understand the nature of the marginally significant moderation for optimizing demands, we conducted simple slopes analysis examining intervention effects at low (-1 SD), mean, and high (+1 SD) levels of leader AI symbolization. The results suggest that employees who face low levels of leader AI symbolization do not significantly benefit from the intervention in terms of increased demand optimization behavior (*B* = 0.027*, p* = .871). At mean levels of leader AI symbolization, marginal effectiveness of the intervention was found (*B* = 0.232*, p* = .054). Moreover, the intervention appeared significantly effective for employees who faced high levels of leader AI symbolization (*B* = 0.436*, p* = .011).

Tabel 8: Simple slopes analysis for optimizing demands

AI Symbolization Level	Intervention Effect (B)	SE	t	p	95% CI	Cohen's d
Low (-1 SD)	0.027	0.168	0.163	.871	[-0.30, 0.36]	0.045
Mean (0)	0.232	0.118	1.966	.054	[0.00, 0.46]	0.383

AI Symbolization Level	Intervention Effect (B)	SE	t	p	95% CI	Cohen's d
High (+1 SD)	0.436	0.167	2.616	.011*	[0.11, 0.76]	0.722

4.5 Empirical Model and Hypotheses Summary

A visualization of empirical findings can be found in Figure 9. Furthermore, Table 7 includes a summarizing overview of the outcomes of the hypotheses.

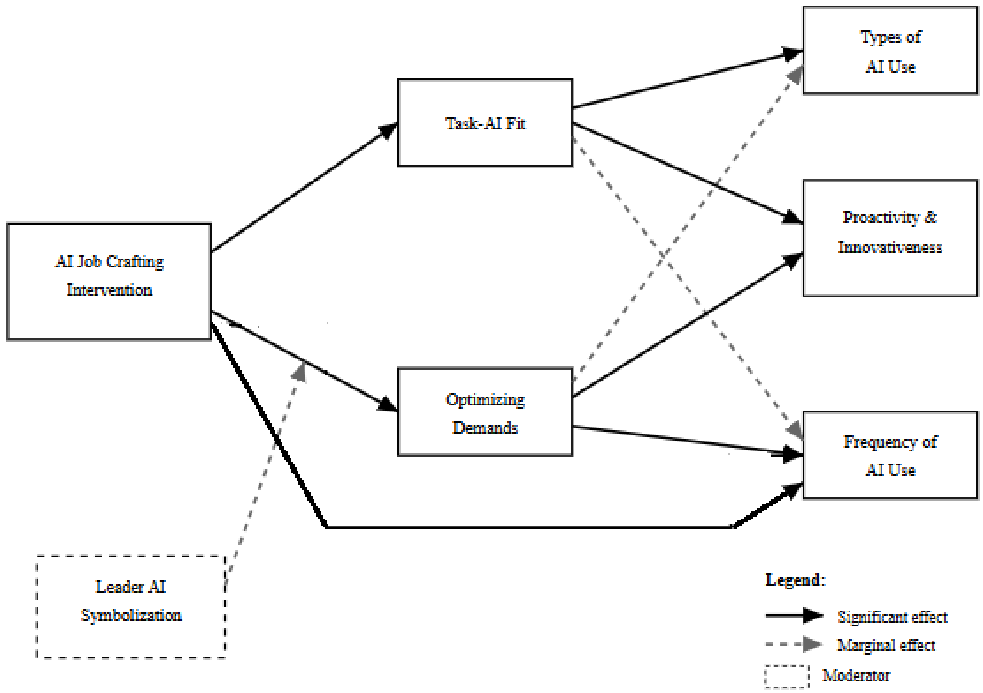

Figure 8: Empirical model

Tabel 9: Hypotheses Evaluation

Hypothesis	Description	Evaluation
Direct intervention effects:		
1	Job crafting behavior	- Seeking resources: Rejected - Optimizing demands: Accepted
2	Human-Task-AI fit	- Task-AI fit: Accepted - Human-AI Fit: Rejected

3	Adaptivity	Rejected
4	Proactivity	Rejected
5	Innovativeness	Rejected
6	AI use	- Types of AI use: Rejected - Frequency AI use: Accepted
	Moderator:	
7	AI Symbolization (positive moderation)	Rejected (Marginal effect)
Indirect effects:	**Mediator: Human-Task-AI fit**	
8a	Adaptivity	Task-AI fit: Rejected Human-AI fit: Rejected
8b	Proactivity	Task-AI fit: Accepted Human-AI fit: Rejected
8c	Innovativeness	Task-AI fit: Accepted Human-AI fit: Rejected
8d	AI use	Task-AI fit: Accepted Human-AI fit: Rejected
	Mediator: Job Crafting	
9a	Adaptivity	Seeking Resources: Rejected Optimizing Demands: Accepted
9b	Proactivity	Seeking Resources: Rejected Optimizing Demands: Accepted
9c	Innovativeness	Seeking Resources: Rejected Optimizing Demands: Accepted
9d	AI use	Seeking Resources: Rejected Optimizing Demands: Accepted (Partial mediation)

4.6 Exploratory analyses

4.6.1 Exploratory main effects

None of the exploratory outcome variables reached significance after Bonferroni correction (*α_corrected = .0042*). One uncorrected marginal trend was found for exhaustion (*B* = -.141,*SE* = 0.079, *t* = -1.77, *p* = .081, *CI* = [-0.296, 0.015]), suggesting a potential decrease in exhaustion after the intervention. However, its confidence interval included zero and the effect did not meet corrected nor conventional significance levels.

Tabel 10: Exploratory Intervention Effects (Linear Mixed Models)

Outcome	B	SE	t	p	95% CI
Exhaustion_Score	-0.141	0.079	-1.77	0.081	[-0.296, 0.015]
General_Attitudes_Score	0.171	0.123	1.39	0.169	[-0.07, 0.412]
Human_AI_Teaming_Score	0.144	0.117	1.24	0.221	[-0.085, 0.373]
Well_being_Score	0.169	0.144	1.17	0.246	[-0.114, 0.452]
AI_Symbolization_Score	-0.262	0.25	-1.05	0.298	[-0.752, 0.228]
Task_Competence_Score	0.074	0.086	0.86	0.392	[-0.095, 0.244]
Engagement_Score	0.089	0.109	0.81	0.42	[-0.125, 0.303]
Performance_Score	0.072	0.099	0.73	0.471	[-0.122, 0.266]
Autonomy_Score	0.069	0.151	0.46	0.649	[-0.227, 0.364]
Evaluation_Score	0.056	0.131	0.43	0.668	[-0.201, 0.314]
Workload_Score	0.032	0.132	0.25	0.807	[-0.226, 0.291]
Interface_Autonomy_Score	-0.011	0.138	-0.08	0.938	[-0.281, 0.259]

Note: B = unstandardized Group × Time coefficient; SE = standard error; CI = 95% confidence interval. α_uncorr = .05; Bonferroni-corrected α_corr = .05/12 tests = 0.0042. No exploratory effects survived the multiple-testing correction. P-values are two-tailed.

4.6.2 Exploratory mediation analysis

Exploratory mediation analyses probed whether the two theory-based mediators, optimizing demands and Task-AI fit, also carried intervention effects to additional outcomes beyond the main model. Across 11 outcomes (22 indirect paths), a Bonferroni-corrected threshold of α = .05/22 = .00227 was applied. No indirect effect met this corrected criterion. Eleven paths were nominally significant at α = .05 (Table 11), showing a coherent pattern: Optimizing demands linked the intervention to more favorable general AI attitudes, autonomy (job and interface), well-being when working with AI, and human-AI teaming; Task-AI fit related the intervention to higher AI evaluation and general attitudes, human-AI teaming, well-being when working with AI, and interface autonomy. Given multiplicity and the exploratory status of these tests, we treat these signals as hypothesis-generating only and refrain from inferential claims. Full ab-coefficients, bootstrapped 95% CIs, and p-values are reported in Table 11.

Tabel 11: Exploratory mediation analysis (Linear Mixed Models)

Mediator	Outcome	Indirect (B)	95% CI	Bootstrap p
Optimizing Demands	General Attitudes	0.077	[0.010, 0.175]	0.008*
	Autonomy	0.085	[0.015, 0.200]	0.016*
	Evaluation of AI	0.077	[0.009, 0.182]	0.016*
	Well-being when working with AI	0.059	[0.011, 0.136]	0.012*
	Human-AI Teaming	0.061	[0.003, 0.163]	0.036*
	Interface Autonomy	0.058	[0.002, 0.144]	0.040*
Task AI Fit	Evaluation of AI	0.171	[0.037, 0.333]	0.012*
	General Attitudes	0.114	[0.022, 0.248]	0.016*
	Human-AI Teaming	0.144	[0.022, 0.289]	0.020*
	Well-being when working with AI	0.106	[0.013, 0.198]	0.028*
	Interface Autonomy	0.087	[0.002, 0.185]	0.048*

Note. N = 61. Indirect = a-Path × b-Path; 95% CI = bootstrap confidence interval; Bonferroni-corrected α_corr = .05/22 tests = 0.00227. No exploratory effects survived the multiple-testing correction. *p* < .05

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4.6.3 Exploratory moderation analysis

Exploratory moderation analyses examined whether demographic and work experience variables moderated intervention effectiveness, applying Bonferroni correction for multiple testing (α = .000625 for 80 tests). Four significant moderation effects emerged at the uncorrected α = .05 level, though none survived the conservative multiple testing correction.

Three variables significantly moderated the intervention's effect on seeking resources behavior (Table 12). Time at organization showed a positive moderation effect (*B* = .266*, p* = .019)*,* with simple slopes analysis revealing that the intervention was ineffective for employees with shorter tenure but showed positive (though non-significant) effects for those with longer organizational experience. Work experience demonstrated a similar positive moderation (*B* = .283*, p* = .023)*,* where the intervention showed negative effects for less experienced workers but positive effects for more experienced employees. Conversely, AI experience showed a negative moderation effect (*B* = -.173*, p* = .039)*,* with the intervention being more effective for participants with lower AI experience and less effective (showing negative effects) for those with higher baseline AI experience.

Age emerged as a significant moderator of adaptivity (*B* = -.024*, p* = .017). Simple slopes analysis revealed that the intervention had a nominal significant negative effect on adaptivity for older employees (*B* = -.477*, p* = .012*, d* = -.955)*,* meaning that older participants in the intervention group showed decreased adaptivity compared to older participants in the control group. For younger employees, the intervention showed no significant effect on adaptivity (*B* = .089*, p* = .615*).* This pattern suggests that the AI job crafting intervention may be counterproductive for adaptivity among older workers, while having minimal impact on younger employees.

Tabel 12: Exploratory Moderation Effects (Linear Mixed Models)

Outcome	Moderator	Three-way B	SE	t	p
Seeking resources	Time at organization	0.266	0.111	2.40	.019*
	Work experience	0.283	0.121	2.34	.023*
	AI experience	-0.173	0.082	-2.12	.039*
Adaptivity	Age	-0.024	0.010	-2.44	.017*

Note. N = 61. No effects survived Bonferroni correction: α_corrected = .05 / 80 = .000625. B_3way = unstandardized coefficient for the Group × Time × Moderator interaction from linear mixed-effects models (random intercepts for participants); moderators were baseline-centered.. SE = standard error. *p < .05.

4.6.4 Covariate effects

Exploratory covariate analyses examined which demographic and experience variables predicted post-intervention outcomes, yielding 19 significant effects ($p < .05$) across 80 tests (Table 11).

General AI experience was the strongest and most consistent predictor, significantly relating to 10 outcomes (B = 0.126–1.159, *all* $p < .05$), including AI evaluation ($B = 0.199$, $p < .001$), Task-AI fit ($B = 0.214$, $p < .001$), and multiple competency, well-being and usage measures. Age showed three negative associations (B = −0.113 to −0.029) with Types of use, Frequency of AI use, and Seeking resources, indicating lower scores for older participants on these targets.
Work experience predicted four outcomes (mixed signs: e.g., *Task competence* $B = 0.170$, p = .013; *Types of use* $B = −0.984$, p = .010). Time at organization showed two negative associations with AI use outcomes (B = −0.759 to −0.487, *both* $p \approx .04$).

These patterns suggest that AI experience and, to a lesser extent, age systematically shape post-intervention levels, while work-related experience variables show more selective and mixed associations.

Tabel 13: Covariate Effects (Linear Mixed Models)

Outcome	Predictor	B	95% CI	p
Frequency of use	**AI experience**	0.775	[0.514, 1.036]	< .001***
Types of use		1.159	[0.714, 1.604]	< .001***
AI evaluation		0.199	[0.091, 0.308]	< .001***
Task-AI fit		0.214	[0.098, 0.329]	< .001***
Human-AI teaming		0.150	[0.042, 0.258]	.008**
Seeking resources		0.189	[0.043, 0.334]	.013*
Well-being		0.126	[0.021, 0.230]	.020*
Interface autonomy		0.142	[0.022, 0.261]	.022*
Human-AI fit		0.133	[0.018, 0.247]	.026*
Innovativeness		0.141	[0.010, 0.272]	.038*
Types of use	**Age**	−0.113	[−0.175, −0.051]	< .001***
Seeking resources		−0.029	[−0.046, −0.011]	.002**
Frequency of use		−0.052	[−0.093, −0.011]	.015*

Seeking resources	**Work experience**	−0.349	[−0.557, −0.142]	.001**
Types of use		−0.984	[−1.718, −0.250]	.010*
Task competence		0.170	[0.038, 0.301]	.013*
Frequency of use		−0.534	[−1.013, −0.054]	.032*
Types of use	**Time at organization**	−0.759	[−1.474, −0.043]	.041*
Frequency of use		−0.487	[−0.947, −0.027]	.042*

Note. N = 61. B = unstandardized coefficient of the baseline predictor in linear mixed-effects models (random intercepts for participants). Predictors were mean-centered at baseline. 95% Wald CIs. Two-tailed p-values. *p < .05, **p < .01, ***p < .001.

4.7 Robustness test

To ensure the reliability of the main findings, comprehensive robustness checks were conducted focusing on the three significant confirmatory effects. These parametric analyses examined sampling strategy sensitivity and statistical power.

The optimal sampling strategy (Control + Crossover Control vs Pure Experimental) was compared against two alternative approaches: including all participants (i.e., crossover participants in both samples) and using pure participants only (i.e., excluding crossover participants from both control- and experimental sample). Table 12 presents the results of this comparison.

Tabel 14: Sampling Strategy Comparison for Significant Effects

Outcome	Optimal Sampling		All Participants		Pure Only	
	B (SE)	p	B (SE)	p	B (SE)	p
Frequency AI use	0.623 (0.209)	.004**	0.594 (0.236)	.014*	0.594 (0.236)	.014*
Optimizing demands	0.277 (0.115)	.020*	0.210 (0.125)	.096	0.210 (0.125)	.096
Task-AI fit	0.314 (0.141)	.030*	0.306 (0.154)	.054	0.306 (0.154)	.054

Note. N = 61 (optimal), 53 (alternatives). B = unstandardized coefficient; SE = standard error. *p < .05, **p < .01.

The sampling strategy comparison revealed mixed consistency across approaches. Frequency AI use demonstrated robust significance across all sampling strategies ($p \leq .014$), providing strong evidence for this intervention effect. However, optimizing demands and Task-AI fit showed sensitivity to the sampling approach, reaching significance only with the optimal strategy *($p = .020$ and $p = .030$, respectively)* while becoming non-significant with alternative approaches ($p = .096$ and $p = .054$).

This pattern validates the decision to exclude crossover experimental data due to demonstrated carry-over effects. The finding that optimizing demands and Task-AI fit reached significance only with the optimal strategy supports the theoretical rationale for excluding contaminated data, suggesting that alternative approaches may mask genuine intervention effects through sequence-related confounding.

Statistical Power

Post-hoc power analyses revealed excellent statistical power for all significant effects. With effect sizes ranging from $d = 0.81$ to $d = 1.08$ and approximately 30 participants per group, achieved power exceeded 0.99 for all three outcomes, indicating that the sample size was more than adequate to detect the observed intervention effects.

5. Discussion

While existing literature has increasingly called for training and interventions to support employees in AI adaptation (Afiouni & Pinsonneault, 2022; Mo et al., 2024), and although job crafting in AI contexts has been studied theoretically and observationally (Cheng et al., 2023; Perez et al., 2022), no concrete empirical interventions have been developed to train employees in these crucial skills. This study addresses this gap by developing and testing the first JD-R-based job crafting intervention (Demerouti and peeters 2019) specifically designed for AI-integrated contexts. Our findings provide the first empirical evidence that brief, online job crafting interventions can effectively modify both perceptual (fit) and behavioral outcomes in AI contexts, demonstrating the potential to effectively complement top-down driven AI integration approaches.

This study demonstrates that, in the evolving era of AI-induced workplace changes, employees can learn to maintain control, enhance their behavioral competencies, and improve their AI usage through targeted job crafting interventions. Specifically, our training showed strong direct effects on demand optimization behavior ($d = .87$)*,* Task-AI fit ($d = .81$), and most notably, AI usage frequency ($d = 1.08$). The latter is particularly significant given the growing organizational imperative to enhance employee AI engagement and utilization (Dell'acqua et al., 2025).

Beyond these direct effects, mediation analyses revealed dual underlying mechanisms through which additional intervention effects appeared. Both demands optimization and Task-AI fit mediated the intervention's effect on proactivity and innovativeness. Moreover, demand optimization partially mediated the effects of AI usage frequency, and Task-AI fit fully mediated the AI usage variety effect.

No significant effects emerged for seeking resources, Human-AI fit, or adaptivity, revealing important nuances in intervention effectiveness across job crafting dimensions.

In the remainder of this section, we discuss how these results refine theoretical understandings of job crafting in the age of AI, provide actionable implications for organizations seeking to guide AI integration, and outline key avenues for future research.

5.1 Theoretical implications

5.1.1 Human-AI Collaboration

While previous research has primarily focused on technology acceptance models that treat technology as static and emphasize one-time user adoption (Davis, 1989; Venkatesh et al., 2003), these approaches fail to capture how AI continually reshapes workplace demands and resources (Demerouti, 2022; Parker & Grote, 2022a). We address this gap by integrating Human-Task-AI fit theory (Goodhue & Thompson, 1995) with the Job Demands-Resources (JD-R) model (Demerouti et al., 2001), treating AI as a dynamic element whose value depends on continuous alignment among employee capabilities, task requirements, and technical functionalities. This integration provides a comprehensive pathway from AI integration to psychological and work outcomes: Human-Task-AI fit determines whether AI functions as a job resource (e.g., enhancing autonomy or reducing workload) or job demand (e.g., creating technostress or complexity), which then drives motivation or strain processes that ultimately affect employee well-being and performance (Bakker & Demerouti, 2007; Chuang et al., 2025; Demerouti, 2022; Goodhue & Thompson, 1995). Crucially, both the fit- and demands-resources balance are dynamic. The same AI system can shift from burden to benefit as employees, tasks, and contexts evolve, introducing the need for ongoing bottom-up adaptation rather than static top-down implementation.

Our findings provide empirical support for this integrated framework. The intervention directly enhanced two of the core elements from the framework: Optimizing demands and Task-AI fit, demonstrating that employees can indeed favorably shift their JD-R balance and improve task-technology alignment. Moreover, enhancing these core elements ultimately led to improved performance outcomes (see 5.1.2) and potentially improved personal outcomes (see 5.2). These effects indicate that combining fit- and JD-R theory form a valuable perspective to approach AI integration.

The integrated framework and empirical results from our job crafting intervention further support the argument for employee agency in effective AI integration and work redesign (Demerouti, 2022). Employee agency is essential during AI integration because of AI's dynamic nature, individual differences in response, and employees' unique positioning to identify task-specific misalignments (Cheng et al., 2023; Chuang et al., 2025; Dell' et al., 2023; Mukherjee & Dhar, 2023). The effectiveness of our intervention, which is based on our integrated framework, indicates that a bottom-up approach in work design successfully operationalizes the dynamic, and employee-driven adaptation to AI integration. Rather than being passive recipients of technology, employees can actively shape how AI integrates into their work to achieve more favorable outcomes.

(Davis, 1989; Venkatesh et al., 2003)(Demerouti, 2022; Parker & Grote, 2022a)(Goodhue & Thompson, 1995)(Goodhue & Thompson, 1995)(Goodhue & Thompson, 1995)(Goodhue & Thompson, 1995)(Demerouti et al., 2001).(Demerouti et al., 2001).(Demerouti et al., 2001).(Demerouti et al., 2001).(Chuang et al., 2025; Grover et al., 2022; Verma & Singh, 2022)(Chuang et al., 2025; Grover et al., 2022; Verma & Singh, 2022)(Chuang et al., 2025; Grover et al., 2022; Verma & Singh, 2022)(Chuang et al., 2025; Demerouti, 2022; Vrontis et al., 2022)(Chuang et al., 2025; Demerouti, 2022; Vrontis et al., 2022)(Chuang et al., 2025; Demerouti, 2022; Vrontis et al., 2022)(Demerouti, 2022)(Demerouti, 2022)(Demerouti, 2022)(Cheng et al., 2023; Chuang et al., 2025; Dell' et al., 2023; Mukherjee & Dhar, 2023)(Cheng et al., 2023; Chuang et al., 2025; Dell' et al., 2023; Mukherjee & Dhar, 2023)(Cheng et al., 2023; Chuang et al., 2025; Dell' et al., 2023; Mukherjee & Dhar, 2023)

(Demerouti, 2022)(Demerouti, 2022)(Demerouti, 2022)(Demerouti, 2022)(Demerouti, 2022)(Demerouti, 2022)(Dell' et al., 2023)(Dell' et al., 2023)(Dell' et al., 2023)(Dell' et al., 2023)(Cheng et al., 2023; Chuang et al., 2025)(Cheng et al., 2023; Chuang et al., 2025)(Cheng et al., 2023; Chuang et al., 2025)(Cheng et al., 2023; Chuang et al., 2025)(Mukherjee & Dhar, 2023)(Mukherjee & Dhar, 2023)(Mukherjee & Dhar, 2023)

5.1.2 Parallel underlying mechanisms

Our study reveals two complementary mechanisms through which job crafting interventions foster AI adaptation: demand optimization and Task-AI fit. Responding to the call in literature to identify mediating mechanisms through which job crafting interventions work (Demerouti et al., 2019). While recent research by Pekaar and Demerouti (2023) identified demand optimization as a mechanism for proactive sustainability behavior, our findings demonstrate its broader applicability across multiple relevant AI-era outcomes. Furthermore, whereas increasing person-environment fit is an important mechanism in job crafting interventions, our findings specify this mechanism for human-AI collaboration, revealing that Task-AI fit serves as the critical alignment in AI-integrated contexts.

5.1.2.1 Behavioral competencies: Proactivity and Innovativeness

Both proactivity and innovativeness showed full mediation through our dual pathways, providing among the first empirical indications that these competencies can be systematically developed through targeted intervention via these pathways. This extends Pekaar and Demerouti's (2023) recent finding beyond sustainability contexts, suggesting that demand optimization serves as a generalizable mechanism for proactive behavior. When employees restructure work demands, they both free up time and energy, an develop agency and problem-solving capabilities that manifest in both initiative-taking (proactivity) and creative solution generation (innovativeness) (Mukherjee & Dhar, 2023; Pekaar & Demerouti, 2023).

The Task-AI fit pathway showed that perceptual alignment between tasks and AI capabilities independently fosters these competencies. This extends person-job fit theory (Erdogan & Bauer, 2005) to AI contexts, demonstrating that when employees understand how AI aligns with their work, they can better identify opportunities for improvement and innovation. While Ok and Lim (2022) theorized sequential relationships between fit, engagement, and innovativeness, our intervention provides first indications that fit can be intentionally enhanced to directly foster behavioral competencies.

The parallel operation of both mechanisms suggests that AI-era competencies emerge through multiple routes, both through tangible work restructuring and through cognitive reframing of task-technology relationships. This dual-pathway structure offers organizations flexibility in intervention design based on employee needs and organizational constraints.

Whereas both mechanisms contributed to behavioral competencies in parallel, AI usage demonstrated distinct pathway specialization, with each mechanism driving a separate dimension of usage behavior.

5.1.2.2 Differential pathways to AI utilization

Different dimensions of AI usage respond to distinct mechanisms. Usage frequency showed both direct intervention effects and partial mediation through demand optimization, while usage variety operated exclusively through Task-AI fit.

The frequency pathways jointly appear motivational and friction-reducing. First, when employees optimize demands (partial mediation), they achieve multiple simultaneous benefits that converge to increased usage frequency. From a material perspective, demand optimization removes practical barriers and frees up time and energy previously consumed by inefficient processes or demands, enabling employees to better act on their intentions to use AI (Pekaar & Demerouti, 2023). From a motivational perspective, successfully restructuring work demands enhances feelings of autonomy and control, for which we found preliminary confirmation in our exploratory analysis. This aligns with self-determination theory (Ryan & Deci, 2000), suggesting that autonomy satisfaction drives motivation for technology engagement (Demerouti & Peeters, 2018; Mukherjee & Dhar, 2023). Second, the direct effect on frequency resonates with Social Cognitive Theory (Bandura, 1997), as intervention activities may have provided mastery experiences and exposure to peers' successes, which enhanced self-efficacy and translated directly into more frequent AI usage.

Conversely, the variety pathway requires deeper cognitive processing. Employees expand their AI applications only after developing clear mental models of how AI capabilities map onto diverse task requirements. This finding refines Technology-to-Performance Chain theory (Goodhue & Thompson, 1995) by demonstrating that while technical fit may be less critical for usage intensity, it becomes essential for application breadth.

The distinct pathways leading to separate AI-usage outcomes suggest that AI usage is not a one-dimensional construct. Prior research already concluded that system use can be multidimensional, but that conceptualizations will vary depending on context. Our findings suggest that AI usage should be approached as at least a two-dimensional construct, aligning with recent research on the adoption of generative AI who empirically studied AI usage in forms of frequency and variety as well (Bick et al., 2024).

Taken together, our findings advance job crafting intervention and AI integration theory in three ways. First, they demonstrate that AI adaptation operates through parallel pathways for competencies but specialized pathways for AI usage dimensions, extending recent work by Pekaar and Demerouti (2023) beyond sustainability contexts to AI integration. Moreover, this dual-mechanism framework specifies how employee agency translates into concrete AI adaptation behaviors, moving beyond theoretical propositions to preliminary empirical intervention pathways. Second, they provide first empirical indications that Task-AI fit serves as the critical perceptual alignment in human-AI collaboration, refining Task-Technology Fit theory for AI contexts. Third, they suggest that AI usage is not a unidimensional construct, with at least usage frequency and variety operating through distinct mechanisms. To conclude, effective AI integration is not just about understanding how technology fits, but about experiencing control and agency over the integration process.

5.1.3 Boundary conditions: Leader AI symbolization

While observational research shows that leader AI symbolization facilitates natural job crafting behaviors (He et al., 2023; W. Li et al., 2024; Mo et al., 2024), it remained unclear whether this also influences structured intervention effectiveness.

Our findings provide the first empirical evidence that leader AI symbolization functions as a boundary condition for intervention success. Simple slopes analysis revealed that employees with low leader AI symbolization showed no intervention benefit (B = 0.027, p = .871), while those with high symbolization demonstrated significant improvements in demand optimization behaviors (B = 0.436, p = .011).

This extends existing intervention literature by demonstrating that AI-specific leadership behaviors may be prerequisite for training success, rather than merely additive. Unlike general leadership support, which Demerouti et al. (2021) found maintained intervention effects above and beyond leadership influences, leader AI symbolization appears to function as a legitimizing signal that determines intervention receptiveness (Demerouti et al., 2021). This bridges observational job crafting research with intervention studies by showing that the same leadership factors promoting natural behaviors also moderate structured training effectiveness.

Practically, these findings suggest that AI job crafting interventions should not be deployed as standalone solutions but require adequate leader AI symbolization as a foundational condition for success.

5.1.4 Absent effects

5.1.3.1 Seeking resources

In contrast to existing literature that shows how job crafting interventions effectively improved of seeking resources (Dubbelt et al., 2019; Gordon et al., 2018). Our findings reveal important nuances in the effectiveness of different job crafting strategies in AI-settings. While optimizing demands showed significant improvement, seeking resources remained unchanged, suggesting that different job crafting dimensions that may be differentially responsive to AI-focused intervention approaches. Several explanations may account for this pattern.

First, optimizing demands may be more concrete and actionable than seeking resources. Demand optimization often involves specific, observable changes to work processes and task arrangements, while resource seeking may require more complex interpersonal navigation and organizational awareness that requires longer development periods (Demerouti et al., 2017).

Second, contextual factors may influence which job crafting strategies employees are most prone to develop. Knight et al. (2021) demonstrated that high workload prior to job crafting interventions promotes demand optimization, while low workload promotes seeking resources. Given that our participants showed baseline workload scores toward the higher end of the scale (*M* = 3.64 out of 5, for both experimental and control sample), this pattern aligns with Knight et al.'s findings and may explain participants' greater engagement with demand optimization strategies (Knight et al., 2021).

Third, intervention design and timing factors may have contributed to these differential effects. The seeking resources module may have required different pedagogical approaches or longer implementation periods to show effects. Furthermore, the sequential order of the intervention may have influenced the effect on seeking resources (Demerouti et al 2019).

Lastly, measurement limitations may have obscured seeking resources improvements. Demerouti et al. (2017) noted in their study that generic seeking resources scales may fail to capture contextual forms of resource acquisition, missing nuanced, context-specific resource-seeking behaviors. Similarly, Hulshof (2020) suggested that if employees do not consciously recognize small resource gains (e.g., brief feedback interactions) as resource increasement, and measurement scales do not query these behaviors specifically enough, intervention effects may remain undetected (Hulshof et al., 2020). Our study may have experienced similar measurement limitations, where participants engaged in resource-seeking behaviors that were not adequately captured by our scale items.

Future research should investigate optimal intervention designs for different job crafting dimensions, examine whether sequential or longer-duration interventions might better develop resource-seeking capabilities, and develop more sensitive, context-specific measures of job crafting behaviors in AI-integrated workplaces.

5.1.3.2 Human-AI fit

Our findings that Task-AI fit serves as a significant variable and mechanism, whereas Human-Task AI fit did not, reveal important potential nuances within the Human-Task-AI fit construct that advance theoretical understanding. While Task-Technology Fit theory encompasses the alignment between task characteristics, technology functionalities and individual abilities (Goodhue & Thompson, 1995), our findings suggest that these components may be of differential importance in the context of AI integration. Task-AI fit, measuring taskfunctionality alignment (Jarupathirun & Zahedi, 2007), may be more fundamental because it addresses the basic question of whether AI can actually support work requirements. Human-AI fit, measuring individual-technology complementarity (Wu & Chen, 2017; Yu & Yu, 2010), may become important only after basic Task-AI alignment is established. Initially, the intervention was aimed at a more holistic job crafting approach that could potentially influence task, individual and environmental factors. However, the practical implementation appears to have resonated most strongly at the task level, where employees learned to align their work activities with AI functionalities. Perez et al. (2022) also found that job crafting among employees in an AI context primarily regarded altering tasks. This task-focused adaptation may explain why Task-AI fit emerged as the stronger mediation in our study.

One potential theoretical explanation for the difference in effect on Task-AI fit and Human-AI fit can be found in Afiouni and Pinsonneault's (2022) sequential ripple model of AI job crafting. They theoretically propose that "task" is the closest element to technology, because AI integration triggers a new distribution of tasks between the employee and AI. Therefore, they argue that employees begin with job crafting at the task level (Afiouni & Pinsonneault, 2022). Although this remains a theoretical proposition requiring empirical validation, our finding that Task-AI fit improved significantly while Human-AI fit did not, provides some preliminary support for this task-level first hypothesis, suggesting that AI integration may indeed follow a hierarchical progression from task-level to individual-level adaptation. However, the current study's design cannot establish the sequential nature of this process. These findings point to the need for longitudinal research to test whether task-level adaptation indeed precedes and facilitates individual-level changes over time, and whether different intervention components may be needed to address different phases of AI adaptation.

However, we must acknowledge that the Task-AI fit and Human-AI fit scales showed high intercorrelation in the experimental group (r = .848 > .800 threshold), which may limit our ability to definitively distinguish between these constructs in this sample. While this correlation was lower in the larger control- and the combined datasets, caution is required when interpreting the differential effects between these fit dimensions. The high correlation raises fundamental questions about construct distinctiveness in AI contexts. This may reflect either (1) measurement overlap in current scales, (2) participants' inability to distinguish task-level from individual-level fit during early AI adoption, or (3) that these theoretically distinct constructs empirically converge in practice. Future research should employ alternative measurement approaches (e.g., behavioral indicators, supervisor ratings) to disentangle these possibilities.

5.2 Exploratory findings

Beyond our confirmatory hypotheses, we conducted exploratory analyses to examine whether the intervention's effects extend to broader AI integration outcomes and whether individual differences moderate intervention effectiveness. While these findings require cautious interpretation due to multiple testing considerations, they offer preliminary insights into the wider implications of job crafting interventions in AI contexts.

5.2.1 Broader intervention impact

Job crafting interventions have consistently demonstrated broad impacts across diverse workplace contexts, influencing various dimensions of work experience, well-being, and performance (Demerouti et al., 2019; Dubbelt et al., 2019; Gordon et al., 2018; van den Heuvel et al., 2015). This pattern reflects the systemic nature of job crafting behaviors within the JD-R framework, where changes in demands and resources create ripple effects across multiple work outcomes (Dubbelt et al., 2019).

Our exploratory mediation analyses examined whether AI workplace integration represents another context where job crafting interventions exhibit this characteristic broad impact. We tested four categories of workplace outcomes: AI attitudes (general attitudes toward AI, AI evaluation), autonomy perceptions (interface autonomy, job autonomy), well-being indicators (well-being when working with AI), and collaborative experiences (human-AI teaming).

The findings suggest that AI workplace integration indeed follows the established pattern of broad job crafting intervention effects. Both demand optimization and Task-AI fit showed nominal mediation effects across multiple outcome domains, with demand optimization influencing six outcomes (AI evaluation, general AI attitudes, perceived job autonomy, interface autonomy, well-being when working with AI, and human-AI teaming) and Task-AI fit affecting five outcomes (AI evaluation, general AI attitudes, interface autonomy, well-being when working with AI, and human-AI teaming).

These spillover effects align with established job crafting theory while extending it into AI-specific territory. The improvement in job autonomy through demand optimization reflects the established principle that proactively reshaping work processes inherently involves exercising agency and control (Mukherjee & Dhar, 2023). More notable are the effects on AI-specific outcomes that represent relatively new terrain for job crafting research. Interface autonomy, which is the sense of control over AI system interactions (Peters et al., 2018), emerged as responsive to both pathways. This suggests that job crafting mechanisms may be particularly relevant for human-AI collaboration experiences. Similarly, the mediation effects on human-AI teaming quality and AI evaluation represent among the first empirical indications that job crafting interventions might be functional to influence relational and perceptual aspects of human-AI collaboration.

The consistency of these exploratory patterns with established job crafting intervention research provides preliminary indications that AI workplace integration represents a natural extension of contexts where employee-driven work design approaches prove effective. This perspective aligns with calls for sociotechnical approaches to AI implementation (Parker & Grote, 2022a) by demonstrating how employee-driven work design can potentially address the multidimensional challenges of AI integration simultaneously.

5.2.2 Individual differences in intervention responsiveness

Several baseline employee characteristics emerged as significant moderators of intervention outcomes, suggesting that personalized approaches may enhance the effectiveness of job crafting interventions in AI contexts.

5.2.2.1 AI-adaptation and age-related challenges

Contrary to our theoretically grounded expectations, the intervention showed no overall effect on adaptivity across the sample. This finding is particularly noteworthy given theoretical arguments that job crafting should enhance adaptive capabilities (Petrou et al., 2012; Vakola et al., 2023). Several factors may explain this unexpected pattern across all participants. From a mechanisms perspective, Vakola et al. (2023) specifically demonstrated that seeking resources (rather than optimizing demands) was the job crafting dimension that enhanced adaptive performance. Given that our intervention failed to improve the seeking resources dimension, the absence of adaptivity effects becomes more theoretically aligned, as the pathway that typically drives adaptivity improvements was not activated. Additionally, methodological factors may have limited our ability to detect adaptivity changes. Baseline adaptivity scores were high across both young and older participants, suggesting potential ceiling effects that constrained the range for improvement.

However, exploratory simple slopes revealed a significant age-related moderation: older participants reported lower adaptivity after the intervention, whereas younger participants did not differ. This unexpected finding can be better understood through the finding from recent job crafting research that empowerment interventions encourage older employees to build on existing strengths rather than develop loss-regulation strategies (Kooij et al., 2022). However, the latter may be crucial for adapting to disruptive AI-related change in which tasks, skillsets, and inherently job resources may shift in nature. In this context, older workers may not have strengthened the accommodative strategies needed to cope with disruption, while simultaneously being encouraged to stretch their existing resources (Kooij et al., 2022). This explanation aligns with the negative slope we observed among older participants. This pattern is consistent with broader research showing that older workers often experience skill mismatches, heightened uncertainty, and technostress when facing automation and digitalization, requiring stronger facilitating conditions to successfully adapt (Aisa et al., 2023). Our findings suggest that short, self-directed interventions focusing on autonomy may be insufficient, or even counterproductive, for older workers. Instead, more structured programs combining empowerment with concrete resource-seeking opportunities (e.g., mentoring and technical training) may be necessary to help older employees sustain adaptive responses to technological disruption (Chang et al., 2023).

5.2.2.2 Experience-related responsiveness

Multiple experience-related factors influenced how employees responded to the intervention. Employees with extensive AI experience showed less resource-seeking behaviors, suggesting they may have already developed such strategies through trial and error, making them less responsive to structured guidance. This aligns with expertise development literature indicating that interventions are most effective when addressing genuine skill gaps rather than reinforcing existing capabilities (Kluger & DeNisim, 1996).

Additional patterns emerged around other baseline characteristics. Employees with higher organizational tenure and work experience benefited more from the intervention in terms of seeking resources. This suggests their time and experience give them a better understanding and higher knowledge of what beneficial resources are available, and where to find them. In a slightly similar vein did Kooij et al. (2017) find more positive job crafting responsiveness (strength crafting) for older employees due to better insights in themselves (Kooij et al., 2017). When assuming that work experience and organizational tenure are related to time, and therefore age, our findings tentatively suggest similar results for seeking resources in AI settings.

5.3 Limitations and Future Research

5.3.1 External validity and generalizability

Several factors limit the generalizability of our findings to broader organizational contexts. First, voluntary participation may attracted employees who were already more motivated or positive about AI than the general working population. This self-selection bias may inflate intervention effects and limit generalizability to employees who are resistant or skeptical about AI.

Furthermore, contextual sample issues in this study's sample further limit external validity. The final sample included a substantial proportion of participants from a single Dutch organization (Veneta: 12/28 experimental, 8/33 control), yet organizational context was not controlled for in the analyses. This overrepresentation may limit the external validity of findings to other sectors, organizational cultures, and national contexts. Additionally, the convenience sampling approach and significant baseline differences in age and educational level between groups further constrain the generalizability of results to broader working populations. The control group was significantly older (M = 38.73 vs. 32.14 years) and more highly educated than the experimental group. These differences may affect how employees respond to AI training, as younger workers or those with different educational backgrounds might have different baseline comfort levels with technology or learning preferences (Riddell & Song, 2012; Venkatesh & Davis, 2000). Future research should aim to validate these findings by replicating the study in different organizational contexts. This could include sampling and comparison between technology-driven and traditional companies, or employees with different levels of AI expertise or skepticism.

Cultural and contextual factors also limit generalizability. Our findings emerged from a predominantly Dutch organizational context, which may not translate directly to countries with different workplace cultures, AI adoption rates, or regulatory environments. Organizations with varying levels of AI maturity, technological infrastructure, or employee AI experience may see different intervention outcomes.

Future research should replicate this study across different sectors, cultures, and countries with varying AI-maturity levels to test the generalizability of results. Additionally, studies should examine intervention effectiveness across different employee populations, including AI-skeptical workers and diverse demographic groups.

5.3.2 Internal validity and design

Several methodological factors may compromise the internal validity of our findings and limit our ability to draw strong causal conclusions. Substantial differential attrition between groups threatens external validity. The experimental group experienced considerably higher dropout rates (65.5%) compared to the control group (31.9%), potentially introducing systematic selection bias. Dropout analysis revealed that control group completers differed from dropouts on baseline proactivity levels, suggesting that the final sample may not be representative of the broader population of employees facing AI integration. This pattern appears to be a common challenge in online intervention research (Ghielen et al., 2018; Verelst et al., 2021). The demanding nature of multi-module training and daily goal-setting assignments may burden participants and lead to selective attrition of less motivated individuals (Rodríguez-Ardura & Meseguer-Artola, 2020). Future research my address these issues by reconsidering the design of the experiment. For example, by scheduling more time between events for the participants to “take a breath”, or breaking the training down into smaller modules.

The study design also involved methodological compromises that may affect internal validity. Although participant randomization was initially conducted using a systematic Python script, subsequent manual reallocation was necessary. Some Veneta employees were moved from experimental to control groups to address unexpected group imbalances. While this decision was made with careful consideration of potential contamination effects, such post-randomization adjustments may have introduced unknown biases. These biases potentially compromise the randomized controlled design.

Contamination between groups represents another validity concern. The online delivery format made it difficult to prevent control group participants from independently engaging in AI-related learning during the study period. Control participants could access AI tools, watch educational videos, or discuss AI applications with colleagues without our knowledge. This potential contamination could underestimate true intervention effects by improving control group performance. Future research may benefit from adding one or more items to the control group’s post measure that help control for such factors.

The brief 14-day interval between pre- and post-measurements raises questions about the sustainability of observed intervention effects. While significant improvements were found for Task-AI fit, optimizing demands, and AI usage frequency, it remains unclear whether these changes represent durable shifts or temporary responses. The changes could reflect lasting behavioral and cognitive improvements, or they might simply be temporary responses to the intervention stimulus (Van Wingerden et al., 2017). The absence of longer-term follow-up measurements prevents assessment of intervention effect persistence and potential decay over time. Furthermore, investigating mediation effects in cross sectional data is risky and may result in incorrect conclusions about mediating mechanisms (Maxwell & Cole, 2007). In future research, implementing at least three instead of two measurements over a longer period of time (e.g., pre-test, post-test, and a follow-up test three months later) may give more conclusive findings about causal and long-term effects.

Finally, the crossover design for control group participants introduced complexity in the analytical approach. While this design maximized recruitment and provided additional experimental data, it created analytical challenges. Crossover participants were excluded from the primary experimental sample due to demonstrated carry-over effects. This decision reduced the effective sample size and may have limited our ability to detect moderating effects or smaller intervention impacts.

5.3.3 Measurement and construct validity

Several measurement-related constraints may affect the precision and validity of our findings. The reliance on self-report measures throughout the study introduces risks of common method bias, social desirability responding, and leniency effects (Koopmans et al., 2014; Randall, 1991). These biases may be particularly pronounced for certain measures. For example, participants might feel pressure to rate their supervisors favorably when rating leader AI symbolization.

Scale modifications undertaken to improve reliability may have compromised construct validity and comparability with existing literature. Specifically, we removed two items from the seeking resources scale and one item from the adaptivity scale. While this improved internal consistency (Cronbach's α), it may have altered the constructs being measured. Although these modifications were theoretically justified, the lack of sensitivity analysis represents a methodological limitation. This complicates interpretation and cross-study comparison. Future research intending to use these scales would benefit from confirmatory factor analyses, to make sure that construct validity is maintained.

The use of ordinal scales for AI usage variables may have been suboptimal for our analytical approach. We measured frequency and types of use on ordinal scales but employed linear mixed-effects modeling. While mixed-effects models are relatively robust to violations of normality assumptions (Schielzeth et al., 2020), the ordinal nature of these key outcome variables ideally require non-parametric analytical approaches (Mircioiu & Atkinson, 2017). This may have affected the precision of effect size estimates and statistical inference. Future research should consider analyses approaches that are specifically appropriate for these ordinal data.

Finally, power constraints limit our ability to detect smaller effects. The final sample size ($N = 61$) was sufficient to detect the large effect sizes observed in our significant results, as confirmed by post-hoc power analyses (*power* > *0.99* for all significant effects). However, this sample size may have been insufficient to reliably detect smaller effects, such as those potentially present for seeking resources, Human-AI fit, or moderating effects of leader AI symbolization. The absence of significant effects for these variables may therefore reflect insufficient statistical power rather than genuine null effects. Future research should ensure that a sufficient sample size is attained to address these issues.

5.4 Practical implications

This study provides empirical support that a brief, online job crafting intervention can effectively empower employees to adapt to AI-integrated workplaces, yielding significant practical implications for both organizations and individual employees. The findings challenge purely technocentric implementation strategies by demonstrating that bottom-up, employee-driven work design is a critical complement to top-down AI integration efforts.

5.4.1 Organizational and Leadership Recommendations

Shift focus from passive AI acceptance to active employee agency: Traditional technology rollouts often focus on user acceptance and technical training. Our findings demonstrate the value of a sociotechnical approach that facilitates employees with the skills to proactively shape their interaction with AI. Organizations should therefore complement technical AI deployments with employee-focused programs that foster job crafting capabilities. The online, self-paced, and brief format of our intervention shows that such programs can be scalable, cost-effective, and implemented with minimal disruption to daily work.

Prioritize training on Task-AI fit and demand optimization: The intervention was most effective in enhancing Task-AI fit and optimizing demands behaviors. This suggests that practical training should focus on these concrete, actionable areas. Rather than abstract training on AI capabilities, organizations should guide employees in analyzing their specific tasks to identify where AI can add value and how they can streamline or simplify AI-related work processes. The mediation results indicate that focusing on these two areas not only increases AI usage but also serves as a powerful, indirect pathway to fostering essential behavioral competencies like proactivity and innovativeness.

Develop a nuanced strategy for increasing AI usage: Our results reveal that different dimensions of AI usage are driven by distinct mechanisms.

1. To increase frequency of AI use, interventions should focus on motivational aspects by helping employees optimize demands. Reducing friction and empowering employees to make AI-related work easier directly translates to more frequent engagement.
2. To increase the variety of AI applications, interventions must focus on a capability pathway by improving Task-AI fit. Employees expand their use of AI to new tasks only after they develop a clearer understanding of how AI's functionalities align with their specific work requirements.

Leverage leadership AI-Symbolization: The moderation findings reveal that leader AI engagement serves as a boundary condition for intervention success. Organizations should ensure managers actively demonstrate AI usage and share experiences before implementing employee-level interventions. This is not about mandating AI use, but about creating psychological safety through visible leadership engagement. Simple slopes analysis showed that without adequate leader symbolization, intervention benefits disappear, while high symbolization enables significant improvements.

5.4.2 Employee-Level Applications

Adopt a proactive "crafter" mindset: This research demonstrates that employees are not passive recipients of technology. Instead, they have the agency to shape how AI integrates into their work. Individual employees should feel empowered to move beyond simply adapting to AI. The primacy of demand optimization in driving multiple positive outcomes suggests that employees should begin their AI journey by identifying and restructuring inefficient work processes rather than immediately seeking additional resources or training. Practical applications include creating prompt libraries for recurring tasks, establishing clear workflows for AI-assisted activities, and strategically scheduling AI tasks during optimal energy periods, which are approaches that our intervention participants successfully implemented within a two-week timeframe.

Focus on Task-Fit Before Mastering the Tool: The distinction between the significant improvement in Task-AI fit versus the non-significant change in Human-AI fit offers a practical lesson. Instead of feeling overwhelmed by the need to become an "expert" in AI, employees can achieve better results by taking a task-centric approach. They should first analyze their specific tasks and then ask: "How can this AI tool help me with this specific activity?" This practical, bottom-up approach is more likely to lead to successful and meaningful AI use than a top-down focus on mastering all of a tool's features.

Recognize that Small Behavioral Changes Cultivate Broader Competencies: The mediation findings provide a powerful insight for personal development: key competencies like proactivity and innovativeness can emerge from concrete, daily behaviors. Employees should not feel pressured to be more innovative with AI. Instead, by focusing on the tangible goals of making a process more efficient (optimizing demands) or finding a better way to use AI for a report (improving Task-AI fit), they are laying the groundwork from which these valuable, future-proof competencies can enhance.

6. Conclusions

This study addressed the critical question: "Does an online self-training on job crafting increase employee behavioral competencies and improve effective employment of AI in an organization?" Our findings provide a clear affirmative answer with important nuances.

The intervention directly influenced AI usage frequency (d = 1.08), demand optimization behaviors (d = .87), and Task-AI fit (d = .81). Moreover, mediation analyses revealed that both demand optimization and improved Task-AI fit served as pathways that linked the intervention to enhanced proactivity and innovativeness. Furthermore, improved Task-AI fit arose as the pathway towards increased AI usage variety, whereas demand optimization appeared as additional indirect pathway towards increased AI usage frequency. These findings demonstrate that brief, structured job crafting training can systematically develop employee capabilities for AI-integrated work environments, moving beyond reactive adaptation to proactive workplace redesign.

Theoretically, this research makes several contributions. First, it offers the first empirical support for the integration of Human-Task-AI fit theory with the Job Demands-Resources model. Specifically, it shows how technical alignment translates into psychological and performance outcomes. Second, it adds support to why traditional technology acceptance models fall short in AI contexts, necessitating employee agency and work design perspectives. Third, it operationalizes job crafting theory for AI contexts, providing the first empirical support that structured interventions can develop these crucial capabilities.

For practice, our findings offer guidance for organizations implementing AI systems. Rather than relying on technical training only, organizations should invest in job crafting capabilities as well. The differential effectiveness across job crafting dimensions suggests to start with demand optimization and improving perceptual Task-AI fit, as these proved more immediately actionable than resource-seeking approaches. The dual mediation pathways suggest that improvements in these behaviors generate positive spillover effects to multiple work dimensions, thereby maximizing the intervention's impact.

Several limitations should be taken into account. The modest sample size (N = 61), varying attrition between groups, and the brief 14-day interval limit conclusions about robustness and sustainability. Furthermore, the varying effectiveness of the job crafting modules reveals that different strategies may require different approaches or longer development periods. Additionally, the voluntary participation may have attracted employees who were already motivated to improve in these topics, which limits generalizability to AI-resistant populations.

Future research should address these limitations through larger-scale, and longitudinal studies, to test the intervention's sustainability and examine optimal designs for different job crafting dimensions. Furthermore, as differences in AI experiences entail differential intervention responsiveness, personalized training approaches may be necessary. Lastly, testing the intervention across different cultures and sectors would establish broader generalizability of the intervention effectiveness.

In an era of ongoing AI-induced workplace changes, this research demonstrates the effectiveness of employee agency and job crafting interventions as a solution to help employees adapt. Consequently, it becomes crucial for organizations to complement their top-down AI-integration with this bottom-up work design approach. They should empower employees to proactively shape their AI-work relationships to foster employee development, performance, and well-being, ultimately improving their AI integration efforts. The key lies not in the technology itself, but in giving employees the tools and autonomy to make AI work for them.

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Appendices

Appendix 1: Baseline equivalences test

Final sample baseline descriptives and equivalences

Category	Variable	M (SD) Control	M (SD) Experimental	t(59)	p	Cohen's d
Demographics	Age	38.73 (12.61)	32.14 (12.16)	2.07	.043*	0.53
	Educational level	3.58 (0.79)	2.89 (1.03)	2.92	.005**	0.75
	Work experience	3.06 (1.09)	2.82 (1.16)	0.83	.409	0.21

	Time in organization	2.42 (1.15)	2.18 (1.33)	0.77	.442	0.20
	Experience AI	3.64 (1.60)	3.64 (1.75)	–0.02	.988	–0.00
Outcome variables	Seeking resources	3.20 (0.67)	3.13 (0.70)	0.40	.687	0.10
	Optimizing demands	3.60 (0.64)	3.59 (0.64)	0.04	.965	0.01
	Task–AI fit	3.67 (0.56)	3.67 (0.82)	–0.02	.987	–0.00
	Human–AI fit	3.56 (0.57)	3.60 (0.65)	–0.25	.806	–0.06
	Adaptivity	3.76 (0.57)	3.80 (0.60)	–0.31	.761	–0.08
	Proactivity	3.86 (0.48)	3.93 (0.62)	–0.50	.622	–0.13
	Innovativeness	3.57 (0.70)	3.60 (0.61)	–0.18	.859	–0.05
	Frequency of AI use	3.52 (1.66)	3.46 (1.71)	0.12	.907	0.03
	Types of use	3.79 (2.41)	3.89 (2.27)	–0.17	.862	–0.04
	Well-being	3.95 (0.52)	4.07 (0.46)	–0.96	.339	–0.25
	Performance	3.73 (0.39)	3.79 (0.41)	–0.65	.517	–0.17
	Engagement	3.76 (0.72)	3.85 (0.63)	–0.50	.618	–0.13
	Workload	3.63 (0.72)	3.63 (0.78)	–0.03	.979	–0.01
	Exhaustion	2.53 (0.56)	2.57 (0.59)	–0.31	.761	–0.08
	AI symbolization	3.25 (0.94)	3.33 (0.95)	–0.36	.724	–0.09
	Human–AI teaming	3.22 (0.53)	3.17 (0.55)	0.34	.734	0.09

General attitudes	3.94 (0.49)	3.95 (0.60)	−0.05	.960	−0.01
Evaluation	3.64 (0.64)	3.82 (0.65)	−1.12	.267	−0.29
Interface autonomy	3.76 (0.51)	3.88 (0.62)	−0.84	.406	−0.22
Task competence	3.74 (0.50)	3.70 (0.44)	0.38	.707	0.10
Autonomy	4.11 (0.45)	4.10 (0.65)	0.11	.912	0.03

Note. M = mean; *SD* = standard deviation. Independent-samples *t*-tests (two-tailed) with homogeneity of variances checked via Levene's test; Welch's correction was applied when variances were unequal. Degrees of freedom vary per variable due to missingness (df ≈ 59). Cohen's *d* = ($M_{control}$ − $M_{experimental}$) / SD_{pooled}. $p < .05$, *$p < .01$.

Appendix 2: Descriptive statistic additional outcome variables

Descriptive Statistics for Additional Outcome Variables by Group and Time

Variable	Control Group (n = 33)		Experimental Group (n = 28)	
	Pre-intervention	Post-intervention	Pre-intervention	Post-intervention
Well-being & Performance				
Well-being	4.00 [0.33]	4.00 [0.33]	4.00 [0.33]	4.06 (0.38)
Performance	3.75 [0.50]	3.75 [0.75]	3.75 [0.50]	3.78 (0.38)
Engagement	4.00 [0.33]	4.00 [0.33]	3.83 (0.70)	3.96 (0.55)
Exhaustion	2.38 [0.50]	2.56 (0.52)	2.59 (0.61)	2.47 (0.48)
AI Attitudes & Evaluation				
General Attitudes	3.94 (0.49)	4.00 [0.25]	3.96 (0.59)	4.00 [0.25]
AI Evaluation	3.64 (0.64)	3.67 (0.50)	3.82 (0.65)	3.90 [0.45]
Human-AI Teaming	3.00 [0.89]	3.36 (0.50)	3.17 (0.55)	3.33 (0.60)
Work Environment				
Workload	3.63 (0.72)	3.56 (0.61)	3.63 (0.78)	3.65 (0.71)
Autonomy	4.00 [0.67]	4.00 [0.67]	4.17 [0.92]	4.00 [1.00]

Interface Autonomy	3.76 (0.51)	3.70 (0.58)	3.88 (0.62)	3.82 (0.58)
Task Competence	3.74 (0.50)	3.75 [0.50]	3.70 (0.44)	3.86 (0.33)
Leadership				
AI Symbolization	3.25 (0.94)	3.21 (1.01)	3.33 (0.95)	3.04 (0.98)

Note. Values represent means (standard deviations) for normally distributed variables and medians [interquartile ranges] for non-normally distributed variables. All variables measured on 5-point Likert scales.

Appendix 3: Main intervention effects

Main Intervention Effects: Confirmatory Analyses (Linear Mixed Models)

Outcome	B	SE	t	p	d	95% CI
Frequency of AI use	0.62	0.21	2.98	.004**	1.08	[0.21, 1.03]
Optimizing Demands	0.28	0.12	2.40	.020*	0.87	[0.05, 0.50]
Task–AI fit	0.31	0.14	2.23	.030*	0.81	[0.04, 0.59]
Adaptivity	−0.21	0.13	−1.61	.112	−0.59	[−0.45, 0.04]
Human–AI fit	0.14	0.09	1.48	.142	0.54	[−0.07, 0.49]
Types of AI use	−0.49	0.44	−1.12	.268	−0.41	[−1.35, 0.37]
Innovativeness	−0.06	0.11	−0.54	.591	−0.20	[−0.27, 0.16]
Proactivity	−0.01	0.14	−0.10	.917	−0.04	[−0.29, 0.26]
Seeking Resources	0.00	0.14	0.02	.986	0.01	[−0.27, 0.28]

Note. N = 61 participants (122 observations). B = unstandardized coefficient for the Group × Time interaction; SE = standard error; t = t-value; p = two-tailed p-value; d = Cohen's d; 95% CI = 95% confidence interval for B. *p < .05. **p < .01.

Appendix 4: Mediation analysis

Mediator	Outcome	a-Path (*B*)	p(a)	b-Path (*B*)	p(b)	Indirect (95% CI)	Bootstrap p	Mediation Type
Optimizing Demands	Proactivity	0.277	.020*	0.458	<.001**	0.127 [0.023, 0.242]	.014*	Full
	Innovativeness	0.277	.020*	0.307	.001**	0.085 [0.011, 0.197]	.022*	Full

	Frequency of AI use	0.277	.020*	0.504	.010*	0.139 [0.013, 0.338]	.026*	Partial
	Types of Use	0.277	.020*	0.596	.098	0.165 [−0.014, 0.462]	.090	Marginal
Task–AI Fit	Proactivity	0.314	.030*	0.212	.009**	0.067 [0.004, 0.144]	.030*	Full
	Innovativeness	0.314	.030*	0.203	.012*	0.064 [0.001, 0.160]	.046*	Full
	Types of Use	0.314	.030*	1.028	.001**	0.323 [0.031, 0.795]	.020*	Full
	Frequency of AI use	0.314	.030*	0.385	.024*	0.121 [−0.021, 0.367]	.112	Marginal

Note. N = 61. a-Path = effect of intervention (Group × Time) on mediator; b-Path = effect of mediator on outcome controlling for intervention; Indirect = a × b with 95% bootstrap confidence interval; Bootstrap p = p-value for indirect effect; *p < .05; **p < .01

Appendix 5: Moderation Analyses

AI Symbolization as Moderator of Group × Time Effects (Linear Mixed Models)

Outcome	B (3-Way)	SE	t	p	B (Simple Slope)	p
Optimizing Demands Score	0.22	0.12	1.82	.073†	0.27	.018*
Seeking Resources Score	0.05	0.15	0.30	.764	0.00	.999

Note. N = 61. B = unstandardized coefficient for the Group × Time × Moderator interaction (“3-Way”) and for the simple slope of Group × Time at +1 SD of the moderator; SE = standard error; t = t-value; p = two-tailed p-value. †p < .10; *p < .05.

Appendix 6: Exploratory main effects

Exploratory Main Effects: Group × Time Interaction (Linear Mixed Models)

Outcome	B	SE	t	p	d	95% CI
Exhaustion Score	−0.14	0.08	−1.77	.081†	−0.64	[−0.30, 0.01]
General Attitudes Score	0.17	0.12	1.39	.169	0.51	[−0.07, 0.41]
Human–AI Teaming Score	0.14	0.12	1.24	.221	0.45	[−0.08, 0.37]

Well-being Score	0.17	0.14	1.17	.246	0.43	[−0.11, 0.45]
AI Symbolization Score	−0.26	0.25	−1.05	.298	−0.38	[−0.75, 0.23]
Task Competence Score	0.07	0.09	0.86	.392	0.31	[−0.09, 0.24]
Engagement Score	0.09	0.11	0.81	.420	0.30	[−0.13, 0.30]
Performance Score	0.07	0.10	0.73	.471	0.26	[−0.12, 0.27]
Autonomy Score	0.07	0.15	0.46	.649	0.17	[−0.23, 0.36]
Evaluation Score	0.06	0.13	0.43	.668	0.16	[−0.20, 0.31]
Workload Score	0.03	0.13	0.25	.807	0.09	[−0.23, 0.29]
Interface Autonomy Score	−0.01	0.14	−0.08	.938	−0.03	[−0.28, 0.26]

Note. N = 61 participants (122 observations). B = unstandardized coefficient for the Group × Time interaction; SE = standard error; t = t-value; p = two-tailed p-value; d = Cohen's d; 95% CI = 95% confidence interval for B. †p < .10; *p < .05; **p < .01.

Appendix 7: Exploratory mediation effects

Exploratory Mediation Analysis Results: Linear Mixed Models with Bootstrap CIs

Mediator	Outcome	a-Path (B)	b-Path (B)	Indirect (B)	95% CI	Bootstrap p	Mediation Type
Optimizing Demands	General Attitudes	0.277	0.279	0.077	[0.010, 0.175]	0.008	Full
Task AI Fit	Evaluation	0.314	0.547	0.171	[0.037, 0.333]	0.012	Full
Optimizing Demands	Well Being	0.277	0.214	0.059	[0.011, 0.136]	0.012	Full
Task AI Fit	General Attitudes	0.314	0.363	0.114	[0.022, 0.248]	0.016	Full
Optimizing Demands	Autonomy	0.277	0.308	0.085	[0.015, 0.200]	0.016	Full
Optimizing Demands	Evaluation	0.277	0.279	0.077	[0.009, 0.182]	0.016	Full
Task AI Fit	Human AI Teaming	0.314	0.459	0.144	[0.022, 0.289]	0.020	Full
Task AI Fit	Well Being	0.314	0.339	0.106	[0.013, 0.198]	0.028	Full
Optimizing Demands	Human AI Teaming	0.277	0.222	0.061	[0.003, 0.163]	0.036	Full

Optimizing Demands	Interface Autonomy	0.277	0.208	0.058	[0.002, 0.144]	0.040	Full
Task AI Fit	Interface Autonomy	0.314	0.277	0.087	[0.002, 0.185]	0.048	Full
Task AI Fit	Workload	0.314	0.245	0.077	[-0.006, 0.191]	0.060	Marginal
Human AI Fit	Human AI Teaming	0.210	0.500	0.105	[-0.018, 0.279]	0.108	None
Human AI Fit	Evaluation	0.210	0.520	0.109	[-0.016, 0.272]	0.112	None
Human AI Fit	General Attitudes	0.210	0.363	0.076	[-0.021, 0.205]	0.116	None
Human AI Fit	Well Being	0.210	0.339	0.071	[-0.020, 0.186]	0.132	None
Human AI Fit	Autonomy	0.210	0.308	0.065	[-0.024, 0.182]	0.136	None
Human AI Fit	Interface Autonomy	0.210	0.277	0.058	[-0.021, 0.151]	0.140	None
Human AI Fit	Workload	0.210	0.245	0.051	[-0.019, 0.134]	0.144	None
Human AI Fit	Task Competence	0.210	0.196	0.041	[-0.029, 0.109]	0.148	None
Human AI Fit	Exhaustion	0.210	-0.017	-0.004	[-0.047, 0.039]	0.156	None
Seeking Resources	General Attitudes	0.003	0.044	0.000	[-0.031, 0.025]	0.992	None
Seeking Resources	Evaluation	0.003	0.138	0.000	[-0.040, 0.052]	0.980	None
Seeking Resources	Human AI Teaming	0.003	0.127	0.000	[-0.037, 0.045]	0.984	None
Seeking Resources	Well Being	0.003	0.024	0.000	[-0.013, 0.022]	0.844	None
Seeking Resources	Autonomy	0.003	-0.080	-0.000	[-0.029, 0.038]	0.916	None
Seeking Resources	Interface Autonomy	0.003	-0.041	-0.000	[-0.031, 0.026]	0.988	None

Seeking Resources	Workload	0.003	0.160	0.000	[-0.059, 0.047]	0.956	None
Seeking Resources	Task Competence	0.003	-0.120	-0.000	[-0.027, 0.043]	0.968	None
Optimizing Demands	Task Competence	0.277	0.020	0.006	[-0.035, 0.045]	0.792	None
Optimizing Demands	Exhaustion	0.277	-0.017	-0.005	[-0.040, 0.037]	0.816	None
Optimizing Demands	Workload	0.277	-0.007	-0.002	[-0.088, 0.079]	0.864	None
Optimizing Demands	Autonomy	0.277	0.308	0.085	[0.015, 0.200]	0.016	Full
Optimizing Demands	Interface Autonomy	0.277	0.208	0.058	[0.002, 0.144]	0.040	Full
Task AI Fit	Evaluation	0.314	0.547	0.171	[0.037, 0.333]	0.012	Full
Task AI Fit	General Attitudes	0.314	0.363	0.114	[0.022, 0.248]	0.016	Full

Appendix 8: Exploratory moderation effects

Exploratory Moderation Analyses: Group × Time × Moderator Interactions (Linear Mixed Models)

Outcome	Moderator	B	SE	t	df	p	95% CI
Adaptivity	AI experience	–0.020	0.077	–0.26	61	.796	[–0.171, 0.131]
Autonomy	AI experience	0.038	0.091	0.42	61	.677	[–0.141, 0.218]
Engagement	AI experience	–0.071	0.065	–1.09	61	.281	[–0.198, 0.057]

Evaluation	AI experience	–0.125	0.078	–1.61	61	.113†	[–0.278, 0.027]
Exhaustion	AI experience	–0.060	0.048	–1.26	61	.214	[–0.153, 0.033]
Frequency of AI use	AI experience	0.133	0.124	1.07	61	.289	[–0.110, 0.375]
General Attitudes	AI experience	–0.032	0.074	–0.44	61	.664	[–0.178, 0.113]
Human–AI Fit	AI experience	0.034	0.085	0.40	61	.687	[–0.132, 0.200]
Human–AI Teaming	AI experience	0.021	0.070	0.31	61	.760	[–0.116, 0.159]
Innovativeness	AI experience	0.041	0.066	0.62	61	.540	[–0.089, 0.170]
Interface Autonomy	AI experience	–0.005	0.083	–0.06	61	.949	[–0.169, 0.158]
Optimizing Demands	AI experience	0.030	0.070	0.43	61	.672	[–0.107, 0.167]
Performance	AI experience	0.035	0.060	0.58	61	.565	[–0.083, 0.152]
Proactivity	AI experience	0.004	0.085	0.04	61	.967	[–0.163, 0.170]
Seeking Resources	AI experience	0.173	0.082	2.12	61	.039*	[0.013, 0.333]
Task Competence	AI experience	–0.032	0.052	–0.62	61	.538	[–0.134, 0.070]
Task–AI Fit	AI experience	0.124	0.083	1.50	61	.140	[–0.038, 0.287]
Types of Use	AI experience	0.144	0.260	0.55	61	.582	[–0.365, 0.653]
Well-being	AI experience	–0.068	0.087	–0.78	61	.438	[–0.239, 0.103]
Workload	AI experience	0.045	0.114	0.39	61	.699	[–0.181, 0.271]
Adaptivity	Tenure (Time at organization)	–0.266	0.111	–2.40	61	.020*	[–0.487, –0.045]

Autonomy	Tenure (Time at organization)	–0.009	0.132	–0.07	61	.946	[–0.272, 0.254]
Engagement	Tenure (Time at organization)	–0.071	0.094	–0.75	61	.457	[–0.257, 0.115]
Evaluation	Tenure (Time at organization)	–0.039	0.112	–0.35	61	.729	[–0.263, 0.185]
Exhaustion	Tenure (Time at organization)	–0.005	0.068	–0.07	61	.945	[–0.142, 0.132]
Frequency of AI use	Tenure (Time at organization)	0.107	0.174	0.62	61	.538	[–0.238, 0.452]
General Attitudes	Tenure (Time at organization)	–0.094	0.104	–0.90	61	.372	[–0.300, 0.112]
Human–AI Fit	Tenure (Time at organization)	0.023	0.120	0.20	61	.840	[–0.216, 0.262]
Human–AI Teaming	Tenure (Time at organization)	–0.049	0.099	–0.49	61	.627	[–0.246, 0.148]
Innovativeness	Tenure (Time at organization)	0.090	0.094	0.96	61	.339	[–0.097, 0.277]
Interface Autonomy	Tenure (Time at organization)	0.034	0.124	0.28	61	.781	[–0.212, 0.281]
Optimizing Demands	Tenure (Time at organization)	0.037	0.102	0.36	61	.719	[–0.167, 0.241]
Performance	Tenure (Time at organization)	0.022	0.087	0.25	61	.804	[–0.152, 0.196]
Proactivity	Tenure (Time at organization)	–0.044	0.126	–0.35	61	.726	[–0.294, 0.206]
Seeking Resources	Tenure (Time at organization)	–0.246	0.143	–1.72	61	.090†	[–0.531, 0.039]
Task Competence	Tenure (Time at organization)	–0.109	0.083	–1.32	61	.193	[–0.275, 0.057]
Task–AI Fit	Tenure (Time at organization)	0.217	0.126	1.72	61	.091†	[–0.035, 0.469]
Types of Use	Tenure (Time at organization)	0.239	0.394	0.61	61	.543	[–0.540, 1.018]
Well-being	Tenure (Time at organization)	–0.102	0.128	–0.80	61	.427	[–0.358, 0.154]

Workload	Tenure (Time at organization)	–0.039	0.110	–0.35	61	.726	[–0.257, 0.179]
Adaptivity	Work experience	–0.283	0.121	–2.34	61	.023*	[–0.520, –0.045]
Autonomy	Work experience	0.067	0.143	0.47	61	.639	[–0.217, 0.351]
Engagement	Work experience	–0.041	0.102	–0.40	61	.690	[–0.243, 0.161]
Evaluation	Work experience	–0.041	0.124	–0.33	61	.742	[–0.289, 0.207]
Exhaustion	Work experience	–0.009	0.075	–0.12	61	.905	[–0.158, 0.140]
Frequency of AI use	Work experience	0.180	0.180	1.00	61	.320	[–0.179, 0.539]
General Attitudes	Work experience	0.081	0.111	0.73	61	.467	[–0.136, 0.298]
Human–AI Fit	Work experience	0.105	0.127	0.83	61	.409	[–0.143, 0.354]
Human–AI Teaming	Work experience	0.004	0.105	0.04	61	.969	[–0.202, 0.210]
Innovativeness	Work experience	0.009	0.099	0.10	61	.924	[–0.185, 0.204]
Interface Autonomy	Work experience	0.060	0.124	0.48	61	.631	[–0.184, 0.304]
Optimizing Demands	Work experience	0.062	0.104	0.60	61	.550	[–0.141, 0.266]
Performance	Work experience	0.084	0.089	0.95	61	.345	[–0.089, 0.258]
Proactivity	Work experience	–0.050	0.127	–0.39	61	.696	[–0.299, 0.199]
Seeking Resources	Work experience	–0.283	0.121	–2.34	61	.023*	[–0.520, –0.045]
Task Competence	Work experience	–0.068	0.078	–0.87	61	.386	[–0.220, 0.084]
Task–AI Fit	Work experience	0.043	0.127	0.34	61	.737	[–0.206, 0.292]

Types of Use	Work experience	–0.276	0.395	–0.70	61	.486	[–1.050, 0.497]
Well-being	Work experience	0.119	0.130	0.91	61	.364	[–0.135, 0.372]
Workload	Work experience	0.046	0.118	0.39	61	.699	[–0.186, 0.278]

Note. N = 61 for all models. B = unstandardized coefficient for the Group × Time × Moderator interaction; SE = standard error; t = t-value; df = degrees of freedom; p = two-tailed p-value († p < .10; * p < .05); 95% CI = 95% confidence interval for B.

Appendix 9: Simple slopes analyses exploratory moderation analyses

Outcome	Moderator	Moderator Level	Moderator Value	Intervention Effect (B)	SE	t	p	95% CI	Cohen's d
Seeking Resources	Time at Organization	Low (-1 SD)	-1.227	-0.324	0.200	-1.624	.109	[-0.72, 0.07]	-0.468
		Mean (0)	0.000	-0.004	0.141	-0.028	.978	[-0.28, 0.27]	-0.006
		High (+1 SD)	1.227	0.316	0.199	1.588	.117	[-0.07, 0.71]	0.456
Seeking Resources	Work Experience	Low (-1 SD)	-1.112	-0.329	0.197	-1.665	.101	[-0.72, 0.06]	-0.474
		Mean (0)	0.000	-0.019	0.140	-0.136	.892	[-0.29, 0.26]	-0.028
		High (+1 SD)	1.112	0.290	0.199	1.461	.149	[-0.10, 0.68]	0.419
Seeking Resources	AI Experience	Low (-1 SD)	-1.647	0.289	0.199	1.452	.151	[-0.10, 0.68]	0.417
		Mean (0)	0.000	-0.011	0.140	-0.076	.940	[-0.29, 0.26]	-0.015

Outcome	Moderator	Moderator Level	Moderator Value	Intervention Effect (B)	SE	t	p	95% CI	Cohen's d
		High (+1 SD)	1.647	-0.310	0.199	-1.557	.124	[-0.70, 0.08]	-0.447
Seeking Resources	Age	Low (-1 SD)	-12.683	-0.306	0.204	-1.499	.139	[-0.71, 0.09]	-0.442
		Mean (0)	0.000	-0.026	0.147	-0.178	.859	[-0.31, 0.26]	-0.038
		High (+1 SD)	12.683	0.254	0.213	1.189	.239	[-0.16, 0.67]	0.366
Adaptivity	Age	Low (-1 SD)	-12.683	0.089	0.177	0.506	.615	[-0.26, 0.44]	0.179
		Mean (0)	0.000	-0.194	0.127	-1.524	.132	[-0.44, 0.06]	-0.388
		High (+1 SD)	12.683	-0.477	0.185	-2.586	.012*	[-0.84, -0.12]	-0.955

Appendix 10: Measurement Instrument

Pre-Measure

Start van blok: Consent

<p data-end="72" data-start="49"><strong data-end="70" data-start="49">Dear participant,
 </p> <p data-end="262" data-start="74">Thank you for taking part in this study. This research focuses on how employees deal with AI-related changes in their work and how they can optimize their way of working in this context.</p> <p data-end="602" data-start="264">By participating, you help us gain a better understanding of how people adapt to the rise of AI in the workplace. You will answer some questions about your experiences and work approach.

The questionnaire takes approximately 30 minutes to complete. There are no right or wrong answers – it is about your personal opinion and experience.
 </p> <p data-end="658" data-start="604">Thank you in advance for your time and contribution!
 </p> <p data-end="713" data-is-last-node="" data-is-only-node="" data-start="660"><strong data-end="677" data-start="660">Best regards,<br data-end="680" data-start="677" /> The research team of TU Eindhoven</p>

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For more information about this study, your rights as a participant, and how the data is handled, please read the informed consent form: Informed consent

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*

By signing this form, I declare that:

- ☐ I have obtained sufficient information about the research project from the separate information sheet. I have read the information sheet and have had the opportunity to ask questions afterward. My questions have been answered to my satisfaction.
- ☐ I am voluntarily participating in this research project. There is no explicit or implicit pressure for me to take part in this study. I understand that I can withdraw from participation at any time without having to explain why, and that I am not required to answer any questions I do not wish to answer.
- ☐ I am aware that my personal data will be collected and used for the research project, as explained in the attached information sheet.

Einde blok: Consent

Start van blok: Blok 9

Watch the video below (English subtitles available):

 <iframe allowfullscreen="true" frameborder="0" height="550" scrolling="no" src="https://www.youtube.com/embed/3b8aOxitBQY?si=Jst2RjJeS-GBbQrM" width="1000"></iframe>

Einde blok: Blok 9

Start van blok: Demographics

What is your gender?

- ○ Male
- ○ Female
- ○ Other: ____
- ○ I would rather not say

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*

What is your age?

____

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What is your level of education? (select the highest achieved)

- ◯ Highschool
- ◯ Vocational education
- ◯ Bachelor's degree
- ◯ Master's degree
- ◯ PhD / Doctorate
- ◯ Other, namely: ____

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How many years of experience do you have as a professional?

- ○ 0-2
- ○ 3-5
- ○ 5-10
- ○ 10+

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How many years have you been working for your current employer?

- ◯ 0-1
- ◯ 2-3
- ◯ 4-5
- ◯ 5+

Do you work at Veneta.com?

- ◯ Yes
- ◯ No

Which department do you work in? (Only general insights are shared with Veneta. Individual information/data remains inaccessible to Veneta)

- ◯ Human Resources
- ◯ Product Owners
- ◯ Inside Sales

In which industry do you work (e.g., finance, human resources, etc.)

____

____

____

____

How would you evaluate your experience with the use of AI in your work?

- ◯ Beginner – I have only recently started using AI or I have minimal experience with it.
- ◯ Incidental user – I use AI tools now and then, but it's not central to my work.
- ◯ Regular user – I use AI regularly as part of my work process and understand its applications well.
- ◯ Advanced user – I make intensive use of AI tools, optimize their usage and work with various AI applications to improve my work.

Einde blok: Demographics

Start van blok: Job crafting

A job and work environment contain different work aspects that can be supportive or demanding. Which aspects have an influence on you?

Below are a number of statements about behavior at work. The purpose is for you to indicate to what extent you display this behavior in your work.

	Never	Rarely	Regularly	Often	Always
I make sure that I can decide myself how to do my work	○	○	○	○	○
I make sure that I have sufficient variety in my work activities.	○	○	○	○	○
I ask others for feedback on my performance	○	○	○	○	○
I ask my collueges for advice	○	○	○	○	○
I ask my supervisor for advice	○	○	○	○	○

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To what extent do you exhibit the following behavior at your work?

	Never	Rarely	Regularly	Often	Always
I simplify work processes or procedures to make my job easier.	○	○	○	○	○
I come up with solutions to accomplish my work in an easier way.	○	○	○	○	○
I improve work processes or procedures to make my job easier.	○	○	○	○	○
I look for ways to do my work more efficiently.	○	○	○	○	○
I change work processes or procedures which delay my work.	○	○	○	○	○

Einde blok: Job crafting

Start van blok: Human-Task-AI fit

The following questions are about your experience or expectations of how the AI helps you complete your tasks.
 <div style="margin-left:8px">- If you have already used the AI system, please base your answers on your actual experience.</div> <div style="margin-bottom:11px; margin-left:8px">- If you have not used the AI system yet, answer based on how you think the system will perform in the future.</div> In helping me to

perform the assigned task(s), the functionalities of the AI are/will be:

	1	2	3	4	5	
Very inadequate	◯	◯	◯	◯	◯	Very adequate
Very inapproapriate	◯	◯	◯	◯	◯	Very compatible with the task
Not useful at all	◯	◯	◯	◯	◯	Very useful
Very compatible with the task	◯	◯	◯	◯	◯	Very compatible with the task
Not helpful at all	◯	◯	◯	◯	◯	Very helpful
Not sufficient at all	◯	◯	◯	◯	◯	Very sufficient
Did not make the task easy at all	◯	◯	◯	◯	◯	Made the task very easy
In general, did not fit the task at all	◯	◯	◯	◯	◯	Best fit the task

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In this section, you answer questions about how well the AI system aligns with your skills, needs, and task requirements.

 Have you not used the AI system yet? Then answer the questions based on how you think the system will work in the future. Try to imagine how the system would work together with your skills and needs while performing your tasks.

 <span style="font-

family:"Calibri",sans-serif">How would you rate the following statements regarding your collaboration with the AI System ?

	Completely disagree	Disagree	Neutral	Agree	Completely agree
I can complete my tasks working with the AI system	○	○	○	○	○
I can improve my task performance working with the AI system	○	○	○	○	○
Working with the AI helps me to achieve my task requirements	○	○	○	○	○
It is easy to understand and use the AI system to perform my tasks	○	○	○	○	○
The AI system supports me in this task by providing what I need to complete it effectively	○	○	○	○	○
The AI system complements my skills in performing my tasks	○	○	○	○	○
Overall, the AI system fits well with my needs, my skills, and the requirements of the task.	○	○	○	○	○

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How would you rate the following statements regarding your collaboration with the AI System?

	Completely disagree	Disagree	Neutral	Agree	Completely agree
When working with the AI system, I feel that the AI system relieves me of tasks I am less inclined to do myself.	○	○	○	○	○
When working with the AI system, we can achieve more together than I or the AI system can alone.	○	○	○	○	○
The AI system takes on important complementary tasks that I would otherwise not get to due to lack of time.	○	○	○	○	○
When working together with the AI system, we complement each other ideally.	○	○	○	○	○
Working with the AI system means I can concentrate fully on the important aspects of my work.	○	○	○	○	○
The AI system takes over tasks that I actually enjoy and would rather do myself.	○	○	○	○	○

Working with the AI system leads to me only doing leftover work that actually bores me.	○	○	○	○	○
When working with the AI, at the end of the day I ask if I want to continue this work.	○	○	○	○	○
I feel like a real team when working with the AI.	○	○	○	○	○
Working with the AI system allows me to develop more creative solutions.	○	○	○	○	○
Working with the AI system inspires me.	○	○	○	○	○
Working with the AI system makes me feel like I'm part of a real team.	○	○	○	○	○

Einde blok: Human-Task-AI fit

Start van blok: System attitudes

It is important for us to know whether you already use AI and what your attitude and opinion is about AI.

The average number of times I use AI per week is:

- ◯ 0 times
- ◯ 1-2 times
- ◯ 3-5 times
- ◯ 6-10 times
- ◯ 11-15 times
- ◯ 15+ times

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Complete the sentence:

 I use AI for __ different types of tasks (e.g., translation, summarizing, structuring, etc.)

- ◯ 1
- ◯ 2
- ◯ 3
- ◯ 4
- ◯ 5
- ◯ 6
- ◯ 7
- ◯ 8
- ◯ 9
- ◯ 10+

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Your attitude toward AI in general:

	Completely disagree	Disagree	Neutral	Agree	Completely agree
I believe that AI will improve my life.	○	○	○	○	○
I believe that AI will improve my work.	○	○	○	○	○
I think I will use AI technology in the future.	○	○	○	○	○
I think AI technology is positive for humanity.	○	○	○	○	○

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I find/experience the support of generative AI

	1	2	3	4	5	
Very bad	○	○	○	○	○	Very good
Very foolish	○	○	○	○	○	Very wise
Very unfavorable	○	○	○	○	○	Very favorable
Very harmful	○	○	○	○	○	Very benificial
Very negative	○	○	○	○	○	Very positive

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To what extent do you agree with these statements about your well-being while working with AI?

	Completely disagree	Disagree	Neutral	Agree	Completely agree
I feel comfortable working with the AI system.	○	○	○	○	○
I can imagine that working with such an AI system will be fun for me in the long run.	○	○	○	○	○
I can imagine that working with such an AI system will help me in the long run.	○	○	○	○	○

Einde blok: System attitudes

Start van blok: Work characteristics

Work characteristics may affect how you use AI. This section examines some of those characteristics.

How do you rate the following statements about your workload?

	Completely disagree	Disagree	Neutral	Agree	Completely agree
I have to work very fast.	○	○	○	○	○
I have a lot of work to do.	○	○	○	○	○
I have to work extra hard to get something done.	○	○	○	○	○
I work under time pressure.	○	○	○	○	○

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How do you rate the following statements about autonomy in your job?

	Completely disagree	Disagree	Neutral	Agree	Completely agree
Do you have freedom in carrying out your tasks?	○	○	○	○	○
Can you decide for yourself how to perform your work?	○	○	○	○	○
Can you participate in decisions that affect your work?	○	○	○	○	○

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How do you rate the following statements about engagement?

	Completely disagree	Disagree	Neutral	Agree	Completely agree
At my work, I feel bursting with energy	○	○	○	○	○
I am enthusiastic about my job	○	○	○	○	○
I am immersed in my work	○	○	○	○	○

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How do you rate the following statements about your energy at work?

	Completely disagree	Disagree	Neutral	Agree	Completely agree
There are days when I feel tired before I arrive at work	◯	◯	◯	◯	◯
After work, I tend to need more time than in the past in order to relax and feel better	◯	◯	◯	◯	◯
I can tolerate the pressure of my work very well	◯	◯	◯	◯	◯
During my work, I often feel emotionally drained	◯	◯	◯	◯	◯
After working, I have enough energy for my leisure activities	◯	◯	◯	◯	◯
After my work, I usually feel worn out and weary	◯	◯	◯	◯	◯
Usually, I can manage the amount of my work well	◯	◯	◯	◯	◯
When I work, I usually feel energized	◯	◯	◯	◯	◯

Pagina-einde

How do you rate the following statements about performance?

	Completely disagree	Completely disagree	Neutral	Agree	Completely agree
I almost always perform better than an acceptable level.	○	○	○	○	○
I often perform better than can be expected from me.	○	○	○	○	○
I often put extra effort in my work.	○	○	○	○	○
I intentionally expend a great deal of effort in carrying out my job.	○	○	○	○	○

Einde blok: Work characteristics

Start van blok: Psychological needs

How do you rate the following statements about interface competence?
 (Interface competence refers to how skilled and confident you feel when using the technology. This includes whether you find the interface easy to understand and use.)

	Completely disagree	Disagree	Neutral	Agree	Completely agree
I feel very capable and effective at using the technology.	○	○	○	○	○
I feel confident in my ability to use the technology.	○	○	○	○	○
Learning how to use the technology was difficult.	○	○	○	○	○
I found the interface and controls confusing.	○	○	○	○	○
It wasn’t easy to use this technology.	○	○	○	○	○

How do you rate the following statements about interface autonomy?

	Completely disagree	Disagree	Neutral	Agree	Completely agree
The technology provides me with useful options and choices.	○	○	○	○	○
I can get the technology to do the things I want it to.	○	○	○	○	○
I feel pressured by the technology.	○	○	○	○	○
The technology feels intrusive.	○	○	○	○	○
The technology feels controlling.	○	○	○	○	○

Pagina-einde

How do you rate the following statements about task competence?

	Completely disagree	Disagree	Neutral	Agree	Completely agree
I feel confident in my ability to do my tasks	○	○	○	○	○
It is easy to do my tasks	○	○	○	○	○
I find my tasks too challenging	○	○	○	○	○
I find the tasks too difficult to do regularly.	○	○	○	○	○

Einde blok: Psychological needs

Start van blok: Competencies

How do you rate the following statements about adaptability

	Completely disagree	Disagree	Neutral	Agree	Completely agree
I adapt well to changes in core tasks	○	○	○	○	○
I cope with changes to the way I have to do my core tasks	○	○	○	○	○
I learn new skills that help me adapt to changes in my core tasks	○	○	○	○	○

Pagina-einde

How do you rate the following statements about proactivity?

	Completely disagree	Disagree	Neutral	Agree	Completely agree
I initiate better ways of doing my core tasks	○	○	○	○	○
I come up with ideas to improve the way in which my core tasks can be done	○	○	○	○	○
I make changes to the way my core tasks are done	○	○	○	○	○

Pagina-einde

How do you rate the following statements about innovativeness?

	Completely disagree	Disagree	Neutral	Agree	Completely agree
At work I sometimes demonstrate originality.	○	○	○	○	○
My work requires me to make innovative decisions.	○	○	○	○	○
I make time to pursue my own ideas or projects.	○	○	○	○	○
I am constantly thinking of new ideas to improve my workplace.	○	○	○	○	○
Among my colleagues I am the first one to try. new ideas and methods	○	○	○	○	○

Einde blok: Competencies

Start van blok: Organizational influences

A leader's attitude can influence the attitude and opinions of team members

How do you rate the following statements about your leader's attitude towards AI?

	Completely disagree	Disagree	Neutral	Agree	Completely agree
My supervisor initiates discussions related to artificial intelligence (AI) with me.	○	○	○	○	○
My supervisor expresses his or her interest in AI to me.	○	○	○	○	○
My supervisor informs me of his or her affiliations with AI-related online or offline communities.	○	○	○	○	○
My supervisor displays many AI-related items in his or her workplace (e.g. AI-related posters, humanoid robot models, etc.).	○	○	○	○	○
My supervisor shares recent news on AI with me.	○	○	○	○	○
My supervisor defends for AI whenever it was criticized by someone.	○	○	○	○	○

Einde blok: Organizational influences

Start van blok: Blok 10

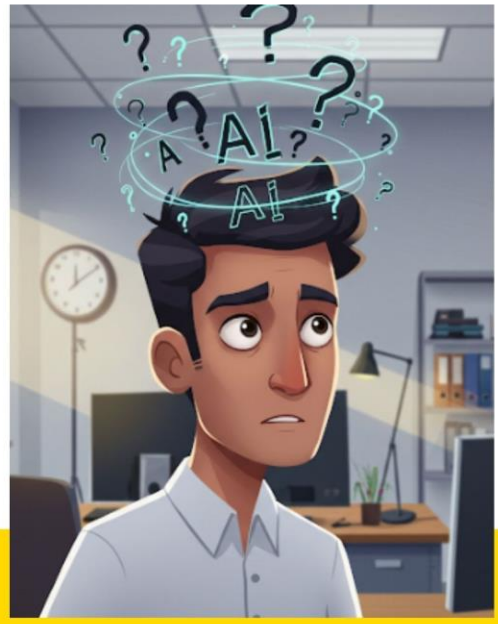
Watch the next video (After viewing, click once more on the next page to submit the survey.)

 <iframe allowfullscreen="true" frameborder="0" height="550"

scrolling="no" src="https://www.youtube.com/embed/KPfml7IRj74?si=tNK6yV9Il7sK1uKq" width="1000"></iframe>

Einde blok: Blok 10

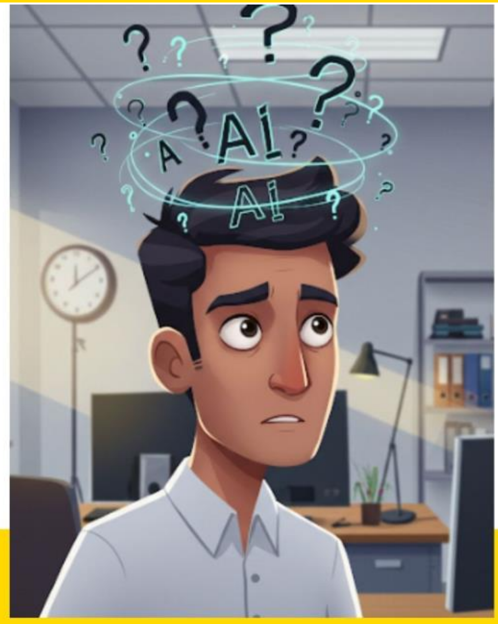
Appendix 11: Module presentations



Onderzoeksmotivatie - AI op werk

- Hoe ga je als werknemer om met AI-gerelateerde veranderingen?
- Hoe zet je deze veranderingen om in jouw voordeel?

Terug naar inhoudsopgave



Onderzoeksmotivatie - AI op werk

Training:
Werknemers bekrachtigen en trainen om proactief te reageren op de komst van AI op de werkvloer.
We focussen op:

- Jouw welzijn
- Jouw krachten en behoeften

Maak jezelf op een positieve manier klaar voor een wereld waar AI steeds meer aanwezig zal zijn.

Terug naar inhoudsopgave

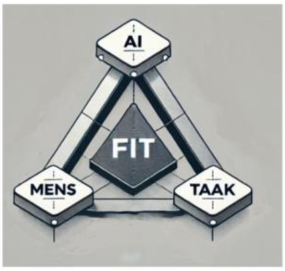
Wat gaan we leren?

Je hebt meer invloed dan je denkt!

Terug naar inhoudsopgave

Mens-Taak-AI fit

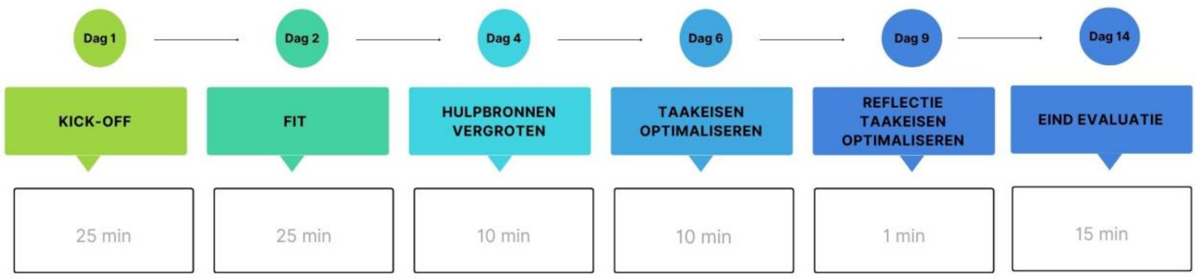
- Laat AI JOU en JOUW WERK ondersteunen.



Job crafting

- Geef je werk vorm op een manier waardoor AI in jouw werk-plaatje past.
  - Kleine, slimme aanpassingen

Trainingsoverzicht



Modules met een video en opdrachten die aansluiten bij jouw werk --> zo min mogelijk extra tijd kwijt.

- Volg de module 's ochtends.
- Breng je kleine module-doelen in praktijk tijdens de rest van de dag + dag erna.


Onthoud:
• AI is er om jou te ondersteunen.
• Deze training helpt je om de regie te pakken.
Tot morgen!

Fit

Mens-Taak-AI fit

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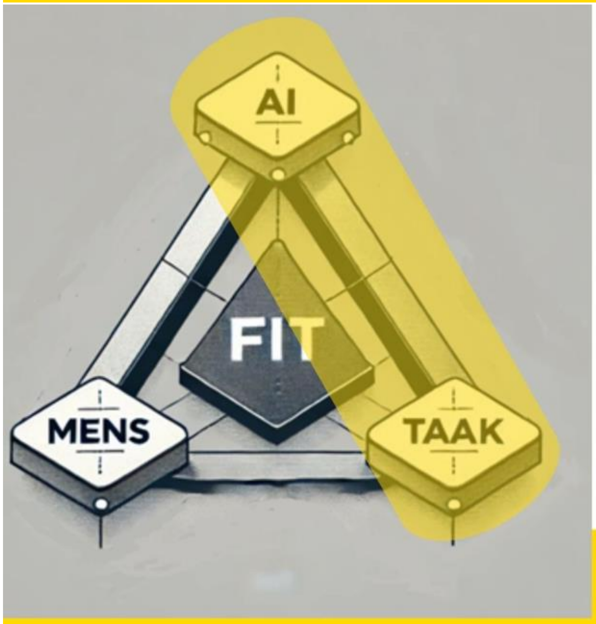
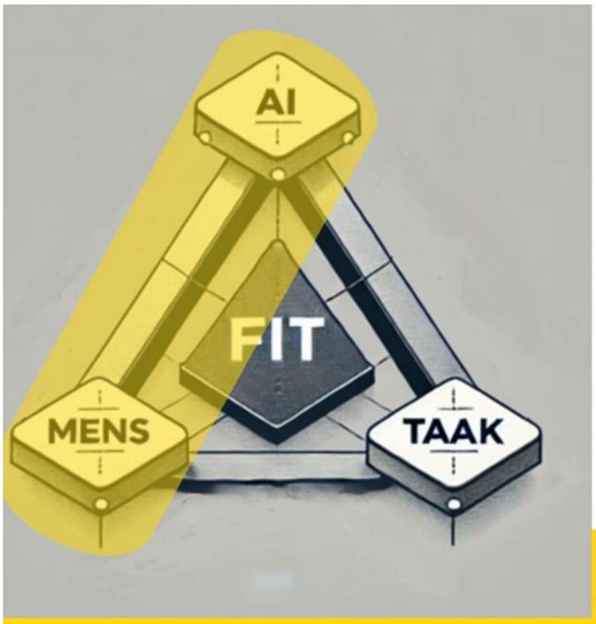


Mens-Taak-AI fit

Tussen je taken en de AI

- Kan de AI de taak effectief ondersteunen?
- Passen de AI's functionaliteiten bij de taak?
- Levert de AI de juiste output?

Terug naar inhoudsopgave



Mens-Taak-AI fit

Tussen jou en de AI
- Begrijp je hoe je de AI kunt aansturen?
- Kun je de output van de AI goed beoordelen?
- Voel je je comfortabel met de samenwerking?

Terug naar inhoudsopgave

Mens-Taak-AI fit

Een goede fit ontstaat op drie niveaus
1. Tussen jou en je taken
2. Tussen je taken en de AI
3. Tussen jou en de AI

Terug naar inhoudsopgave

Wat gaan we vandaag doen?

Terug naar inhoudsopgave

Fit verbeteren

Vier opdrachten:

1. Jouw huidige gedachten en kennis over AI
2. Jouw taken ontleden
3. Samenwerkingsplan tussen jou en AI
4. Plan omzetten in SMART-doelen

SMART:
- Specifiek: Wat wil je precies bereiken?
- Meetbaar: Hoe weet je dat het gelukt is?
- Acceptabel: Is het haalbaar binnen je werk?
- Relevant: Past het bij wat jij en je werk nodig hebben?
- Tijdgebonden: Wanneer ga je het doen?

Aan de slag

Maak de opdrachten om te ontdekken hoe je AI kunt inzetten als:
- Efficiëntie-versterker
- Denk partner
- Assistent

Werk vandaag en/of morgen aan je SMART-doelen

Onthoud:

- Een goede afstemming tussen jou, je taken, en de AI is cruciaal voor succesvol AI-gebruik.
- Je acties hoeven niet groot te zijn, kijk wat bij jou past.

Succes!

Trainingsoverzicht

Modules met een video en opdrachten die aansluiten bij jouw werk --> zo min mogelijk extra tijd kwijt.

- Volg de module 's ochtends.
- Breng je kleine module-doelen in praktijk tijdens de rest van de dag + dag erna.

Inhoud

- Wat is fit?
- Mens-Taak-AI fit
- Wat gaan we doen?
- Aan de slag!

Fit

Welke van de twee monteurs is het meest "ready for the job"?

Terug naar inhoudsopgave

Fit

Welke van de twee monteurs is het meest "ready for the job"?

Een monteur heeft o.a. behoefte aan:
- Een outfit die praktisch en veilig is
- Al het benodigde gereedschap voor zijn/haar klussen
- Een bus om dat gereedschap in mee te nemen

Terug naar inhoudsopgave

Fit

Definitie: De afstemming tussen
- Persoonlijke voorkeuren, vaardigheden, en behoeften
- Werkomgeving en taken

Terug naar inhoudsopgave

Fit

Een goede fit kan leiden tot
- tevredenheid↑
- betrokkenheid↑
- prestaties↑
- controle↑
- stress↓

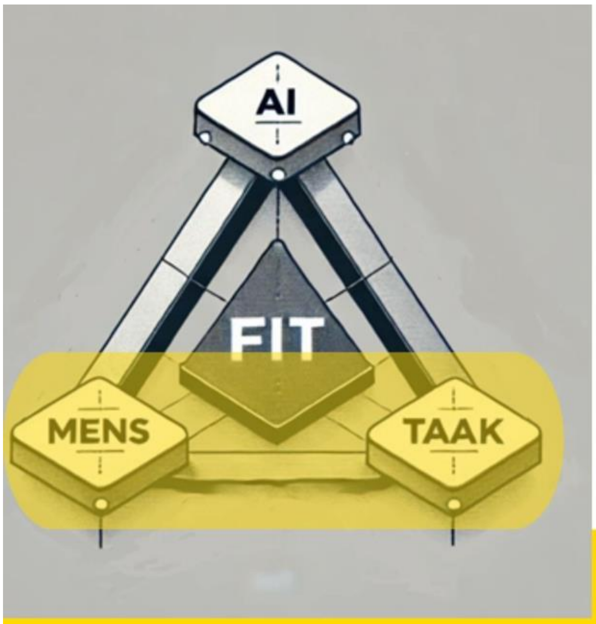
Terug naar inhoudsopgave

Mens-Taak-AI fit

Drie belangrijke onderdelen die samen bepalen hoe succesvol je met AI kunt werken

1. Jij als mens
   - kennis, vaardigheden, voorkeuren
2. Je taken
   - eisen en uitdagingen
3. De AI
   - mogelijkheden en beperkingen

Terug naar inhoudsopgave



Mens-Taak-AI fit

Tussen jou en je taken

- Passen de taken bij jouw expertise en vaardigheden?
- Kun je je sterke punten benutten?

Terug naar inhoudsopgave

Hulpbronnen vergroten

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Hulpbronnen voor Peter

"Als ik de week-cijfers in AI gooi krijg ik analyses die nergens op slaan. Wat gaat er mis?"

Hulpbronnen voor Peter

"Als ik de week-cijfers in AI gooi krijg ik analyses die nergens op slaan. Wat gaat er mis?"

Hulpbronnen om goed en veilig data te analyseren met AI:

- Een collega vragen om zijn mentor te zijn
- Tijd maken om de AI-voorschriften van het bedrijf te lezen
- Klein beginnen, met één taak

Hulpbronnen voor Peter

"Als ik de week-cijfers in AI gooi krijg ik analyses die nergens op slaan. Wat gaat er mis?"

Hulpbronnen om goed en veilig data te analyseren met AI:

- Een collega vragen om zijn mentor te zijn
- Tijd maken om de AI-voorschriften van het bedrijf te lezen
- Klein beginnen, met één taak

Resultaat:
Peter vindt steeds meer manieren om snel inzichten te halen uit de week-cijfers. Zo verhoogt hij de kwaliteit van de wekelijkse stand-up meeting.

Terug naar inhoudsopgave

Waarom hulpbronnen!?

Terug naar inhoudsopgave

Door bewust met je hulpbronnen bezig te zijn:

- Werk je **efficiënter** en met meer **plezier**
- Voel je je **zekerder** in het gebruik van AI
- Kun je beter **omgaan met nieuwe uitdagingen**
- Houd je meer **energie** over voor wat echt belangrijk is

Wat gaan we vandaag doen?

Terug naar inhoudsopgave

Hulpbronnen verhogen

1. Hulpbronnen kiezen die bij JOU passen.
2. SMART-doelen maken om deze hulpbronnen te verkrijgen of in te zetten.

Aan de slag

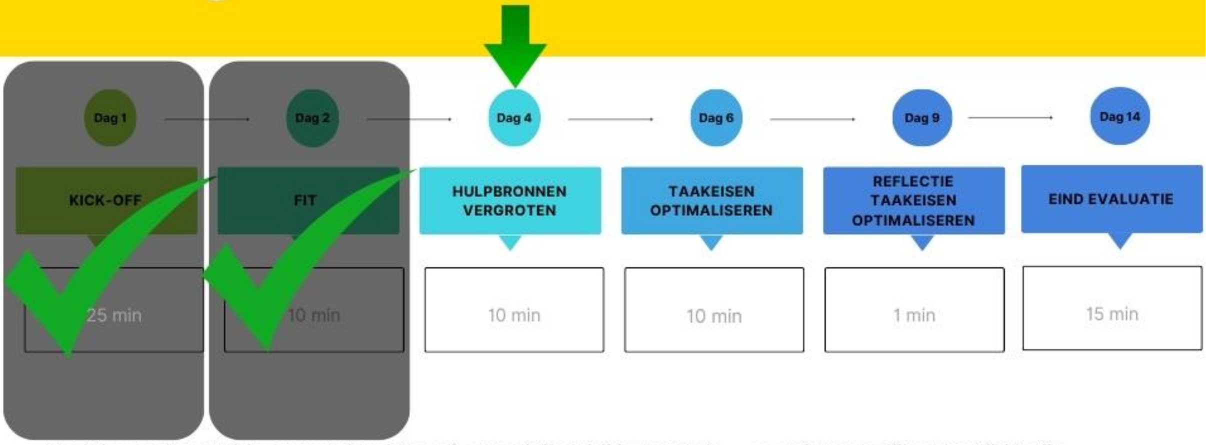
Maak de opdrachten om te ontdekken om te ontdekken welke hulpbronnen voor jou nuttig zijn.
Werk vandaag en/of morgen aan je SMART-doelen.

Onthoud:

- Hulpbronnen zijn alle middelen die jou helpen om goed, vruchtbaar, en met plezier AI te gebruiken.
- Je kunt zelf zorgen voor meer hulpbronnen.
- Kies stappen die het best bij jou passen (groot of klein, maakt niet uit).

Succes!

Trainingsoverzicht



Modules met een video en opdrachten die aansluiten bij jouw werk --> zo min mogelijk extra tijd kwijt.

- Volg de module 's ochtends.
- Breng je kleine module-doelen in praktijk tijdens de rest van de dag + dag erna.

Inhoud

- Wat zijn hulpbronnen?
- Hulpbronnen voor AI-gebruik
- Wat gaan we doen?
- Aan de slag!

Hulpbronnen

Hulpbronnen tijdens een verbouwing:

- Advies van experts
- Hulp van vrienden
- Geleend gereedschap
- Tijd om te leren hoe de klus moet worden uitgevoerd

Hulpbronnen

Definitie: Middelen die je helpen om je werk goed, op tijd, en met plezier te doen.

Terug naar inhoudsopgave

Hulpbronnen

Definitie: Middelen die je helpen om je werk goed, op tijd, en met plezier te doen.

Voorbeelden op werk:

- Fysieke middelen:
  - Snellere computer
  - Tweede scherm
  - Goede werkplek

Minder tastbare zaken:

- Coachend leidinggevende
- Hulp van collega's
- Tijd om nieuwe dingen te leren
- Autonomie bij het inrichten van je werkzaamheden
- Feedback

Terug naar inhoudsopgave

Hulpbronnen voor Eva

"Ik snap niet hoe AI me kan helpen bij posts schrijven!"

Terug naar inhoudsopgave

Hulpbronnen voor Eva

"Ik snap niet hoe AI me kan helpen bij posts schrijven!"

Hulpbronnen om AI beter te gebruiken:

- Elke week een uurtje experimenteren
- Tips uitwisselen collega's
- Een korte online cursus volgen over prompts schrijven

Terug naar inhoudsopgave

Hulpbronnen voor Eva

"Ik snap niet hoe AI me kan helpen bij posts schrijven!"

Hulpbronnen om AI beter te gebruiken:

- Elke week een uurtje experimenteren
- Tips uitwisselen collega's
- Een korte online cursus volgen over prompts schrijven

Resultaat:

- Eva schrijft en optimaliseert met gemak haar post door AI slim in te zetten.

Terug naar inhoudsopgave

Taakeisen optimaliseren

EINDHOVEN UNIVERSITY OF TECHNOLOGY

Sarah's taakeisen optimaliseren

Hoe Sarah haar taakeisen optimaliseerde:

- Een stappenplan opzetten.
- Succesvolle prompts bewaren in een document.
- AI samenwerking inplannen na haar koffie moment.
- Krachten bundelen: Collega Mark helpt Sarah met prompten, in ruil helpt Sarah hem bij het nalopen van teksten die hij samen met AI heeft gemaakt.

Resultaat: Werken met AI kost Sarah nu veel minder energie en frustratie, en ze kan zich beter concentreren op het creatieve deel van haar werk.

Wat gaan we vandaag doen?

Terug naar inhoudsopgave

Taakeisen optimaliseren

1. Identificeer taakeisen die je makkelijk kunt optimaliseren, en maak een SMART-doel (of meerdere) om jouw taken comfortabeler of efficiënter te maken.
2. Werk vandaag en/of morgen aan je SMART-doelen.

Onthoud:

- Taakeisen zijn aspecten die je moet voldoen of doorstaan en doorlopend energie of tijd kosten. Door taakeisen te optimaliseren en processen te versoepelen kan je energie besparen.
- Je acties hoeven niet groot te zijn, kijk wat bij jou past.

Succes!

Trainingsoverzicht

Modules met een video en opdrachten die aansluiten bij jouw werk --> zo min mogelijk extra tijd kwijt.

- Volg de module 's ochtends.
- Breng je kleine module-doelen in praktijk tijdens de rest van de dag + dag erna.

Inhoud

- Wat zijn taakeisen?
- Taakeisen optimaliseren.
- Wat gaan we doen?
- Aan de slag!

Taakeisen

Definitie: Aspecten van je werk die je moet voldoen en (doorlopend) energie kosten.

Taakeisen

Definitie: Aspecten van je werk die je moet voldoen en (doorlopend) energie kosten

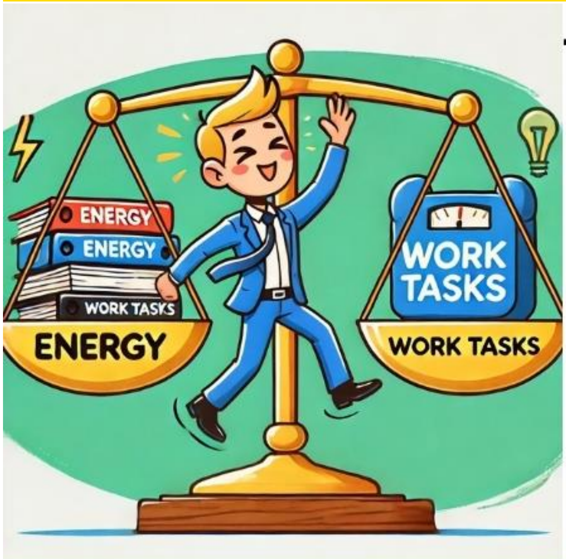
Voorbeelden op werk:

- Langdurig staan of zwaar tillen
- Hoge werkdruk, strakke deadlines
- Cognitieve belasting
- Werkzaamheden die door elkaar lopen
- Onduidelijkheid
- Regelmatige verandering
- Nieuwe aspecten op werk

Taakeisen

Definitie: Aspecten van je werk die je moet voldoen en (doorlopend) energie kosten.

Veel en/of aanhoudende taakeisen kunnen je energie opmaken en uitputten. Zeker als je niet op tijd herstelt.



Taakeisen optimaliseren

Definitie: Versimpelen van taken en het verbeteren van processen.

AI taakeisen voor Sarah

"AI kost mij te veel energie. Ik vergeet steeds hoe ik dingen moet doen en krijg pas resultaat na tien pogingen."

Sarah's taakeisen optimaliseren

Hoe Sarah haar taakeisen optimaliseerde:

- Een stappenplan opzetten.
- Succesvolle prompts bewaren in een document.
- AI samenwerking inplannen na haar koffie moment.
- Krachten bundelen: Collega Mark helpt Sarah met prompten, in ruil helpt Sarah hem bij het nalopen van resultaten.

Regie in jouw baan met AI

AI job Crafting Training - Evaluatie

TU/e EINDHOVEN UNIVERSITY OF TECHNOLOGY

Onthoud:

- Jij kunt regie nemen over jouw werk(omgeving) en deze beter bij jou laten passen

Bonus na de vragenlijst:

- Maak de vragenlijst af en ontvang een samenvatting van een recente publicatie (Harvard Business School) over AI-samenwerking en prompt-technieken + de key take away's van de afgelopen trainingsweken

Inhoud

- Terugblik op de training
- Ervaringen en lessen delen
- Vragenlijst (Deze keer iets korter 🙂)
    - Bonus: Samenvatting recente publicatie Harvard Business School (e-mail)

Sleutel aan je baan in het AI-tijdperk

Training:
Werknemers bekrachtigen en trainen om **proactief in te spelen** op de komst van AI op de werkvloer.

We focussen op:
- Jouw welzijn
- Jouw krachten en behoeften

Maak jezelf op een **positieve** manier klaar voor een wereld waar AI steeds meer aanwezig zal zijn.

Terug naar inhoudsopgave

Je hebt meer invloed dan je denkt!

Job crafting (sleutelen aan je baan)

Proactief je baan aanpassen zodat deze beter bij je past

- Hulpbronnen verhogen
- Taakeisen optimaliseren

Je hebt meer invloed dan je denkt!

Job crafting (sleutelen aan je baan)

- Hulpbronnen verhogen
- Taakeisen optimaliseren

↓

- Werkbetrokkenheid en motivatie
- Open voor verandering (e.g., AI)
- Hogere prestaties
- Minder stress

Jullie gebruikten AI voor:

Terug naar inhoudsopgave

Productiviteit:

- Tekst
- Software analyse en testing
- Dashboard analyse
- CV screening
- Project management
- Toetsvragen ontwikkelen
- SQL-queries
- Emails
- Data analyse
- Rapportages
- Feedback (schrijven en/of ontvangen)
- Taken- en prioriteiten lijsten

Creativiteit:

- Nieuwe perspectieven
- Alternatieve oplossingen
- Scenario's uitwerken

Aan welke hulpbronnen hadden jullie behoefte?

Gezochte hulpbronnen

- Educatief prompting materiaal
- Ervaringen uitwisselen
- Feedback over AI gebruik
- Hulp van collega's
    - Templates
    - Prompt verbetering
    - Etc.

Appendix 12: Human-Task-AI Fit module

Human-Task-AI fit Module

Start van blok: Standaard vragenblok

Fit video Welcome to the Human-Task-AI Fit Module!

 Before we start with the assignments, please watch the following video. You can find a supporting document in English Here. Also, you can turn on automatic subtitles.

 <iframe height="550" src="https://www.youtube.com/embed/nWe-X5cH-dw" width="1000"></iframe>

Pagina-einde

Q32 Knowledge about AI

 In this exercise, we will map out your knowledge, perception, and beliefs about AI. You will also briefly collaborate with your generative AI (e.g., ChatGPT, Microsoft Copilot, etc.) to learn about AI..

Pagina-einde

Initial thoughts <h2><u style="font-family: Arial, Helvetica, sans-serif; font-size: 18px;">Instructions</u>: <b style="font-family: Arial, Helvetica, sans-serif; font-size: 18px;">Write down your thoughts about AI. What do you think it is and what it can do? What impact do you think AI will have on jobs?</h2>
 Examples: <ul> "AI will take over my job" "AI can only help me with simple tasks" "AI is not yet advanced enough for the workplace"

○ Thought 1 ____

○ Thought 2 ____

○ Thought 3 ____

Pagina-einde

Q17 Let's start with your (first) collaboration with AI.

 In the block below, you will find a text/prompt that you can give to your generative AI. This type of request is called a "prompt." The prompt is supplemented with your input from the previous instruction. When you give this prompt to your generative AI, the response will include an explanation of AI and a reaction to your initial thoughts about AI.

Pagina-einde

Q18 Instruction: Read the prompt in the block below and copy it. Open a new chat with your generative AI system, paste the prompt into the chat, send the message, and see what response you get. Then, proceed to the next instruction.

Q4 <table border="1" cellpadding="1" cellspacing="1" style="height: 200px; width: 750px;" summary="Kopieren en plakken in jouw generatieve AI systeem"> <caption> <div style="text-align: left;">Prompt:</div> </caption> <tbody> <tr> <td><i>“</i>You are an AI expert who helps employees explore the AI landscape in relation to their own job roles. I would like you to do the following: 1) Provide me with a simple explanation of AI in approximately 120 words. 2) Then, in about 150 words, explain what generative AI is, how it works, and how it can assist me in an accessible way. 3) Read my initial thoughts on AI and respond briefly. Do you understand my ideas? What do AI experts say about them? Give me a positive and constructive explanation of why my ideas may or may not be correct. Below are my thoughts:<i> 1) </i>${q://QID1/ChoiceTextEntryValue/1}, 2) ${q://QID1/ChoiceTextEntryValue/2}, 3) ${q://QID1/ChoiceTextEntryValue/3}<i>”</i></td> </tr> </tbody> </table>

Pagina-einde

Q21 Instruction: What does the AI response say about your initial thoughts on AI? Reflect below on your initial ideas about AI based on the AI explanation.

 Consider the following questions when writing your response: <ul> Did the AI's explanation confirm or challenge your original ideas? Did you learn something new about AI? Has your opinion changed after reading the AI's response? Why or why not?

Q20

Thought reflection 1 ${q://QID1/ChoiceTextEntryValue/1}

____

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Thought reflection 2 ${q://QID1/ChoiceTextEntryValue/2}

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Thought reflection 3 ${q://QID1/ChoiceTextEntryValue/3}

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Q22 Task decomposition

 It can be challenging to determine how you can and want to use AI. In this exercise, we will map out common tasks and identify subtasks that you might work with AI.

 If you already use AI frequently in your work, you can choose whether to focus on your current AI usage or explore a new application.
 Remember: The focus is on the fit between you, your work, and AI.

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Q23 Instruction:

 1) Identify one or two main tasks you will be working on regularly in the coming period.
 2) Break these tasks down into subtasks and assess each subtask: <div style="margin-left: 40px;">- Do you enjoy it, or does it drain your energy? Why do you evaluate the subtask this way?
 - Does the nature of the task align with your interests or strengths, or do you find it boring or difficult?

 Examples of Tasks and Subtasks:
 Task 1: Reporting; Subtasks: Data collection & analysis, Structuring the report, Writing & summarizing, Formatting, Automating report generation
 Task 2: Employee performance analysis; Subtasks:Analyzing performance metrics, Predicting productivity, Automated performance reporting</div>

Main Task(s) Write down one (or two) main tasks

○ Main Task 1: ____

○ Main Task 2 (optioneel): ____

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Subtasks 1 Subtasks per main task:

	Main Task 1		
	Subtask 	<strong data-end="4437" data-start="4414">Personal assessment (e.g., enjoyable, challenging, annoying, etc.)	Reason (e.g., I am good/bad at this, it is too simple, it takes time, etc.)
1)			
2)			
3)			
4)			
5)			
6)			

Subtasks 2 If you are not adressing a second main task, skip this part and go to the next section.

	Main Task 2 (optional)		
	Subtask	Personal assessment	Reason
Klik om optie 1 te schrijven			
Klik om optie 2 te schrijven			
Klik om optie 3 te schrijven			
Klik om stelling 4 te schrijven			
Klik om stelling 5 te schrijven			
Klik om stelling 6 te schrijven			

Pagina-einde

Q10 <h2>Collaboration with AI</h2> <div> </div> <p>Look at the subtasks you have rated as challenging or annoying. Choose three subtasks where AI could assist or support you. For these three subtasks, we will map out how AI can work for you.

 Not sure how AI can help you? You can:</p> <li style="margin-left: 8px;">Check the overview below for inspiration <li style="margin-left: 8px;">Directly ask your generative AI system which of your subtasks it can assist with

Q28 Instruction: Create an overview of your collaboration with AI. Choose two or more subtasks from the previous instruction where you want to involve AI over the next two days. Define your role, AI's role, and the collaboration process for each specific subtask. Use the example below and then use the open table to structure your AI plan.

Q27 <h2> </h2> <ul style="margin-bottom:11px"> <div style="margin-bottom:11px; margin-left:8px">Examples of AI Applications:</div> <table class="MsoTableGrid" style="border-collapse:collapse;border:none;width:800px;" width="703"> <tbody> <tr> <td style="border-bottom:1px solid black; padding:0cm 7px 0cm 7px; height:30px; border-top:1px solid black; border-right:1px solid black; border-left:1px solid black" valign="top">Category</td> <td style="border-bottom:1px solid black; width:178px; padding:0cm 7px 0cm 7px; height:30px; border-top:1px solid black; border-right:none; border-left:none" valign="top">Subcategory</td> <td style="border-bottom:1px solid black; width:353px; padding:0cm 7px 0cm 7px; height:30px; border-top:1px solid black; border-right:1px solid black; border-left:none" valign="top">Use cases</td> </tr> <tr> <td style="border-bottom:none; padding:0cm 7px 0cm 7px; height:94px; border-top:none; border-right:1px solid black; border-left:1px solid black" valign="top"><span style="font-family:Arial,Helvetica,sans-

serif;">1. AI to enhance efficiency </td> <td style="border-bottom:1px solid black; width:178px; padding:0cm 7px 0cm 7px; height:94px; border-top:none; border-right:none; border-left:none" valign="top"><i>Automate routine activities </i></td> <td style="border-bottom:1px solid black; width:353px; padding:0cm 7px 0cm 7px; height:94px; border-top:none; border-right:1px solid black; border-left:none" valign="top">- Grammar and spell check
 - Documenting meetings
 - Organizing and reporting
 - Structuring data
 </td> </tr> <tr> <td style="border-bottom:1px solid black; padding:0cm 7px 0cm 7px; height:160px; border-top:none; border-right:1px solid black; border-left:1px solid black" valign="top"> </td> <td style="border-bottom:1px solid black; width:178px; padding:0cm 7px 0cm 7px; height:160px; border-top:none; border-right:none; border-left:none" valign="top"><i>Time-saving support</i></td> <td style="border-bottom:1px solid black; width:353px; padding:0cm 7px 0cm 7px; height:160px; border-top:none; border-right:1px solid black; border-left:none" valign="top">- Analyzing information
 - Summarizing information
 - Creating initial drafts of emails and reports
 - Converting keywords into fully written texts
 - Generating action-plans </td> </tr> <tr> <td style="border-bottom:none; padding:0cm 7px 0cm 7px; height:97px; border-top:none; border-right:1px solid black; border-left:1px solid black" valign="top">2. AI as a sparring partner</td> <td style="border-bottom:1px solid black; width:178px; padding:0cm 7px 0cm 7px; height:97px; border-top:none; border-right:none; border-left:none" valign="top"><i>Idea exploration / Creative support </i></td> <td style="border-bottom:1px solid black; width:353px; padding:0cm 7px 0cm 7px; height:97px; border-top:none; border-right:1px solid black; border-left:none" valign="top">- Brainstorming new ideas
 - Exploring perspectives
 - Giving counter arguments
 - Evaluating trade-offs
 - Suggesting (alternative) solutions

 </td> </tr> <tr> <td style="border-bottom:1px solid black; padding:0cm 7px 0cm 7px; height:137px; border-top:none; border-right:1px solid black; border-left:1px solid black" valign="top"> </td> <td style="border-bottom:1px solid black; width:178px; padding:0cm 7px 0cm 7px; height:137px; border-top:none; border-right:none; border-left:none" valign="top"><i>Feedback and work improvement</i></td> <td style="border-bottom:1px solid black; width:353px; padding:0cm 7px 0cm 7px; height:137px; border-top:none; border-right:1px solid black; border-left:none" valign="top">- Critical thinking support
 - Evaluating and feedback
 - Suggesting improvements
 </td> </tr> <tr> <td style="border-

bottom:none; padding:0cm 7px 0cm 7px; height:75px; border-top:none; border-right:1px solid black; border-left:1px solid black" valign="top">3. AI for learning and growth </td> <td style="border-bottom:1px solid black; width:178px; padding:0cm 7px 0cm 7px; height:75px; border-top:none; border-right:none; border-left:none" valign="top"><i>Enhance understanding</i></td> <td style="border-bottom:1px solid black; width:353px; padding:0cm 7px 0cm 7px; height:75px; border-top:none; border-right:1px solid black; border-left:none" valign="top">- Explaining complex concepts
 - Clarifying difficult texts
 - Exploring different styles of explanation
 </td> </tr> <tr> <td style="border-bottom:1px solid black; padding:0cm 7px 0cm 7px; height:68px; border-top:none; border-right:1px solid black; border-left:1px solid black" valign="top"> </td> <td style="border-bottom:1px solid black; width:178px; padding:0cm 7px 0cm 7px; height:68px; border-top:none; border-right:none; border-left:none" valign="top"><i>Learning and development</i></td> <td style="border-bottom:1px solid black; width:353px; padding:0cm 7px 0cm 7px; height:68px; border-top:none; border-right:1px solid black; border-left:none" valign="top">- Processing and integrating feedback
 - Identifying learning points
 - Testing and expanding your knowledge
 </td> </tr> </tbody> </table>

Collaboration Plan <ol style="margin-bottom:11px"> <div style="margin-bottom:11px; margin-left:8px">Example Answer: <table border="1" cellpadding="1" cellspacing="1" style="width:1100px;"> <tbody> <tr> <td> </td> <td>Subtask</td> <td>Your role</td> <td>AI's role</td> <td> Collaboration</td> </tr> <tr> <td> Example 1: </td> <td>Preparing for a meeting</td> <td>I provide AI with the context and purpose of the meeting.</td> <td>Identifies key objectives of the meeting and suggests relevant questions to ask.</td> <td>Review the AI’s output and note valuable points to help with meeting preparation.</td> </tr> <tr> <td> Example 2:</td> <td>Writing a text or email</td> <td>I outline the key points of my message and provide them to the AI.</td> <td>Understands the purpose and key points of the text. Then generates the desired text.</td> <td>Read through the suggested text carefully, making small adjustments and improvements if needed.</td> </tr> <tr> <td> Example 3:</td> <td>Merging and organizing multiple documents/emails/data</td> <td>I provide AI with the context of the subtask and supply the relevant data.</td> <td>Identifies all relevant information, recognizes sources and content, structures, and organizes the information while avoiding duplication.

 <em data-end="1151" data-start="1140">Optional:
 - Organizes the information in table format
 - Reports insights from the structured information</td> <td>Review the output for accuracy and completeness.</td> </tr> </tbody> </table> </div>

	Your collaboration with AI			
	Subtask	Your role	AI's role	Collaboration
1)				
2)				
3)				

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Einde blok: Standaard vragenblok

Start van blok: Block 1

Q30 Getting Started with AI – The Next Step: Converting Your AI Plan into SMART Goals

 This will help you collaborate effectively with AI. SMART stands for:
  Specific: Clearly and concretely define your goal. What exactly do you want to achieve? Measurable: Ensure you can measure whether you have achieved your goal. How will you know if you've reached it? Achievable: Is the goal realistic and feasible within your current work situation? Relevant: Ensure the goal is important for your work and aligns with your strengths and needs. Time-bound: When will you do it?

Einde blok: Block 1

Start van blok: Block 2

Q31 Instructions: Formulate SMART goals for each planned AI collaboration from the previous step.
 <u>Note</u>: Set the goals so that you can start working on them today or tomorrow (or your next workday).

Fit SMART-goal <table border="1" cellpadding="1" cellspacing="1" style="width:600px;"> <tbody> <tr> <td> <li data-end="626" data-start="68"> <p data-end="626" data-start="70"><strong data-end="108" data-start="70">Example 1: Preparing for a meeting – This afternoon from 13:00 to 13:15, I will prepare for my meeting using AI. I provide AI with details about the meeting topic, attendees, and stakeholders (such as the HR business partner or Marketing manager), as well as relevant developments from previous meetings or activities. I also share my role, responsibilities, and objectives. Next, I ask AI to help me think of potential questions I can ask, anticipate questions others might ask me, and identify key objectives and perspectives from the stakeholders.
 </p> <li data-end="937" data-start="628"> <p data-end="937" data-start="630"><strong data-end="661" data-start="630">Example 2: Writing an email – Tomorrow at 10:00, I will use AI to draft an email for a client, covering multiple topics. First, I write down all my thoughts without worrying about structure, style, or spelling. Then, I let AI generate a well-structured email, which I review and refine before sending.</p>   </td> </tr> </tbody> </table>

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Einde blok: Block 2

Appendix 13: Seeking Resources module

Seeking resources - Copy

Start van blok: Standaard vragenblok

Hi, welcome to this new module of the training!
 <p data-end="166" data-is-last-node="" data-is-only-node="" data-start="51">Before we move on to new content, take a moment for a brief self-reflection exercise to evaluate the past two days.</p>
 <button aria-label="Kopiëren" data-testid="copy-turn-action-button"></button>
 <button aria-label="Goede reactie" data-testid="good-response-turn-action-button"></button><button aria-label="Slechte reactie" data-testid="bad-response-turn-action-button"></button>
 <button aria-label="Voorlezen" data-testid="voice-play-turn-action-button"></button><button aria-label="In canvas bewerken"></button><button aria-expanded="false" aria-haspopup="menu" data-state="closed" id="radix-:r6v:" type="button"></button>
 <button aria-expanded="false" aria-haspopup="menu" data-state="closed" id="radix-:r6v:" type="button"></button>

Pagina-einde

Pagina-einde

<strong data-end="16" data-is-only-node="" data-start="0">Instruction:<br data-end="19" data-start="16" /> Reflect on your AI usage for your selected subtasks. Assess its impact on your workflow and identify potential improvements or adjustments.

	Reflection AI-collaboration
	___
Did you work towards your goals?	
Did you achieve your goals?	
Was the AI support aligned with your expectations and goals?	
Looking back on your experience working with AI for these goals, what adjustments would you make?	

Einde blok: Standaard vragenblok

Start van blok: Blok 1

Today, we will focus on job crafting
<h1> </h1>

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<p data-end="328" data-start="0">Job crafting

 In the videos, we will discuss work-related resources and job demands. In the following exercises, you will map out these aspects and reflect on how to monitor them as you continue shaping your role. You will create a plan to implement small, concrete adjustments and explore the potential effects on your work and well-being.</p> <p data-end="402" data-is-last-node="" data-is-only-node="" data-start="330">
 Today and tomorrow, you will focus specifically on seeking resources.

 Watch the next video with subtitles, or read an English summary below the video:
 <iframe allowfullscreen="true" frameborder="0" height="600" src="https://www.youtube.com/embed/Ut084qQKW14?feature=shared" width="1050"></iframe>

 </p> <h3 data-pm-slice="1 1 []">English summary of the video:
 Introduction</h3> <p>AI technology is evolving rapidly, with new features and improvements emerging every month. Instead of focusing solely on the AI tools available today, this training aims to equip employees with the skills and mindset needed to work effectively with both current and future AI developments in their roles. A crucial part of this process is identifying and utilizing the necessary resources for AI integration.</p> <h3>Understanding Resources</h3> <p>Resources are essential tools and support systems that help individuals perform their work efficiently, on time, and with job satisfaction. Just as a home renovation requires expert advice, borrowed tools, and time to learn new skills, AI adoption in the workplace necessitates both tangible and intangible resources.</p> <h4>Types of Workplace Resources</h4> <ol data-spread="false" start="1"> <p>Physical Resources: Faster computers, dual monitors, ergonomic workspaces</p>   <p>Intangible Resources: Supportive leadership, colleague collaboration, learning opportunities, autonomy, feedback</p>   <p>AI acts as a powerful tool, but its effectiveness depends on how well employees can access and leverage these resources.</p> <h3>Case Studies</h3> <h4>Case 1: Eva (Marketing Specialist)</h4> <p>Eva struggled with using AI to draft social media posts. She enhanced her resources by:</p> <ul data-spread="false"> <p>Dedicating an hour weekly to AI experimentation</p>   <p>Sharing tips with colleagues</p>   <p>Taking an online course on prompt engineering</p>   <p>Outcome: Eva became proficient in AI-assisted content creation, improving efficiency and effectiveness.</p> <h4>Case 2: Peter (Team Leader)</h4> <p>Peter attempted AI-driven data analysis but encountered inaccurate results and uncertainty about company AI policies. To overcome these challenges, he:</p> <ul data-spread="false"> <p>Sought mentorship from a colleague</p>   <p>Studied the company's AI guidelines</p>   <p>Started with small-scale AI tasks</p>   <p>Outcome: Peter improved his ability to extract insights from data, enhancing the quality of team meetings.</p> <h3>Why Enhancing Resources Matters</h3> <p>By proactively managing resources, employees can:</p> <ol data-spread="false" start="1"> <p><span style="font-

size:19px;">Work more efficiently and with greater satisfaction</p>   <p>Gain confidence in AI usage</p>   <p>Adapt to new challenges with resilience</p>   <p>Preserve energy for more meaningful tasks</p>   <h3>Action Plan for Employees</h3> <p>To maximize AI adoption, employees should:</p> <ol data-spread="false" start="1"> <p>Identify resources that fit their needs</p>   <p>Set SMART (Specific, Measurable, Achievable, Relevant, Time-bound) goals to strengthen these resources</p>   <p>Implement their personalized action plan</p>   <h3>Conclusion</h3> <p>Resources are crucial for successful AI integration. Employees should assess their own needs, take proactive steps, and leverage available support systems to enhance their AI skills. By doing so, they will not only improve their job performance but also future-proof their careers in an AI-driven workplace.</p>

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<p data-end="26" data-start="0"><strong data-end="24" data-start="0">Seeking Resources
 </p> <p data-end="348" data-start="28">Resources are the physical, social, or organizational means that help you perform your work more effectively and reduce stress. These can range from useful tools and systems to support from colleagues or supervisors. By actively seeking out these resources, you can work more efficiently and with greater satisfaction.
 </p> <p data-end="505" data-is-last-node="" data-is-only-node="" data-start="350">Resources can also support you in integrating AI into your daily tasks. However, the types of resources that are beneficial may vary from person to person.</p>

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<p data-end="99" data-start="60">Examples of Resources You Can Seek:
 </p> <p data-end="158" data-start="101"><strong data-end="156" data-start="101">Leveraging Knowledge and Experience from Colleagues</p> <ul data-end="321" data-start="159"> <li data-end="214" data-start="159">Asking colleagues who already work with AI for tips <li data-end="269" data-start="215">Learning from successful AI applications by others <li data-end="321" data-start="270">Regularly exchanging experiences about AI usage
   <p data-end="356" data-start="323"><strong data-end="354" data-start="323">Expanding Your AI Knowledge</p> <ul data-end="948" data-start="357"> <li data-end="439" data-start="357">Improving your understanding of Generative AI and Large Language Models (LLMs) <li data-end="508" data-start="440">Taking a short Microsoft course: Fundamentals of Generative AI <li data-end="753" data-start="509">Watching relevant videos: <ul data-end="753" data-start="541"> <li data-end="672" data-start="541"><em data-end="575" data-start="543">Explainer Video: Generative AI (← A well-balanced and clear explainer video with strong storytelling and practical relevance) <li data-end="753" data-start="675"><em data-end="693" data-start="677">How I Use LLMs (← A deeper and slightly more technical take on AI usage)   <li data-end="848" data-start="754">Searching YouTube for AI videos tailored to your field: <em data-end="846" data-start="812">"Generative AI for [your field]" <li data-end="905" data-start="849">Reading blog posts <li data-end="948" data-start="906">Reviewing your company’s AI principles
   <p data-end="983" data-start="950"><strong data-end="981" data-start="950">Developing Prompting Skills</p> <ul data-end="1435" data-start="984"> <li data-end="1031" data-start="984"> <p>Researching effective prompt techniques</p> <li data-end="1281" data-start="1032">Watching relevant videos: <ul data-end="1281" data-start="1064"> <li data-end="1164" data-start="1064"><em data-end="1088" data-start="1066">Insightful Use Cases (Illustration of use cases for professionals) <li data-end="1281" data-start="1167">Summary Video of Google's Prompting Course (← A 9-hour Google prompt engineering course condensed into 20 minutes)   <li data-end="1341" data-start="1282">Reading a <strong data-end="1310" data-start="1294">prompt guide: <em data-end="1339" data-start="1312">Tina Huang - Prompt Guide <li data-end="1380" data-start="1342">Practicing different prompt styles <li data-end="1435" data-start="1381">Taking time to refine your frequently used prompts
   <p data-end="1474" data-

start="1437"><strong data-end="1472" data-start="1437">Making Time for Experimentation</p> <ul data-end="1623" data-start="1475"> <li data-end="1511" data-start="1475">Scheduling moments to try out AI <li data-end="1572" data-start="1512">Learning and discovering through playful experimentation <li data-end="1623" data-start="1573">Testing different AI applications in your work

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<h3 data-end="22" data-start="0"><u><strong data-end="20" data-start="4">Instruction:</u></h3> <p data-end="145" data-start="23">Look back on your reflection about AI usage during the fit module. Which resources could help you make better use of AI?</p> <p data-end="261" data-is-last-node="" data-is-only-node="" data-start="147">Formulate a goal for today or tomorrow to enhance a resource for AI usage (keep the <strong data-end="240" data-start="231">SMART principles in mind).</p>

<p data-end="65" data-start="51"><strong data-end="63" data-start="51">Example:</p> <ul data-end="670" data-start="67"> <li data-end="208" data-start="67"> <p data-end="208" data-start="69"><strong data-end="94" data-start="69">Not yet SMART version (this does not necessarily need to be written down):<br data-end="150" data-start="147" /> <em data-end="206" data-start="152">"I will learn about prompts to speed up my writing."
 </p> <li data-end="670" data-start="210"> <p data-end="670" data-start="212"><strong data-end="230" data-start="212">SMART version:<br data-end="233" data-start="230" /> <em data-end="668" data-start="235">"To make my writing more efficient, I will spend the next two days dedicating 20 minutes per day (10:00-10:20) to learning about prompt techniques. On Day 1, I will watch the recommended video tutorial on basic prompt techniques and take notes on the three most important tips. On Day 2, I will apply these three techniques while writing or rewriting my weekly report and document the difference compared to my old way of working."</p>

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<p data-end="59" data-start="0">🎯 <strong data-end="57" data-start="3">Yes – You have successfully completed this module!
 </p> <p data-end="161" data-start="61"><strong data-end="75" data-start="61">Good news: Within a few minutes, you will receive a summary of the key insights in your inbox.</p> <h3 data-end="189" data-start="163"><strong data-end="187" data-start="167">Your next steps:</h3> <p data-end="357" data-start="190">- Over the next two working days, you will put your new SMART goals into practice.<br data-end="275" data-start="272" /> - After that, we will move on to the final module: <strong data-end="355" data-start="326">"Optimizing Job Demands."
 </p> <p data-end="404" data-is-last-node="" data-is-only-node="" data-start="359"><strong data-end="404" data-is-last-node="" data-start="359">Good luck applying your new knowledge! 💪</p>

Einde blok: Blok 1

Appendix 14: Demand optimization module

Optimizing demands - Copy

Start van blok: Standaard vragenblok

Hi! Today, we will continue with the second dimension of job crafting: Optimizing Job Demands.

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But first, a brief reflection.

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<u>Instruction</u>: Look back on the past two days where you have sought or expanded resources to optimize your work with AI. Answer the following questions:

	Reflection: Increasing Resources
Have you worked on your goals?	
Have you achieved your goals?	
Do you think the increased resources will help you in using AI?	

Einde blok: Standaard vragenblok

Start van blok: Blok 1

Watch the video about optimizing demands with automatic subtitles, or read an English summary below the video:

 <iframe allowfullscreen="true" frameborder="0" height="600" src="https://www.youtube.com/embed/qQmQlcaOd7Q?feature=shared" width="1050"></iframe> <p data-pm-slice="1 1 []">Optimizing Demands for AI Usage
 </p> <h3>Introduction</h3> <p>Every workday consists of tasks that energize you and tasks that drain your energy. This module aims to help employees optimize their daily AI-related tasks, making their work not only more efficient but also more enjoyable. By effectively optimizing negative factors, employees can boost their productivity, well-being, and satisfaction when working with AI.
 </p> <h3>Understanding Task Demands</h3> <p>Task Demands are aspects of your work that you must meet and that continuously consume your energy and time. High

or persistent demands can deplete your energy, especially if you do not recover adequately. With the introduction of AI, new or increased demands may arise, making it essential to manage them effectively.
 </p> <h4>Examples of Task Demands</h4> <ul data-spread="false"> <p>High workload and tight deadlines</p>   <p>Cognitive strain</p>   <p>Unclear or overlapping tasks</p>   <p>Regular changes or new tasks</p>   <p>Uncertainty about how to use AI effectively
 </p>   <h3>Optimizing Task Demands</h3> <p>Optimizing demands refers to simplifying tasks and improving processes to make work more manageable and efficient. This approach ensures that working with AI provides real benefits instead of merely adding stress or pressure.
 </p> <h4>Strategies for Optimization</h4> <ol data-spread="false" start="1"> <p>Create a Prompt Library: Save successful AI prompts in one place, reducing the need to repeatedly figure out the right wording.</p>   <p>Plan Strategically: Choose the best times to work with AI when you have enough focus and energy. Avoid moments right after intense meetings or at the end of a long day.</p>   <p>Develop a Workflow: Establish a clear step-by-step plan for recurring tasks that involve AI, from preparation to final output.</p>   <p>Collaborate with Colleagues: Exchange tasks with colleagues to leverage each other's strengths. For example, someone skilled at writing prompts can assist you in return for your help in reviewing AI-generated texts.
 </p>   <h3>Case Study: Sarah (Marketing Specialist)</h3> <p>Sarah struggled with using AI due to high mental effort and frustration from repeated trial-and-error attempts. To address this, she:</p> <ul data-spread="false"> <p>Created a step-by-step plan for common AI tasks.</p>   <p>Documented successful prompts for future use.</p>   <p>Scheduled AI-related tasks for when she felt most energized (e.g., after her morning coffee).</p>   <p>Partnered with a colleague, Mark, who excelled at writing prompts while she assisted him with proofreading AI-generated content.
 </p>   <p>Outcome: Sarah now experiences less frustration and mental strain, allowing her to focus more on the creative aspects of her work.

 </p> <h3>Action Plan for Employees</h3> <ol data-spread="false" start="1"> <p>Identify task demands that are causing friction or energy loss.</p>   <p>Set SMART (Specific, Measurable, Achievable, Relevant, Time-bound) goals to reduce these demands.</p>   <p>Use one or more of the four strategies to optimize your work.</p>   <p>Apply the improvements today or tomorrow to enhance your workflow.
 </p>   <h3>Conclusion</h3> <p>Task demands are inevitable, but they can be managed and optimized. By streamlining processes and working smarter with AI, employees can save energy and achieve more with less effort. Small actions can make a significant difference, enhancing overall job satisfaction and performance.</p> <p>Good luck with the exercises, and see you in the next module!</p>

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Optimizing job demands:
 Job demands are the aspects of your work that you need to endure and that require your energy and time. Optimizing these demands means finding ways to reduce unnecessary workload, tackle inefficiencies, or make stressful tasks easier. This helps you achieve a better balance in your work and ensures you have energy left for the things that truly matter.

<p data-end="162" data-start="110"><strong data-end="160" data-start="110">Examples of Optimizing Your Tasks/Job Demands:</p> <p data-end="476" data-start="167">
 <strong data-end="204" data-start="167">Storing Quality Prompts in a File<br data-end="207" data-start="204" /> Writing effective prompts can be challenging and time-consuming. Identify which subtasks you frequently use AI for. For each subtask, create a universal prompt or prompt template that you can easily access whenever needed, making your workflow smoother and faster.
 </p> <p data-end="918" data-start="481"><strong data-end="525" data-start="481">Scheduling AI Tasks at Strategic Moments</p> <li data-end="918" data-start="481"><u>If using AI feels easy or relieving</u>, schedule AI-related tasks during times of the day when your energy or focus tends to be low. This way, AI can help you stay productive while allowing you to take it easy. <li data-end="918" data-start="481"><u>If you find AI use challenging or stressful</u>, plan AI tasks during moments when you feel more energized and motivated, such as after lunch or following an enjoyable meeting.
 <strong data-end="982" data-start="923">Creating a Workflow (With or Without Colleague Support) <p data-end="1247" data-start="923">Develop a clear step-by-step plan for completing a subtask with AI, so you don’t have to figure it out from scratch each time. Think about what preparation and materials you need, which prompt to use, and how to structure your workflow for the best results.
 </p> <p data-end="1598" data-start="1252"><strong data-end="1285" data-start="1252">Task Swapping with Colleagues<br data-end="1288" data-start="1285" /> If you believe generative AI can help with your (sub)task but you’re unsure how, consider collaborating with a colleague who enjoys working with AI. They might be able to complete the task more efficiently. In return, you can support them with something you excel at (which doesn’t have to be AI-related).</p>

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In the next step, you will create SMART goals to optimize your tasks/job demands.

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<p><u>Instruction</u>: Which tasks do you want to optimize to reduce stress or discomfort and enhance your well-being and performance? Choose one or more tasks you wish to optimize. Then, write down how you plan to optimize the task in the form of a SMART goal.</p>

<p data-end="218" data-start="78"><strong data-end="119" data-start="93">Not-yet-SMART version:<br data-end="122" data-start="119" /> “I want to explore how collaborating with a colleague can help us both make better use of AI.”</p> <p data-end="632" data-start="220"><strong data-end="238" data-start="220">SMART version:<br data-end="241" data-start="238" /> “To enhance our efficiency through collaboration, I will ask my colleague Sarah to help me improve AI prompts for creating marketing summaries this week. In return, I will support Sarah by spending half an hour assisting her with processing price analyses</p>

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<p data-end="155" data-start="0">🎯 <strong data-end="57" data-start="3">Yes - You have successfully completed this module!<br data-end="60" data-is-only-node="" data-start="57" /> Good news: You will receive a summary of the key insights in your inbox within a few minutes.
 </p> <p data-end="304" data-is-last-node="" data-is-only-node="" data-start="157"><strong data-end="177" data-start="157">Your Next Steps:<br data-end="180" data-start="177" /> Over the next two working days, you will put your new SMART goals into practice.
 <br data-end="263" data-start="260" /> Good luck applying your new knowledge! 💪</p>

Einde blok: Blok 1