UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

DOES PROTEAN CAREER ORIENTATION MODERATE THE RELATIONSHIP BETWEEN AI USE AND JOB CRAFTING? A MIXED-METHOD EXAMINATION

A THESIS

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirements for the

Degree of

MASTER OF SCIENCE

By PIPER WINSETT

Norman, Oklahoma

2026

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A THESIS APPROVED FOR THE

DEPARTMENT OF PSYCHOLOGY

BY THE COMMITTEE CONSISTING OF

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Table of Contents

Abstract

Artificial intelligence (AI) has rapidly entered the workplace, enabling workers to reshape their jobs through job crafting. However, little is known about how self-directed, values-driven individuals use AI to align their jobs with their strengths, interests, and development. Using time-lagged data, this mixed-methods study examined the relationship between AI use and job crafting behaviors, considering the role of self-directed protean career orientation (PCO). Results showed positive associations among PCO, AI use, and job crafting behaviors; however, PCO did not moderate the relationships between AI use and job crafting. Findings also showed that self-directed PCO predicts workers' use of AI for automation and dual uses, as well as enhanced task crafting behaviors. This paper advances theory on emerging conceptualizations of AI use and offers novel insights into how high PCO workers use AI to shape their work. Furthermore, I discuss how integrating AI technologies may benefit workers by enhancing their productivity, work meaningfulness, and well-being.

Keywords: protean career orientation, artificial intelligence, job crafting

Does Protean Career Orientation Moderate the Relationship Between AI Use and Job Crafting? A Mixed-Method Examination

Rapid artificial intelligence (AI) adoption is transforming how people approach their work, creating new opportunities to automate, augment, and redesign their work roles (Parker & Grote, 2022; Raisch & Krakowski, 2021; Wilkens, 2020). Many, if not most, organizations have integrated AI technologies into their daily work processes (Watson et al, 2020). Ongoing advancements in AI technologies require both organizations and workers to continually adapt to avoid stagnation and remain competitive (Teece, 1992), emphasizing the importance of fostering a workforce that values continuous learning and development (Kundi et al., 2025; Le et al., 2023). In other words, organizations need adaptable, self-motivated workers who can effectively navigate roles changed by AI (Martin et al., 2012). However, not all proactive behaviors are the same; some workers innovate, while others prioritize efficiency (Sarkees & Hulland, 2009). How workers proactively use AI tools to enhance their work experience likely depends on how they approach and manage their overall careers, in other words, their career orientations. Accordingly, recognizing the role of career orientations is crucial for creating policies and practices that influence the effectiveness of integrating AI technologies in the workplace.

Current research has begun exploring AI's role in the workplace regarding how people initiate meaningful change within their jobs, otherwise known as job crafting (e.g., Cheng et al., 2023), but a significant gap remains concerning the role of individual career orientation. In my search of the literature, I did not find any empirical research that examined the relationship between AI use, job crafting behaviors, and career orientation. Therefore, the current study explored the role that a protean career orientation (PCO), which values autonomy and alignment with personal values, plays in the relationship between workers' AI use and job crafting behaviors (Hall, 2004). Addressing this gap is important because it relates to broader questions about how self-directed and values-driven individuals might leverage AI to actively shape their work experiences, potentially influencing their performance and well-being in different ways. Thus, the present study examined how PCO relates to workers' use of AI and the extent to which they engage in job crafting behaviors with the time freed up by AI, offering empirical insights into how career orientation is associated with how individuals use AI to automate basic work tasks or enhance their roles for personal and professional growth.

Using the Job Demands-Resources (JD-R) model as a guiding framework, I integrate existing conceptualizations of automation and augmentation uses of AI with career theory to examine how workers utilize AI technologies to actively shape their jobs and how these approaches vary based on individual career orientation. Prior studies have examined the relationship between PCO and job crafting (e.g., Ahmad et al., 2021; Booysen, 2021; Kim & Hong, 2023), as well as the relationship between AI use and job crafting (e.g., Li et al., 2024), however, limited research exists that integrates these literatures into a comprehensive framework. To bridge this empirical gap, the current study tested the moderating effect of PCO on the relationship between workers' AI use and job crafting behaviors.

The career orientation literature mainly focuses on PCO as a predictor of various work outcomes. For example, scholars have examined PCO's main effects on work-life balance (Direnzo et al., 2015), career satisfaction (Kundi et al., 2021), and psychological well-being (Li, 2018). Very few studies explore PCO as a moderating variable (Hall et al., 2023; Hou et al., 2025). Yet, scholars have highlighted the need to examine contexts in which PCO may moderate various relationships (Gubler et al., 2014; Hall et al., 2018). Therefore, the purpose of this study is to examine the moderating role of PCO in how workers use AI to engage in job crafting related to their personal resources (Kooij et al., 2017). Additionally, this research explores whether high protean workers report different AI usage and crafting activities, given their additional available time, compared to less protean-oriented workers.

Using a mixed-method approach and lagged design with a Prolific sample of 578 individuals, this study advances theory on AI use in the workplace, career theory, and job crafting by testing hypotheses concerning how PCO as a personal resource moderates the effect of AI use as a job resource. Quantitatively, using Likert-scale self-report measures, I tested the hypothesis that PCO moderates the relationship between workers' AI use and job crafting behaviors, specifically that this relationship would be stronger for job crafting toward one's development than for crafting toward one's strengths or interests. Figure 1 summarizes these hypotheses and provides a summary of key results.

Consistent with prior work (e.g., Fryczyńska & Pleśniak, 2024; Li, 2018), I expected evidence for this moderation to be found for the self-directed dimension of PCO as opposed to the values-driven dimensions. Therefore, the hypotheses focused on self-directed PCO. Nevertheless, similar effects were tested for values-driven PCO. Qualitatively, responses to open-ended prompts about how workers describe using AI to accomplish tasks at work were used to compare workers who are higher versus lower in PCO. Codes for these responses were used to address hypotheses about how workers higher in PCO leverage AI relative to those lower in PCO, consistent with conceptualizations of automation and augmentation. Finally, codes for open-ended responses about how workers use the time freed up by AI were used to address research questions about how workers higher in PCO engage in job crafting behaviors compared to those lower in PCO.

In addressing these hypotheses and research questions, the current study provides valuable insights for both scientific research and practical applications. First, it provides the first known empirical investigation of the relationship between AI use and job crafting, considering the moderating effect of PCO, and offers insights into individual differences that may help explain why some workers leverage AI differently from others. Findings speak to these differences as they relate to leveraging AI for automation. Furthermore, to my knowledge, no empirical studies have examined PCO from a personal resource perspective. Thus, this study makes a new contribution to the literature by integrating career theory and the JD-R model to examine how PCO workers craft their roles to align with their personal strengths, interests, and development. Finally, the present study offers practical insights into how the integration of AI technologies can benefit workers through enhanced meaning, engagement, and well-being (e.g., Boehnlein & Baum, 2022; Petrou et al., 2012; Tims et al., 2012; Van Wingerden et al., 2017) as well as organizations more broadly by encouraging continuous adaptation and fostering a more competitive workforce (Wong et al., 2017).

In the following sections, I review the existing literature on AI adoption in the workplace, how individuals may engage in job crafting behaviors, and outline recent findings on PCO. I identify theoretical gaps in the existing research and explain how this study aims to bridge them. Next, I describe the sample and procedure and discuss the measures of interest. Then, I describe the findings for the relevant hypotheses and research questions. Finally, I discuss the theoretical and practical implications of the findings with recommendations for future research that intersects and extends theory on PCO, AI use, and job crafting.

Artificial Intelligence in the Workplace

The adoption of AI in organizational settings has steadily increased in recent years (Frey & Osborne, 2017; Huang & Rust, 2018). Empirical findings show AI serves as a valuable tool in alleviating demanding work tasks, allowing workers to work more efficiently and effectively

(Bankins & Formosa, 2023). In the workplace, AI can be utilized in two primary ways: to automate or augment work, and these two approaches are not mutually exclusive. Automation refers to offloading repetitive or routine tasks to AI for completion, with minimal human intervention. In contrast, augmentation involves collaborating with AI to enhance work tasks, typically through a human-AI feedback loop (Raisch & Krakowski, 2021).

Using AI has been linked to various positive work outcomes (García-Madurga et al., 2024; Loureiro et al., 2023; Pereira et al., 2023). For example, in a systematic literature review, Pereira et al. (2023) show that at the individual level, AI can enhance productivity, job satisfaction, commitment, motivation, career development, and work-life balance. At the team level, using AI can improve collective performance, productivity, and cohesiveness. Finally, at the organizational level, AI can boost overall performance, promote corporate citizenship behaviors, foster a positive organizational culture, and support long-term sustainability (Pereira et al., 2023). Similarly, using a mixed-method approach, Loureiro et al. (2023) conducted semi-structured interviews asking individuals to explain their perceptions of working with AI technologies. Qualitative results show that participants report enhanced feelings of happiness, reduced workload, decreased stress and anxiety, and increased productivity and efficiency (Loureiro et al., 2023).

Clearly, integrating AI in organizational contexts offers a plethora of benefits. As a result, emerging literature has begun exploring how workers utilize AI to craft their work. For example, one study found support for a positive relationship between organizational AI adoption and job crafting behaviors, which was moderated by an individual's internal locus of control (Cheng et al., 2023). In other words, workers who took personal responsibility for their jobs saw the use of AI technologies as opportunities to engage in promotion-focused job crafting, like seeking out additional job resources and challenging job demands. In contrast, workers who had an external locus of control tended to engage in more prevention-focused job crafting behaviors, such as decreasing aspects of their job that they considered hindrances (e.g., automating tedious tasks) (Cheng et al., 2023). While locus of control and PCO are both individual difference variables that emphasize taking responsibility for one's outcomes (i.e., PCO's self-directed dimension), they are meaningfully distinct in that protean workers prioritize freedom, continuous learning, and alignment with their work and values. As AI continues to be integrated into the workplace, it is essential to examine how individuals are likely to utilize these technologies to adapt their jobs to meet their personal needs and preferences, and which individuals are more likely to do so.

Job Crafting

Job crafting refers to the process through which workers proactively change, modify, and redefine their jobs to better align with their wants, needs, and preferences (Tims & Bakker, 2010; Wrzesniewski & Dutton, 2001). Extensive research has linked job crafting to many positive work outcomes, including enhanced job satisfaction, higher work engagement, improved job performance, greater meaning at work, better person-job fit, reduced burnout, and lower turnover intentions (Sei & Dar, 2019; Tims et al., 2012; Tims & Bakker, 2010). Additionally, job crafting interventions have been shown to enhance workers' engagement and contextual performance, providing valuable insights for improving worker well-being (Costantini & Weintraub, 2022; Oprea et al., 2019; Van Wingerden et al., 2017). Therefore, job crafting can be seen as a strategy to foster more meaningful work, or, in other words, thriving.

Two of the most prominent conceptualizations of job crafting are role-based and resource-based crafting (Demerouti, 2014). Wrzesniewski and Dutton (2001) argue for the role-based perspective, which encompasses three primary dimensions: task, relational, and cognitive crafting. Task crafting involves the adjustments workers make to the number, scope, and type of work tasks they undertake. Relational crafting occurs when workers change the quality and frequency of their work interactions with coworkers. Finally, cognitive crafting consists of changes individuals make to how they think about and approach their jobs, in other words, their "work identity" (Wrzesniewski & Dutton, 2001).

In contrast, the resource-based perspective of job crafting is grounded in the JD-R Model and posits that job crafting consists of behaviors that balance work demands and resources to fit one's needs better (Demerouti, 2014; Tims & Bakker, 2010). Within this perspective, scholars define job crafting as engaging in resource-seeking, challenge-seeking, or demand-reducing behaviors (Demerouti, 2014; Petrou et al., 2012). More specifically, job resources are aspects of a person's job that help in achieving work goals, reducing stress, or encouraging personal learning and development opportunities. On the other hand, job demands can be further categorized into hindrance or challenge stressors, where hindrance stressors contribute to strain, and challenge stressors tend to yield positive outcomes, such as enhanced job satisfaction and commitment. Challenge-seeking behaviors refer to the pursuit of opportunities to engage in the discovery of new skills, tasks, or responsibilities, thereby promoting a sense of mastery (Petrou et al., 2012).

While most of the job crafting literature draws on the perspective established by the seminal work of Wrzesniewski and Dutton (2001), the current study focuses on job crafting from the resource perspective, specifically focusing on how workers build their personal resources, that is, job crafting toward one's strengths, interests, and development (Kooij et al., 2017; Kuijpers et al., 2020). Job crafting towards strengths involves adjustments that individuals make in their daily tasks to utilize their existing skills or knowledge. Crafting towards one's interests entails modifying tasks to be more aligned with what an individual finds enjoyable or engaging (Kooij et al., 2017). Lastly, job crafting towards development refers to the changes workers make to create opportunities for learning and personal growth (Kuijpers et al., 2020).

In the context of AI in the workplace, examining job crafting from a personal resource perspective is essential to understanding how workers use AI technologies to align better or adapt their work, ultimately enhancing their work experience (Burke et al., 2015; Kooij et al., 2017; Kuijpers et al., 2020). Viewing AI as a valuable resource that enables job crafting behaviors, the following hypothesis was tested:

> *Hypothesis 1:* There is a positive relationship between AI use and job crafting towards (a) strengths, (b) interests, and (c) development.

While this study examined the relationship between AI use and the adjustments workers make to their work tasks, it also addressed the broader context involving workers' career orientations, specifically that of PCO. Although existing literature links job crafting to PCO with regard to task, cognitive, and relational crafting (e.g. Kim & Hong, 2023), there is a paucity of research connecting job crafting and PCO with respect to building personal resources (i.e., strengths, interests, and development). As Burke et al. (2015) assert, careers are, in fact, defined by an individual's strengths, interests, and values. Therefore, considering PCO's core principles of self-improvement and the alignment of one's work to personal values, examining the relationship between AI use and job crafting from a personal resource perspective can provide new insight into how the integration of AI is related to outcomes outside its intended purpose. Additionally, considering how workers leverage AI tools to pursue their strengths, interests, and development can help organizations better manage the integration of new AI technologies toward a variety of near- and distal-term outcomes that together enhance worker well-being and organizational effectiveness (Lo Presti et al., 2023). In this sense, AI is a job resource that affords workers the opportunity to job craft, and PCO is a motivation-based, personal resource that boosts and directs job crafting behaviors given by the opportunities afforded by AI tools.

Protean Career Orientation

Individual differences in career orientations are often described as either traditional or contemporary (Booysen, 2021). Traditional career orientations are characterized by valuing and adhering to the hierarchical structure within an organization, thereby placing the responsibility for one's career success in the hands of one's employer (Hirschi & Koen, 2021). This contrasts with contemporary career orientations, which emphasize prioritizing the individual over that of the organization (Arthur et al., 2005).

Research suggests that globalization, heightened competition, and technological advancements have changed organizational structures, thereby contributing to the emergence of new career types (Grimland et al., 2012). One of the most prominent and influential contemporary career types is PCO (Hall, 2004). A protean orientation is an approach to managing one's career that values continuous learning, adaptability, and autonomy (Briscoe et al., 2006; Hall et al., 2018). This orientation is a modern approach to career development that emphasizes individual freedom, self-development, and the alignment of one's career with personal, intrinsic values (Hall, 2004). Instead of prioritizing external motivations such as job security, financial compensation, or advancement within the organizational hierarchy, individuals with a protean orientation are primarily driven by internal motivations, aligning their careers with their own values rather than those imposed by societal norms or their organizations (Briscoe et al., 2006; Sullivan & Baruch, 2009).

Prior research has identified numerous relationships between PCO and favorable work outcomes, including enhanced organizational commitment, career satisfaction, proactive career behavior, organizational citizenship behaviors, subjective and objective career success, improved task performance, and enhanced engagement (Briscoe et al., 2006; Herrmann et al., 2015; Kundi et al., 2025; Lo Presti et al., 2019). Individuals with high levels of PCO also demonstrate greater adaptability and are more likely to report enhanced indicators of workplace well-being (Gubler et al., 2014; Li, 2018). Similarly, scholars have found that protean workers generally experience positive outcomes both within and outside of work (Direnzo et al., 2015).

The protean career was inspired by the Greek god, Proteus, who was mythologized to have the ability to change shape at will. Thus, protean individuals are believed to thrive in environments that require constant adaptation (Hall, 1996; Sargent & Domberger, 2007). The protean career comprises two core dimensions: self-directed and values-driven, with the overarching goal to achieve psychological success, or the feeling of reaching the most important goals in life (Hall, 1996). The *self-directed* dimension refers to the degree to which individuals take responsibility for their career by initiating learning opportunities and continuously investing in self-development (Direnzo et al., 2015). The *values-driven* dimension reflects individuals' alignment of personal goals and values with their career. In other words, one's values and goals serve as the primary motivators behind career decisions, and their alignment with one's career acts as a benchmark for measuring success (Sargent & Domberger, 2007). Within the scholarly literature, PCO is typically measured as comprising these two dimensions, rather than as a composite construct. Meta-analytic findings show these two dimensions are related (ρ = .58, 95% CI = .55, .61, k = 65, N = 20,738), yet meaningfully distinct (Wiernik & Kostal, 2019).

Scholars suggest that to foster a protean career, an individual must possess certain metacompetencies, or abilities that facilitate the acquisition of other or further competencies, including self-awareness and adaptability (Hall & Chandler, 2005; Hall & Moss, 1998). These two metacompetencies are important to engaging in continuous learning and flourishing in volatile, uncertain, complex, and ambiguous environments (Burke et al., 2015). Self-awareness enables a person to identify their strengths and weaknesses, which guides them in focusing on areas for change when necessary (Oh & Koo, 2021). Being self-aware also relates to a person's capacity to gather self-feedback, develop accurate self-perceptions, and adjust one's self-concept as necessary (Gubler et al., 2014). Adaptability, on the other hand, involves having the ability to change one's behavior and the motivation to implement that change (Kundi et al., 2025). Highly adaptable individuals tend to thrive in environments that value independence and readily embrace new situations (Martin et al., 2012). Put succinctly, self-awareness enables a person to sense when changes are needed, while adaptability guides the actions required to make those changes. Together, adaptability and self-awareness foster an overall self-directed learner, comprising a crucial dimension to PCO (Hall & Chandler, 2005).

Research also suggests the protean careerist is highly concerned with personal satisfaction and self-fulfillment, given their strong values-driven preference (Hall et al., 2018). Therefore, PCO is argued to enhance one's career satisfaction both directly, by enabling a positive perspective in the face of difficulty or change, and also indirectly, through engaging in behaviors that enhance the meaningfulness of one's work (Wiernik & Kostal, 2019). This aligns with the basic assumption that having control over the work environment and defining success on one's own terms fosters greater intrinsic motivation and career satisfaction (Alok & Rajthilak, 2023; Briscoe et al., 2006; Gagné & Deci, 2005; Hall et al., 2018; Wiernik & Kostal, 2019). Autonomy and intrinsic motivation are critical given the rapidly changing nature of today's workplace, as those who take responsibility for their success and align their goals with internal values may find greater meaning in their daily work and overall careers (Direnzo et al., 2015).

The Moderating Role of PCO

Studies have examined PCO as a predictor of various work outcomes, including subjective career success (Ahmad et al., 2021; Grimland et al., 2012), work-life balance (Direnzo et al., 2015), and career satisfaction (Fryczyńska & Pleśniak, 2024). Other research has focused on PCO as an outcome variable, predicted by various organizational factors (e.g., Wong et al., 2017). While there is a rich literature on PCO as both a predictor and an outcome variable, there is scant research on the moderating role of PCO (Hall et al., 2023; Hou et al., 2025). In fact, recent literature highlights this need explicitly (Hall et al., 2018, p. 146). Moreover, to my knowledge, no studies have examined the moderating role of PCO on job crafting behaviors related to building personal resources (i.e., job crafting toward strengths, interests, and development). Therefore, this study addressed these gaps in the existing literature by examining how workers leverage AI tools to job craft and how this relationship may depend on their career orientations. In this vein, PCO is a motivation-based, personal resource variable that augments the extent to which workers take advantage of AI tools to build additional personal resources to manage their job performance and overall careers. In particular, it is the self-directed aspect of PCO that primarily matters in how workers may use AI to build their personal resources.

Self-directed versus Values-driven PCO

It is typical in the PCO literature for researchers to examine the self-directed and values-driven dimensions separately, and it is not uncommon to examine only one dimension depending on the theoretical goals of the study (e.g., De Vos & Soens, 2008; Hall et al., 2023). Much of the rationale for examining the two PCO dimensions independently stems from differences in how they involve proactive behaviors. Conceptually, self-directed PCO explicitly speaks to how workers proactively build additional resources to manage their job performance and careers, whereas the values-driven dimension speaks more to how workers find meaning in the fit between their overall careers and their personal values (Direnzo et al., 2015).

The self-directed dimension of PCO aligns with the core premise of job crafting as both emphasize self-management, proactivity, and autonomy. Whereas job crafting pertains to the more granular, daily tasks workers perform, PCO relates to a broader motivation to manage one’s career. Accordingly, the two share many similarities (Booysen, 2021; Kim & Hong, 2023; Lo Presti et al., 2023). For example, job crafting enables individuals to reshape their roles to better align with their values and interests, promoting greater autonomy at work (Bruning & Campion, 2018; Demerouti, 2014; Tims et al., 2022). Autonomy is a vital factor and defining characteristic of the protean career (Hall, 1996). Additionally, studies show that those who actively engage in job crafting are more likely to seek opportunities for learning and personal growth (e.g., Kim & Hong, 2023), similar to the tendency of protean workers to engage in continuous development (Hall, 2004). Empirically, the existing literature linking PCO and job crafting is quite limited and mainly focused on crafting from the role-based perspective (e.g., Kim & Hong, 2023; Kundi et al., 2021, 2025).

However, in one empirical paper, Kundi et al. (2025) found evidence for a reciprocal relationship between PCO and job crafting, where individuals with a stronger PCO were more likely to craft their jobs, and those who engaged in more job crafting behaviors tended to develop a stronger PCO. As such, both PCO and job crafting can be viewed as personal-resource variables, with PCO as the broader motivation driving specific resource-building crafting behaviors. Unfortunately, Kundi et al. (2025) examined job crafting solely from the role-based perspective and did not distinguish between the self-directed and values-driven dimensions of PCO.

As AI is likely to continue to be integrated into the workplace, serving as a valuable resource for workers to leverage, it is important to consider how workers will shape their roles given the time AI affords them and how career orientations will influence these decisions. For example, in a narrative review, Burke et al. (2015) argued that adopting a self-directed and values-driven approach to one's career facilitates the 'crafting' of a role in pursuit of greater meaning (p. 240). Empirical findings support this idea, such that protean workers, especially those with a strong self-directed career focus, are more likely to engage in job crafting behaviors that include seeking job resources and challenges (Sei & Dar, 2019). Therefore, workers with a self-directed PCO are more likely to take action to customize their jobs to align with their personal values and achieve meaningful results. Building on previous empirical findings and the similarities between job crafting and PCO's self-directed dimension, the following hypothesis was tested:

> *Hypothesis 2*: The positive relationship between AI use and job crafting is moderated by a self-directed PCO, such that the relationship is stronger for workers with higher than lower self-directed PCO.

Continuous Learning, Self-directed PCO, and Development Crafting

Research shows that highly self-driven individuals are more likely to seek out opportunities for learning and development due to their heightened internal motivation (Kundi et al., 2025; Lo Presti et al., 2023; Sei & Dar, 2019). This may be because pursuing development requires a strong level of self-awareness to identify areas for growth and requires the motivation to engage in relevant learning opportunities (Kuijpers et al., 2020). As protean workers tend to be highly self-aware and adaptable, they are more likely to develop new skills to obtain future resources (Hall & Chandler, 2005; Hall & Moss, 1998).

Workers prioritize the acquisition of resources they deem valuable (Hobfoll, 1988). Resources can comprise several categories, including conditions, energies, objects, and personal characteristics. Personal characteristics, in particular, may include features such as self-efficacy, knowledge, and skills (Ten Brummelhuis & Bakker, 2012). This perspective assumes that those who acquire resources are more likely to obtain future resources, resulting in a resource gain spiral (Hobfoll, 1989, 2002). In the present study, I consider this perspective, along with the JD-R model, to explain why individuals high in PCO, specifically those who are more self-directed, seek additional resources, such as engaging in behaviors aimed at enhancing their development.

As mentioned previously, a notable characteristic of PCO is the engagement in continuous learning. The seminal work of Hall (1996) posits that an individual's career is comprised of continuous learning cycles and identity shifts. These ongoing learning stages consist of repeated trials of exploration, testing, establishment, and finally mastery, before repeating the cycle over again (Hall, 1996). These cycles are thought to persist throughout the entirety of one's career, in which performance slowly increases in exploration and trial phases, then increases rapidly during establishment, before plateauing at mastery, followed by another phase of exploration. According to Hall's (1996) framework of career stages, the longer a person engages in these learning cycles throughout their career, the more their performance grows exponentially over time, and the baseline level of performance begins to rise during subsequent exploration phases.

These repeated series of learning stages relate to broader theories of learning, especially Hardy and colleagues' Dynamic Exploration Exploitation Learning (DEEL) Model (Hardy et al., 2019, 2024). The DEEL Model is a self-regulated learning framework based on control theory, curiosity, and skill acquisition (Hardy et al., 2019). It posits that trade-offs occur in a training or development environment where learners assess gaps in their knowledge, that is, what they think they know versus what they want to know, referred to as information-knowledge gaps. These information-knowledge gaps guide decisions to engage in either exploratory (i.e., expanding knowledge) or exploitative (i.e., refining existing knowledge) behaviors throughout the learning process. This framework helps explain how knowledge gaps influence decisions about allocating resources and effort toward either learning-focused or achievement-focused behavior (Hardy et al., 2024). In the present study, as protean workers are believed to engage in continuous cycles of learning, it is expected that those higher in PCO will be more aware of these information-knowledge gaps. In other words, high PCO workers, particularly self-directed ones, are expected to possess a high level of self-awareness that enables them to identify areas for improvement and be highly motivated to proactively address these gaps by exploring development opportunities.

Systematic review findings support this idea, showing that protean individuals are more likely to seek growth opportunities and new experiences, rather than focusing solely on improving their current routines (Kim & Hong, 2023). Likewise, a qualitative study conducted by Clark (2009) found that protean workers displayed a lifelong learning attitude, indicating a willingness to adapt to changing circumstances, and possessed highly developed self-assessment skills that allowed them to make accurate evaluations of areas for improvement. Additionally, according to Sei and Dar (2019), protean workers possess a promotion-focused regulatory orientation. In other words, these individuals are more likely to increase job resources and take on challenging demands, rather than rely solely on their current strengths or interests.

While there is no existing literature, to my knowledge, that has examined the relationship between PCO considering the DEEL model, recent research has integrated theories of job crafting to notions of exploration and exploitation (Zhang et al., 2025). Using a sample of 115 workers and a 10-day diary design, Zhang et al. (2025) framed job crafting towards strengths and development in terms of exploitation and exploration, respectively, and how such crafting related to enhanced task and creative performance. Using the exploration-exploitation framework, they positioned job crafting towards strengths as an exploitative strategy through which workers modify their work to leverage existing strengths and deepen their expertise. Conversely, job crafting for development is viewed as an exploratory strategy where workers seek learning opportunities that promote growth. The authors argue that engaging in exploitative behavior or crafting towards strengths reduces uncertainty in task execution and leads to more consistent performance outcomes. In this way, job crafting focused on strengths enables workers to produce positive results, thereby enhancing task performance. In contrast, the authors argued that when workers engage in development crafting, they explore options through experimentation, which encourages innovative and creative problem-solving. These hypotheses were supported. Findings showed a positive relationship between job crafting towards strengths and enhanced daily task performance, as well as a significant positive relationship between job crafting towards development and creative performance. Notably, the authors also examined how strengths crafting relates to enhanced creative performance and whether development crafting is linked to improved task performance. Interestingly, they did not find evidence for these relationships, which suggests that development and strengths crafting are meaningfully distinct processes that might affect worker outcomes in unique ways.

Relatedly, recent research on creativity links exploration and exploitation behaviors to goal orientations (Steele et al., 2021). In this context, goal orientations refer to how an individual approaches goals in achievement settings. For example, a mastery-approach goal orientation is focused on mastering a task and fully understanding the content. A performance-approach goal orientation, on the other hand, reflects an individual's desire to prove their competence and outperform others. Lastly, a performance-avoidance goal orientation is focused on avoiding performing worse than others. Steele et al. (2021) found that a mastery orientation is positively related to both exploration and exploitation behaviors, while a performance-approach orientation was negatively related to exploration. Additionally, exploration and exploitation were found to have unique relationships to creativity, characterized by displaying novelty and usefulness. The more exploration an individual engaged in, the more their product was perceived as novel, while the more exploitation they pursued, the more useful their product was seen. This suggests that a mastery goal orientation, or the preference to prioritize learning over performance, may be especially helpful in creative contexts, where workers engage in both exploration and exploitation strategies.

Other scholars have examined the relationship between various goal orientations and PCO (Lin, 2015). For example, a study by Lin (2015) found evidence for the mediating effect of goal orientation on the relationship between protean career attitudes and perceived employability, indicating that individuals with protean attitudes tend to display a strong desire to engage in more challenging work and acquire new skills. A strong learning-goal orientation was characterized as adapting to change in terms of one's employment, job content, conditions, or even location, which was found to fully mediate the link between PCO and perceived employability (Lin, 2015). Put differently, findings indicate PCO is associated with a learning-focused orientation (mastery) rather than an achievement-focused one (performance). Taken together, these findings support the idea that workers high in PCO may be more inclined to engage in crafting behaviors aimed at personal development rather than those focused on strengths and interests.

As intrinsic motivations and proactive behavior guide these individuals, high PCO workers are expected to use AI more strategically to craft their jobs compared to those low in PCO. Indeed, meta-analytic findings indicate the self-directed dimension of PCO tends to be highly correlated with overall career self-management behaviors, particularly engaging in development activities, as opposed to the values-driven dimension (Wiernik & Kostal, 2019). With respect to job crafting specifically, Sei and Dar (2019), in a sample of 406 workers, found evidence of a positive link between self-directed PCO and job crafting, especially in seeking resources and challenges, whereas the values-driven dimension was not associated with job crafting. More generally, workers who are highly self-directed tend to seek more growth and developmental opportunities through their job crafting behaviors (Bankins & Formosa, 2023). Therefore, when it comes to leveraging AI for building personal resources, the moderating role of self-directed PCO is especially relevant for development crafting. Accordingly, I tested the following hypothesis:

> *Hypothesis 3*: The moderating effect of self-directed PCO on the relationship between AI use and job crafting is stronger for development crafting than for strengths and interests crafting.

PCO and AI Automation and Augmentation

As protean workers value autonomy in their daily tasks and aim to grow personally and professionally, it is expected that they will look for AI tools that help support their learning and skill development (Hall, 2004). As mentioned previously, AI use is primarily conceptualized as either automation or augmentation, with automation referring to tasks that require little to no human intervention, and augmentation containing a human-AI feedback loop (Raisch & Krakowski, 2021). Research suggests automation can be especially helpful in situations where tedious tasks can be offloaded to AI, allowing workers to conserve their limited resources to devote to more complex work tasks (Raisch & Krakowski, 2021). In other words, as AI frees up time by completing simple tasks, workers can focus on aspects of their job that require more meaningful effort (Agrawal et al., 2023; Li & Yeo, 2024). In this sense, workers who are high in PCO may offload some of their more repetitive tasks to AI and use the time AI frees up to engage in activities that reflect learning and knowledge gain. Therefore, I tested the following hypothesis:

> *Hypothesis 4*: Self-directed PCO is positively associated with using AI for automation activities.

As stated earlier, using AI for automation and augmentation is not mutually exclusive. Workers may engage in behaviors that reflect high levels of both automation *and* augmentation. Using AI for augmentation has been shown to support learning and knowledge development (e.g., Shao et al., 2025) and to enhance human creativity by facilitating the generation of novel ideas (e.g., Eapen et al., 2024). Augmentation aligns with PCO's values of continuous learning, personal growth, and autonomy by enhancing workers' capabilities and offering opportunities for exploration, creativity, and skill development (Enholm et al., 2022; Li & Yeo, 2024; Nguyen & Elbanna, 2025; Wilson & Daugherty, 2018). As it is expected that workers high in PCO will prioritize using AI to promote greater knowledge gains, the final hypothesis I tested was as follows:

> *Hypothesis 5*: Self-directed PCO is positively associated with using AI for augmentation activities.

Research on AI use varies in how it views automation and augmentation—whether as separate, distinct applications or as compatible elements that can work together (Kumar et al., 2023). The existing literature provides explicit examples of automation and augmentation in organizational settings. For instance, automation might involve a customer service company using AI chatbots to relieve workers of basic, repetitive tasks, allowing them to focus on more complex work. Conversely, augmentation could include AI tools that automatically identify errors in large data sets for humans to review and correct (Nguyen & Elbanna, 2025). Overall, the literature suggests that automation involves anything that can be offloaded to technology, offering more rational and efficient processing, while augmentation aims to support human decision-making, offer new insights, promote creativity, or enhance worker intuition and reasoning (Raisch & Krakowski, 2021). Unfortunately, there is limited research that examines the specific ways in which workers may use automation or augmentation in their daily work tasks (Alla, 2025; Enholm et al., 2022). While there is a paucity of research aimed at clarifying these conceptualizations in terms of actual worker behavior, the current effort explores whether any differences emerge in types of automation or augmentation among high PCO workers versus low PCO workers. Therefore, I explored the following research question to differentiate between various kinds of automation and augmentation behaviors:

> *Research Question 1:* How do high self-directed protean workers versus low self-directed protean workers differ in their use of AI technologies for automation and augmentation purposes?

While the previous research question addresses actual worker AI use, the final research question aims to determine the various ways in which workers report crafting their roles given the time AI has freed up for them. When AI technologies free up time through automation, augmentation, or both, workers will make decisions about how to reallocate their efforts. As empirical evidence shows high protean workers differ significantly from those lower in PCO in seeking learning opportunities (e.g., Lin, 2015), it is reasonable to assume that the ways they allocate free time may also vary. Therefore, examining how high self-directed protean workers differ from their low self-directed counterparts in the crafting activities they report engaging in helps understand whether time freed up by AI provides opportunities for exploration, learning, and more meaningful work, or if it is more often used for basic, maintenance tasks or less development-oriented activities. Therefore, I examined an additional research question:

> *Research Question 2:* How do high self-directed protean workers differ from low self-directed protean workers in the job crafting activities they report doing given the time they are provided by AI?

Given the emphasis PCO places on autonomy, continuous learning, and adaptability, organizations may benefit from fostering protean ideals among workers to complement the rapid evolution of workplace demands (Kundi et al., 2025). Some researchers even argue that fostering a protean orientation is not merely a luxury, but rather a necessity, given the current dynamic work environment (Hall et al., 2018). Hence, the present study examines whether PCO matters in relation to the use of AI and job crafting in the workplace, and if so, in what ways?

Method

Sample and Procedure

To test the hypothesized model and research questions, data were used from an initial sample of 806 workers (45.8% females; $M_{\text{age}} = 38.3$, $SD_{\text{age}} = 10.7$) working in finance and insurance (55%), and retail (45%) from the United Kingdom (57.3%), United States (33.9%), Canada (4.5%), Australia (2.4%), and New Zealand (1.2%). Participants were predominantly White (80.9%; Asian = 8.1%; Black = 3.8%; Mixed or other = 6.1%) and reported working around 31–40 hours per week, with an average job tenure of 5.25 years ($SD = 5.39$). To provide diversity in the sample, data were collected through the online survey platform Prolific (Behrend et al., 2011), which has been shown to yield high-quality responses compared to other popular online data collection platforms (Douglas et al., 2023). Workers from these industries were recruited, as they are likely to be among the most affected by AI in terms of job structure, functions, and skills (Loureiro et al., 2021). Data were collected from a larger multi-wave dataset, where participants completed a battery of measures, many of which were not relevant to the current study. Data from the initial prescreening survey and the first two waves are used to test the hypothesized model and related research questions.

Initially, 806 workers responded to a short prescreening survey, approximately 3 minutes long, which included demographic questions, measures of career orientation, and questions regarding their AI use. Due to either failure to complete proper Prolific procedures or duplicate submissions, data from 134 participants were removed. Two weeks later, in Wave 1, 672 participants were invited to complete a 10-minute survey regarding their AI use and general work experiences. Removals were made for participants who failed attention checks or did not complete the survey, resulting in 578 participants (response rate = 71.7%). Wave 2 data were collected four weeks later, during which participants answered questions about their work experiences over the past month.

The final sample retained included workers (44.2% female; $M_{\text{age}} = 39.4$, $SD_{\text{age}} = 10.9$) in finance and insurance (56.2%), and retail (43.8%) from the United Kingdom (60.3%), United States (31.1%), Canada (4.2%), Australia (2.6%), and New Zealand (1.7%). Participants were predominantly White (83.1%; Asian = 8.0%; Black = 3.5%; Mixed or other = 5.4%) and reported working around 31–40 hours per week, with an average job tenure of 5.68 years ($SD = 5.64$).

To account for systematic attrition bias, I performed two types of tests using data from participants who dropped out and those who completed the study through Wave 2. First, a chi-square test was conducted to determine whether attrition rates differed significantly across key categorical demographic variables (e.g., White versus Non-White, male versus non-male, and finance and insurance versus retail). Chi-square tests showed significant differences based on race, $\chi^2(1, N = 806) = 7.14$, $p = .008$, such that attrition was lower than expected among White participants (26%) versus Non-White participants (37%). There was no differential attrition based on sex ($\chi^2(1, N = 800) = 1.39$, $p = .24$) or industry ($\chi^2(1, N = 800) = 1.65$, $p = .20$).

Second, *t*-tests were conducted to compare differences across continuous demographic variables (e.g., age, job tenure) as well as PCO. Importantly, PCO did not differ significantly across those who completed the study and those who did not, $t(804) = 0.65$, $p = .65$. Results showed differential attrition by age ($M_{\text{lost}} = 35.56$, $SD_{\text{lost}} = 9.75$; $M_{\text{retained}} = 39.43$, $SD_{\text{retained}} = 10.93$), $t(804) = -4.67$, $p < .001$, $d = -.37$), and job tenure ($M_{\text{lost}} = 4.20$, $SD_{\text{lost}} = 4.55$; $M_{\text{retained}} = 5.68$, $SD_{\text{retained}} = 5.64$), $t(804) = -3.55$, $p = .003$, $d = -.28$).

Measures

The variables of interest for this study include relevant control variables, AI use, PCO, and measures of job crafting related to strengths, interests, and development. In addition to these variables, which were used to test the quantitative hypotheses, participants also provided open-ended responses regarding their AI use in more detail. The open-ended responses were analyzed qualitatively to explore whether high protean workers use AI differently from low protean workers.

Before Wave 1. *Control Measures.* Demographic questions were included to serve as control variables that may be related to the relevant research questions, including participants' age, sex, racial status (white/nonwhite), and job tenure.

PCO. Protean career orientation was measured using a shortened measure by Porter et al. (2016) in which participants responded to 7 items on a 7-point scale (1 = *Strongly Disagree*; 2 = *Disagree*; 3 = *Somewhat Disagree*; 4 = *Neither Agree nor Disagree*; 5 = *Somewhat Agree*; 6 = *Agree*; 7 = *Strongly Agree*). The scale included both self-directed and values-driven dimensions.

Sample items include: “I am responsible for my success or failure in my career,” “Where my career is concerned, I am very much my own person,” “It doesn’t matter much to me how other people evaluate the choices I make in my career,” and “I navigate my own career, based upon my personal priorities, as opposed to my employer’s priorities.” Coefficient alpha reliabilities for the self-directed and values-driven scores were .77 and .68, respectively. Omega reliabilities were .78 and .68 for the self-directed and values-driven scores, respectively.

Wave 1. *AI Use.* AI use was measured using a three-item scale adapted from Tang et al. (2022): “I used AI technology to carry out many of my job functions,” “I spent a lot of the time working with or developing AI technology,” and “I worked with AI technology to make important work decisions.” Participants responded to items regarding their AI use in the past month on a 7-point scale (1 = *Strongly Disagree*; 2 = *Disagree*; 3 = *Somewhat Disagree*; 4 = *Neither Agree nor Disagree*; 5 = *Somewhat Agree*; 6 = *Agree*; 7 = *Strongly Agree*). Coefficient alpha and omega reliabilities for the AI use scores were .90 and .90, respectively.

Wave 2. *Job Crafting.* Job crafting was examined at Wave 2, establishing temporal precedence for AI use measured at Wave 1. Job crafting was measured using an adapted 9-item scale from Kooij et al. (2017) and Kuipers and Kooij (2020). Participants responded to items regarding their work experiences in the past month on a 7-point Likert scale (1 = *Never*; 2 = *Rarely*; 3 = *Sometimes*; 4 = *Regularly*; 5 = *Often*; 6 = *Very Often*; 7 = *All the Time*). Items for strengths crafting included “I changed my job to use my current knowledge and capacities to the fullest,” “I made sure that I take on tasks that I am good at,” and “In my work tasks, I tried to take advantage of my strengths as much as possible.” Items for interest crafting included “I made sure that I took on tasks that I like,” “I actively looked for tasks that match my own interests,” and “I organized my work in such a way that I could do what I find interesting.” Items for development crafting included “I looked for opportunities to use different current skills in my work,” “I looked for tasks through which I could develop myself,” and “I looked for tasks that activate unused knowledge and skills.” Coefficient alpha reliabilities for the strengths, interests, and development crafting scores were .74, .91, and .88, respectively. Omega reliabilities were .75, .91, and .88 for the strengths, interests, and development crafting scores, respectively.

AI Uses, Job Crafting Activities, and Perceived Benefits. Participants were asked about the AI technologies they used to carry out their job functions in the past. Specifically, if they rated the following item, “In the past month, I used AI to give me more time to do other things at work,” (1 = *Strongly Disagree*; 2 = *Disagree*; 3 = *Somewhat Disagree*; 4 = *Neither Agree nor Disagree*; 5 = *Somewhat Agree*; 6 = *Agree*; 7 = *Strongly Agree*) a score of four or higher, they were prompted to answer three open-ended questions. Open-ended response prompts included: 1) “Describe what was done by the AI technology,” 2) “Describe the other things you did because of the time given to you,” and 3) “Describe how doing these other things was helpful.”

Six trained undergraduate and graduate research assistants reviewed participant responses independently and developed a bottom-up coding schema. Using a constant comparison approach, coding was done iteratively in batches of 20–30 participants. The three trained graduate assistants then reviewed codes and held regular consensus meetings to resolve any disagreements that arose. Themes were developed by collapsing emerging codes into dimensions and then sorting them into a hierarchy, considering both emerging conceptualizations of automation and augmentation (e.g., Raisch & Krakowski, 2021) as well as existing theories of job crafting (Tims et al., 2022). Figure 2 shows the hierarchical organization of automation, augmentation, and dual automation-augmentation codes that emerged. Figure 3 shows the hierarchical organization of codes that emerged for job crafting activities.

Results

Table 1 presents the descriptive statistics, reliabilities, and intercorrelations for all study variables. AI use was positively correlated with the self-directed dimension of PCO ($r = .18$, $p < .001$), as well as job crafting towards strengths ($r = .18$, $p < .001$), interests ($r = .18$, $p < .001$), and development ($r = .31$, $p < .001$). The self-directed dimension of PCO was positively correlated with job crafting (JC-strengths: $r = .27$, $p < .001$; JC-interests: $r = .29$, $p < .001$; and JC-development: $r = .32$, $p < .001$). The correlation between AI use and the values-driven dimension of PCO was near zero ($r = .05$, $p = .15$), and likewise the correlations between values-driven PCO and crafting were near zero (JC-strengths: $r = .08$, $p = .05$; JC-interests: $r = .08$, $p = .04$; JC-development: $r = .01$, $p = .78$).

Hypotheses

AI Use and Job Crafting

To examine the relationship between AI use and job crafting, including the role of PCO, I conducted moderated multiple regression (MMR) analyses using R (v4.4.1; R Core Team, 2024). To test Hypothesis 1, three separate moderated regression analyses, one for each dimension of job crafting, were conducted to test the relationship between AI use and crafting, considering the role of self-directed PCO (See Tables 2–4). All models were conducted using the base R “stats” and “psych” packages (v4.4.1; Revelle, 2026).

All control variables (age, sex, race, and tenure) were entered in the first step (Model 1). The main effects for AI use were entered in Model 2, followed by the main effect of self-directed PCO in Model 3. To test the moderation hypotheses, the AI use × self-directed PCO interaction term was entered in Model 4. While not hypothesized, to explore the role of the values-driven dimension of PCO, Model 5 included relevant control variables, and main effects for AI use and values-driven PCO, followed by the AI use × values-driven interaction term entered in Model 6. Both moderators were mean-centered per the recommendations of Aiken and West (1991). Finally, I tested the robustness of the effects in Model 7 by including control variables, all study variables, and both PCO interaction terms. The results are summarized in Tables 2, 3, and 4 for JC-strengths, interests, and development, respectively.

Effects of Self-directed PCO

Moderated multiple regression analyses indicated that the addition of the main effects of AI use and self-directed PCO in Model 2 and 3 added significantly to the prediction of all three dimensions of job crafting (ΔR^2s ranged from .04 to .10, *p*s < .001), when controlling for age, sex, race, and job tenure, which as a group did not account for a statistically significant amount of variance in Model 1 for any of the crafting dimensions. Hypotheses 1a, 1b, and 1c, which hypothesized there would be a positive relationship between AI use and job crafting, were supported: $\beta = .19$ ($p < .001$; $\Delta R^2 = .04$), $\beta = .20$ ($p < .001$; $\Delta R^2 = .04$), and $\beta = .32$ ($p < .001$; $\Delta R^2 = .10$) for JC-strengths, interests, and development, respectively.

The main effect for self-directed PCO was significant for all three dimensions of crafting: JC-strengths, $\beta = .25$, $p < .001$, $\Delta R^2 = .06$; JC-interests, $\beta = .28$, $p < .001$, $\Delta R^2 = .07$; and JC-development, $\beta = .28$, $p < .001$, $\Delta R^2 = .07$. Workers who reported greater self-directed PCO reported greater job crafting. However, contrary to Hypotheses 2 and 3, adding the AI use × self-directed PCO interaction term in Model 4 did not contribute significantly to the prediction of any of the three types of job crafting (βs = .03–.05, *p*s > .05); therefore, Hypotheses 2 and 3, which stated that the moderating effect of self-directed PCO on the AI use-job crafting relationship would be stronger for high PCO workers than for low PCO workers, and that this relationship would be stronger for development crafting than for strengths or interest crafting, were not supported. The main effect of self-directed PCO was significant across all models, whether or not the AI use × self-directed PCO interaction term was included. Thus, self-directed PCO was positively associated with job crafting, but the results did not provide evidence that self-directed PCO moderates the positive relationship between AI use and crafting.

Effects of Values-driven PCO

As stated above, although not hypothesized, MMR was also used to examine the main effects for values-driven PCO and its interaction with AI use in explaining variance in job crafting. The results showed weak and near-zero main effects for all three dimensions of crafting (JC-strengths: $\beta = .08$, $p = .08$; JC-interests: $\beta = .10$, $p = .049$; JC-development: $\beta = -.01$, $p = .83$), and the interaction term was not statistically significant for any of the crafting dimensions (JC-strengths: $\beta = -.02$, $p = .73$; JC-interests: $\beta = .00$, $p = .88$; JC-development: $\beta = -.03$, $p = .48$). Thus, the results showed that values-driven PCO did not play much, if any, role in job crafting behaviors.

Overall, PCO did not moderate the relationship between AI use and job crafting. However, both AI use and self-directed PCO were positively related to job crafting towards strengths, interests, and development, whereas relationships for value-driven PCO were near-zero and generally not statistically significant.

Using AI to Get Other Things Done at Work

To test Hypotheses 4 and 5, that high self-directed PCO workers report using AI for more automating and augmenting activities to give them time to do other things at work, and address Research Question 1 (detailed below), which asked how high self-directed PCO workers differ from those lower in PCO in their use of AI technologies, responses to open-ended questions were coded and collapsed into hierarchies based on existing conceptualizations of automation and augmentation (Raisch & Krakowski, 2021). As such, findings showed workers described using AI in ways that reflected automation, augmentation, or dual automation-augmentation uses (Figure 2). Table 5 displays the complete hierarchy of workers' reported AI uses, including counts for each code, counts for high- and low-self-directed PCO workers (i.e., top and bottom tertiles), definitions for each code, and example sentiments.

PCO Predicting Automation and Augmentation AI Uses. If participants answered a four or above (1–7; *Strongly Disagree – Strongly Agree*), to the following item: "In the past month, I used AI technology to give me more time to do other things at work," then they were prompted with three open-ended questions for which qualitative data were coded: 1) Describe what was done by the AI technology. 2) Describe the other things you did because of the time given to you by the AI technology. 3) Describe how doing these other things was helpful. Consistent with Hypotheses 4 and 5, which stated that high self-directed PCO workers report greater use of AI technologies for automation and augmentation purposes, the correlation between self-directed PCO and scores on this AI use item was .21 ($p < .001$). Additionally, participants were grouped into low- and high-tertile PCO groups if they scored less than 5.25 or above 6.00 on the self-directed PCO scale, respectively. As expected, based on the correlation coefficient, results showed that workers in the high PCO group scored higher on the AI use item that prompted the open-ended response questions than workers in the low PCO group, $\chi^2 = 17.70$, $df = 1$, $p < .001$ (Table 6).

Three logistic regression analyses were conducted to examine the association of a self-directed PCO on the likelihood that a worker reported using AI for automation, augmentation, or dual-use (see Tables 7–9). All models were conducted using the base R "stats" and "psych" packages (v4.4.1; R Core Team, 2024; Revelle, 2026). To address Hypotheses 4 and 5, which relate to the first open-ended response question regarding workers' AI use, logistic regressions were conducted in two steps. Data were analyzed using General Linear Modeling (GLM) in R, including both participants who unlocked the open-ended responses, that is, who responded a four or above to the AI use measure, and those who did not ($N = 578$; $n = 298$ responded ≥ 4 and were prompted the open-ended response; $n = 280$ who responded < 4 and did not prompt the open-ended response box). First, control variables (age, sex, race, and job tenure) were entered in Step 1, and self-directed PCO was entered in Step 2.

In support of Hypothesis 4, which stated that those higher in PCO would report more automating behaviors than those lower in self-directed PCO, logistic regression results showed PCO significantly predicted the probability of a worker reporting using AI in ways that reflect automation ($\beta = .35$, $p < .001$). Adding self-directed PCO significantly improved model fit in Step 2, $\chi^2(1) = 11.78$, $p < .001$. As shown in Table 7, a one standard deviation increase in self-directed PCO was associated with 42% higher odds of reporting AI uses that reflect automation (odds ratio [OR] = 1.42, CI [1.16, 1.76]). Therefore, Hypothesis 4 was supported. Self-directed PCO was positively associated with using AI tools for automation purposes to give workers more time to do other things—job craft—at work.

For Hypothesis 5, which stated that those higher in PCO would report more augmenting behaviors than those lower in self-directed PCO, logistic regression results summarized in Table 8 showed PCO did not reach statistical significance in predicting AI use for augmentation ($\beta = .23$, $p = .14$). Therefore, Hypothesis 5 was not supported.

Although not formally hypothesized, an additional logistic regression was conducted to examine whether PCO predicts the probability that a worker reports dual automation-augmentation uses of AI. With a two-tailed test, the results showed that self-directed PCO did not reach conventional levels of statistical significance in predicting dual AI use ($\beta = .21$, $p = .051$). However, given that Hypotheses 4 and 5 for automation and augmentation both predicted greater use for those higher in PCO, a one-tailed test is appropriate for determining the statistical significance of the effect. As such, the effect was statistically significant ($p = .026$). Moreover, adding self-directed PCO to the control model did significantly improve model fit, $\chi^2(1) = 3.93$, $p = .047$. As shown in Table 9, a one standard deviation increase in PCO was associated with 21% higher odds of reporting AI use for dual-use automation-augmentation (odds ratio [OR] = 1.23, CI [1.00, 1.53]). Therefore, self-directed PCO was positively associated with dual automation-augmentation use of AI tools to give workers more time to do other things—job craft—at work.

Research Questions

To address Research Questions 1 and 2 (Figures 2 and 3, respectively), which asked how high self-directed PCO workers differ from those with lower PCO in their use of AI technologies and job crafting activities, I compared high versus low self-directed PCO participants at both (1) the level of the broad themes (Level 2) that emerged and (2) the level of the specific codes (Level 1) that emerged and were collapsed under high-order, broad themes.

Self-directed PCO and the Specific Types of Using AI to Get Other Things Done at Work

Regarding Research Question 1 and the types of AI use, the preceding logistic regression analyses for Hypotheses 4 and 5 already showed that high self-directed PCO workers were more likely to use AI for automation and dual automation-augmentation. To answer Research Question 1, I followed up these regression analyses by examining the relationship between PCO and each Level 1 code. Overall, across all 18 Level 1 AI use codes, there was a pattern of greater AI use among high self-directed PCO workers; specifically, high PCO workers showed greater use in 14 of the 18 codes (78%). In general, the differences were small and non-significant. Notably, however, self-directed PCO workers significantly showed greater use of AI to *gather data and information* ($\beta = .73$, $p = .007$, OR = 2.07, CI [1.24, 3.62]).

Self-directed PCO and Types of Job Crafting Afforded by AI

Regarding Research Question 2 on the types of job crafting activities workers reported engaging in, 15 Level 1 codes emerged and were collapsed into three broad, higher-order themes (Level 2): time-spatial crafting (i.e., non-work-related crafting), task crafting, and relational crafting (i.e., work-related crafting). Table 10 displays the complete hierarchy of workers' job crafting behaviors, including counts for each code, counts for high- and low-self-directed PCO workers (i.e., top and bottom tertiles), definitions for each code, and example sentiments.

Similar to the analyses above for Hypotheses 4 and 5, I conducted logistic regression analyses at the broader theme level (Level 2) to answer Research Question 2. The results are summarized in Tables 11, 12, and 13 for time-spatial, task, and relational crafting, respectively. Overall, the effects showed a greater tendency for high self-directed PCO workers to job craft, but only the effect for task crafting was statistically significant ($\beta = .34$, $p < .001$, OR = 1.41, CI [1.18, 1.69]; time-spatial $\beta = .20$, $p = .19$; relational $\beta = .17$, $p = .16$). I then followed these regression analyses by examining the PCO effects for each of the Level 1 codes. Overall, across all 15 Level 1 use codes, there was a pattern of greater crafting among high self-directed PCO workers; specifically, high PCO workers reported greater crafting on 14 of the 15 codes (93%). In general, the differences were small and non-significant. However, within task crafting, the effect for the completion of *more basic and routine tasks* was statistically significant ($\beta = .33$, $p = .003$, OR = 1.40, CI [1.12, 1.75]), and within relational crafting, the effect for *enhanced* *coworker interactions* was also statistically significant ($\beta = .57$, $p = .03$, OR = 1.77, CI [1.08, 3.00]).

Discussion

The purpose of this study was to empirically examine the role PCO plays in the relationship between workers' AI use and job crafting related to their personal resources (i.e., strengths, interests, and development). Additionally, this study provides novel qualitative insights into how workers use AI for automation, augmentation, and dual purposes in terms of how they engage in various job crafting behaviors and how these uses and behaviors differ based on workers' PCO. Using MMR to analyze 578 workers in retail, finance, and insurance, the results showed that self-directed PCO and AI use were positively associated with crafting toward one's strengths, interests, and development. However, no evidence was found for the hypothesized moderating role of PCO on AI use-job crafting relationships.

Consistent with my hypotheses, MMR results revealed significant positive relationships between workers' AI use and job crafting towards strengths, interests, and development. These findings suggest that AI tools are a valuable resource that enables job crafting, particularly in enhancing workers' personal resources. Prior research shows that when workers shape their work situations through job crafting, this enhances the extent to which they find meaningfulness in their work (Vuori et al., 2012). Work meaningfulness is defined as the extent to which workers perceive their work as important, significant, and worthwhile. Research shows job autonomy is a key predictor of work meaningfulness, and meaningfulness is positively associated with enhanced job satisfaction (Wandycz-Mejias et al., 2025). My findings position AI as a useful tool that provides workers opportunities to engage in job crafting that fosters more meaningful work and ultimately supports worker well-being.

Consistent with prior research (e.g., Kim & Hong, 2023; Lo Presti et al., 2023; Oh & Koo, 2021), results also showed evidence of a positive relationship between self-directed PCO and job crafting behaviors. These findings are supported by previous research highlighting PCO as reflecting the responsibility that workers assume as they develop their careers through various resource-seeking strategies (Bazine et al., 2025; Li et al., 2022). As PCO is defined by a preference for autonomy and self-direction, and job crafting allows workers greater control over modifying their professional lives, workers with high PCO engage in more job crafting behaviors. In other words, workers who proactively change their jobs via crafting develop a greater sense of ownership in their work and careers more broadly. These findings suggest that job crafting provides workers the freedom and control to change the scope of their work tasks, ultimately encouraging greater self-direction in how they approach their jobs and careers.

Additionally, findings showed evidence for a positive association between self-directed PCO and workers' reported use of AI. This is consistent with prior findings by Kong et al. (2023) that show high PCO workers are more likely to engage and collaborate with AI technologies. Workers with high self-directed PCO are likely to see AI as an opportunity rather than a threat. Findings by Sei and Dar (2019) support this idea, showing that high PCO workers, especially those who are self-directed, are more likely to engage in job crafting behaviors, such as increasing resources and challenging work demands, rather than reducing hindering work demands. This suggests that workers high in PCO are more likely to seek opportunities that increase their resources, enabling them to readily adapt to changing work environments, especially those impacted by AI integration.

Contrary to my hypotheses, self-directed PCO was not a significant moderator for any of the AI use-job crafting relationships. One explanation for the lack of evidence that PCO moderates the AI use-job crafting relationship is the extent to which workers trust the AI, which may serve as a key precondition for PCO's moderating role. Recent studies have found support for the mediating mechanisms of AI trust and intrinsic motivation (Jiang & Chen, 2026; Kong et al., 2023). For example, Kong et al. (2023) examined the moderating role of PCO in the relationship between workers' AI trust and AI collaboration. Findings showed support for the moderating role of PCO, such that the positive relationship between AI trust and AI collaboration was stronger for those higher in PCO. These findings suggest that workers' trust motivates collaboration with AI technologies for proactive workers, thereby benefiting workers' well-being and productivity. In this sense, if high PCO workers do not view AI as trustworthy, then they are not likely to leverage AI in a way that enables job crafting.

Jiang and Cheng (2026) similarly examined the relationship between AI trust and PCO, mediated by intrinsic motivation. Using self-determination theory (SDT), which posits that intrinsic motivation is based on personal interest, growth needs, and self-fulfillment goals, the authors hypothesize that workers' intrinsic motivation is stronger when competence and autonomy needs are satisfied. These needs correspond with PCO's self-directed and values-based aspects. Without trust in AI, the role of PCO is weakened if these needs are not fulfilled. In other words, when individuals perceive AI as reliable and useful, they feel more capable and autonomous themselves, which in turn would be associated with greater proactive behavior. Jiang and Cheng's (2026) findings support this idea, suggesting that giving individuals reliable AI can spark intrinsic motivation and, later, translate into a higher PCO.

Another possible explanation for the non-statistically significant interaction between AI use and PCO may be whether organizations had formally adopted AI technologies into workers' daily processes. The extent to which organizations formally adopt the use of AI technologies limits worker autonomy and likely obviates the role of self-directed PCO. In a similar vein, if AI is mandated, it may undermine workers' intrinsic motivation to use it. This explanation is consistent with situational strength theory. Situational strength is defined as implicit or explicit cues that convey the desirability of certain behaviors (Meyer et al., 2010). In other words, situational strength reflects the extent to which individuals feel social pressure to engage in or refrain from particular behaviors in certain settings. In strong contexts, behavioral variance is reduced, and individual personality traits are weakened in trait-outcome relationships. Consistent with situational strength theory, if workers are given clear instructions and reinforcement for how AI is to be used, for what tasks, and when, this limits the role of worker proactivity, suggesting that the relationship between PCO and using AI at work may depend on external factors like organization-wide AI policies and practices.

Theoretical Contributions

The present study makes three key theoretical contributions to the literature. First, this research provided the first known empirical examination of the role PCO plays in workers' AI use and job crafting behaviors aimed at building personal resources (i.e., strengths, interests, and development). Previous research has primarily used role-based perspectives to examine the association between PCO and job crafting behaviors (Kim & Hong, 2023; Kundi et al., 2021, 2025). This study, however, considered job crafting from the resource-based perspective, grounded in the JD-R Model, viewing AI as a valuable resource workers can leverage to enable job crafting behaviors. Additionally, this research addressed the explicit call from scholars to examine contexts in which PCO may moderate work relationships (Hall et al., 2018, p. 146), but it showed main effects rather than moderation.

Second, this research provided novel insights into how self-directed PCO workers use AI technologies for automation, augmentation, and dual uses. Specifically, the results showed PCO positively predicted the use of AI for automation. This is likely due to high PCO workers' preference for more meaningful, fulfilling, or challenging work. Seeing AI as a tool, they prefer to offload tedious tasks to AI, alleviating some of their workload and allowing them to focus on more value-adding work. Indeed, recent research shows that using AI enhances workers' productivity, creative work, decision-making, and relationship-building (Law & Varanasi, 2025; Pereira et al., 2023). Contrary to my expectations, PCO did not predict the use of AI for augmentation. Consistent with the rationale supporting PCO workers' use of AI for automation, high PCO workers may simply prefer to offload basic, mundane tasks to AI to engage in more complex and creative work.

Lastly, I explored how high PCO workers use the time AI frees up for them (i.e., job crafting) and how they perceive engaging in these activities as helpful (i.e., benefits of job crafting) compared to workers low in self-directed PCO. Findings revealed that PCO positively predicted task crafting. This suggests workers high in PCO are more likely to shape their roles in ways that align with their needs, ultimately enhancing the extent to which they find meaning in their work. This is consistent with the fundamental tenets of both PCO and job crafting, as it demonstrates that self-directed workers seek out additional resources with which they can align their jobs with their personal preferences (Sultana & Malik, 2019). Prior research supports this idea, such that those who actively shape their job tasks start to view themselves as in control of shaping their overall careers. In fact, Kim and Hong (2023) argue that task crafting is a foundation with which workers can adopt protean career attitudes.

In particular, findings showed that high PCO workers reported using the time AI freed up time for them to *gather information and data.* This is consistent with prior findings showing that high PCO workers proactively seek out new information, expanding and building upon existing knowledge (Lin, 2015). Additionally, while not statistically significant at the crafting level (Level 2), self-directed PCO workers reported greater relational crafting, particularly in reporting that using AI helped to *enhance interactions with coworkers*. These results shed light on how PCO workers use AI to foster deeper, more meaningful relationships, which could also serve as a personal value (i.e., values-driven dimension of PCO) for many individuals working in retail, finance, and insurance industries. I speculate that proactively enhancing the quality and quantity of work relationships reflects the tendency of high PCO workers to take personal responsibility for their work outcomes. In this sense, the use of AI to engage in relational crafting may constitute a self-directed action in which workers not only change the scope of their work tasks but also their interpersonal relationships with coworkers and clients.

Limitations and Future Research

The present study is not without limitations. One of which is that the sample was limited to workers in retail, finance, and insurance, thus limiting the generalizability of the findings to other occupations that differ with respect to core work activities, as well as the integration of AI technologies. Additionally, as mentioned above, I did not account for other key variables that likely play important roles in workers' use of AI. There are likely many contextual and personal factors to consider, such as the formal adoption of AI technologies by organizations and their AI governance policies and practices (i.e., AI work climate) and workers' resistance and self-efficacy with AI technologies (Ma et al., 2025; Marangunić & Granić, 2015; Marikyan et al., 2026; Venkatesh & Davis, 1996).

Another limitation concerns differential attrition across participant demographic variables. Specifically, workers who identified as Non-White, were younger, or had less job experience were less likely to complete the study than their counterparts. This raises concerns regarding the representativeness of the final sample, potentially skewing the relevance of the results toward White, older, and more experienced workers. Given the overrepresentation of these groups, the results should be interpreted with caution concerning the generalizability of the results to more racially diverse, younger, and less experienced workers.

Additionally, future studies should examine the role of organizational culture, which likely influences how workers perceive their opportunities to be autonomous and self-directed in general, and to use AI technologies more specifically (Suvaci, 2018). Cultures of innovation and continuous learning (Enholm et al., 2022; Murire, 2024) likely create environments that encourage the proactive use of AI technologies. Minimally, such variables could be used as covariates to better isolate the effects of AI use and PCO on job crafting. However, as previously mentioned, future research should also address their potential moderating roles based on theory, thus expanding the scope of variables considered.

Additionally, the current study examined only how workers report that using AI benefited them, thereby neglecting the potential double-edged nature of AI use and its potential harms. Lastly, conceptualizations of AI use in the workplace are still in their infancy. As this study showed, given the large number of dual automation-augmentation uses, it is difficult to disentangle automation and augmentation, as the myriad of specific uses of AI appear to involve a blend of the two. Future research is needed to better elucidate the key differences and similarities among the various uses of AI technologies. Empirically supported frameworks of AI use are also needed to better guide future theory regarding important antecedents, outcomes, and moderators. Without empirically supported frameworks, construct proliferation (Bowling et al., 2026) regarding AI use could become a problem to interdisciplinary advances, as different scientific disciplines struggle to find common ground on the key AI-integration challenges that need theory-driven recommendations (Fügener, 2026; Raisch & Krakowski, 2021).

Future studies should also more explicitly integrate Hardy and colleagues' DEEL model (Hardy et al., 2019, 2024) to examine the relationship between workers' AI use and job crafting behaviors, while considering the role of PCO. Exploration and exploitation involve behaviors directed toward learning new information, a prominent element of PCO, whether that involves extending knowledge in breadth (i.e., exploration) or depth (i.e., exploitation). Thus, it may be fruitful to examine how workers specifically use AI to explore or exploit, and whether one's PCO influences the extent to which workers use exploration and exploitation strategies in relation to their job crafting behaviors.

Practical Implications

The present study carries several implications for organizations seeking to integrate AI technologies into workers' daily processes. The findings suggest that workers benefit from using AI and have greater opportunities to offload tedious tasks, allowing them to engage in more meaningful, value-adding work (i.e., job crafting). Results also show that high PCO workers use AI and report more benefits compared to low PCO workers. Therefore, organizations should foster PCO, especially self-directed PCO, among workers by providing ample autonomy in allowing workers to 1) use AI technologies and 2) craft their jobs according to their preferences. Research shows that when workers proactively craft toward their personal resources, they experience greater job and career satisfaction as well as organizational commitment (Kundi et al., 2022), benefiting both workers and organizations.

Organizational leaders should value PCO in dynamic work environments and encourage workers to self-manage their job behaviors and overall careers. Greater flexibility and autonomy from high PCO workers likely inspire their low PCO coworkers to engage in more self-directed, proactive behaviors. Workers already high in PCO will be even more motivated and self-directed in their work when they see that their organizational leaders value proactive workers (Lin, 2015). As such, workers with high PCO should be considered organizational assets, as they prioritize continuous learning and adaptation and take personal responsibility for their success, all of which are key elements for achieving success in today's world of work, given the recent rise of AI technologies. In other words, workers who engage in continuous learning should be rewarded, as organizations can reinforce proactivity to help align workers' personal development with the integration and development of new technologies.

Likewise, organizations should assess job candidates' attitudes toward using AI, in addition to their career autonomy, as these may predict their ability to adapt to a changing work environment (Jiang & Chen, 2026). This combination of autonomy and attitudes toward using AI likely has implications for workers' success and well-being in environments heavily affected by AI integration (Van Den Broek, 2025). Ultimately, organizations need to enable and encourage workers to actively shape their roles and foster a culture that promotes continuous learning alongside the use of AI technologies, whether by offloading tasks or by actively collaborating with AI. The importance of adaptability will remain essential in AI-dominated industries, where competitiveness depends on workers' ability to keep pace with emerging technologies (Golgeci et al., 2025).

Organizations should also be more strategic in how they integrate AI technologies. In doing so, organizations can allow workers to focus on more complex, meaningful work by having AI take over repetitive tasks. This may encourage greater alignment with personal values, enhancing worker well-being and improving productivity and efficiency when tedious tasks can be automated. Additionally, encouraging collaboration with AI while still allowing for autonomy can lead to positive performance outcomes, such as enhanced creativity and innovation (Przegalinska et al., 2025).

Finally, organizations should encourage workers' use of AI tools, positioning AI as a resource to be leveraged. Organizations can do this by implementing trustworthy AI technologies. In this way, workers see AI as a resource that is accurate and effective in helping with work processes and as a means to develop new skills and refine current ones. If workers are more likely to see and believe in AI's ability to offer benefits, they may be more likely to collaborate with it. Organizations can invest in AI literacy and trust-building programs to increase trust, reduce uncertainty, and lower resistance to AI (Kong et al., 2023). Ultimately, organizations should openly communicate the purpose, benefits, and limitations of AI to encourage proactive adoption and use, ultimately benefiting both workers and organizations.

Conclusion

As workers adapt to increasing AI integration into the workplace, adopting a self-directed, values-driven approach to careers is crucial. AI offers opportunities for job crafting that enhance workers' personal resources. This study examined PCO's role in AI-job crafting relationships. Quantitative results showed positive associations among PCO, AI use, and job crafting, but the results did not support PCO as a moderator on the AI-crafting relationships. Qualitative results provided some distinctions between workers' use of AI for automation and augmentation purposes, but they also showed substantial overlap. Workers used AI for task, relational, and time-spatial crafting, with implications for enhancing workers' efficiency, interpersonal relationships, and work-life balance. High PCO workers reported using AI in ways that reflect automation and reported greater task crafting compared to those low in self-directed PCO. This research contributes to an emerging literature on automation and augmentation AI uses by revealing their specific aspects and showing how workers proactively use AI to craft their jobs. In practice, organizations should prioritize fostering PCO among workers, especially self-directed PCO, as these individuals are more likely to use AI technologies intentionally and take ownership of, and create greater meaning in, their tasks through job crafting.

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Table 1

Descriptive Statistics and Intercorrelations of Study Variables

Variables	*M*	*SD*	1	2	3	4	5	6	7	8	9	10
1. Age	39.43	10.93										
2. Sex	0.44	0.50	−.05									
3. Race	0.17	0.37	−.16	−.05								
4. Job Tenure	5.68	5.64	.45	−.04	−.14							
5. AI Use	3.31	1.62	−.07	−.16	.07	.05	(.90)					
6. SD-PCO	5.58	0.85	.10	−.05	.07	.05	.18	(.77)				
7. VD-PCO	5.30	0.99	.09	−.14	.08	.02	.05	.42	(.68)			
8. JC-Strengths	4.30	1.12	.06	−.02	−.02	.05	.18	.27	.08	(.74)		
9. JC-Interests	4.36	1.30	.06	.01	−.03	.04	.18	.29	.08	.73	(.91)	
10. JC-Development	4.22	1.27	.07	−.05	.01	.01	.31	.32	.01	.66	.64	(.88)

Note. $N = 578$. PCO = protean career orientation; SD = self-directed dimension; VD = values-driven dimension; JC = job crafting. Sex (0 = male, 1 = female); race (0 = White, 1 = Non-White). Tenure = job tenure in years. Coefficient alpha reliability for each measure is shown in parentheses on the diagonal. $r \geq |.08| = p < .05$, $r \geq |.10| = p < .01$, $r \geq |.14| = p < .001$. All tests are two-tailed.

Table 2

Multiple Moderated Regression Results Predicting Job Crafting Towards Strengths

	Model 1		Model 2		Model 3		Model 4		Model 5[a]		Model 6		Model 7[b]	
Variables	β	95% CI	β	95% CI	β	95% CI	β	95% CI	β	95% CI	β	95% CI	β	95% CI
Age	.05	–.04, .14	.07	–.02, .16	.04	–.06, .12	.03	–.06, .11	.07	–.03, .15	.07	–.03, .15	.03	–.06, .11
Sex	–.01	–.10, .07	–.02	–.07, .10	–.01	–.06, .10	–.01	–.06, .10	–.02	–.06, .10	–.02	–.06, .10	–.01	–.06, .10
Race	–.01	–.09, .08	–.02	–.10, .07	–.04	–.12, .05	–.04	–.12, .05	–.03	–.11, .06	–.02	–.11, .07	–.04	–.12, .05
Tenure	–.02	–.06, .11	.02	–.08, .10	.02	–.07, .09	.02	–.07, .10	.02	–.07, .10	.02	–.08, .10	.02	–.07, .10
AI Use			.19***	.11, .27	.15***	.07, .23	.15***	.07, .24	.19***	.11, .27	.19***	.11, .27	.15***	.07, .23
SD-PCO					.25***	.17, .33	.25***	.16, .33					.26***	.17, .35
AI Use × SD-PCO							–.03	–.10, .05					–.03	–.12, .05
VD-PCO									.08	–.01, .15	.08	–.01, .15	–.03	–.12, .05
AI Use × VD-PCO											–.02	–.10, .07	.02	–.06, .11
R^2	.00		.03***		.09***		.09***		.04		.04		.09***	
ΔR^2			.04***		.06		.00		.01*		.00		.00	

Note. $N = 578$. PCO = protean career orientation; SD = self-directed dimension; VD = values-driven dimension; JC = job crafting. Sex (0 = male, 1 = female), race (0 = White, 1 = Non-White). Tenure = job tenure in years. β = regression coefficients, CI = confidence intervals. All R^2 values are adjusted. [a]ΔR^2 compared to Model 2. [b]ΔR^2 compared to Model 4. *$p < .05$, **$p < .01$, ***$p < .001$. All tests are two-tailed.

Table 3

Multiple Moderated Regression Results Predicting Job Crafting Towards Interests

	Model 1		Model 2		Model 3		Model 4		Model 5[a]		Model 6		Model 7[b]	
Variables	β	95% CI	β	95% CI	β	95% CI	β	95% CI	β	95% CI	β	95% CI	β	95% CI
Age	.05	–.04, .14	.07	–.02, .15	.02	–.06, .11	.02	–.06, .11	.06	–.03, .15	.06	–.03, .15	.02	–.06, .11
Sex	.01	–.07, .09	.04	–.04, .12	.05	–.03, .13	.05	–.03, .13	.05	–.03, .13	.05	–.03, .13	.05	–.03, .13
Race	–.02	–.11, .07	–.03	–.12, .05	–.05	–.14, .03	–.06	–.14, .03	–.04	–.13, .05	–.04	–.13, .05	–.06	–.14, .03
Tenure	.00	–.07, .11	–.01	–.08, .09	.00	–.08, .09	.00	–.08, .09	–.01	–.08, .09	–.01	–.08, .09	.00	–.08, .09
AI Use			.20***	.11, .28	.15***	.07, .23	.15***	.07, .23	.19***	.11, .28	.19***	.11, .28	.14***	.07, .23
SD-PCO					.28***	.19, .35	.28***	.20, .36					.29***	.20, .38
AI Use × SD-PCO							.03	–.05, .10					.01	–.07, .09
VD-PCO									.08*	.00, .16	.08*	.00, .16	–.03	–.12, .05
AI Use × VD-PCO											.00	–.07, .09	.03	–.06, .11
R^2	.00		.03***		.10***		.10***		.04***		.04***		.10***	
ΔR^2			.04***		.07***		.00		.01*		.00		.00	

Note. $N = 578$. PCO = protean career orientation; SD = self-directed dimension; VD = values-driven dimension; JC = job crafting. Sex (0 = male, 1 = female), race (0 = White, 1 = Non-White). Tenure = job tenure in years. β = regression coefficients, CI = confidence intervals. All R^2 values are adjusted. [a]ΔR^2 compared to Model 2. [b]ΔR^2 compared to Model 4. *$p < .05$, **$p < .01$, ***$p < .001$. All tests are two-tailed.

Table 4

Multiple Moderated Regression Results Predicting Job Crafting Towards Development

	Model 1		Model 2		Model 3		Model 4		Model 5[a]		Model 6		Model 7[b]	
Variables	β	95% CI	β	95% CI	β	95% CI	β	95% CI	β	95% CI	β	95% CI	β	95% CI
Age	.09	–.01, .17	.12*	.02, .19	.07	–.02, .15	.07	–.02, .15	.12*	.02, .20	.12*	.02, .20	.07	–.02, .15
Sex	–.05	–.13, .04	.00	–.08, .08	.01	–.07, .09	.01	–.07, .08	.00	–.08, .08	.00	–.08, .08	.00	–.08, .07
Race	.02	–.07, .11	.00	–.08, .09	–.02	–.10, .06	–.02	–.10, .06	.00	–.08, .09	.00	–.08, .09	–.01	–.09, .07
Tenure	–.05	–.11, .06	–.08	–.14, .03	–.07	–.13, .03	–.06	–.13, .03	–.08	–.14, .03	–.08	–.14, .03	–.07	–.13, .02
AI Use			.32***	.24, .40	.27***	.20, .36	.28***	.21, .36	.32***	.24, .40	.32***	.24, .41	.27***	.20, .36
SD-PCO					.28***	.20, .36	.28***	.19, .35					.34***	.25, .42
AI Use × SD-PCO							–.05	–.12, .02					–.07	–.14, .01
VD-PCO									–.01	–.09, .07	–.01	–.09, .07	–.15***	–.23, –.06
AI Use × VD-PCO											–.03	–.11, .05	.03	–.05, .11
R^2	.00		.10***		.17***		.17***		.10***		.10***		.19***	
ΔR^2			.10***		.07***		.00		.00		.00		.02***	

Note. N = 578. PCO = protean career orientation; SD = self-directed dimension; VD = values-driven dimension; JC = job crafting. Sex (0 = male, 1 = female), race (0 = White, 1 = Non-White). Tenure = job tenure in years. β = regression coefficients, CI = confidence intervals. All R^2 values are adjusted. [a]ΔR^2 compared to Model 2. [b]ΔR^2 compared to Model 4. *p < .05, **p < .01, ***p < .001. All tests are two-tailed.

Table 5

Hierarchy of Codes Describing What AI Did, Definitions, and Example Responses

Level 2	Count	Level 1	Count	Low PCO	High PCO	Definition	Examples
Automation	162	*Takes over basic tasks*	56	18	21	AI handling routine, repetitive, or administrative tasks, reducing manual effort, and increasing efficiency.	"AI completes transactions using external websites on behalf of the company." "Call screening and filtering."
		Gathering data/information	30	5	22	AI collecting, retrieving, or aggregating data and information from various sources for user or organizational needs.	"Find potential buyers for a client and to understand the market in which our client operates and the key competitors." "We use it to speed up searching for policies and previous decisions."
		Organizing /sorting/ processing	38	10	19	AI managing, categorizing, or processing data or items systematically for easier access or analysis.	"Organizing stock orders." "Manually inputting information by reading certain files and uploading to software, minimizing human error."
		Assisting customers	26	10	13	AI directly supporting customer needs, answering questions, or providing guidance.	"AI made it easier to filter options for my clients." "I am a customer service agent. Customers who need help talk to an AI chat bot before potentially getting in touch with me."

		Tracking & monitoring	8	1	4	AI observing ongoing processes, activities, or statuses, often providing real-time updates or alerts.	“Data checks.” “AI checked that the information typed in the system matched what was on the document provided and if not returned it highlighting the error.”
		Assisting with security	4	0	1	AI functions related to cybersecurity, protection of data, or other measures to ensure system/organization integrity.	“Cybersecurity tasks related to cloud computing and collaboration platforms including email.” “Verification of Client IDs and Documents.”
Augmentation	57	*Assisting with creative tasks*	38	14	16	AI assisting with or producing creative content, such as artwork, stories, design concepts, or other that require a combination of originality and usefulness.	“Articles were written for our monthly newsletter and our website.” “Used AI to generate voiceover for YouTube video.”
		Assisting with complex tasks	19	4	9	AI assisting with or managing abstract or intricate, multi-step tasks involving multiple interdependent components, producing outputs requiring higher-level problem-solving and analysis.	“Marketing sales pitches.” “…to assisting in building an investment portfolio.”

Dual-use automation-augmentation	146	*Assisting with documents/ reports/contracts*	30	5	15	AI generating and assisting in writing of formal documents, structured reports, or contractual agreements, typically requiring accuracy and adherence to specific formats.	“Was extremely efficient in producing a body of work for me.” “The AI technology has assisted a lot with creating or populating business plan templates.”
		Assisting with analytics	28	6	14	AI assisting with or performing data analysis, identifying patterns, or generating insights from large datasets.	“I used AI to create a pivot to assist with analyzing a large amount of data.” “In my role as an Accountant, the AI technology performs tasks like data categorization, and pattern recognition.”
		Assisting with general correspondences	30	11	11	AI composing and/or sending non-specific correspondences (i.e., emails, letters) that could be sent to various audiences.	“Sending out automated reminder letters to parents about trips.” “Composing emails.”
		Assisting with planning & forecasting	24	10	9	AI assisting with or predicting future trends, events, or needs and creating plans based on available data (i.e., strategic planning, strategic forecasting)	“Forecasted sales of perishable produce items.” “We use AI technology to assist with home repair estimates.”
		Assisting with decision-making	16	3	10	AI providing recommendations or making choices based on data analysis or predefined criteria.	“AI technology helps recommend pricing rates for loans.” “Reviewing finance applications and deciding whether they are approved, declined or need to be reviewed by a human.”
		Assist as a general assistant/chatbot	18	7	6	AI functioning as a virtual assistant or chatbot, handling a variety of user inquiries and providing support.	"Use chatbots regularly to determine HR decisions to

					ensure uniform approach by all members of the business.” “I looked up certain laws and regulations for finance and had AI explain them to me in a simple way.”
Summarizing & proofreading text	15	2	8	AI condensing/summarizing long texts or checking written material for errors, grammar, and clarity. (Not data related)	“Helps with proofreading and rewrites.” “Generate meeting summaries."
Writing code	8	1	4	AI assisting in generating or completing programming code for software development, statistical, or automation purposes.	“The chatbot I use is designed to create code…” “It worked out a bunch of issues with my scripts for automation and fixed them.”
Assisting with customer correspondences	11	5	4	AI composing and/or sending non-specific correspondences (i.e., emails, letters) specifically tailored for customer, suppliers, clients, and other external stakeholders.	“AI is quite good at masking the fact you’re sending a customer a copy-pasted email response.” “Draft up wording for me to use a starting point for client communication.”
Assisting with training & development	9	1	6	AI aiding in training or development activities	“We use it to help train apprentices. Ai is good for help with studying, planning layouts and learning code.” “Develop in depth but bite-size training programs.”

Assisting with coworker correspondences	0	0	0	AI composing and/or sending non-specific correspondences (i.e., emails, letters) intended for internal communication between colleagues and other internal stakeholders	"It was utilized to word weekly catchup updates for colleagues." "I used AI technology to write out emails to coworkers."

Note. *N* = 578 (Number of responses = 298; count of total coded = 413). Hierarchy of codes developed with corresponding counts and example codes for participants reflecting AI uses reported in Wave 2. Italicized codes represent the first-order codes developed. The count represents the total count of all participants who provided open-ended responses in Wave 2. Low PCO indicates the number of participants who scored less than 5.25 on the self-directed PCO measure (i.e., the bottom tertile); High PCO indicates the number of participants who scored higher than 6.00 on the self-directed PCO measure (i.e., the top tertile). PCO = protean career orientation. Participants responded to the following survey item: "In the past month, I used AI technology to give me more time to do other things at work." If participants answered a four or above (1–7; Strongly Agree – Strongly Disagree), then they were prompted with the three following open-ended questions for which qualitative data were coded: 1) Describe what was done by the AI technology. 2) Describe the other things you did because of the time given to you by the AI technology. 3) Describe how doing these other things was helpful. Workers reported AI uses reflect responses to prompt 1) Describe what was done by the AI technology.

Table 6

Contingency Table for High vs. Low PCO on AI Use Item: Unlocking the Open-Ended Response Boxes

	Responded ≥ 4	
	No	Yes
High SD-PCO	56 (38.6%)	89 (61.4%)
Low SD-PCO	106 (63.1%)	63 (36.9%)

Note. SD = self-directed; PCO = protean career orientation. Numbers indicate the frequency of participants in each group. Parentheses indicate column percentages for the PCO group. Participants who unlocked the box: $n = 280$; participants who did not unlock the box: $n = 298$; participants in the high PCO group: $n = 145$; participants in the low PCO group: $n = 168$. Participants in the low PCO group scored less than 5.25 on the self-directed PCO measure; those in the high PCO group scored above 6.00. Responded ≥ 4 column refers to participants' responses on the following survey item: "In the past month, I used AI technology to give me more time to do other things at work." If participants answered a four or above (1–7; Strongly Agree – Strongly Disagree), then they were prompted with the three following open-ended questions for which qualitative data were coded: 1) Describe what was done by the AI technology. 2) Describe the other things you did because of the time given to you by the AI technology. 3) Describe how doing these other things was helpful. $\chi^2 = 17.70$, $df = 1$, $p < .001$.

Table 7

Logistic Regression Results Predicting Automation AI Uses

	Model 1		Model 2			
Variables	β	*SE*	β	*SE*	*OR*	95% CI
Age	−.08	.11	−.13	.11	0.88	0.70, 1.09
Sex	−.01	.10	.00	.10	1.00	0.83, 1.22
Race	.05	.10	.02	.10	1.02	0.83, 1.24
Tenure	.16	.10	.15	.10	1.16	0.95, 1.42
SD-PCO			.35***	.11	1.42	1.16, 1.76
Pseudo R^2	.00		.02			
Model fit	$\chi^2(4) = 2.63$, $p = .62$		$\chi^2(5) = 13.60$, $p = .02$			
Model comparison			$\Delta\chi^2(1) = 11.78$, $p < .001$			

Note. $N = 578$. SD = self-directed; PCO = protean career orientation. Sex (0 = male, 1 = female), race (0 = White, 1 = Non-White). Tenure = job tenure in years. β = regression coefficients; *SE* = standard error; *OR* = odds ratio; CI = confidence interval. Pseudo R^2 = McFadden's R^2.
$^*p < .05$, $^{**}p < .01$, $^{***}p < .001$. All tests are two-tailed.

Table 8

Logistic Regression Results Predicting Augmentation AI Uses

	Model 1		Model 2			
Variables	β	*SE*	β	*SE*	*OR*	95% CI
Age	–.01	.16	–.13	.16	0.88	0.64, 1.20
Sex	.11	.14	.12	.14	1.13	0.86, 1.50
Race	–.08	.16	–.10	.16	0.90	0.64, 1.21
Tenure	.06	.15	.06	.15	1.06	0.78, 1.40
SD-PCO			.23	.15	1.25	0.94, 1.70
Pseudo R^2	.00		.01			
Model fit	$\chi^2(4) = 1.40, p = .85$		$\chi^2(5) = 3.60, p = .60$			
Model comparison			$\Delta\chi^2(1) = 2.33, p = .13$			

Note. $N = 578$. SD = self-directed; PCO = protean career orientation. Sex (0 = male, 1 = female), race (0 = White, 1 = Non-White). Tenure = job tenure in years. β = regression coefficients; *SE* = standard error; *OR* = odds ratio; CI = confidence interval. Pseudo R^2 = McFadden's R^2.
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$. All tests are two-tailed.

Table 9

Logistic Regression Results Predicting Dual Automation-Augmentation AI Uses

	Model 1		Model 2			
Variables	β	*SE*	β	*SE*	*OR*	95% CI
Age	.07	.11	.05	.11	1.05	0.84, 1.30
Sex	–.31**	.10	–.31**	.10	0.74	0.60, 0.90
Race	.15	.10	.13	.10	1.14	0.93, 1.39
Tenure	–.04	.11	–.05	.11	0.95	0.77, 1.17
SD-PCO			.21‡	.11	1.23	1.00, 1.53
Pseudo R^2	.02		.03			
Model fit	$\chi^2(4) = 12.40, p = .01$		$\chi^2(5) = 15.90, p = .007$			
Model comparison			$\Delta\chi^2(1) = 3.93, p = .047$			

Note. $N = 578$. SD = self-directed; PCO = protean career orientation. Sex (0 = male, 1 = female), race (0 = White, 1 = Non-White). Tenure = job tenure in years. β = regression coefficients; *SE* = standard error; *OR* = odds ratio; CI = confidence interval. Pseudo R^2 = McFadden's R^2.
‡$p = .051$, *$p < .05$, **$p < .01$, ***$p < .001$. All tests are two-tailed.

Table 10

Hierarchy of Codes Describing Benefits Reported from AI Use, Definitions, and Example Responses

Level 3	Level 2	Count	Level 1	Count	Low PCO	High PCO	Definition	Examples
Work-related crafting	Task crafting	361	*More basic & routine tasks*	185	62	82	AI's role for enhancing individuals by allowing users to work more efficiently and get more basic, routine, admin tasks accomplished. Particularly focused on AI offloading basic tasks to divert worker's time and energy elsewhere.	"It allowed me to focus on more relative things at work and simplified certain tasks." "It helped me get through my to-do-list quicker."
			Enhanced complex work	46	13	18	AI assisting with and/or giving users more time to accomplish complex tasks that require advanced knowledge, multiple steps, or is somewhat abstract.	"Allows time for more complex activities." "I was able to help customers with more complex problems."
			Enhanced training & development	22	6	11	AI assisting with and/or giving users more time for learning and skill development, providing training resources, or aiding in personal or professional growth.	"I have a team of 12 so I could focus on coaching and mentoring. It helps the team with their development." "The workload saving was significant, it allowed colleagues to self-guide in their knowledge and test compliance without senior in person monitoring of that understanding."

Enhanced value-adding work	14	2	4	AI assisting with and/or giving users more time to focus on higher-value activities, thus contributing to tasks or outputs that add value to their goals and the organization's goals.	"Helping more with the bigger problems gives me more of a chance to make a difference." "It allowed me more time to focus on the core part of my job."
More projects	22	9	11	AI assisting with and/or giving users more time to take on or manage more projects due to saved time or increased capacity.	"This freed up time for reviewing other projects." "I was able to work on larger projects with no fixed deadlines."
Enhanced planning & forecasting	21	6	11	AI assisting with and/or giving users more time to enhance the predicting of trends or planning future actions, allowing users to prepare and implement effectively (i.e., strategic planning, strategic forecasting).	"It helped me to determine the market direction to increase profit." "Long term planning including further investment in warehouse technology."
Enhanced decision making	19	5	4	AI assisting with and/or giving users more time to enhance the decision-making processes, or the actual decisions made in the organization.	"I had more time to do things where I had to use judgement." "Better evaluation and more informed decisions by not wasting time on the options the AI had already discounted."
Enhanced creative work	12	2	5	AI assisting with and/or giving users more time for creative work activities, such as generating ideas, assisting with design,	"I was able to dedicate my time to other creative, brain-intensive tasks like graphic design and video editing."

						aiding in other artistic processes, and outputs that require a combination of originality and usefulness.	"AI provides me with additional time to spend on the core creative parts of my job and takes away the more routine aspects."
		Enhanced research	11	3	7	AI assisting with and/or giving users more time to gather or analyze information for research purposes, making the research process faster or more comprehensive.	"I was able to research prices and sales records online for future listings." "More time spent on quality research."
		Enhanced analytics	9	3	4	AI assisting with and/or giving users more time to enhance data analysis, providing insights, visualizations, or analytics that support better understanding.	"Unlocked richer analytics." "It saves me time from having to manually track sales figures."
Relational crafting	102	*Enhanced interactions with customers*	71	23	30	AI assisting with and/or giving users more time for customer communications, making interactions with customers smoother, more effective, and personalized.	"Saved time so I could focus on the customers more..." "I had more time with customers answering their questions… and form a relationship with customers"
		Enhanced interactions with coworkers	31	4	20	AI assisting with and/or giving users more time to interact with and collaborate among team members, improving internal interactions.	"I was able to converse more with my subordinates and help them with their duties." "I was able to focus more on my team and push forward with our other initiatives I was able to speak to them on

								a more one on one basis. Benefited my relationship with my team in the workplace.”
Non-work-related crafting	Time-spatial crafting	57	*Improved well-being & work-life balance*	57	19	28	AI assisting with and/or giving users more time towards reducing stress, workload, or time spent on tasks, positively impacting users' work-life balance or overall well-being.	“It improved the quality of my life, and I got to spend more time with my family.” “It meant I didn’t have to work overtime to complete the tasks assigned to me.”

Note. N = 578 (Number of responses = 298; count of total coded = 548). Hierarchy of codes developed with corresponding counts and example codes for participants reflecting AI benefits reported in Wave 2. Italicized codes represent the first-order codes developed. The count represents the total count of all participants who provided open-ended responses in Wave 2. Low PCO indicates the number of participants who scored less than 5.25 on the self-directed PCO measure; High PCO indicates the number of participants who scored higher than 6.00 on the self-directed PCO measure. PCO = protean career orientation. Participants responded to the following survey item: “In the past month, I used AI technology to give me more time to do other things at work.” If participants answered a four or above (1–7; Strongly Agree – Strongly Disagree), then they were prompted with the three following open-ended questions for which qualitative data were coded: 1) Describe what was done by the AI technology. 2) Describe the other things you did because of the time given to you by the AI technology. 3) Describe how doing these other things was helpful. Workers reported AI uses reflect responses to prompts. 2) Describe the other things you did because of the time given to you by the AI technology, and 3) Describe how doing these other things was helpful.

Table 11

Logistic Regression Results Predicting Time-spatial Crafting

	Model 1		Model 2			
Variables	β	*SE*	β	*SE*	*OR*	95% CI
Age	–.04	.16	–.07	.06	0.93	0.68, 1.27
Sex	–.16	.14	–.16	.15	0.85	0.64, 1.13
Race	.17	.14	.15	.14	1.16	0.87, 1.50
Tenure	.07	.15	.07	.15	1.07	0.79, 1.41
SD-PCO			.20	.15	1.22	0.91, 1.66
Pseudo R^2	.01		.01			
Model fit	$\chi^2(4) = 3.10, p = .53$		$\chi^2(5) = 4.80, p = .44$			
Model comparison			$\Delta\chi^2(1) = 1.75, p = .19$			

Note. $N = 578$. SD = self-directed; PCO = protean career orientation. Sex (0 = male, 1 = female), race (0 = White, 1 = Non-White). Tenure = job tenure in years. β = regression coefficients; *SE* = standard error; *OR* = odds ratio; CI = confidence interval. Pseudo R^2 = McFadden's R^2.
$^*p < .05$, $^{**}p < .01$, $^{***}p < .001$. All tests are two-tailed.

Table 12

Logistic Regression Results Predicting Task Crafting

	Model 1		Model 2			
Variables	β	*SE*	β	*SE*	*OR*	95% CI
Age	.00	.09	–.05	.10	0.95	0.79, 1.15
Sex	–.20*	.09	–.19*	.09	0.82	0.70, 0.98
Race	.04	.09	.01	.09	1.01	0.84, 1.21
Tenure	.07	.09	.06	.09	1.06	0.89, 1.28
SD-PCO			.34***	.09	1.41	1.18, 1.69
Pseudo R^2	.01		.03			
Model fit	$\chi^2(4) = 6.80$, $p = .15$		$\chi^2(5) = 19.80$, $p = .001$			
Model comparison			$\Delta\chi^2(1) = 14.33$, $p < .001$			

Note. $N = 578$. SD = self-directed; PCO = protean career orientation. Sex (0 = male, 1 = female), race (0 = White, 1 = Non-White). Tenure = job tenure in years. β = regression coefficients; *SE* = standard error; *OR* = odds ratio; CI = confidence interval. Pseudo R^2 = McFadden's R^2.
*$p < .05$, **$p < .01$, ***$p < .001$. All tests are two-tailed.

Table 13

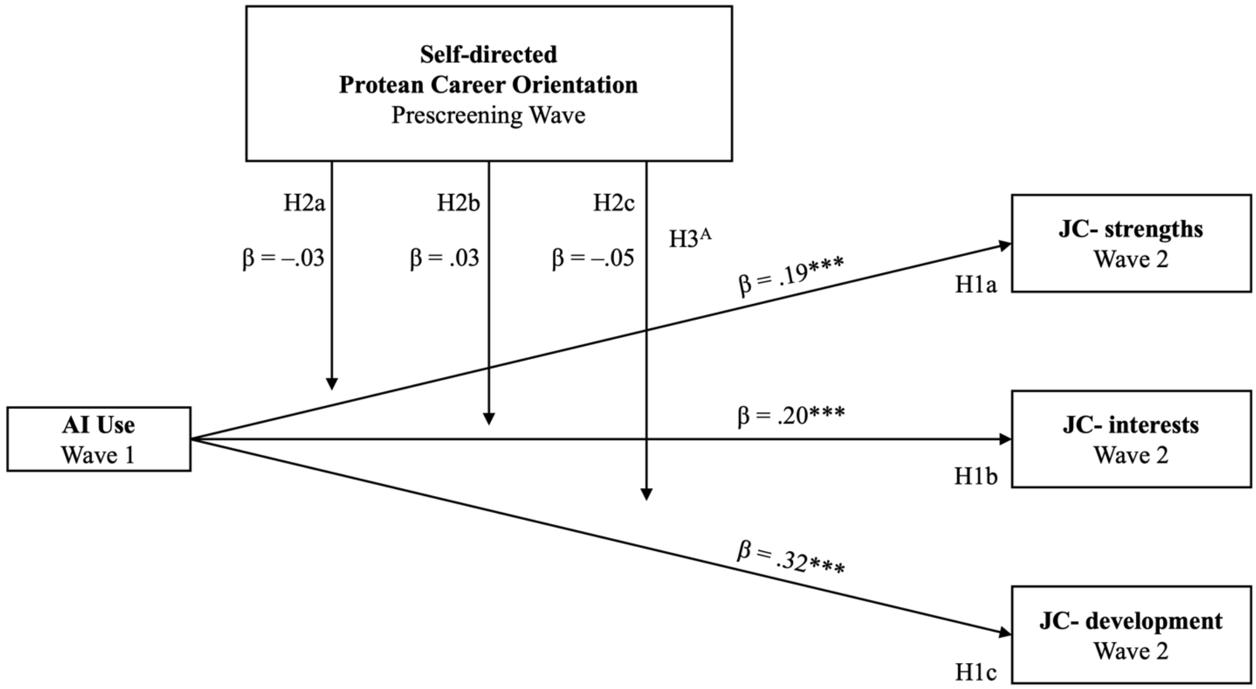
Logistic Regression Results Predicting Relational Crafting

	Model 1		Model 2			
Variables	β	*SE*	β	*SE*	*OR*	95% CI
Age	–.24	.13	–.26	.14	0.77	0.59, 1.00
Sex	–.25*	.12	–.25*	.12	0.78	0.62, 0.98
Race	.01	.12	.00	.12	1.00	0.78, 1.25
Tenure	.17	.12	.17	.12	1.19	0.94, 1.49
SD-PCO			.17	.12	1.18	0.94, 1.51
Pseudo R^2	.02		.02			
Model fit	$\chi^2(4) = 7.90$, $p = .10$		$\chi^2(5) = 9.80$, $p = .08$			
Model comparison			$\Delta\chi^2(1) = 2.04$, $p = .15$			

Note. $N = 578$. SD = self-directed; PCO = protean career orientation. Sex (0 = male, 1 = female), race (0 = White, 1 = Non-White). Tenure = job tenure in years. β = regression coefficients; *SE* = standard error; *OR* = odds ratio; CI = confidence interval. Pseudo R^2 = McFadden's R^2.
$^*p < .05$, $^{**}p < .01$, $^{***}p < .001$. All tests are two-tailed.

Figure 1

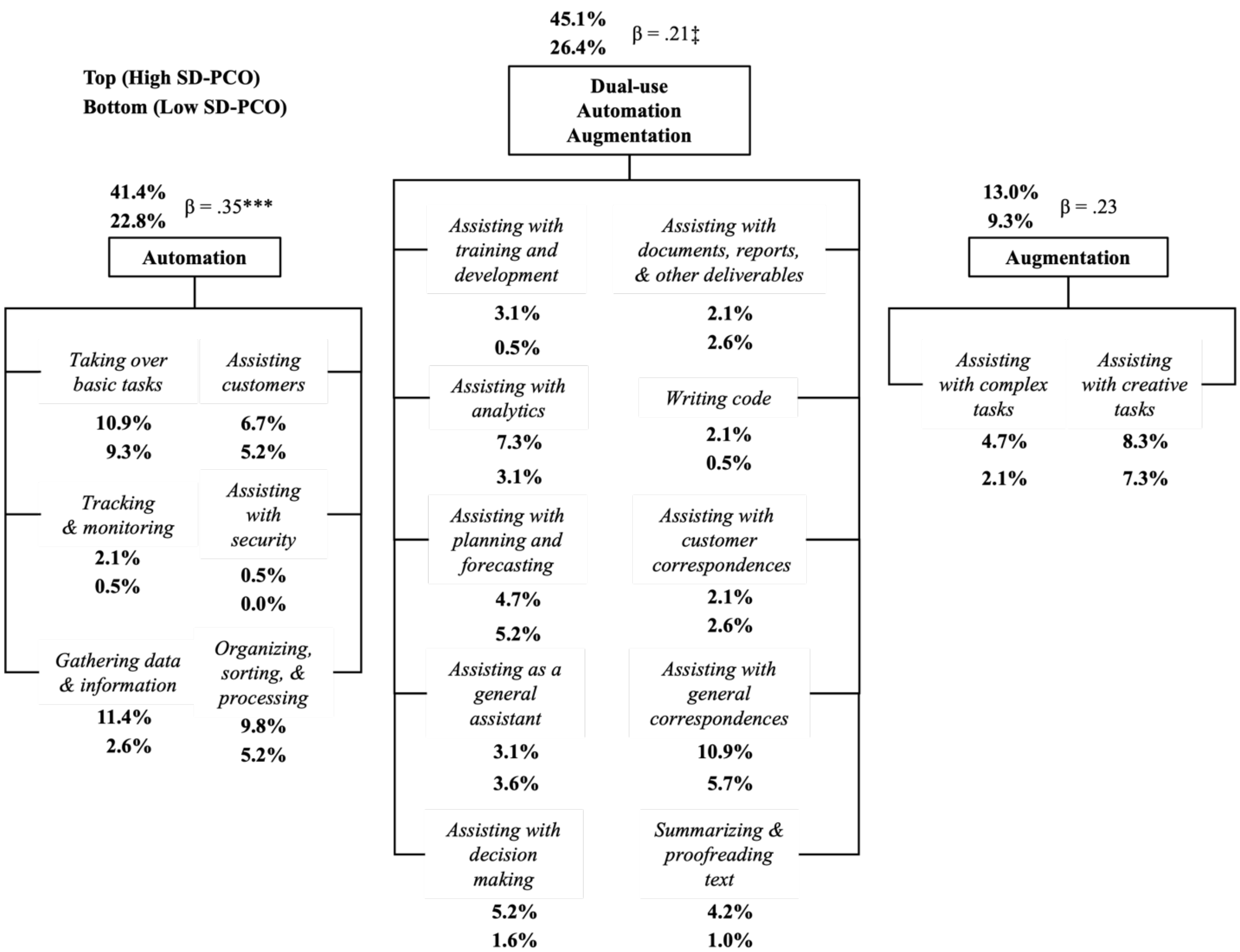
Hypothesized Model with Moderated Multiple Regression Results



Note. H = hypothesis. JC = job crafting. H3^{A} = Hypothesis 3 predicted a larger moderating effect for JC-development relative to JC-strengths and interest. ***p < .001, two-tailed.

Figure 2

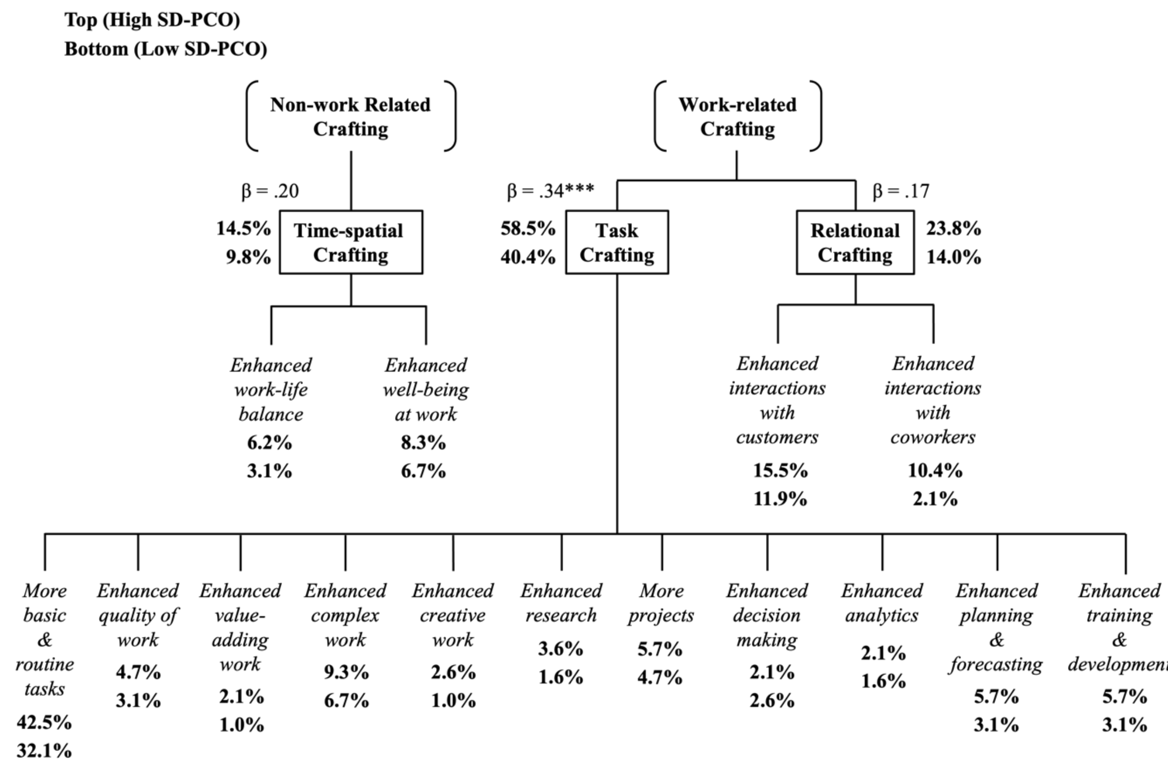
Hierarchical Structure of AI Use Codes with High vs. Low Tertile Comparison of Self-directed PCO Workers



Note. $N = 578$. Automation, augmentation, and dual-use themes comprise the coded responses of participants when asked to describe what the AI technology did. PCO = protean career orientation. PCO tertiles were split based on the self-directed dimension. Percentages are the raw number of responses coded under their respective themes, out of 193 (90 responses) individuals in the low PCO group (scored less than 5.25 on the self-directed PCO measure) and 193 (142 responses) individuals in the high PCO tertile (scored greater than 6.00). Not included in the figure are 192 (72 responses) individuals (those who scored greater than 5.25 and less than 6.00), who were grouped in the "middle tertile." β = logistic regression coefficient for self-directed PCO predicting automation, augmentation, and dual automation-augmentation AI uses.
‡$p = .051$, *$p < .05$, **$p < .01$, ***$p < .001$. All tests are two-tailed.

Figure 3

Hierarchical Structure of AI-Enabled Job Crafting with High vs. Low Tertile Comparisons of Self-directed PCO Workers



Note. $N = 578$. Time-spatial, task, and relational crafting themes comprise the coded responses of participants when asked to describe the other things they did with the time AI gave them, and how doing these other things was helpful. PCO = protean career orientation. PCO tertiles were split based on the self-directed dimension. Percentages are the raw number of responses coded under their respective themes, out of 193 (88 responses) individuals in the low PCO group (scored less than 5.25 on the SD-PCO measure) and 193 (138 responses) individuals in the high PCO tertile (responded greater than 6.00). Not included in the figure are 192 (72 responses) individuals (those who scored greater than 5.25 and less than 6.00), who were grouped in the "middle tertile." β = logistic regression coefficient for self-directed PCO predicting time-spatial, task, and relational crafting. *$p < .05$, **$p < .01$, ***$p < .001$. All tests are two-tailed.