Balancing the Benefits and Challenges of AI: Understanding its Impact on Employee Work Engagement and Burnout

by

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Abstract

This thesis explored how artificial intelligence (AI) impacts work engagement and burnout, using the Job Demands-Resources (JD-R) model to examine AI as both a job resource and demand. Key AI factors included Perceived Adaptability, Quality, Personal Utility, AI use anxiety, and AI-induced job insecurity. The study investigated how personal resources moderate the AI–well-being relationship. Employees with higher personal resources may better leverage AI for performance, while those with lower resources may experience AI as a greater demand. Multi-wave cross-sectional data were collected from employees across industries utilizing AI. Measures included the Utrecht Work Engagement Scale, Shirom-Melamed Burnout Measure, and scales for personal resources. Data analysis involved multiple regression and moderation tests, with post hoc probing for significant effects. Results revealed that perceived quality and utility of AI positively predicted work engagement, while AI use anxiety significantly predicted burnout. Findings offered insights into AI's dual role in shaping employee health.

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List of Abbreviations

AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
OHP	Occupational Health Psychology
GPT	Generative Pretrained Transformer
S-O-R	Stimulus-Organism-Response
JD-R	Job Demands - Resources
ICTs	Information Communication Technologies
SDT	Self-Determination Theory
UWES	Utrecht Work Engagement Scale
TAM	Technology Acceptance Model
JI	Job Insecurity
COR	Conservation of Resources
AIR	AI as a Resource
AID	AI as a Demand
IER	Insufficient Effort Responding
IRI	Instructed Response Item
AAAW	Attitudes Toward Artificial Intelligence at Work
WE	Work Engagement
SMBM	Shirom Melamed Burnout Measure
OCCSEFF	Occupational Self-Efficacy

LOT	Life Orientation Test

Balancing the Benefits and Challenges of AI: Understanding its Impact on Employee Work Engagement and Burnout

Artificial Intelligence (AI) has become one of the most quickly adopted technologies of all time according to many popular media sources. One source cites data that suggests in the two years of the ChatGPT's existence the number of users grew to 77.8 million. According to their report, this is twice the number of users of smartphones and tablets within their first two years. (Lebow, 2023) The access to generative AI, like ChatGPT, may contribute to why this extreme adoption has occurred. In addition to the relatively easy access, it is easy to use. Essentially, you can ask any question, and it can output detailed information. The access to such an advanced tool presents a lot of questions of how AI will impact society, work, and the individuals at work.

Some have termed this current age of technology as the "Fourth Industrial Revolution," though AI has been in development for years. AI was first coined by computer scientists and AI academics during the Dartmouth conferences in the mid-20th century, signifying a pivotal moment in the establishment of the field. The conferences laid the groundwork for conceptualizing intelligent machines and exploring the potential of machines to mimic human cognitive functions. At that time, AI referred to the ability to input information into a computing system and receive an output in response. A simple illustration of this concept is a calculator, where an individual could enter a function, such as 1 + 4, and promptly obtain the result, which is 5. Since the inaugural Dartmouth conference in 1956, the landscape of artificial intelligence and computer systems has witnessed remarkable advancements. From early rule-based systems to the contemporary era of machine learning and neural networks. For example, most people use everyday applications like search engines and virtual assistants developed by companies such as Google and IBM. As AI and machine learning (ML) tools become increasingly integrated into society, particularly in the workplace, there is a growing need to better understand how workers use them, their impact on workers, and the potential antecedents and outcomes of the human-AI relationship (Bankins et al., 2023).

What is AI?

To understand how AI may affect workers and work-related outcomes we should define AI. Focusing on the intelligence aspect, AI attempts to learn, solve problems or achieve some type of goal. In other words, AI refers to computing systems that solve tasks similarly to how humans do (Kaplan, 2016). Within AI systems, there are two more advanced forms: ML and deep learning (DL). ML systems involve algorithms that learn from input and use the acquired knowledge to provide future outputs. DL models represent a subset of ML, utilizing artificial neural networks to learn data representations with multiple levels of abstraction, mimicking the functioning of a biological brain. Examples of DL applications include virtual assistants, chatbots, vision in automated vehicles, and personalized feeds on social media applications (Fan et al., 2023).

AI in the Workplace

In the context of AI in the workplace, AI and employees can form a connection that speeds up and streamlines the data-gathering and decision-making process (Tang et al. 2023) Makarius et al. (2020) propose a matrix illustrating how AI integrates into the workplace. One category represents the scope of AI (i.e., content-changing vs. context-changing AI), while the other represents the level of AI novelty. "Content changing" refers to changes occurring in a specific domain, primarily based on the component knowledge of the associated system. "Context changing" refers to changes that may occur in broader task domains or across various jobs (Makarius et al., 2020). Within each combination (e.g., content-changing x high level of AI novelty, context-changing AI x low level of AI novelty), there is a classification of the relationship, the role AI takes on, and the role the human plays. For this paper, the focus is on what the authors classify as augmentation, alteration, and amplification.

Augmentation (content changing and a medium level of AI novelty) refers to AI that enhances the work at hand through a specific content area. This relationship is complementary, and the human is viewed as a collaborator. An example of this AI classification presented by Makarius et al. (2020) are surgical robots. Another example could be an AI application, like GitHub Copilot, that can help present code for developers as they type (Dakhel et al. 2023). Alteration (context-changing and a medium level of AI novelty) includes deep learning models and is viewed as a symbiotic relationship where the human role is to be a co-creator, leading to the highest levels of sociotechnical capital. According to Makarius et al. (2020), this relationship can fundamentally change the way work is currently performed and will impact the future workforce due to the high responsiveness from the connectedness of the AI and human relationship. An example of Alteration AI use in the workplace is the use of DALL-E by organizations to create marketing, communication, or training visuals. Amplification refers to AI that individuals could use to output data, and the human makes decisions based on how they deem fit. An example of amplification AI are customer service chatbots which can assist human customer service workers by handling inquiries on a larger scale and can potentially be used to inform future customer service decision making.

As research in the past has noted, technological change can impact not only organizations but also employees and society at large (Makridis & Han, 2021). With the popularity of AI growing in recent years, there has been much discussion on its impact on the future of work (Bankins et al., 2023). Industrial and organization psychology research surrounding AI is still in its infancy. This is a space where occupational health psychology

(OHP) researchers can advance research. The ever-changing nature of AI may present a challenging task for researchers, with findings not necessarily generalizing to newer models.

A common topic researched concerning the relationship between AI and the workplace is employees' attitudes (Brougham & Haar, 2018; Fukumura et al., 2021; Horodyski, 2023; Presbitero & Teng-Calleja, 2022). Job insecurity and psychological distress are pathways that lead to the perception that AI will take over their job. As a result, this leads them to engage in more career exploration behaviors (Presbitero & Teng-Calleja, 2022). Some have found positive perceptions and a greater intention to use AI. In the area of personnel selection and other talent management areas, there appears to be a push to adopt AI tools (Fan et al., 2023; Hickman, 2022; Speer, 2018). The focus of this thesis is the effect that AI has on the people who use it in the workplace. A key benefit of AI that has been researched is increased productivity. One study done by Dell'Acqua and colleagues (2023) found that, in comparison to highly skilled workers who were not allowed to use AI, participants who used AI and had an overview of how to use chat GPT-4 outperformed them by 38% and 42.5%, respectively. GPTs, short for Generative Pre-trained Transformers, are ML models that output a text response after a prompt by the user.

Several other types of individual outcomes have been examined. For example, one study found, using the S-O-R (Stimulus-Organism-Response) Model, several positive outcomes from the use of smart technologies, including physical forms of technology and processes like AI and blockchain technology. That study specifically focused on logistics employees and found that smart technology positively affected corporate trust, self-efficacy, well-being, and learning (Jiang et al., 2022). It should be noted that other studies have found negative outcomes associated with automation/AI, including negative relationships with job satisfaction, job stress, and overall health (Nazareno & Schiff, 2021).

Regarding the research surrounding human and AI collaboration, several key theories have been used, including the unified theory of acceptance and use of technology, AI aversion, job design theory, conservation of resources theory, social exchange theory, and affordance theory (Bankins et al., 2023). In this study, the focus is on adding to our understanding of the impact of AI on workers through a job-demands resources lens. Specifically, the focus of the paper is to examine specific ways AI acts as a job resource and job demand. In this paper I intend to add to the limited AI-human research in the OHP space.

AI and Job Demands-Resources Theory

The Job Demands-Resources (JD-R) model, developed by Demerouti et al. (2001), provides a framework for understanding how job demands (e.g., workload, time pressure) and job resources (e.g., autonomy, support) impact burnout and engagement. The model suggests that excessive demands can lead to burnout, while sufficient resources help mitigate demands, fostering engagement and well-being. Demands are unique in that there are two types of demands. Hindrance job demands involve excessive or undesirable constraints that interfere with or inhibit an individual's ability to achieve valued goals. Challenge job demands are defined as demands that are costly but can potentially promote personal growth and achievement (Bakker & Demerouti, 2017; Cavanaugh et al., 2000). Despite distinctions being drawn between the constructs, challenge demands may be experienced as hindrance demands (and vice versa; Bakker & Demerouti, 2017).

Further examinations of JD-R theory have incorporated other variables like motivation and job satisfaction (Bakker & Demerouti, 2007). This includes the examination of other outcomes like motivation, strain, job satisfaction, and job performance. As noted by Bakker and Demerouti (2017), the relationship between demands and resources can vary based on the job context. Typically, job resources lead to increased motivation (e.g., work engagement, commitment, and flourishing), job satisfaction, and job performance. Additionally, job resources can help lessen the relationship between job demands and negative outcomes. Job Demands are usually associated with more negative health outcomes (e.g., exhaustion, job-related anxiety, and distress).

Although there has been limited in-depth research on AI within JD-R model, this paper assumes that AI shares similar characteristics with technology in this context. Understanding these existing resources and demands may therefore provide valuable insights into the potential demands and resources that AI might introduce in the workplace. Technology, when considered as part of job demands and resources, has been found to exhibit qualities of both demands and resources. Scholze and Hecker (2023) expanded the JDR model by incorporating “digital job demands” and “digital job resources”. Within the digital demands, the authors included availability, work intensification, and dependence. In short, availability refers to employees constantly being available, which can hurt their work-life boundaries. Hu et al. (2021) describe a similar construct labeled as “Availability Expectation” within the context of information and communication technologies (ICTs). This construct reflects the perceived pressure to extend work-related availability beyond standard working hours, driven by the pervasive connectivity afforded by ICTs and the implicit expectation to remain continuously responsive. Work intensification refers to the increased volume of work that may come because of the speed at which technology allows for work to be completed. Dependence, as the term implies, refers to the perceived inability to complete work tasks without the aid of technology. Individuals who exhibit high levels of dependence may be more vulnerable to the negative effects of demands such as ICT hassles- challenges that arise from technical issues during the use of ICT, which can disrupt workflow and hinder task completion (Hu et al. 2021). Technology, and in this case, artificial intelligence, can function as a demand by increasing the perception that it may lead to job displacement. This concern aligns closely with the construct of techno-insecurity. Ragu-Nathan et al. (2008) define techno-insecurity as the fear of job loss, either due to automation facilitated by ICTs or the perception that others with greater ICT proficiency may render one's skills obsolete. The job resources mentioned in their extended version of the model include collaboration, efficiency, and autonomy. Technology allows for several applications that improve collaboration (e.g., emails, online repositories to share information and virtual meetings). Autonomy refers to how workers have greater control over how they carry out their tasks (Scholze & Hecker, 2023).

AI as a Job Resource

To examine the dual role of AI tools as both a job resource and a job demand, it is important to first establish the theoretical connections between AI and each relevant construct. As previously mentioned, job resources are variables that lead to work engagement outcomes. Within the construct of job resources, there are two types: job resources (e.g., resources mentioned earlier) and personal resources (e.g., resilience, self-efficacy, optimism, and proactivity). In this study, I argue that in some ways AI serves as a job resource. Despite AI itself being a job resource, there may be other personal resources at play that affect its relationship with work and psychological outcomes. Both job and personal resources follow the same theoretical pathway. First, both constructs positively impact each other. For instance, if an individual feels they have more autonomy in their work, this may lead to feelings of high selfefficacy or optimism. Second, resources are positively associated with work engagement. Work engagement refers to the extent to which individuals are energetic and involved in their work.

Bakker et al. (2023) point out two types of outcomes associated with work engagement: motivational (e.g., increased creativity, exploration, and work-to-family facilitation) and job related (e.g., job performance, task performance, job satisfaction, and job commitment). Third, work engagement leads to better work performance. Finally, proactive behaviors can impact resources positively and, as a result, positively impact work engagement. Also, proactive behaviors can come from work engagement (Bakker et al., 2023). In the context of JD-R research, three types of proactive behaviors are common in research: job crafting, proactive vitality management, and playful work design.

AI has been found to have positive impacts on productivity and some well-being outcomes. Previous research examining AI and autonomy has yielded positive results. For example, when AI was viewed as supporting autonomy, it led to increased exploration and, as a result, improved innovation and performance among hospitality workers. Additionally, AI trust and increased proactive personality increase the relationship between exploration and improved innovation (Kong et al., 2023). In that article, the authors examined autonomy-supportive AI and the dependent variables through self-determination theory (SDT). Perhaps "autonomy supportive" AI can be better understood as a job resource. Outside of increased autonomy, AI tools could potentially serve as additional resources. As mentioned earlier, a major focus of this study is to explore how AI tools function as resources. Specifically, the aim is to evaluate them through the lens of technology resources, as discussed by Scholze and Hecker (2023). Like other technologies, AI tools may enhance collaboration and efficiency in the workplace.

Several studies have examined the relationship between AI adoption and employee engagement (Dutta & Mishra, 2025; Dutta et al., 2022; Rožman et al., 2022). Others have focused specifically on the relationship between AI use and work engagement, measured through the Utrecht Work Engagement Scale (UWES) (Theben et al., 2023; Wijayati et al., 2022). The UWES is particularly relevant to this research as it captures employees' emotional connection to their work across three dimensions: vigor, dedication, and absorption. Moreover, the scale is widely used in JD-R research. Although the cited studies report notable findings, some present conflicting results, focusing more on the organizational implementation of AI and its effect on employee engagement. This thesis takes a different approach by investigating how individuals' engagement with their work is influenced by their positive evaluations of AI tools.

In this study, the extent to which AI is assessed as a resource is by measuring the extent the individual holds certain attitudinal prescriptions to the tool. Attitudes can be defined as evaluative or affective predispositions towards an object, idea, or issue (Fishman et al., 2021). Measuring AI with this scale allows us to gain a better understanding of how the individual perceives the tool in their workplace. In Park and colleagues' (2024) paper, five distinct dimensions of attitudes toward artificial intelligence in the workplace were identified- *Perceived human-likeness of AI, Perceived adaptability of AI, Perceived quality of AI, Job insecurity,* and *Personal utility of AI.* Based on the definitions constructed by the authors (Park et al. 2024), *Perceived adaptability of AI, Perceived quality of AI,* and *Personal utility of AI* capture the attitudes that best reflect the construct of job resources. The authors describe this grouping as the "functional evaluation" of AI. *Perceived adaptability* refers to the extent to which an individual believes that AI technology is capable of learning and adjusting to different contexts or tasks. As a job resource, perceived adaptability enables AI to potentially integrate more seamlessly into diverse and evolving work processes, reducing friction in use and enhancing task efficiency and user support. *Perceived quality of AI* and *Personal Utility of AI* go hand in hand where the former taps into the extent that individuals feel that the information that they receive is accurate while the later examines the perceived usefulness of the AI. *Perceived Quality of AI* captures an employee's belief that AI systems are accurate, reliable, and effective in providing information. High-quality AI tools can serve as critical job resources by reducing uncertainty and the likelihood of task failure, thereby enhancing employees' confidence and engagement. When workers trust the systems, they interact with, they are more likely to rely on them in ways that alleviate workload and support performance. In other words, an individual relies on their evaluation of if the technology is reliable and accurate and if using it brings some value to their work. *Personal Utility of AI* extends this line of thinking. The construct refers to the extent to which individuals perceive AI technologies as beneficial to their specific work tasks and personal growth by increasing their confidence. Within the JD-R framework, this perception functions as a motivational job resource by enhancing employees' engagement and performance by aligning AI capabilities with personal work objectives. These dimensions closely align with the constructs of perceived ease of use and perceived usefulness from the Technology Acceptance Model (TAM; Davis, 1989). Although originally developed to explain technology adoption, these constructs have also been interpreted in workplace contexts as job resources, given their association with increased work engagement (Khoza et al., 2024).

With the understanding that AI use has been found to be positively related to several positive outcomes and technology in the workplace has been shown to be a valuable job resource, the following three hypotheses are presented (see Figure. 1 for hypothesized model):

Hypothesis 1: *Perceived Adaptability of AI* (Perceived Adaptability) is positively related to Work Engagement

Hypothesis 2: *Perceived Quality of AI* (Perceived Quality) is positively related to Work Engagement

Hypothesis 3: *Personal Utility of AI* (Personal Utility) is positively related to Work

Engagement

AI as a Job Demand

In contrast to its role as a job resource, the implementation of AI at work can also be seen as a significant job demand. According to JD-R theory, job demands are aspects of a job that require sustained effort and are associated with certain physiological and psychological costs, such as stress or burnout (Bakker & Demerouti, 2007). A major concern that makes AI a job demand is job insecurity. A common theme in research about attitudes toward AI is the concern that it will replace jobs currently held by humans, leading to unemployment (Koo et al., 2021; Nam, 2019).

When considered as a job resource, AI is often associated with positive work outcomes such as increased efficiency, support with complex tasks, and enhanced engagement. However, when AI is perceived as a job demand, it can contribute to negative psychological responses. Employees may hold pre-existing beliefs or concerns about AI, such as fears of job replacement or reduced relevance, which can shape negative attitudes and lead to adverse outcomes. Fear and anxiety are closely related emotional responses, with fear typically arising from an immediate perceived threat and anxiety more often associated with the anticipation of future threats (APA Dictionary). Mental inhibitors of technology readiness, such as discomfort and insecurity (Parasuraman, 2000), have been linked to growing fears of job loss in the face of technological change (Lemay et al., 2020). In the context of AI in the workplace, it is this anticipatory nature of potential job displacement or skill obsolescence that more accurately evokes anxiety rather than immediate fear. Given this, the focus of this thesis is on anxiety rather than fear to describe the emotional response to AI-induced job insecurity.

Job insecurity (JI), as defined by Heaney and colleagues (1994), is the "perception of a potential threat to continuity in one's current job" (p. 1431). JI is characterized by three features: subjectivity, uncertainty, and vulnerability. As AI is increasingly introduced in the workplace, employees may feel uncertain about the future of their jobs, leading to heightened anxiety. This uncertainty can negatively affect their emotional well-being, with potential consequences for their mental and physical health as well as job performance (Sverke et al., 2002). AI can contribute to all three aspects of job insecurity: employees may feel vulnerable to being replaced by AI, uncertain about the long-term implications of AI integration, and subjectively experience these changes as threatening. This form of organizational change has been associated with creating unpredictability and thus increasing JI (Jiang et al., 2021).

According to Conservation of Resources (COR) theory (Hobfoll, 1989), individuals strive to retain, protect, and build valuable resources such as time, energy, income, and social standing. AI-related job insecurity threatens these critical resources, particularly those tied to employment stability and personal status. When employees perceive a potential loss of these resources, they are more likely to experience anxiety and stress, which undermines their psychological wellbeing. The JD-R model (Bakker & Demerouti, 2007) complements this perspective by suggesting that when job demands, such as job insecurity, are not balanced by adequate resources, the risk of burnout increases. Burnout, characterized by physical fatigue, emotional exhaustion, and cognitive weariness (Shirom et al., 2005), may emerge as a consequence of prolonged exposure to resource-draining demands. Thus, the persistent presence of AI in the workplace, by threatening perceptions of job stability and increasing demand, can contribute to chronic stress and, over time, heighten employees' susceptibility to burnout (Aybas et al., 2015).

Thus, I propose the following hypothesis (see Figure 2 for hypothesized model):

Hypothesis 4: *AI-induced job insecurity* is positively related to burnout.

Beyond the fear that AI will or at least has the potential to displace workers, another demand associated with AI is *AI use anxiety*, the anxiety related to utilizing the technology effectively. Park et al. (2024) note that this anxiety reflects a general disposition toward technological innovation, focusing on “anxious feelings about the practical usage of AI at work” (p. 925). While the origins of this anxiety are beyond the scope of this thesis, several explanations exist. For instance, Li and Huang (2020) present seven dimensions of AI anxiety, including privacy violation anxiety (the fear that AI will monitor behavior or collect personal data), learning anxiety (fear of lacking the ability to understand AI), existential risk anxiety (fear that AI will negatively affect society), and artificial consciousness anxiety (fear that AI will achieve human-level consciousness). These dimensions offer insight into how the practical and existential concerns surrounding AI use can manifest as emotional burdens for employees. *AI use anxiety* may be exacerbated in organizational contexts where technology adoption is pressured rather than encouraged (Park et al., 2024). Although this thesis focuses on voluntary AI use, it remains plausible that anxiety could emerge in such settings.

AI-use anxiety functions as a job demand that drains emotional and cognitive resources. At work. individuals who feel intimidated by Generative AI, or uneasy using it in front of others, may perceive its integration as both a technical challenge and an emotional burden. This anxiety may stem from fears of making mistakes, difficulty keeping pace with rapid technological change, or uncertainty about how to interact effectively with AI tools. These experiences could lead to feelings of helplessness (Greer & Wethered, 1984; Meier, 1983) and reduced control over one’s work (Shirom & Melamed, 2006; Taris et al., 2005), both of which are well-established predictors of burnout. Although some research has linked AI use to other negative outcomes like loneliness (Tang et al., 2023), the present study focuses more narrowly on use-specific anxiety as a source of psychological strain. In this way, AI use anxiety represents not just a reaction to new technology, but a meaningful demand that can contribute to burnout (Wood et al., 2022). Thus, I propose the following hypothesis (see Figure 2 for hypothesized model):

Hypothesis 5: *AI use anxiety* is positively related to burnout.

Personal Resources and the AI-Human Relationship

Personal resources refer to aspects of the self that relate to resilience and individuals' sense of their ability to control and impact their environment successfully (Xanthopoulou et al., 2007). Personal resources are activated by job resources in the work context. Through the activation of personal resources, and consequently more control over the work, the individual may experience higher work engagement. Bakker and colleagues (2023) review mentioned several individual characteristics that can better predict the job resource and work engagement relationship. Examples include conscientiousness, positive affect, proactive personality (Christian et al., 2011), self-efficacy, optimism, and self-esteem (Mäkikangas et al., 2013; Xanthopoulou et al., 2007, 2009). For the study, occupational self-efficacy, optimism, conscientiousness, and proactive personality will be the personal resources of interest in AI use and the outcomes at hand. Though there is no specific evidence that says that specific personal resources should be examined, these resources have been researched across several studies that support the JD-R model (Bajaba et al., 2022; Bandura, 1989; Chaudhary et al., 2012; Chen et al., 2001; Lin et al., 2015; Luthans et al., 2006; Scheier & Carver, 1985; Segerstrom, 2007). Also, there is some theoretical support for their relation to AI and work engagement as laid out in the following paragraphs.

Self-efficacy generally pertains to individuals' perceptions of their capability to meet demands across various contexts. In the context of this study, this refers to the individual’s perception of their capability to meet the demands of their job roles and work environments. Before interacting with AI, individuals who are higher in self-efficacy likely feel they can handle their job effectively. By using AI, they can experience more of the augmenting effects thus leading to increased work engagement. Alternatively, self-efficacy can serve as a buffer between demands and burnout, by individuals navigating their ability to effectively maneuver in their work even in the face of stressors (Friedman, 2003).

The second personal resource examined in this paper is proactive personality. This personality characteristic reflects a positive approach to their work environment where they seek opportunities to impact the work they do. Bakker and colleagues (2012) examined the relationship between proactive personality and work engagement and in-role performance where they found significant direct and indirect effects. Through the identification and utilization of opportunities, they argue that individuals with proactive personalities can manipulate their work environment to improve effectiveness. In a sense, a certain level of proactivity is necessary to utilize AI tools, like ChatGPT, as they require the user to insert some form of a prompt. Proactive individuals in organizations that encourage the use of AI or require the use of it may still experience more engagement through the act of job crafting. Job crafting is the act of changing one’s task or relational boundaries of their work through physical and cognitive means (Wrzesniewski & Dutton, 2001).

An example of this personal resource in action in the AI context has been exemplified in the research mentioned previously in the paper (Kong et al., 2023). In this case, the authors argue that proactive individuals can more easily adapt to an “AI-integrated” workplace and seek the opportunities provided by AI. They found significant indirect effects of AI-supported autonomy on “exploration” which had a significant direct effect on innovative performance. Exploration was defined as behaviors that reflect being curious, willing to take risks, and dedicating effort to learning new things (Kong et al., 2023). Individuals who seek the assistance of generative AI may use the tool to improve work functioning or use the tools to quickly learn about a variety of topics. Regardless, the intention to use AI to augment work may be amplified by individuals who have a higher proactive personality and thus may experience more engagement. Individuals who may experience increased JI or anxiety to use AI, may utilize this resource to identify ways that they can preserve their lost resources and find ways to build them up. This may come in the form of seeking out training to find a job less likely to be impacted in the future.

The third personal resource of interest is conscientiousness. Within the JD-R model, conscientiousness can be viewed as a critical personal resource that influences both how individuals perceive and respond to job demands. Conscientious employees are likely to approach their work with an initiative-taking mindset, seeking out resources and strategies to mitigate the negative effects of high job demands. Furthermore, their inherent goal-oriented nature and strong sense of duty may lead them to utilize job resources more effectively, thereby enhancing their overall job satisfaction and performance. Conscientiousness has been shown to have a significant relationship with work engagement (Christian et al., 2011). Conscientious individuals tend to have positive work traits like being thorough, well-organized, and goal oriented. Conscientiousness can also be conceptualized as an indicator of trait-oriented work motivation (Bakker et al., 2012).

Previous research has examined the relationship between personality characteristics and attitudes towards AI and consequently AI use. Park and Woo (2022) found conscientiousness related positively to some AI attitudes. Specifically, it relates to affective attitudes and functionality evaluation. That is, for highly conscientious individuals, AI is often seen as a tool that augments their work, thus leading to more positive experiences (p. 86). The driving force for the intention to use AI for conscientious individuals is the extent to which the user perceives the usefulness of the AI tool. If there is a significant relationship between AI use and work engagement, conscientious individuals may recognize and seek out the utility, thus experiencing more work engagement. As it relates to burnout, conscientiousness is negatively correlated (Alarcon et al., 2009). With our understanding of the role of conscientiousness as a resource, high conscientiousness may allow individuals to buffer the effects of JI and use anxiety on burnout using proactive coping strategies, self-discipline, and a strong sense of responsibility toward their tasks and goals. This leads to the final personal resource examined in this thesis.

The final personal resource examined in this thesis is optimism. Optimism generally refers to the tendency to believe that you will experience positive outcomes in life. This belief can increase the likelihood of taking action (Xanthopoulou et al., 2007). As discussed, much of the conversation surrounding AI has centered on the displacement some workers may face due to its implementation. However, individuals with higher levels of optimism might focus on the benefits that AI brings to their organization or work. It is plausible that even if such individuals experience AI-induced job insecurity, their optimism could buffer them from burnout, leading to lower burnout levels compared to those with lower optimism. This can be mapped onto both the affective and persistence pathways of optimism and the Big Five personality traits (Sharpe et al., 2011). The affective pathway describes the relationship between optimism and neuroticism. That is, more optimistic individuals tend to experience more positive affectivity and a more positive worldview. Additionally, they tend to show high agreeableness tendencies. In the context of AI attitudes, optimism is positively related to agreeableness and negatively related to neuroticism. Neuroticism, the inverse of emotional stability, along with self-efficacy, are components of another construct core self-evaluations, a personality characteristic and personal resource researched across the OHP literature and positively related to work engagement (Bipp et al., 2019; Kammeyer-Mueller et al., 2009).

For this thesis, I examined if these individual differences help better understand the AIhuman relationship. Due to the lack of literature that specifically addresses these relationships, I will address them with four research questions:

Research Question 1: A) Does occupational self-efficacy moderate the relationship between AI resources and work engagement such that those who are higher in occupational selfefficacy report more work engagement? B) Does occupational self-efficacy moderate the relationship between AI demands and burnout such that those who are higher in occupational self-efficacy report less burnout?

Research Question 2: A) Does proactive personality moderate the relationship between AI resources and work engagement such that those who have a higher proactive personality report more work engagement? B) Does proactive personality moderate the relationship between AI demands and burnout such that those who are higher in proactive personality report less burnout?

Research Question 3: A) Does conscientiousness moderate the relationship between AI resources and work engagement such that those who have higher conscientiousness report more work engagement? B) Does proactive personality moderate the relationship between AI demands and burnout such that those who are higher in conscientiousness report less burnout?

Research Question 4: A) Does optimism moderate the relationship between AI resources and work engagement such that those who have higher optimism report more work engagement? B) Does optimism moderate the relationship between AI demands and burnout such that those who are higher in proactive personality report less burnout?

The growing integration of AI into many areas of work has prompted research into its impact on employee job performance and other outcomes that AI can augment. However, there remains a significant gap in understanding how AI affects specific outcomes within OHP, such as work engagement. Work engagement is a critical factor in employee well-being and productivity, yet research examining the implications of AI for this outcome is still limited. This thesis seeks to address this gap by exploring the relationship between AI and work engagement through the lens of the JD-R theory.

AI, as a resource, holds the potential to reduce task complexity and enhance productivity. It also has the potential to be a job demand for some individuals. Particularly, individuals who fear AI will replace them in the future. In addition to extending current research on AI, work engagement, and burnout, this thesis will also investigate the role of personal resources in moderating this relationship. By examining both AI as both a job resource and demand and the moderating role personal resources have, this research aims to provide a more comprehensive understanding of how AI impacts employee well-being. This is an important and timely study as AI continues to be an increasingly prevalent workplace tool.

Method

Sample and Procedure

This study was approved by the Auburn University Institutional Review Board (IRB Protocol #STUDY00000410), and all participants provided informed consent prior to participation. I collected data on a sample of employed adults through the crowdsourcing platform Prolific. Specifically, I screened for individuals who work in a setting where using a computer is a regular part of the job (i.e., office workers or managers). Individuals within the sample were allowed to use some form of generative AI (e.g., ChatGPT, Microsoft Copilot, Gemini, etc.). I used several prescreen options provided by Prolific to prescreen for participants. Specifically, I prescreened for Current Country of Residence (United States), Age (18–99), Employment Status (Full-Time, Part-Time), and Weekly AI use (Once a Week, 2-6 times a week, Every day, Multiple times every day). I aimed to capture responses from people who use generative AI or other AI tools to assist in their work. For this thesis, I examined only individuals who use AI in their work. I also collected data on how often they typically use AI throughout the course of the week to account for different degrees of use. I wanted to capture responses from people who use generative AI or other AI tools to assist in their work. For this thesis, I examined only individuals who use AI in their work. I collected data on how often they typically use AI throughout the course of the week to account for different degrees of use.

I collected data through an online Qualtrics survey. Using the crowdsourcing platform, Prolific, allowed me to collect data from a more diverse sample that spans different industries. Ideally, this will allow for greater generalizability of results. Given that the survey was selfreported I collected data over two time points to reduce the possibility of common method variance (Podsakoff et al., 2003, 2012). At the time one collection, I collected eligibility status data. At the second time point, one week later, I collected data on the AIR and AID measures, as well as the personal resources variables. At the third time point, one week later, I collected data on the outcome variables- work engagement and burnout. There are several benefits of collecting data over multiple time points. One is it allows for the limitation of fatigue a participant might experience with long surveys. Another is utilizing a one-week time lag allowed for participants to reflect on recent events while minimizing recall bias. Also, longer intervals run the risk of participant attrition (Podsakoff et al., 2012). Previous research in the OHP literature has used and support the use of a one-week or similar method to account for common method variance (Ganster et al, 1986; Podsakoff & Organ, 1986).

To mitigate insufficient error responding (IER), the increase of measurement error from participants carelessly endorsing a few items due to temporary inattentiveness or the random selection of response options to rush through a questionnaire (Huang et al., 2015), I used instructed response items (IRI) method. This method involved instructing the participant to select a specific option from the answer scale. IRIs is an attention check method that indicants possible careless responding if the incorrect answer is selected. For example, “This is an attention check item. Please select 'strongly disagree" for this item” was an IRI used in wave 2. It should be noted that a participant can still engage in careless responding and pass a single IRI. With multiple IRIs the chances of passing all when careless responding will be less likely. Some have questioned the potential negative effect on subsequent items; however, evidence has shown that IRIs does not necessarily have this negative impact (Gummer et al., 2021; Shamon & Berning, 2020).

An initial sample of 400 participants was recruited to complete an eligibility survey on April 21, 2025. Based on their responses, participants who met the eligibility criteria were invited to return for Wave 2 of data collection. After removing ineligible participants and those whose responses did not match their prescreening information or failed the single instructed response item (IRI), 369 participants were invited to take part in Wave 2, which began on April 28, 2025. Of those, 314 participants completed the Wave 2 survey.

Thirteen participants were not invited to the final wave due to failing two IRIs, survey timeouts, or submitting incomplete responses. This resulted in 301 participants being invited to Wave 3, which began May 5, 2025, of whom 262 completed the survey. An additional seven participants were excluded from the final sample due to inconsistent responses across waves. Specifically, these participants initially reported using generative AI but later indicated they had not or selected a usage frequency earlier in the study and later reported never using generative AI (DeSimone et al., 2015). As part of the study, data was collected on participants' use of generative artificial intelligence, including whether they had used AI tools and the frequency with which they used them. These AI use and frequency measures were administered across all waves, allowing for the detection of inconsistencies in self-reported usage patterns over time. In such cases, participants were considered unreliable and were removed from the analyses.

In accordance with Prolific's guidelines, only one IRI was included in Waves 1 and 3, as the average completion time was under five minutes. For Wave 2, participants were required to fail both IRIs to be removed. For data quality purposes, all participants who failed IRIs at any wave were excluded from analyses. The final sample prior to outlier screening consisted of 255 participants, ranging in age from 19 to 78 years ($M = 39.94$, $SD = 11.55$). Just under half identified as female (49.4%), and the majority were White (69.1%). Participants were a mix of full- and part-time workers, with most (78%) employed full-time and working an average of 38.53 hours per week ($SD = 10.56$). They represented a range of industries including education, finance, healthcare, human resources, and information technology, among others. All participants reported using AI to assist with their work, with most (83.1%) reporting that their use of generative AI was voluntary. In terms of frequency, participants reported using generative AI a few times per week (47.1%), daily (42.7%), or rarely (10.2%). Regarding tools, participants reported using ChatGPT (25.1%), Google Gemini (2.4%), a combination of multiple applications (71.7%), or other tools (0.8%).

Measures

AI as a Resource: AI as a resource (AIR) was assessed using three dimensions of the *Attitudes Toward Artificial Intelligence Scale at Work* (AAAW; Park et al., 2024). I adapted all three resources dimensions similarly. The adaptation was made to better reflect attitudes toward AI currently being used in the workplace and to allow for the direct interpretation of responses in the context of generative AI, specifically. The Perceived Adaptability of AI dimension from the AAAW, which consists of four items. Participants rated the items on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Sample items included " Generative AI learns from experience at work." and "Generative AI can learn at work." All adapted items for these dimensions are listed in Appendix A. Cronbach's alpha was 0.94.

The "*Perceived Quality of AI*" dimension consisted of five items. Like the other dimension, participants were asked to rate the items on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Sample items included "Generative AI provides workers with a complete set of information." and "Generative AI produces correct information." Cronbach's alpha was 0.83.

I adapted the "*Personal Utility*" dimension of the AAAW, which consisted of four items. Participants rated the items on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Sample items included "Using Generative AI would allow me to have increased confidence in my skills at work." and "Using Generative AI would provide me with personal feelings of worthwhile accomplishment at work." Cronbach's alpha was 0.89.

AI as a Demand: AI as a demand (AID) was assessed using two dimensions of the *Attitudes Toward Artificial Intelligence Scale at Work* (AAAW; Park et al., 2024). First, used the "*Job Insecurity*" dimension of the AAAW, which consists of four items. Participants rated the items on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Like the resource's dimensions, I adapted the items to reflect attitudes specifically toward generative AI. Sample items included "I am worried that what I can do now with my work skills will be replaced by Generative AI." and "I am worried about my career due to Generative AI replacing employees." All adapted items are listed in Appendix A. Cronbach's alpha was 0.89

The second demand was assessed using the "*AI use anxiety*" dimension of the *AAAW,* which consists of four items. Participants rated the items on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Sample items included "Using Generative AI for work is somewhat intimidating to me." and "I would feel nervous operating Generative AI in front of other people at work." Cronbach's alpha was 0.91.

Work Engagement: Work engagement (WE) was assessed using the *Utrecht Work Engagement Scale* (UWES; Schaufeli & Bakker, 2003). The scale consists of 17 items, with six items measuring vigor, five items measuring dedication, and six items measuring absorption. Participants were asked to rate the extent to which they experienced each item over the past month on a 7-point Likert scale, ranging from 0 (Almost Never) to 6 (Always). Sample items included "At my work, I feel bursting with energy" (vigor), " I find the work that I do full of meaning and purpose" (dedication), and "Time flies when I'm working" (absorption). Cronbach's alpha was 0.92.

Burnout: Burnout was assessed using the *Shirom-Melamed Burnout Measure* (SMBM; Shirom & Melamed, 2006, Michel et al., 2022). The scale consists of 14 items, with six items measuring physical fatigue, five items measuring cognitive weariness, and three items measuring emotional exhaustion. Participants were asked to rate the extent to which they experienced each item on a 7-point Likert scale, ranging from 1 (Almost Never) to 7 (Always). Sample items included " I feel physically drained" (physical fatigue), " I feel I'm not focused in my thinking" (cognitive weariness), and " I feel I am not capable of investing emotionally in coworkers and customers" (emotional exhaustion). Cronbach's alpha was 0.96.

Occupational Self-Efficacy: Occupational self-efficacy was measured using the *Occupational Self-efficacy Scale* (OCCSEFF; Schyns & Collani, 2002). The scale consisted of 20 items. The items were developed from four different scales by the original authors. Those scales being: the general self-efficacy subscale by Sherer et al. (1982; 10 items), the generalized self-efficacy scale by Schwarzer (1994; 7 items), the hope scale by Snyder et al. (1991; 2 items), and the heuristic competence scale by Stäudel (1988; 1 item). Participants were asked to rate each item on a 6-point Likert scale, ranging from 1 (Not at All True) to 6 (Completely True). Sample items include "When something doesn't work in my job immediately, I just try harder." and " I feel insecure about my professional abilities. (reverse coded)" Cronbach's alpha was 0.92.

Proactive personality: Proactivity was measured with the *Proactive Personality Scale* by Bateman and Crant (1993) The scale consists of 17 items. Responses will be indicated on a seven-point Likert scale ranging from 1 ("strongly disagree") to 7 ("strongly agree"), with items such as " I excel at identifying opportunities" and "No matter what the odds, if I believe in something I will make it happen." Cronbach's alpha was 0.93.

*Conscientiousness: C*onscientiousness was assessed with 10 items that *International Personality Item Pool* (*IPIP) Conscientiousness Scale* (Goldberg et al., 2006). Participants were asked to rate each item on a 5-point Likert scale, ranging from 1 (Strongly disagree) to 5 (Strongly agree). Sample items include "I pay attention to details." and " I don't see things through. (reverse coded)” Cronbach’s alpha was 0.86.

Optimism: I assessed optimism with the *Life Orientation Test* (LOT; Scheier & Carver, 1985). The LOT consists of 8 items and 4 filler items. Participants were asked to rate each item on a 5-point Likert scale, ranging from 1 (Strongly disagree) to 5 (Strongly agree). Sample items include "In uncertain times, I usually expect the best " and " I rarely count on good things happening to me. (reverse coded)” Cronbach’s alpha was 0.82.

Control Variables: My analyses included four control variables. First, I controlled for age. Previous research suggests that younger individuals adopt technology better and faster than their older counterparts. Second, I controlled for gender as previous research has suggested that men adopt AI quicker and have a more positive perception than women (Aldasoro et al., 2024; Draxler et al., 2023). Third, I controlled for if the participants AI use was required (coded as 0) or it was voluntary (1). The participants were asked “Is your use of generative AI tools voluntary or required by your employer?” and given two response options (voluntary or required). As suggested by Demourti (2022), technology is limited as a resource when the individual is stripped of autonomy to choose to use the technology. Finally, I controlled for AI usage frequency (Dorta-González et al., 2014). The participants were asked “How often do you use Generative AI to assist with your work?” and were provided four options, “Never, Rarely, Few times a week, or Daily”.

Data Analysis

To test the proposed hypotheses and research questions, I ran two linear regressions and moderation analyses (i.e., hierarchical linear regressions). This approach allowed me to examine how the relationship between AAAW dimensions and WE and burnout varies as a function of levels of personal resources. I ensure that all variables were properly coded and cleaned, addressing any missing data through imputation or case removal as necessary. All variables were reviewed and recoded as necessary to ensure consistency (e.g., reverse-coded items were properly aligned). Data cleaning involved checking for invalid values, out-of-range responses, and logical inconsistencies across waves, as previously mentioned. Only one case contained missing data. Because the missing value affected a key variable, the case was removed listwise, resulting in a final sample of 254 participants with complete data. I also checked for linearity, multicollinearity, homoscedasticity, and normality of residuals to meet the assumptions of regression analysis. For each regression and moderation analysis, multivariate outliers were assessed and removed using Mahalanobis distance. Because different predictors were entered into each model, the number of outliers varied depending on the specific personal resource analyzed. The critical chi-square value was based on the number of predictors in each model ($p < .001$)

Using the statistical software SPSS Version 30.0, the first model I tested was used to examine the first three hypotheses. I ran a linear regression where WE was regressed on the five AAAW dimensions. In the second model, I tested the fourth and fifth hypotheses. In this model, I regressed burnout on the five AAAW dimensions. I ran another regression where I regress burnout on the two AID dimensions. For control variables, I included the amount AI is used during the week as well as if the use of AI is voluntary in their work. Demourti (2022) highlights the need to allow for the control and crafting of automating tools. Capturing the extent the use is voluntary gives some sense not only of the autonomy that may exist in the individual's work but perhaps their desire to use the tool. Additionally, I included both age and gender as control variables as previous research has shown that younger adult men tend to adopt AI more frequently (Aldasoro et al., 2024; Draxler et al., 2023) For the remaining research questions, I ran hierarchical regression analyses, including the AAAW dimensions centered and their interaction term with the personal resources, to examine their effects on the DV. The AAAW dimensions and personal resources were grand mean centered by subtracting the mean of each dimension from each participant's score. I examined the significance of the interaction terms to determine if moderation is present. Statistically significant interaction terms indicated that the relationship between the AIIW and the two outcomes depends on the level of personal resources the individual has.

Significant interaction terms were plotted using simple slopes analyses to understand the nature of the interaction and plotting the interaction effect to visualize how the effect of AIR and AID effect on WE and burnout may be higher or lower when associated at different levels of the personal resource. Specifically, I will examine the effect of the low levels of the moderator at 1 standard deviation below the mean and the higher levels at one standard deviation above the mean (Bauer & Curran, 2005; Hayes, 2018; Hayes & Matthes, 2009).

Results

Preliminary Analysis

Before running the regression and moderations model, descriptive statistics and bivariate correlations, and Cronbach's alpha reliability for all study variables were calculated in SPSS and are presented in Table 1. All variables demonstrated acceptable internal consistency with Cronbach's alphas ranging from .82 to .94. Further, the assumptions for linear regression were all satisfied. That is, the variables demonstrated linearity, no multicollinearity between variables residuals, and the variables appeared to be normal, and all Shapiro-Wilks tests were not significant (p > .05). Additionally, the data demonstrated a homoscedastic relationship. Bivariate correlation analyses were run between the variables, and the expected variables were significantly correlated in their expected directions. For example, AIR variables perceived quality (r = .31, p < .001) and personal utility (r = .33, p < .001) were positively associated with WE. Additionally, perceived quality (r = -.21, p < .001) was negatively associated with burnout. Conversely, AI use anxiety (r = .26, p < .001) and AI induced job insecurity (r = .21, p < .001) were positively associated with burnout. Occupational self-efficacy (r = .39, p < .001), proactive personality (r = .58, p < .001), conscientiousness (r = .31, p < .001), and optimism (r = .40, p < .001) were positively associated with work engagement and negatively associated with burnout (r = −.43, r = −.36, r = −.43, r = −.27, respectively, p < .001).

Hypothesis Testing

Hypothesis 1 predicted that Perceived Adaptability would be positively related to WE Hypothesis 2 predicted that Perceived Quality would be positively related to WE. Hypothesis 3 predicted that Personal Utility would be positively related to WE. To test these hypotheses, a hierarchical multiple regression was conducted with WE as the dependent variable. In the first block, control variables were entered: age, gender (0 = female, 1 = male), generative AI requirement status (0 = required, 1 = voluntary), and AI usage frequency. In the second block, the five AAAW dimensions were entered as predictors.

One multivariate outlier was removed based on Mahalanobis distance (df = 15, p < .001). The final analysis was conducted on n = 253 participants. The first model, which included only the control variables, was statistically significant, F (4, 248) = 6.32, p < .001, R^2 = .09. Among the control variables, only AI usage frequency significantly predicted WE (β = .29, p < .001).

The addition of the AAAW predictors in the second block resulted in a significant improvement in the model, $\Delta R^2 = .09$, F (5, 243) = 5.42, $p < .001$, bringing the total explained variance to $R^2 = .18$. In the final model, *Perceived Quality* ($\beta = .17$, $p = .014$) and *Personal Utility* ($\beta = .18$, $p = .014$) were significant positive predictors of WE, supporting Hypotheses 2 and 3. However, *Perceived Adaptability* was not a significant predictor ($\beta = .03$, $p = .682$), providing no support for Hypothesis 1. Additionally, *AI Use Anxiety* ($\beta = -.04$, $p = .501$) and *AI-Induced Job Insecurity* ($\beta = -.09$, $p = .111$) were not significant predictors of WE. Full model statistics are presented in Table 2.

Hypothesis 4 predicted that AI-Induced Job Insecurity would be positively related to burnout. Hypothesis 5 predicted that AI Use Anxiety would positively predict burnout. To test these hypotheses, a second hierarchical multiple regression was conducted using the same predictor structure as described above, with burnout as the dependent variable. The first model, which included the control variables only, was not statistically significant, (F (4, 248) = 0.66, $p = .618$, $R^2 = .01$). None of the control variables significantly predicted burnout. The second model, which added the AAAW predictors, significantly improved model fit, ($\Delta R^2 = .13$, F (5, 243) = 7.17, $p < .001$), with a total explained variance of $R^2 = .14$. In this model, *AI Use Anxiety* was a significant positive predictor of burnout ($\beta = .21$, $p = .002$), supporting Hypothesis 5. In contrast, *AI-Induced Job Insecurity* was not a significant predictor ($\beta = .11$, $p = .072$), providing no support for Hypothesis 4. *Perceived Quality* was negatively associated with burnout ($\beta = -.27$, $p < .001$), whereas the remaining predictors, including *Perceived Adaptability* and *Personal Utility*, were not significant. Full model statistics are reported in Table 3.

Research Question Testing

To test the four research questions, I conducted eight sequential models. Within each model I conducted three blocks of variables. The first block included the same control variables age, gender (0 = female, 1 = male), and generative AI requirement status (0 = Required, 1 = Voluntary). The second block included all five dimensions of AAAW (centered) as predictors and each unique moderator variables. The third block included the interaction terms between the relevant AAAW dimensions and the personal resource moderators. WE and Burnout were both tested as dependent variables within the models. For example, the first moderation analyses included all the variables in the first linear regression with work engagement with the addition of occupational self-efficacy included in the second block as well. The third block included the interaction terms with the three AIR dimensions and occupational self-efficacy (Table 4).

Ten multivariate outliers were removed from the moderation analyses including occupational self-efficacy as the personal resource of interest based on Mahalanobis distance analysis (df = 15, p < .001), the moderations analyses were conducted on n = 244 participants. In the first moderation analysis tested research question 1A- does occupational self-efficacy moderate the relationship between AI resources and work engagement such that those who are higher in occupational self-efficacy report more work engagement? Overall, the results showed that the first model was significant F (4,239) = 6.80, p < .001, R^2=.10. Again, only generative AI use frequency (β = .31, p < .001) significantly predicted WE. The results showed that the addition of occupational self-efficacy showed significant improvement from the first model (ΔR^2=.23, F [6,233] = 13.15, p < .001), suggesting that AI attitudes and occupational self-efficacy significantly predict WE above and beyond the control variables (Table 4). Like in the first regression analysis, *Perceived Quality* (β = .19, p = .005), further supporting hypotheses 2.

Personal utility was no longer a significant predictor. Again, *Perceived Adaptability* did not predict work engagement. Surprisingly, *AI Use Anxiety* (β = .32, p < .001) positively predicted WE, and *AI Induced Job Insecurity* did not have a significant main effect. Additionally, occupational self-efficacy (β = .29, p < .001) significantly predicted WE. The third block included the interaction terms and did not show significant improvement from the second model (ΔR^2=.01, F [3,230] = .61, p = .613) There were no significant interactions.

The second moderation analysis tested research question 1B- does occupational self-efficacy moderate the relationship between AI demands and burnout such that those who are higher in occupational self-efficacy report less burnout? The results showed that the first model was not significant F (4,239) = .74, p = .568, R^2=.01. None of the control variables had a significant relationship with burnout. The addition of occupational self-efficacy showed significant improvement from the first model (ΔR^2=.24, F [6,233] = 12.44, p < .001). Overall, the findings suggest that the AI attitudes and occupational self-efficacy significantly predict burnout above and beyond the control variables (Table 5). With the addition of occupational self-efficacy, neither AID variables significantly predicted burnout. For the AIR variables, *Perceived Quality* (β = -.18, p = .011) negatively associated with burnout. Occupational self-efficacy significantly predicted burnout. The third block included the interaction terms and showed significant improvement from the second model (ΔR^2=.02, F [2,231] = 3.43, p = .034). There was a significant interaction between *AI Induced Job Insecurity* and occupational self-efficacy (β = -.18, p = .015) on burnout. To further interpret the interaction, simple slopes were examined at one standard deviation above and below the mean of occupational self-efficacy. At low levels of occupational self-efficacy (–1 SD), the relationship between AI use anxiety and burnout was, B = 0.15, t = 2.07, p =.04. At high levels of occupational self-efficacy (+1 SD), the relationship was negative, but not statistically significant, $B = -0.15$, $t = -1.28$, $p = .20$. The significant interaction term and the pattern of the simple slopes suggest that occupational self-efficacy moderates the relationship between AI use anxiety and burnout. Specifically, low in occupational self-efficacy appear to experience increased burnout in the context of AI induced job insecurity, whereas individuals low in occupational self-efficacy do not show a significant relationship between AI induced job insecurity and burnout. Simple slopes were plotted in Figure 3.

Thirteen multivariate outliers were removed from the moderation analyses including proactive personality as the personal resource of interest based on Mahalanobis distance analysis (df = 15, p < .001), the moderations analyses were conducted on n = 241 participants. The third moderation analysis tested research question 2A- does proactive personality moderate the relationship between AI resources and work engagement such that those who have a higher proactive personality report more work engagement? The results showed that the first model was significant F (4,236) = 6.26, $p < .001$, R^2=.10. Again, only generative AI use frequency ($\beta = .30$, $p < .001$) significantly predicted WE. The second block included the five AAAW dimensions and proactive personality as the personal resource. The addition of proactive personality showed significant improvement from the first model (ΔR^2=.27, F [6,230] = 16.14, $p < .001$). Overall, the findings suggest that the AI attitudes and occupational self-efficacy significantly predict WE above and beyond the control variables (Table 6). With the addition of proactive personality, *Perceived Quality* ($\beta = .15$, $p = .020$) significantly predicted WE. With the AID variables, only *AI Use Anxiety* positively predicted WE ($\beta = .14$, $p = .003$). Additionally, proactive personality significantly predicted WE ($\beta = .55$, $p < .001$). The third block included the interaction terms and did not show significant improvement from the first model (ΔR^2=.002, F [3,227] = 1.719, p

= .856). None of the variables of interest in research question 2A had a significant interaction.

The fourth moderation analysis tested research question 2B- does proactive personality moderate the relationship between AI demands and burnout such that those who are higher in proactive personality report less burnout? The results showed that the first model was not significant F (4,236) = .69, p = .600, R^2=.01. None of the control variables had a significant relationship with burnout. The addition of proactive personality showed significant improvement from the first model (ΔR^2=.22, F [6,230] = 10.74, p < .001). Overall, the findings suggest that the AI attitudes and proactive personality significantly predict burnout above and beyond the control variables (Table 7). With the addition of proactive personality, Neither AID variable significantly predicted burnout. For the AIR variables, *Perceived Quality* (β = -.19, p = .003) only was negatively associated with burnout. Additionally, proactive personality significantly predicted burnout (β = -.29, p < .001). The third block included the interaction terms and did not show significant improvement from the first model (ΔR^2=.002, F [2,228] = .27, p = .767). There was no significant interaction effects found in model 3.

Eleven multivariate outliers were removed from the moderation analyses including conscientiousness as the personal resource of interest based on Mahalanobis distance analysis (df = 15, p < .001), the moderations analyses were conducted on n = 243 participants. The fifth moderation analysis tested research question 3A- Does conscientiousness moderate the relationship between AI resources and work engagement such that those who have higher conscientiousness report more work engagement? The results showed that the first model was significant F (4,238) = 5.20, p < .001, R^2=.08. Again, only generative AI use frequency (β = .27, p < .001) significantly predicted WE. The addition of conscientiousness to the second block showed significant improvement from the first model (ΔR^2=.15, F [6,232] = 7.43, p < .001).

Overall, the findings suggest that the AI attitudes and conscientiousness significantly predict WE above and beyond the control variables (Table 8). With the addition of conscientiousness, *Personal Utility* (β = .19, p = .008) significantly predicted work engagement, further supporting hypotheses 3. *AI Use Anxiety* (β = .17, p = .020) also positively predicted WE. Conscientiousness significantly predicted WE (β = .19, p = .008). The third block included the interaction terms and did not show significant improvement from the first model (ΔR^2=.01, F [3,229] = .76, p = .519). There were no significant interactions found.

The sixth moderation analysis tested research question 3B- does conscientiousness moderate the relationship between AI demands and burnout such that those who are higher in conscientiousness report less burnout? The results showed that the first model was not significant F (4,238) = .50, p = .737, R^2=.01. None of the control variables had a significant relationship with burnout. The second block included the five AAAW dimensions and conscientiousness. The addition of conscientiousness showed significant improvement from the first model (ΔR^2= .22, F [6,232] = 10.87, p < .001). Overall, the findings suggest that the AI attitudes and conscientiousness significantly predict burnout above and beyond the control variables (Table 9). The only significant AI attitude associated with burnout was *Perceived Quality* (β = -.21, p = .003). Additionally, conscientiousness significantly predicted burnout (β = - .35, p < .001). The third block included the interaction terms and did not show significant improvement from the second model (ΔR^2=.01, F [2,230] = .68, p = .506). There were no significant interaction effects found.

Ten multivariate outliers were removed from the moderation analyses including optimism as the personal resource of interest based on Mahalanobis distance analysis (df = 15, p < .001), the moderation analyses were conducted on n = 230 participants. The seventh moderation analysis tested research question 4A- Does optimism moderate the relationship between AI resources and work engagement such that those who have higher optimism report more work engagement? The results showed that the first model was significant F (4,235) = 6.60, $p < .001$, R^2=.10. Again, only generative AI use frequency ($\beta = .27$, $p < .001$) significantly predicted WE.

The second block included the five AAAW dimensions and optimism as the personal resource. The addition of optimism showed significant improvement from the first model (ΔR^2= .20, F [6, 229] = 11.02, $p < .001$). Overall, the findings suggest that the AI attitudes and optimism significantly predict WE above and beyond the control variables (Table 10). With the addition of optimism, both *Perceived Quality* (β =.19, p = .006) and *Personal Utility* (β =.17, p = .027) positively predicted WE. For the AID variables, *AI Use Anxiety* positively predicted WE (β =.20, p = .005), but *AI Induced Job Insecurity* did not have a significant relationship with WE. Optimism significantly predicted WE ($\beta = .35$, $p < .001$). The third block included the interaction terms and did not show significant improvement from the first model (ΔR^2=.04, F [3,226] = 4.979, p = .002). There were significant interaction effects with *Perceived Adaptability* and Optimism (β = -.14, p = .037) on WE. To further interpret the interaction, simple slopes were examined at one standard deviation above and below the mean of optimism. At low levels of optimism (–1 SD), the relationship between AI use anxiety and burnout was negligible and nonsignificant, $B = -0.03$, t =–0.55, p =.58. At high levels of optimism (+1 SD), the relationship was more negative, and reached statistical significance, $B = -0.24$, $t = -2.57$, p =.01. With the significant interaction term and significant slope, I concluded that optimism moderates the relationship between perceived adaptability and burnout. Specifically, individuals high in optimism appear to experience reduced WE in the context of high perceived adaptability, whereas individuals low in optimism do not show a meaningful relationship between perceived adaptability and WE. Simple slopes were plotted in Figure 4.

The eighth moderation analysis tested research question 4B- does optimism moderate the relationship between AI demands and burnout such that those who are higher optimism report less burnout? The results showed that the first model was not significant F (4,235) = 1.032, p = .391, R^2=.02. None of the control variables had a significant relationship with burnout. The second block included the five AAAW dimensions and optimism. The addition of optimism showed significant improvement from the first model (ΔR^2= .19, F [6,229] = 9.01, p < .001). Overall, the findings suggest that the AI attitudes and optimism significantly predict burnout above and beyond the control variables (Table 11). For the AI attitude variables, *AI Induced Job Insecurity* (β = .13, p = .049) significantly positively predicted burnout and *Perceived Quality* (β = - .18, p < .001) negatively predicted burnout. Additionally, optimism significantly predicted burnout (β = - .30, p < .001). The third block included the interaction terms and did show significant improvement from the second model (ΔR^2=.04, F [2,227] = 5.44, p = .005). Optimism significantly moderated the relationship between *AI use anxiety* and burnout (β = - .15, p = .009). A hierarchical regression analysis was conducted to examine whether optimism moderates the relationship between AI use anxiety and burnout. The interaction term between AI use anxiety and optimism was statistically significant, β =−0.32, SE=0.15, t =−2.17, p = .03, indicating that the strength of the association between AI use anxiety and burnout varied as a function of optimism.

To further interpret the interaction, simple slopes were examined at one standard deviation above and below the mean of optimism. At low levels of optimism (–1 SD), the relationship between AI use anxiety and burnout was negligible and nonsignificant, B = −0.001,

t =−0.01, p =.99. At high levels of optimism (+1 SD), the relationship was more negative, B = −0.32, t = −2.80, p =.006. The significant interaction term and the pattern of the simple slopes suggest that optimism moderates the relationship between AI use anxiety and burnout. Specifically, individuals high in optimism appear to experience reduced burnout in the context of high AI use anxiety, whereas individuals low in optimism do not show a significant relationship between AI use anxiety and burnout. This pattern suggests a potential buffering effect of optimism. Simple slopes were plotted in Figure 5.

Supplemental Moderation Analyses

I conducted exploratory analyses to examine whether the personal resources moderate the relationships between (a) the AI Readiness (AIR) variables and burnout, and (b) the AI Demand (AID) variables and work engagement (WE). These analyses followed the same hierarchical regression procedure used in previous models, with the interaction terms between each AAAW variable and the respective personal resource added in a third block.

There was only one significant interaction that emerged between optimism and the AIR variables in predicting burnout. Specifically, when optimism was included as a moderator, the model significantly improved, ΔR^2 = .05, F (5, 224) = 3.60, p = .004. Of the three AIR interaction terms, optimism moderated the relationship between *Perceived Adaptability* (β = –.18, p = .032) and burnout. A moderation analysis was conducted to examine whether optimism moderates the relationship between perceived adaptability and burnout. The interaction term between perceived adaptability and optimism was statistically significant, B=0.292, SE= 0.15, t =2.00, p = .046, indicating that the association between perceived adaptability and burnout varied by levels of optimism. At low levels of optimism (–1 SD), the relationship between perceived adaptability and burnout was not significant, B = −0.06, t = −0.78, p =.44. At high levels of optimism (+1 SD), the relationship was also nonsignificant, though trending positive, B =0.23, t =1.60, p =.11. Although neither simple slope was significant, the direction and magnitude of the slopes differed, supporting the presence of a moderation effect. A plot of the interaction suggested that perceived adaptability is more positively related to burnout among individuals high in optimism, whereas the relationship is relatively flat for those low in optimism. Although neither simple slope was significant, the direction and magnitude of the slopes differed, supporting the presence of a moderation effect. A plot of the interaction suggested that perceived adaptability is more positively related to burnout among individuals high in optimism, whereas the relationship is relatively flat for those low in optimism. Simple slopes for these interactions are presented in Figures 6.

Regarding the AID variables and work engagement, only one significant moderation effect emerged. When proactive personality was tested as a moderator, the model did not significantly increase the explained variance, $\Delta R^2 = .02$, $F(5, 225) = 1.10$, $p = .361$. Within this model, the interaction between *AI-induced Job insecurity* and proactive personality significantly predicted work engagement ($\beta = -.15$, $p = .03$). This suggests that the strength of the relationship between job insecurity and engagement varies by proactive personality level. Simple slopes analysis revealed that the negative relationship between AI-induced job insecurity and work engagement was significant for individuals high in proactive personality ($B = -0.20$, $t = -2.38$, $p = .02$), but nonsignificant for individuals low in proactive personality ($B = -0.05$, $t = -1.08$, $p = .28$). The simple slopes analysis for this interaction is shown in Figure 7.

Discussion

This study aimed to examine how attitudes toward artificial intelligence in the workplace, conceptualized as resources and demands, relate to work engagement and burnout, and how personal resources such as occupational self-efficacy, proactive personality, conscientiousness, and optimism moderate these relationships.

Consistent with the second and third hypotheses, among the AI attitude dimensions, *Perceived Quality* and *Personal Utility* emerged as significant positive predictors of WE, highlighting the importance of perceiving AI as valuable and useful to one's job. That is, when individuals perceive that generative AI provides complete, well-formatted, and accurate information, as well as enhances their confidence, sense of accomplishment, and control over their work, are significantly associated with increased work engagement. These findings align with the TAM, which emphasizes perceived usefulness and performance quality as critical determinants of technology adoption, utilization, and potential benefits (Khoza et al., 2024). Interestingly, *Perceived Adaptability* did not significantly predict engagement, which may suggest that employees' beliefs about AI's ability to adapt and learn over time are less influential than their evaluations of AI's quality and utility as it relates to work engagement. There could be several explanations for this non-significant finding. First, employee's ability to prioritize AI's present performance and usefulness because these factors have a more direct and observable impact on their daily tasks and motivation, consequently work engagement. For example, a coder using AI to assist with writing code can see if the code being written is accurate and is assisting with their work. Meanwhile, that same coder may not be attentive to if the generative AI is improving and learning from past projects. Additionally, perceptions of adaptability might be more uncertain, making it difficult for employees to link this belief to their current work engagement. Furthermore, adaptability might influence other outcomes than WE, such as learning or innovation, suggesting that its effects could emerge over a longer term.

Regarding the AID relationships with burnout, *AI Use Anxiety* was a consistent positive predictor, supporting hypothesis 5. This finding aligns with emerging research demonstrating that AI use in workplace settings can intensify burnout by imposing new job demands and disrupting established work routines (Dwivedi et al., 2021), with previously mentioned studies showing a positive association between AI awareness and job burnout (Kong et al., 2021). The stress that some employees experience when using generative AI tools appears to contribute directly to increased burnout, suggesting that the immediate emotional burden of AI interaction serves as a significant workplace stressor. *AI Induced Job Insecurity*, however, did not significantly predict burnout in the main analyses but showed some effects when considering personal resources, indicating a more nuanced relationship. This complexity reflects findings that while AI may threaten employees' roles and diminish their sense of personal value (Kong et al., 2021), individual differences in personal resources such as critical skills and personal traits may moderate these effects (Kong et al., 2021). The inconsistent relationship between AI-related job insecurity and burnout suggests that employees' coping mechanisms and access to personal resources play crucial moderating roles. Optimism emerged as a significant moderator. The interaction between *AI Job Insecurity* and optimism significantly predicted burnout, indicating that the effect of job insecurity on burnout was weaker among employees with higher levels of optimism (+1 SD). This suggests that optimistic individuals may be better equipped to psychologically buffer against the stress associated with perceived threats from AI. These findings suggest fostering positive psychological resources to support employee well-being in the face of technological disruption.

In contrast to the AID variables, *Perceived Quality* of generative AI negatively predicted burnout, indicating that positive attitudes toward AI can serve as a protective factor. That is, when individuals perceive that generative AI is presenting them with accurate and complete information, they can better potentially preserve their resources and associated with less burnout. These findings collectively suggest that the relationship between AI and employee burnout is multifaceted, with the quality of AI experiences and individual resource availability serving as key moderating factors in determining whether AI adoption leads to increased stress or workplace enhancement.

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The inconsistent relationship between AI-related job insecurity and burnout suggests that employees' coping mechanisms and access to personal resources play crucial moderating roles. Self-efficacy emerged as a significant moderator in this relationship. The interaction between AI related job insecurity and occupational self-efficacy significantly predicted burnout such that employees with higher self-efficacy (+1 SD) experienced less burnout when facing heightened AI-related job insecurity. This suggests that individuals who believe in their ability to adapt and perform effectively at work are better protected against the negative psychological effects of AIinduced threats. These findings suggest the importance of fostering positive psychological resources to support employee well-being in the face of technological disruption.

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Further evidence of the complexity of AI experiences at work is seen in the moderation analyses. These analyses revealed that personal resources had significant main effects on outcomes but did not consistently moderate the relationships between AI attitudes and work engagement or burnout. In addition to occupational self-efficacy, both optimism and proactive personality were positively associated with work engagement and negatively with burnout, consistent with their established roles as personal resources that foster resilience and motivation.

Optimism demonstrated a complex moderating role. While it buffered the negative effects of AI Use Anxiety on burnout, it also moderated the relationship between perceived adaptability and burnout in an unexpected direction, individuals with higher optimism experienced greater burnout when they perceived AI as highly adaptable. This may suggest that highly optimistic employees hold elevated expectations about AI's potential, and when those expectations are not met or lead to increased change demands, it may result in greater strain or disappointment.

Proactive personality moderated the effect of AI-induced job insecurity on work engagement, suggesting that proactive individuals may remain engaged by actively seeking ways to cope with or overcome the challenges posed by AI-related threats. However, the effort required to continuously manage such threats may also complicate their ability to feel fully satisfied or immersed in their work.

Interestingly, conscientiousness did not emerge as a significant moderator in the relationships between AI attitudes and the outcomes. This suggests that while conscientiousness is typically associated with persistence and goal-directed behavior, it may not offer the same adaptive, protective benefits as forward-looking traits like optimism, proactive personality, or occupational self-efficacy. These distinctions underscore the importance of differentiating among personal resources when examining individual responses to AI in the workplace.

Theoretical and Practical Implications

Theoretically, this study extends the understanding of employees' attitudes toward AI by differentiating key perceptions through the lens of the JD-R model. The results underscore that AI is perceived neither solely as a resource nor purely as a demand but rather holds a dual impact on employees' work experiences. Specifically, this research examined three attitudes reflecting AI as a resource and two attitudes representing AI as a demand. *Perceived quality* and personal utility emerged as positive predictors of engagement, with perceived quality also negatively predicting burnout. Meanwhile, *AI use anxiety* was a significant job demand attitude, positively predicting burnout. These insights deepen theoretical understanding of how personal resources and job demands dynamically interact to shape employee well-being and productivity in AI enhanced workplaces.

This duality of AI's role supports an expansion of technology in the JD-R framework, suggesting that traditional models must evolve to accommodate hybrid tools that function as both resources and demands. In addition, the identification of AI-specific attitudinal constructs provides new theoretical tools for understanding employee reactions to emerging technologies. These constructs enrich existing psychological and occupational models by explaining how nuanced technological perceptions influence well-being. Moreover, this study highlights the moderating role of personal resources like occupational self-efficacy, proactive personality, and optimism. These factors mainly buffer the negative effects of AI-related stressors while amplifying the positive impacts of AI engagement, reinforcing their value in both theory and practice. While high-quality AI can enhance performance, it may also raise expectations and encourage overcommitment, especially among those who feel confident in their ability to manage new technologies. These results illustrate how personal and AI resources can interact to create complex forms of psychological strain in AI-integrated workplaces.

This is consistent with findings from Chuang et al.'s (2025) research. Similarly, they found that generative AI use is negatively associated with AI-related technostress, indicating that such AI tools may help reduce employees' stress levels. Additionally, AI efficacy, defined by perceptions of usefulness and reliability, positively influenced engagement while reducing exhaustion. In contrast, technostress (i.e., adverse psychological impact stemming from the introduction of new technologies) increased exhaustion and work–family conflict, negatively impacting job satisfaction. Exhaustion, in turn, was linked to higher productivity but also greater work–family conflict and lower job satisfaction. While generative AI positively affected productivity, it did not directly impact job satisfaction or work–family conflict; however, it indirectly improved these outcomes by reducing technostress and exhaustion. Engagement was strongly associated with job satisfaction but did not significantly affect productivity or work–family conflict (Chuang et al., 2025). The findings of this paper are aligned their findings which collectively highlight the complex, dual role of AI as both a resource and a demand in the workplace.

From a practical standpoint, organizations aiming to capture the benefits of AI should prioritize enhancing employees' perceptions of AI quality and utility. This can be achieved through targeted training programs and transparent communication about AI capabilities and limitations, which the findings suggest can boost engagement and reduce burnout. Because this functional evaluation of AI (i.e., AI efficacy) was a strong predictor of positive outcomes, interventions that develop these perceptions are especially important. These might include handson training, role-specific demonstrations of AI tools, and confidence-building experiences that foster a sense of control and capability. Additionally, fostering broader personal resources such as occupational self-efficacy and optimism may further empower employees to manage AIrelated demands effectively, thereby reducing burnout risk and improving work–family balance.

Organizations should also provide ongoing support and resources to help employees adapt to evolving AI tools. This can be particularly important for individuals who have higher AI use anxiety. This includes offering accessible technical assistance, facilitating peer learning, and integrating well-being supports that address the emotional and cognitive strain of technological change.

Finally, successful integration of AI into the workplace likely depends not only on technical infrastructure but also on cultural alignment (Schwaeke et al., 2025). Organizations should embed AI-related changes within broader change management practices that involve employees in decision-making, address concerns proactively, and cultivate a culture of openness and adaptability. These strategies reduce AI use anxiety, promote engagement, and help position AI not as a disruptive force, but as an empowering and sustainable workplace resource. To ensure long-term success, it is essential to continuously monitor the impact of AI on employee well-being and work dynamics, enabling timely adjustments to policies, support systems, and training initiatives.

Limitations and Future Research

While the study provides valuable insights, several limitations should be noted. The current design limits causal inferences, and future longitudinal research could clarify the directionality of these relationships. Another limitation of the present study is that the outcomes of interest were measured only at the third time point, rather than across all three time points. This decision was made to minimize participant fatigue and survey burden, given the already extensive battery of measures. However, this approach limited the ability to model changes in these constructs over time and weakened the strength of inferences regarding temporal ordering. Repeated measurement of outcomes is a fundamental principle in longitudinal research, as it allows for the examination of change over time and supports stronger conclusions about directionality and causal relationships (Ployhart & Vandenberg, 2010). Without assessing burnout and work engagement at earlier stages, it is unclear whether changes in the predictors preceded shifts in the outcomes, or whether stable levels of these predictors were associated with later outcomes.

Future research should incorporate multiple time-point assessments of key outcomes to enable more nuanced modeling of developmental trajectories and to test lagged effects. Additionally, including a longer time lag between assessments may better capture the unfolding of work engagement and burnout over time. Additionally, the sample used in this study consisted of workers using a computer was component of their job. Thus, this sample may not fully represent all industries or job types where AI is implemented, suggesting caution in generalizing findings. Future research could compare these results with industry or job specific samples to improve generalizability.

Another limitation of this study is that some survey items were worded to assess anticipated or hypothetical feelings rather than participants' current experiences with generative AI. For example, one of the items used to measure personal utility was "Using Generative AI would allow me to have increased confidence in my skills at work." This limitation may have introduced bias or reduced the accuracy of responses, as individuals might respond differently when reflecting on actual usage compared to beliefs about AI use and capabilities. Future research should consider phrasing items to capture real-time or recent experiences to more precisely assess how AI impacts employee attitudes and outcomes. Perhaps, a better wording of the previously mentioned item to identity the impact of AI as a resource would be, "Using Generative AI allows me to have increased confidence in my skills at work."

Another limitation of this study is the relatively small sample size (n = 254), which may limit the generalizability of the results. Larger samples are needed to confirm moderation effects and explore subgroup differences in future research.

Future research could explore other potential variables, moderators, and mediators, such as organizational support or AI-specific training quality. Investigating different AI technologies and their specific impact on work attitudes and well-being would also enhance the field's understanding of how people's perceptions of AI influence their psychological health. Future models should include AI adoption intentions and AI usage to complete the relationships between AI attitudes and OHP outcomes. This enables us to examine the relationship between individuals' evaluations of AI and their intentions to use it, their actual use, the resulting workplace outcomes, and any effects that extend beyond the workplace. Additionally, considering different types of self-efficacy like general self-efficacy or technical self-efficacy could provide a better understanding of the relationship of self-efficacy as a moderator (Zeng et al. 2022). Previous research indicates that employees' attitudes and anxiety towards AI significantly influence their readiness for AI adoption in the workplace.

AI use anxiety can stem from immediate concerns about increased automation and broader fears about artificial general intelligence (Lemay et al., 2020). This is closely linked to several factors of technostress Future research could examine different approaches to mitigate this anxiety, such as AI training (e.g., improving AI literacy), leadership behaviors (e.g., AI symbolization) (He et al., 2023), and organizational support mechanisms (e.g., clear communication about AI implementation and the impact it will have the individuals job). Past research suggests that high-performance work systems can mitigate the negative effects of AI anxiety on readiness to adopt AI (Suseno et al., 2022). Technology readiness inhibitors are positively related to various AI anxiety factors, including fears of job replacement and sociotechnical illiteracy (Lemay et al., 2020). These findings underscore the importance of addressing employees' psychological responses to AI implementation in the workplace. Though AI induced job insecurity did not significantly predict burnout, it approached significance.

Conclusion

This study underscores the complex interplay between attitudes toward AI, personal resources, and employee outcomes. The attitudes toward AI at work showed significant relationships with WE and burnout. Personal resources exhibited mixed effects as moderators across the AIR, AID, and occupational health outcomes. As AI continues to reshape the workplace, a nuanced understanding of these dynamics will be critical for supporting employee well-being and fostering sustainable organizational performance.

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Table 1

Variable Means, Standard Deviations, Correlations, and Alpha Coefficients

Variable	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1.Age	39.93	11.58															
2.Sex [a]	.51	.50	.02	—													
3.Req. Status [b]	.83	.37	.01	.07	—												
4.Gen. AI Use Freq.[c]	3.33	.65	.02	**−.15**	−.04	—											
5.PerceivedAdaptability	3.82	1.05	.01	.04	−.03	−.04	(.94)										
6.PerceivedQuality	3.77	.75	.04	−.02	−.06	**.27***	**.24***	(.83)									
7.PersonalUtility	3.70	.89	.03	−.06	−.08	**.40***	.08	**.55***	(.89)								
8.AI Use Anxiety	1.99	.99	**−.16**	.09	−.01	**−.20***	.03	−.04	**−.16**	(.91)							
9.AI Induced JI	2.59	1.18	−.09	.04	.04	−.12	−.04	.01	−.04	**.46***	(.89)						
10.Occ. Self-efficacy	4.94	.73	.09	−.11	−.02	.12	.01	**.16***	**.20***	**−.53***	**−.25***	(.92)					
11.Proactive Pers.	5.57	.95	−.12	−.09	−.11	**.23***	.00	**.29***	**.35***	**−.24***	**−.14**	**.62***	(.93)				
12.Conscientiousness	4.24	.64	.05	−.08	.01	**.17***	−.06	**.18***	**.17***	**−.42***	**−.26***	**.68***	**.51***	(.86)			
13.Optimism	3.71	.75	.02	**−.17***	−.01	**.20***	−.01	**.19***	**.24***	**−.38***	**−.17***	**.62***	**.50***	**.48***	(.82)		
14.Work Engagement	5.10	.93	.03	.00	−.10	**.28***	.07	**.31***	**.33***	−.08	−.12	**.39***	**.58***	**.31***	**.40***	(.92)	
15.Burnout	2.75	1.22	.04	.01	.06	−.08	−.02	**−.21***	−.08	**.26***	**.21***	**−.43***	**−.36***	**−.43***	**−.37***	**−.37***	(.92)

Note. n = 254. Bolded* = $p < .01$. Bolded = $p < .05$. Req. Status = Requirement status. Gen = Generative AI. [a] 0 = Female, 1 = Male. [b] 0 = required, 1 = voluntary. [c] Scale of use frequency (1=never, 2 = rarely, 3 = few times a week, 4 = daily). Alpha included along diagonal.

Table 2

Linear Regression of Work Engagement on AAAW

Effect	Estimate	*SE*	B	95% CI		*p*
				LL	*UL*	
Main effects						
Intercept	2.788	.518		1.768	3.809	<.001
Controls						
Age	.002	.005	.020	-.008	.011	.73
Sex [a]	.092	.110	.049	-.125	.308	.40
Requirement Status [b]	-.135	.148	-.053	-.428	.157	.36
Generative AI Use Freq.[c]	.239	.093	.167	.056	.422	.01
Independent Variables						
Perceived Adaptability	.022	.054	.025	-.084	.128	.68
Perceived Quality	.225	.091	.175	.047	.404	.01
Personal Utility	.193	.078	.181	.040	.346	.01
AI Use Anxiety	.043	.063	.045	-.082	.168	.50
AI Induced Job Insecurity	-.083	.052	-.102	-.185	.019	.11

Note. n = 253. CI = confidence interval; *LL* = lower limit; *UL* = upper limit. [a] 0 = Female, 1 = Male. [b] 0 = required, 1 = voluntary. [c] Ordinal scale of use frequency (1= never, 2 = rarely, 3 = few times a week, 4 = daily) [d] 0 = other, 1 = yes. [e] 0 = no, 1 = yes.

Table 3

Linear Regression of Burnout on AAAW

Effect	Estimate	*SE*	B	95% CI *LL*	95% CI *UL*	*p*
Intercept	2.585	.693		1.220	3.951	<.001
Controls						
Age	.010	.006	.091	-.003	.022	.13
Sex [a]	-.060	.147	-.025	−.350	.229	.68
Requirement Status [b]	.123	.199	.037	−.268	.514	.54
Generative AI Use Freq.[c]	.029	.124	.016	-.216	.274	.81
Independent Variables						
AI Use Anxiety	.263	.085	.214	.096	.431	.002
AI Induced Job Insecurity	.126	.070	.122	-.011	.263	.07
Perceived Adaptability	.021	.072	.018	-.121	.163	.77
Perceived Quality	-.452	.121	-.270	-.691	-.213	<.001
Personal Utility	.108	.104	.078	-.097	.313	.30

Note. *n* = 253. CI = confidence interval; *LL* = lower limit; *UL* = upper limit. [a] 0 = Female, 1 = Male. [b] 0 = required, 1 = voluntary. [c] Ordinal scale of use frequency (1=never, 2 = rarely, 3 = few times a week, 4 = daily) [d] 0 = other, 1 = yes. [e] 0 = no, 1 = yes.

Table 4

Moderation Analysis of Work Engagement on AAAW and Occupational Self-Efficacy

	Block 1			Block 2			Block 3		
Effect	Estimate (SE)	*B*	*p*	Estimate (SE)	*B*	*p*	Estimate (SE)	*B*	*p*
Main effects									
Intercept	3.74 (.39) ***		< .001	3.98 (.36) ***		<.001	4.00 (.36) ***		< .001
Controls									
Age	.001 (.01)	.01	.88	.001 (.004)	.03	.54	.00 (.00)	.004	.94
Sex [a]	.13 (.11)	.07	.24	.17 (.10)	.04	.44	.17 (.10)	.09	.09
Requirement Status [b]	-.20 (.15)	-.08	.18	-.08 (.13)	-.09	.13	-.08 (.13)	-.03	.54
Generative AI Use Freq.[c]	.44 (.09) ***	.31	< .001	.33 (.09) **	.16	.01	.33 (.09) ***	.23	< .001
Predictors									
Perceived Adaptability				.02 (.05)	.004	.95	.02 (.06)	.02	.74
Perceived Quality				.24 (.09) **	.14	.04	.28 (.09) **	.21	.003
Personal Utility				.09 (.08)	.10	.16	.08 (.08)	.07	.32
AI Use Anxiety				.30 (.07)	-.01	.92	.29 (.07) ***	.31	< .001
AI Induced Job Insecurity				-.09 (.05)	-.13	.06	-.09 (.05)	-.12	.06
OccSelfEff				.57 (.09) ***	.29	<.001	.56 (.09) ***	.43	< .001
Interaction Terms									
PerceivedAdaptxOccSelfEff							-.02 (.09)	-.01	.87
PerceivedQualitytxOccSelfEff							-.17 (.16)	-.08	.29
PersonalUtilityxOccSelfEff							.02 (.14)	-.01	.90
F	6.80***		< .001	13.15***		<.001	.61		.61
R^2	.10			.33			.34		
Change R^2	.01			.23			.01		

Note. *n* = 244. *** = *p* < .00, ** *p* < .05. CI = confidence interval; *LL* = lower limit; *UL* = upper limit. [a] 0 = Female, 1 = Male. [b] 0 = required, 1 = voluntary. [c] Ordinal scale of use frequency (1=never, 2 = rarely, 3 = few times a week, 4 = daily).

Table 5
Moderation Analysis of Burnout on AAAW and Occupational Self-Efficacy

	Block 1			Block 2			Block 3		
Effect	Estimate (SE)	*B*	*p*	Estimate (SE)	*B*	*p*	Estimate (SE)	*B*	*p*
Main effects									
Intercept	3.04 (.53) ***		< .001	2.33 (.50) ***		<.001	2.14 (.50)***		< .001
Controls									
Age	.004 (.01)	.04	.53	.01 (.01)	.08	.16	.01 (.01)	.10	.09
Sex [a]	-.08 (.16)	-.03	.63	-.16 (.14)	-.07	.25	-.15 (.14)	-.06	.27
Requirement Status [b]	.17 (.21)	.05	.41	.09 (.18)	.03	.62	.13 (.18)	.04	.48
Generative AI Use Freq.[c]	-.16 (.12)	-.09	.18	.04 (.12)	.02	.74	.05 (.12)	.03	.67
Predictors									
AI Use Anxiety				.04 (.09)	.04	.64	-.01 (.10)	-.01	.91
AI Induced Job Insecurity				.09 (.07)	.09	.16	.15 (.07) **	.14	.04
Perceived Adaptability				-.001 (.07)	-.001	.99	-.03 (.07)	-.03	.65
Perceived Quality				-.30 (.12) **	-.18	.01	-.30 (.12) **	-.18	.01
Personal Utility				-.003 (.11)	-.002	.98	-.04 (.11)	-.02	.750
OccSelfEff				-.66 (.12) **	-.39	<.001	-.63 (.12) **	-.37	< .001
Interaction Terms									
AIUseAnxietyxOccSelfEff							.05 (.13)	.03	.70
AIInducedJIxOccSelfEff							-.30 (.12) **	-.18	.02
F	.74		.57	12.44***		< .001	3.43**		.034
R^2	.01			.25			.27		
Change R^2	.01			.24			.02		

Note. *n* = 244. *** = *p* < .00, ** *p* < .05. CI = confidence interval; *LL* = lower limit; *UL* = upper limit. [a] 0 = Female, 1 = Male. [b] 0 = required, 1 = voluntary. [c] Ordinal scale of use frequency (1=never, 2 = rarely, 3 = few times a week, 4 = daily).

Table 6
Moderation Analysis of Work Engagement on AAAW and Proactive Personality

	Block 1			Block 2			Block 3		
Effect	Estimate (SE)	*B*	*p*	Estimate (SE)	*B*	*p*	Estimate (SE)	*B*	*p*
Main effects									
Intercept	3.80 (.38) ***		< .001	4.00 (.34) ***		<.001	4.01 (.34) ***		< .001
Controls									
Age	.002 (.01)	.02	.74	.01 (.004)	.10	.09	.01 (.00)	.09	.11
Sex [a]	.11 (.11)	.07	.31	.12 (.10)	.07	.20	.13 (.10)	.07	.19
Requirement Status [b]	-.17 (.15)	-.07	.24	-.04 (.13)	-.02	.78	-.04 (.13)	-.02	.77
Generative AI Use Freq.[c]	.41 (.09) ***	.30	< .001	.24 (.08)	.18	.003	.25 (.09) **	.18	.003
Predictors									
Perceived Adaptability				.01 (.05)	.01	.85	.01 (.06)	.01	.89
Perceived Quality				.20 (.08) **	.15	.02	.22 (.09) **	.17	.014
Personal Utility				.01 (.08)	.01	.93	.00 (.08)	.00	1.00
AI Use Anxiety				.17 (.06) **	.19	.003	.17 (.06) **	.18	.005
AI Induced Job Insecurity				-.09 (.05)	-.11	.07	-.08 (.05)	-.11	.08
Proactive Personality				.50 (.06) ***	.48	<.001	.48 (.07) ***	.47	< .001
Interaction Terms									
PerceivedAdaptxProactivePers.							.02 (.07)	.01	.82
PerceivedQualitytxProactivePers.							-.10 (.12)	-.06	.39
PersonalUtilityxProactivePers.							.04 (.10)	.02	.71
F	6.26***		< .001	16.14***		<.001	.26		.86
R^2	.10			.364			.37		
Change R^2	.10			.268			.002		

Note. *n* = 241. *** = p < .00, ** p < .05. CI = confidence interval; *LL* = lower limit; *UL* = upper limit. [a] 0 = Female, 1 = Male. [b] 0 = required, 1 = voluntary. [c] Ordinal scale of use frequency (1=never, 2 = rarely, 3 = few times a week, 4 = daily).

Table 7

Moderation Analysis of Burnout on AAAW and Proactive Personality

	Block 1			Block 2			Block 3		
Effect	Estimate (SE)	*B*	*p*	Estimate (SE)	*B*	*p*	Estimate (SE)	*B*	*p*
Main effects									
Intercept	3.07 (.54) ***		< .001	2.26 (.51) ***		< .001	2.20 (.52) ***		< .001
Controls									
Age	.00 (.01)	.04	.51	.01 (.01)	.05	.44	.01 (.01)	.05	.38
Sex [a]	-.07 (.16)	-.03	.66	-.13 (.14)	-.05	.36	-.14 (.14)	-.06	.34
Requirement Status [b]	.15 (.21)	.05	.47	.04 (.18)	.01	.84	.05 (.19)	.01	.81
Generative AI Use Freq.[c]	-.16 (.12)	-.09	.19	.04 (.12)	.07	.31	.13 (.12)	.07	.29
Predictors									
AI Use Anxiety				.12 (.09) **	.14	.04	.17 (.09)	.13	.06
AI Induced Job Insecurity				.17 (.07)	.10	.12	.12 (.07)	.11	.12
Perceived Adaptability				-.03 (.07)	-.02	.72	-.02 (.07)	-.02	.74
Perceived Quality				-.34 (.13) **	-.19	.01	-.35 (.13) **	-.19	.01
Personal Utility				-.01 (.12)	-.01	.92	-.01 (.12)	-.01	.92
Proactive Personality				-.41 (.09) ***	-.29	< .001	-.41 (.09) ***	-.29	< .001
Interaction Terms									
AIUseAnxietyxProactivePers.							-.05 (.12)	-.03	.66
AIInducedJIxProactivePers.							-.02 (.10)	-.18	.83
F	.69		.60	10.74***		< .001	.27		.77
R^2	.01			.228			.22		
Change R^2	.012			.230			.02		

Note. $n = 241$. *** = $p < .00$, ** $p < .05$. CI = confidence interval; *LL* = lower limit; *UL* = upper limit. [a] 0 = Female, 1 = Male. [b] 0 = required, 1 = voluntary. [c] Ordinal scale of use frequency (1=never, 2 = rarely, 3 = few times a week, 4 = daily).

Table 8

Moderation Analysis of Work Engagement on AAAW and Conscientiousness

	Block 1			Block 2			Block 3		
Effect	Estimate (SE)	*B*	*p*	Estimate (SE)	*B*	***p***	Estimate (SE)	*B*	***p***
Main effects									
Intercept	3.93 (.40) ***		< .001	4.51 (.39) ***		<.001	4.55 (.39) ***		< .001
Controls									
Age	.00 (.01)	.01	.91	.00 (.01)	-.01	.54	-.00 (.01)	-.04	.94
Sex [a]	.12 (.12)	.07	.31	.10 (.11)	.05	.44	.10 (.11)	.06	.09
Requirement Status [b]	-.20 (.16)	-.08	.20	-.15 (.15)	-.06	.13	-.14 (.15)	-.06	.54
Generative AI Use Freq.[c]	.38 (.09) ***	.31	< .001	.20 (.09) **	.14	.01	.21 (.09) **	.15	< .001
Predictors									
Perceived Adaptability				.03 (.05)	.04	.95	.04 (.06)	.04	.60
Perceived Quality				.17 (.09) **	.12	.04	.18 (.10)	.14	.06
Personal Utility				.20 (.08)	.19	.16	.23 (.08) **	.21	.004
AI Use Anxiety				.16 (.07)	.17	.92	.15 (.07) **	.16	.03
AI Induced Job Insecurity				-.06 (.05)	-.07	.24	-.06 (.05)	-.08	.24
Conscientiousness				.48 (.11) ***	.29	<.001	.47 (.11) ***	.28	< .001
Interaction Terms									
PerceivedAdaptxCon.							-.01 (.13)	-.01	.91
PerceivedQualitytxCon.							-.06 (.20)	-.02	.76
PersonalUtilityxCon							-.17 (.16)	-.08	.30
F	5.20***		< .001	7.43***		< .001	.76		.52
R^2	.08			.229			.236		
Change R^2	.08			.148			.008		

Note. *n* = 243. *** = *p* < .00, ** *p* < .05. CI = confidence interval; *LL* = lower limit; *UL* = upper limit. [a] 0 = Female, 1 = Male. [b] 0 = required, 1 = voluntary. [c] Ordinal scale of use frequency (1=never, 2 = rarely, 3 = few times a week, 4 = daily).

Table 9

Moderation Analysis of Burnout on AAAW and Conscientiousness

	Block 1			Block 2			Block 3		
Effect	Estimate (SE)	*B*	*p*	Estimate (SE)	*B*	*p*	Estimate (SE)	*B*	*p*
Main effects									
Intercept	2.87 (.53) ***		< .001	2.02 (.51) ***		< .001	1.95 (.50) ***		< .001
Controls									
Age	.01 (.01)	.06	.39	.01 (.01)	.08	.16	.01 (.01)	.11	.06
Sex [a]	-.03 (.16)	-.01	.87	-.04 (.14)	-.07	.25	-.04 (.14)	-.02	.77
Requirement Status [b]	.08 (.21)	.02	.72	.12 (.19)	.03	.62	.15 (.20)	.05	.45
Generative AI Use Freq. [c]	-.13 (.12)	-.07	.29	.07 (.12)	.02	.74	.07 (.12)	.04	.58
Predictors									
AI Use Anxiety				.09 (.09)	.04	.64	.08 (.09)	.06	.39
AI Induced Job Insecurity				.07 (.07) **	.09	.16	.08 (.07) **	.08	.24
Perceived Adaptability				-.02 (.07)	-.001	.99	-.02 (.07)	-.02	.77
Perceived Quality				-.36 (.12) **	-.18	.01	-.38 (.12) **	-.22	.002
Personal Utility				.09 (.10)	-.002	.98	.09 (.10)	.06	.37
Conscientiousness				-.76 (.15) **	-.39	<.001	-.72 (.15) **	-.34	< .001
Interaction Terms									
AIUseAnxietyxCon.							-.08 (.16)	-.04	.60
AIInducedJIxCon.							-.09 (.15)	-.04	.55
F	.50		.74	10.87 ***		< .001	.68 **		.51
R^2	.008			.226			.230		
Change R^2	.008			.218			.004		

Note. *n* = 243. *** = *p* < .00, ** *p* < .05. CI = confidence interval; *LL* = lower limit; *UL* = upper limit. [a] 0 = Female, 1 = Male. [b] 0 = required, 1 = voluntary. [c] Ordinal scale of use frequency (1=never, 2 = rarely, 3 = few times a week, 4 = daily).

Table 10

Moderation Analysis of Work Engagement on AAAW and Optimism

Effect	Block 1			Block 2			Block 3		
	Estimate (SE)	*B*	*p*	Estimate (SE)	*B*	*p*	Estimate (SE)	*B*	*p*
Main effects									
Intercept	3.68 (.39) ***		< .001	4.21 (.36) ***		<.001	4.26 (.37) ***		< .001
Controls									
Age	.002 (.01)	.02	.70	.003 (.004)	.04	.46	.003 (.004)	.04	.51
Sex [a]	.16 (.12)	.08	.18	.22 (.11) **	.12	.04	.23 (.10) **	.13	.03
Requirement Status [b]	-.21 (.15)	-.09	.17	-.13 (.14)	-.05	.35	-.10 (.14)	-.04	.46
Generative AI Use Freq.[c]	.44 (.09) ***	.31	< .001	.23 (.09) **	.16	.01	.22 (.09) **	.15	.01
Predictors									
Perceived Adaptability				-.01 (.05)	-.01	.88	.03 (.05)	.03	.59
Perceived Quality				.25 (.09) **	.19	.01	.28 (.09) **	.21	.002
Personal Utility				.18 (.08)	.15	.03	.14 (.08)	.12	.07
AI Use Anxiety				.19 (.07)	.20	.01	.18 (.07) **	.19	.007
AI Induced Job Insecurity				-.08 (.05)	-.09	.14	-.09 (.05)	-.12	.06
Optimism				.47 (.09) ***	.35	<.001	.56 (.09) ***	.41	< .001
Interaction Terms									
PerceivedAdaptxOptimism							-.21 (.10) **	-.14	.04
PerceivedQualitytxOptimism							-.28 (.15)	-.13	.07
PersonalUtilityxOptimism							-.03 (.13)	-.02	.82
F	6.60***		< .001	11.02***		<.001	.04**		.002
R^2	.101			.302			.346		
Change R^2	.101			.201			.043		

Note. $n = 240$. *** = $p < .00$, ** $p < .05$. CI = confidence interval; *LL* = lower limit; *UL* = upper limit. [a] 0 = Female, 1 = Male. [b] 0 = required, 1 = voluntary. [c] Ordinal scale of use frequency (1=never, 2 = rarely, 3 = few times a week, 4 = daily).

Table 11

Moderation Analysis of Burnout on AAAW and Optimism

	Block 1			Block 2			Block 3		
Effect	Estimate (SE)	*B*	*p*	Estimate (SE)	*B*	*p*	Estimate (SE)	*B*	*p*
Main effects									
Intercept	3.17 (.53) ***		< .001	2.33 (.50) ***		<.001	2.22 (.51)***		< .001
Controls									
Age	.004 (.01)	.04	.50	.01 (.01)	.08	.21	.01 (.01)	.08	.20
Sex [a]	-.01 (.16)	-.002	.97	-.12 (.14)	-.05	.42	-.15 (.14)	-.06	.30
Requirement Status [b]	.16 (.21)	.05	.45	.12 (.18)	.04	.53	.09 (.19)	.03	.63
Generative AI Use Freq.[c]	-.21 (.12)	-.11	.09	.03 (.12)	.02	.80	.04 (.12)	.02	.73
Predictors									
AI Use Anxiety				.10 (.09)	.08	.27	.00 (.10)	-.001	.99
AI Induced Job Insecurity				.14 (.07) **	.13	.049	.15 (.07) **	.15	.03
Perceived Adaptability				.02 (.07)	.02	.80	-.02 (.07)	-.01	.83
Perceived Quality				-.30 (.12) **	-.18	.02	-.31 (.12) **	-.18	.01
Personal Utility				-.02 (.11)	.01	.88	-.04 (.11)	-.03	.70
Optimism				-.52 (.12) ***	-.29	<.001	-.54 (.12) **	-.31	< .001
Interaction Terms									
AIUseAnxietyxOptimism							-.32 (.15)	-.15	.03
AIInducedJIxOptimism							-.16 (.11)	-.10	.15
F	1.03		.57	9.01***		<.001	5.44**		.005
R^2	.017			.205			.241		
Change R^2	.017			.188			.036		

Note. n = 240. *** = p < .001, ** p < .05. CI = confidence interval; *LL* = lower limit; *UL* = upper limit. [a] 0 = Female, 1 = Male. [b] 0 = required, 1 = voluntary. [c] Ordinal scale of use frequency (1=never, 2 = rarely, 3 = few times a week, 4 = daily

Figure 1.

Conceptual Model of Work Engagement Pathway

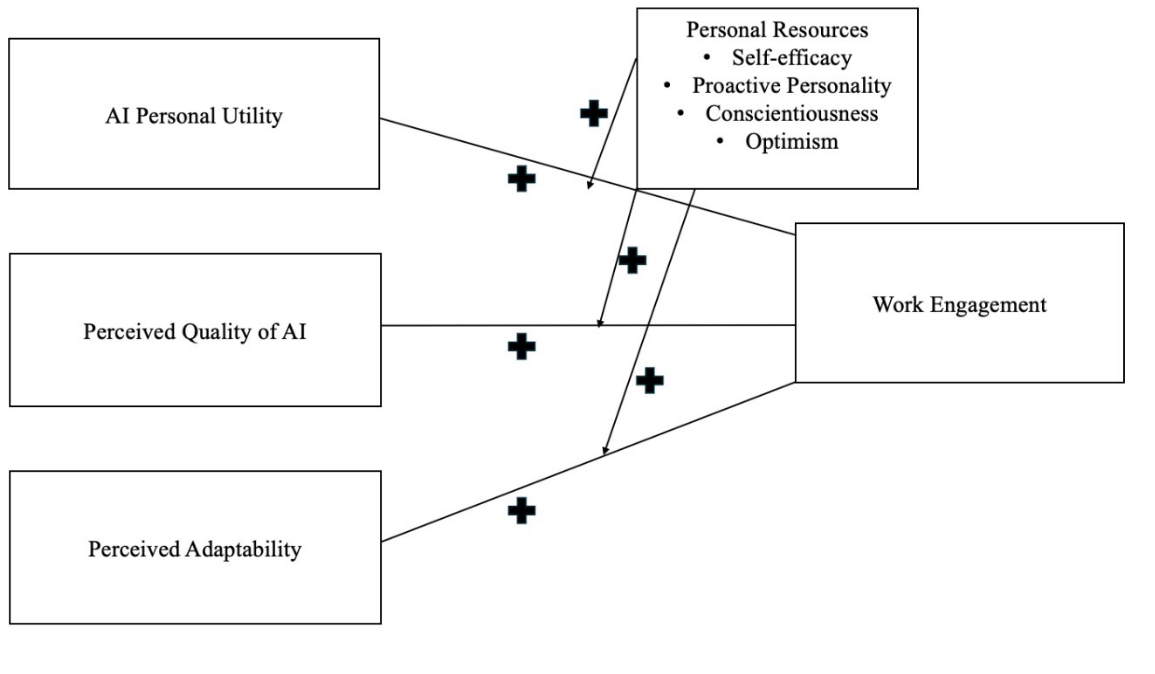


Figure 2.

Conceptual Model of Work Engagement Pathway

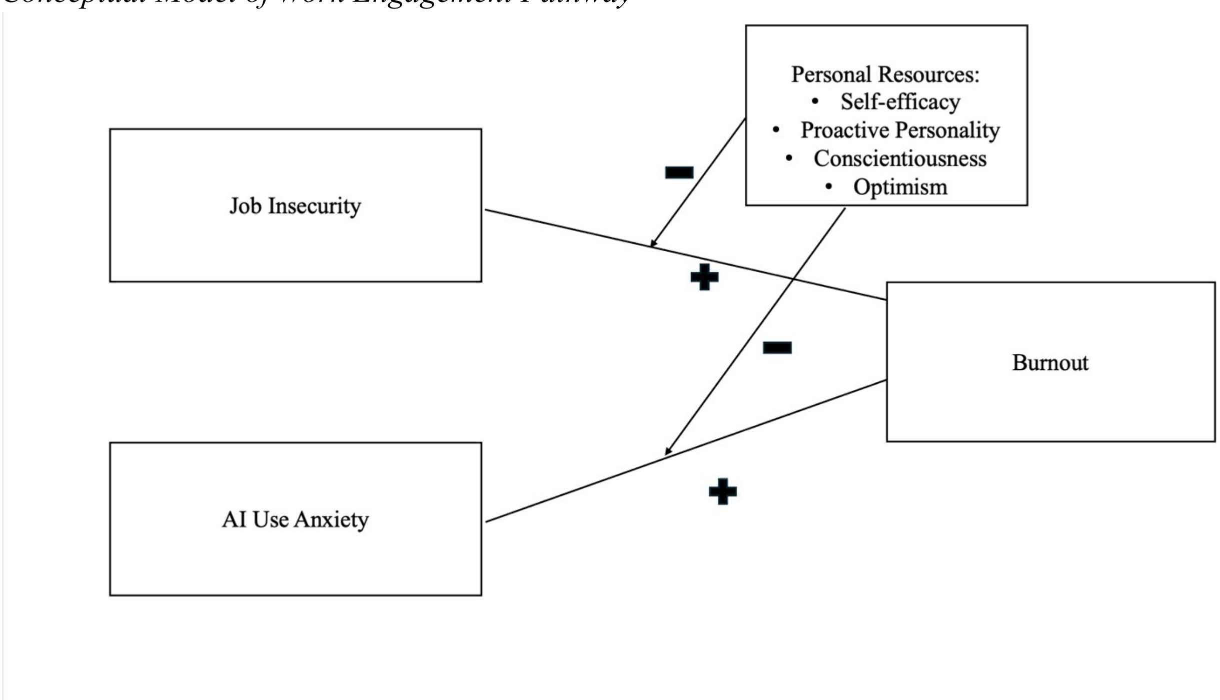


Figure 3

Simple Slopes of AI Induced Job Insecurity and OCCSELF on Burnout

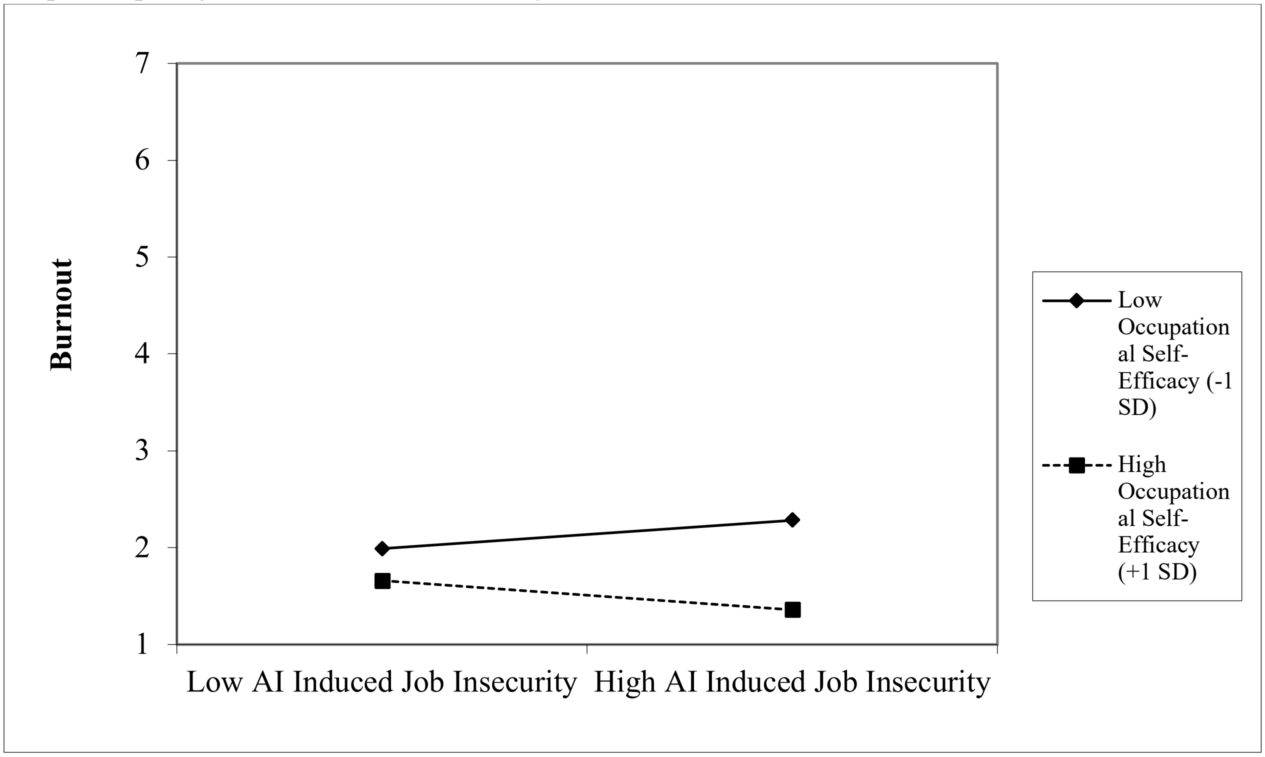


Figure 4

Simple Slopes of Perceived Adaptability and Optimism on Work Engagement

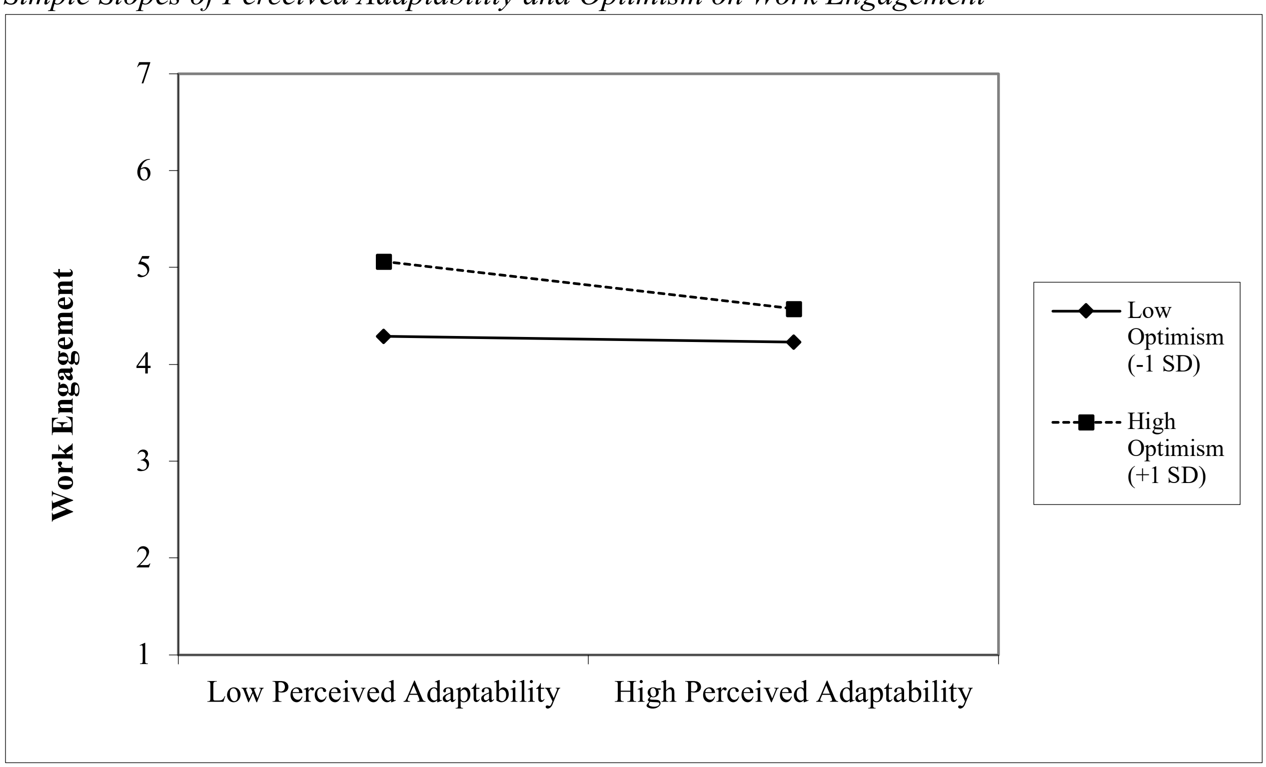


Figure 5

Simple Slopes of AI Use Anxiety and Optimism on Burnout

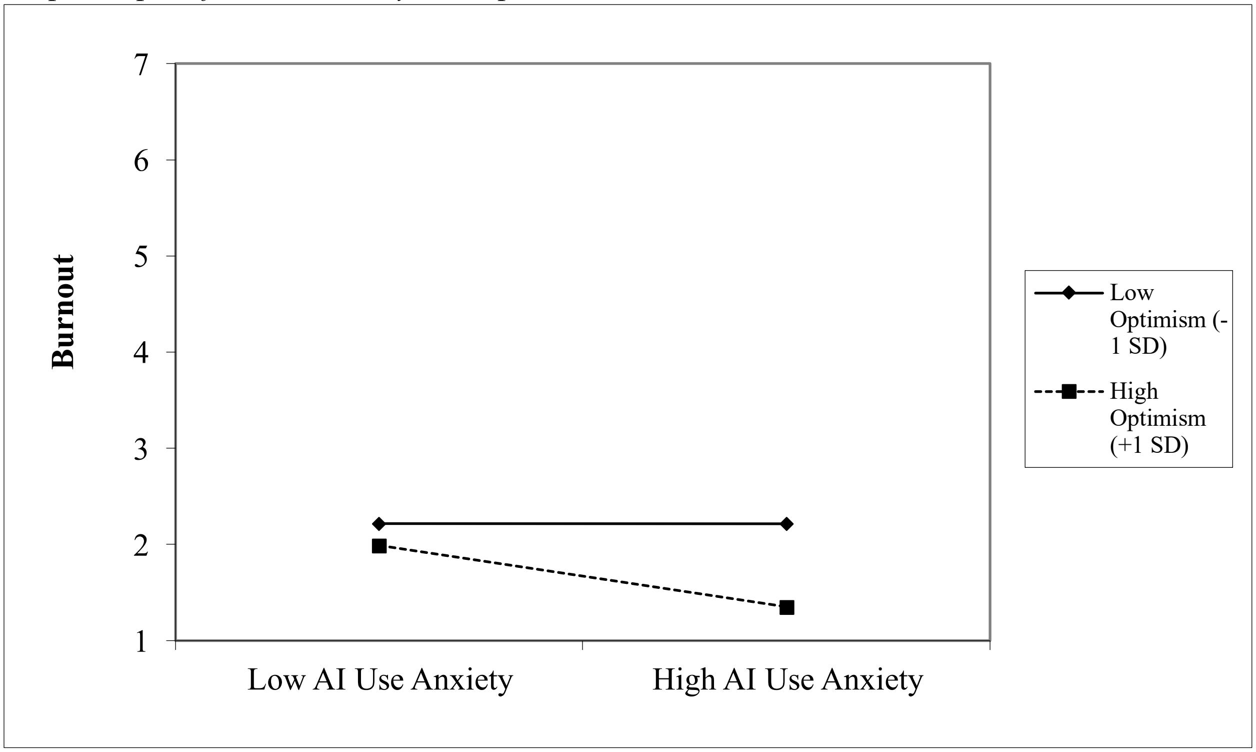


Figure 6

Simple Slopes of Perceived Adaptability and Optimism on Burnout

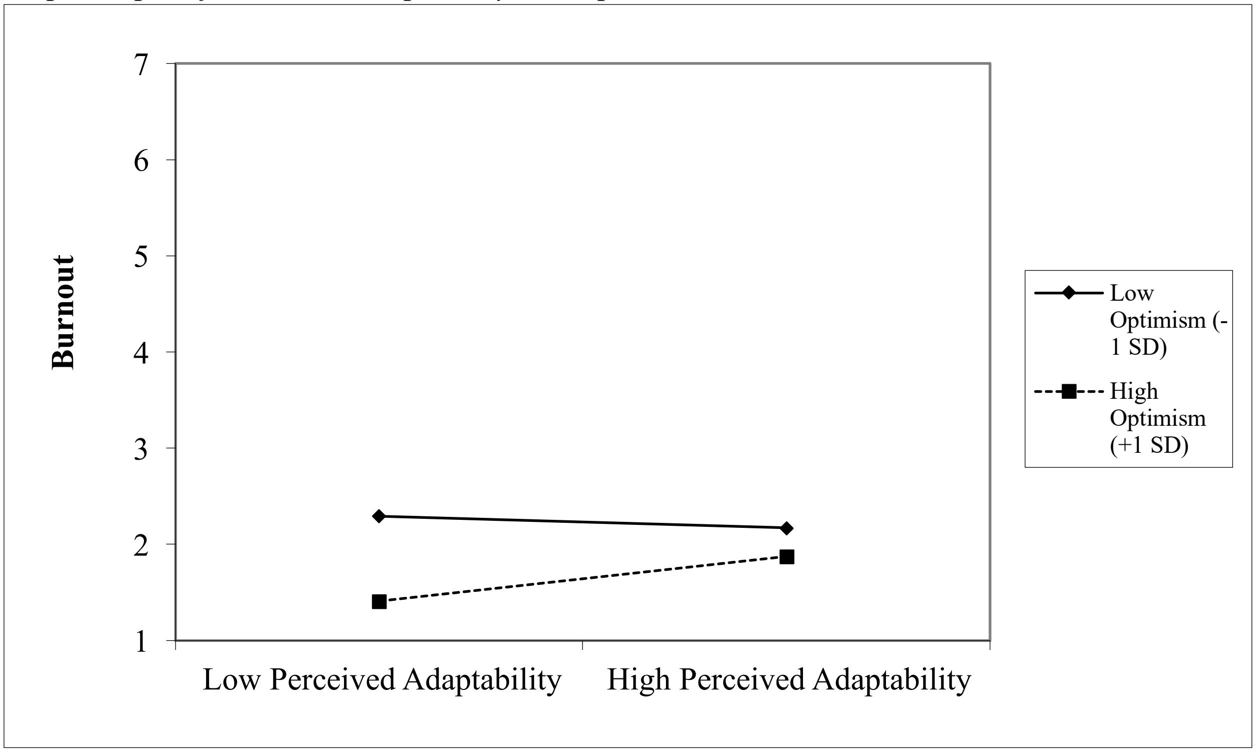
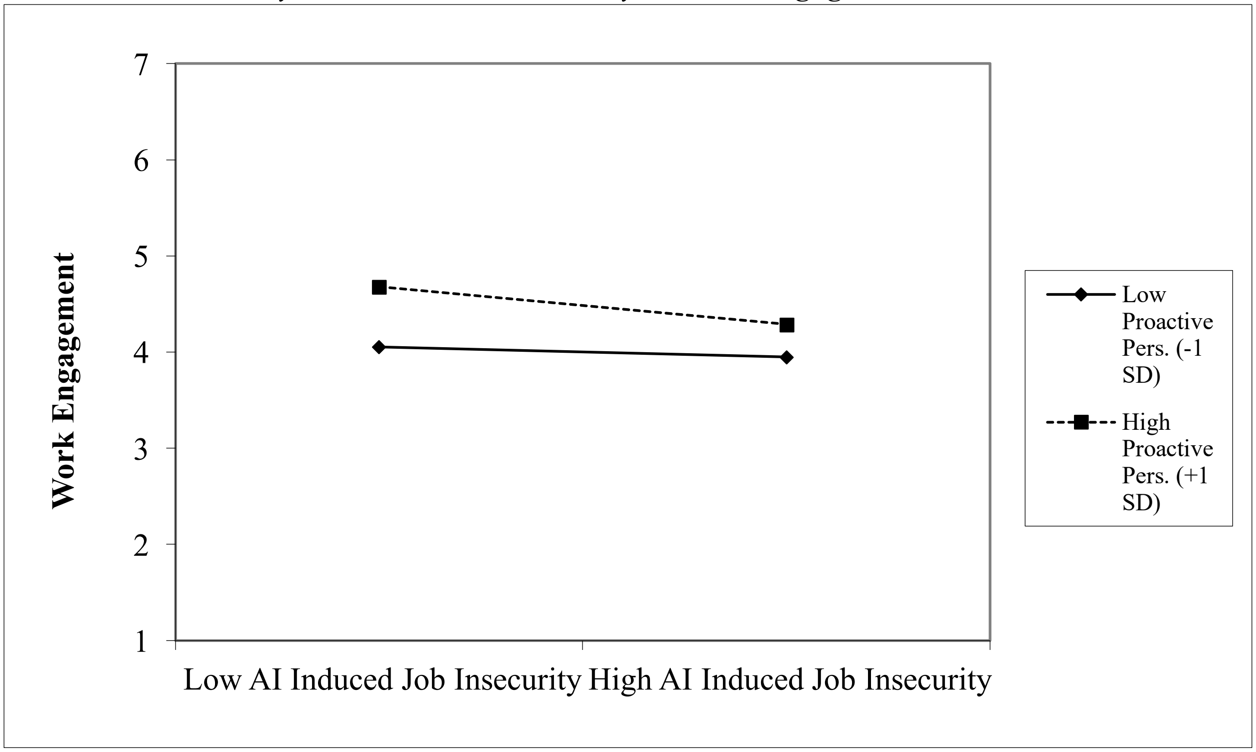


Figure 7

Induced Job Insecurity and Proactive Personality on Work Engagement



Appendix A

Participants were asked to rate the following AAAW items on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree)

Perceived adaptability of AI

Generative AI learns from experience at work.

Generative AI improves itself at work.

Generative AI can learn at work.

Generative AI adapts itself over time at work.

Perceived quality of AI

Generative AI provides workers with a complete set of information.

Generative AI produces correct information.

The information provided by Generative AI is well formatted.

Generative AI operates reliably.

The information from Generative AI is always up to date.

Personal utility of AI

Using Generative AI would allow me to have increased confidence in my skills at work.

Using Generative AI would provide me with personal feelings of worthwhile accomplishment at work.

Using Generative AI would provide me with feelings of enjoyment at work from using the technology.

Using Generative AI would give me greater control over my work.

AI use anxiety

Using Generative AI for work is somewhat intimidating to me.

I would feel nervous operating Generative AI in front of other people at work.

I would feel uneasy if I was given a job where I had to use Generative AI.

I would feel paranoid talking with Generative AI at work.

Job insecurity

I am worried that what I can do now with my work skills will be replaced by Generative AI.

Generative

I think my job could be replaced by Generative AI.

I am worried about Generative AI replacing what humans can do at work.