

UNIVERSITY OF OKLAHOMA
GRADUATE COLLEGE

A MIXED-METHOD EXAMINATION OF AI USE AT WORK: BENEFITS AND HARMS
TO EMPLOYEE WELL-BEING AND THE WORK-FAMILY INTERFACE

A THESIS
SUBMITTED TO THE GRADUATE FACULTY
in partial fulfillment of the requirements for the
Degree of
MASTER OF SCIENCE

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Norman, Oklahoma

2026

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A THESIS APPROVED FOR THE
DEPARTMENT OF PSYCHOLOGY

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Acknowledgments

I would like to thank everyone who supported me throughout this journey, to whom I am forever grateful. First, to my advisor Dr. Eric A. Day, thank you for your time, patience, and mentorship. To my committee members Dr. Yaqing He and Dr. Shane Connelly, thank you for your valuable feedback and support.

To everyone who helped with the qualitative coding: Piper Winsett, Brandon Choi, Anaé Fong-Yan, and Johanna Geffre. I could not have completed this thesis without you. Piper and Brandon, my lab siblings, thank you for your friendship and encouragement.

To Dr. Catherine Bain, for teaching me SEM and helping me every time I wandered into your office. I am forever grateful for your help and admire who you are as a mentor and friend. Additionally, thank you Raechel Sanger for all your advice and allowing me to slowly take over your office.

To Joel, for supporting my academic dreams even when they involve me moving 2,000 miles away. Talking to you is the highlight of my day, and I am lucky to have someone who holds such confidence in my capabilities even when I do not hold it myself.

To the friends I have made in this department, thank you for the many yap sessions and laughs. I am grateful to be surrounded by such wonderful people who remind me what it means to live my life while also being in graduate school.

Lastly, to my friends and family, especially my parents and siblings, thank you for always believing in me and supporting me through every step. I was able to finish this thesis because of all of you. And to my hedgehog, angel Sal, for the many naps we shared at the beginning of this journey and for reminding me to find joy in the smallest moments.

Abstract

Employee use of AI in the workplace has led to benefits such as increased productivity and efficiency, but it is unclear how this extends to the work-family interface. By enabling employees to accomplish work tasks more quickly and allowing them to focus on more meaningful work, AI may reduce work-family conflict and enhance work-family enrichment. However, given the multifaceted nature of AI use and ongoing concerns regarding possible harms to employee-wellbeing and other outcomes, resistance exists among some employees (Bankins et al., 2024; Golgeci et al., 2025). Thus, the three aims of this mixed-method study were to examine (1) the relationships between AI use in the workplace, work-family conflict, and work-family enrichment, (2) the moderating role of AI resistance in the relationship between AI use at work and work-family enrichment, and (3) employees' perceptions of how AI use at work is enhancing and/or harming their well-being across the work-nonwork interface. Results from a sample of 584 Prolific employees showed the use of AI at work was positively associated with work enriching family ($\beta = .50, p < .001$), however AI resistance did not moderate this relationship. Notably, AI use at work was also positively related to work interfering with family ($\beta = .12, p = .012$). Employees broadly viewed AI as enhancing task facilitation and well-being across the work-nonwork interface, but some individuals noted that AI hindered task completion which was associated with negative well-being. These findings underscore the dual nature of AI use in the workplace and the need for organizations to balance productivity and efficiency with employee well-being.

Keywords: Artificial intelligence, AI resistance, employee well-being, work-family conflict, work-family enrichment

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A Mixed-Method Examination of AI Use at Work: Benefits and Harms to Employee Well-being and the Work-Family Interface

The widespread integration of artificial intelligence (AI) has led to research on its potential benefits and harms to employee and organizational outcomes. Although employee AI use, either as automation or augmentation, has been highlighted for increasing productivity, efficiency, and learning (Brynjolfsson et al., 2025; Cui et al., 2026; Pereira et al., 2021; Shao et al., 2024), AI adoption can present challenges regarding accuracy and is associated with concerns of job insecurity (Brynjolfsson et al., 2025; Jeong & Jeong, 2025; Koo et al., 2021). The use of AI is multifaceted, yet there has been limited research on its associations with employee well-being. As employees continue to use AI for more of their everyday tasks it is important to understand how it relates to well-being at work and the extent to which spillover occurs into nonwork domains (Pereira et al., 2021; Shao et al., 2024).

Through AI tools which help to optimize routine tasks and save time, it has been proposed that employees will gain autonomy and experience less stress and mental strain (Bankins & Formosa, 2023; Rony et al., 2024). These benefits can be achieved through augmentation, or human-AI collaboration, as by using AI employees can offload repetitive tasks and focus on creative, complex, or important work (Bankins & Formosa, 2023; Jia et al., 2024). This shift toward higher-value activities can generate positive affect as employees find their work to be more meaningful (Allan et al., 2019). The guiding proposition of my thesis is that reduced time spent on mundane tasks and increased meaningful work resulting from AI use benefit employee well-being outcomes.

Therefore, the purpose of my thesis is to examine how AI use at work is associated with employee well-being, specifically within the work-family interface. Drawing upon the job demands-resources (JD-R) model (Bakker, 2011; Bakker & Demerouti, 2007), the effects of AI

as a job resource likely spill over into the family domain, reducing work-family conflict while benefiting work-family enrichment. The use of AI differs from resources commonly examined in the work-family interface, such as skills, perspectives, and psychological or physical resources (Greenhaus & Powell, 2006; McNall et al., 2010). Nevertheless, AI as a tool that assists with everyday work tasks may hold the function of a resource. The efficiency it provides both through automation and augmentation may reduce stress, time-based conflict, and working hours, all antecedents to work-family conflict (Byron, 2005; Rony et al., 2024). Additionally, augmentation in particular assists with high workloads and enables autonomy for more meaningful work (Bankins et al., 2024; Bankins & Formosa, 2023) which could mitigate stress and generate positive affect, indirectly enhancing work-family enrichment (Greenhaus & Powell, 2006). However, this relationship may be weaker for employees resistant to AI, as its use is unlikely to ultimately generate positive psychological phenomena (Golgeci et al., 2025).

Using a mixed-method approach, my thesis makes two important contributions to the literature. First, to my knowledge, I present the first study to empirically examine AI use and AI resistance within the work-family interface. Specifically, the proposed model (see Figure 1) examines how AI use as a work resource may be negatively related to work-family conflict and positively related to work-family enrichment, with AI resistance moderating the relationship between AI use and work-family enrichment. Additionally, open-ended responses about the benefits and harms of AI use to well-being across the work-nonwork interface provide further context on employees' views of AI use in the workplace. Second, this study presents several implications for organizations continuing to implement AI tools. Although AI use was primarily perceived as beneficial in the work-nonwork interface, organizations should continue to mitigate harms to well-being (e.g. added pressure to produce).

In the following sections, I will first provide an overview of the current literature on AI, its theoretical foundation in the JD-R model, how using AI at work might relate to employee well-being in the work-family interface, and the moderating role of AI resistance. Second, I outline the methodological approach before testing hypotheses and answering research questions about the benefits and harms of AI use at work in a sample of 584 Prolific employees in occupations spanning a variety of industries. Ultimately, I discuss key findings, theoretical contributions, and practical insights for the use of AI in the workplace and its implications for employee well-being.

The Dual Impact of AI in the Workplace

Organizations are increasingly integrating AI into employee tasks, including machine learning, natural language processing, generative AI, chatbots, or intelligent character recognition. Among these technologies, generative AI, a type of machine learning capable of generating new content by examining patterns within existing datasets (Brynjolfsson et al., 2025; Feuerriegel et al., 2023), has become prominent through models like ChatGPT, Claude, Gemini, and Copilot. Employees use these models for tasks such as text generation, code assistance, or summarizing basic information. The adoption of various AI tools, especially generative AI, underscores their utility in supporting diverse workplace functions.

These different forms of AI enable employees to both automate tasks and engage with AI as a collaborative tool. Raisch and Krakowski (2021) outline how automation involves machines taking over repetitive or routine tasks with limited human involvement, whereas augmentation consists of humans closely collaborating with machines to complete tasks. Augmentation specifically represents a feedback loop, where humans learn from machines and in turn machines learn from humans. Although both augmentation and automation are key to optimizing AI

implementation, they have multifaceted implications for organizational performance and employee outcomes.

Automation and augmentation generate a wide variety of benefits for both employees and organizations. One common benefit is efficiency, with AI helping to reduce the time spent on mundane and complex tasks alike (Bankins & Formosa, 2023; Bankins et al., 2024; Sanjaya et al., 2025). In some professions, AI integration has brought a reduction in physical and psychological workload (Lauritzen et al., 2022; Qiu et al., 2022; Rožman et al., 2023) and has facilitated learning (Pereira et al., 2021). The use of generative AI in particular has been associated with increased productivity and task performance (Brynjolfsson et al., 2025; Cui et al., 2026; Noy & Zhang, 2023; Shao et al., 2024), more informal learning in the workplace (Brynjolfsson et al., 2025; Shao et al., 2024), and enhanced creativity (Jia et al., 2024). These diverse benefits demonstrate AI's potential to transform workplaces for the mutual benefit of organizations and employees.

Together, these benefits from AI could result in a more meaningful work experience. Rooted in Job Characteristics Theory (JCT) (Hackman & Oldham, 1976), meaningful work is defined as “the global judgment that one’s work accomplishes significant, valuable, or worthwhile goals that are congruent work with one’s existential values” (Allan et al., 2019, p. 502). JCT outlines skill variety, task identity, and task significance as the core job dimensions that lead to meaningful work (Hackman & Oldham, 1976). When considering AI from a general standpoint, employees can redirect their time from repetitive tasks to those that are more important. Therefore, both automation and augmentation may improve task significance. Human-AI collaboration, however, has been posited as the key to reaching AI’s potential for productivity, efficiency, and meaningful work (Bankins et al., 2024). Augmentation specifically

may increase these dimensions as employees can acquire and use different knowledge and skills, see their work completed from beginning to end, and focus on more value-adding work.

(Bankins & Formosa, 2023). The influence of AI use on perceptions of meaningfulness is important as it is strongly correlated with work engagement and job satisfaction and has also been linked to positive affect (Allan et al., 2019). Furthermore, in one cross-sectional study examining the work-family interface among a sample of parents, employees who experienced more meaningful work reported lower work-family conflict and greater work-family enrichment (Bragger et al., 2021). Overall, AI use, particularly human-AI collaboration, has the potential to create a more meaningful work experience.

Despite these benefits, research has shown there can be various negative consequences from AI integration in organizations. One commonly discussed concern is job insecurity, with studies demonstrating its associations with organizational investment in AI or employee AI use (Jeong & Jeong, 2025; Koo et al., 2021; Sanjaya et al., 2025). Additionally, in a daily diary study with a sample of call-center representatives, employee-AI collaboration was associated with information overload which negatively impacted employees' performance and psychological detachment at the end of the workday (Shao et al., 2024). The use of AI tools can also present challenges regarding accuracy, as they sometimes produce false or misleading information which is problematic for critical work responsibilities (Brynjolfsson et al., 2025). From a mental health perspective, employees face increased stress and anxiety when AI use is not met with sufficient support and training from the organization (Sanjaya et al., 2025).

Employee use of AI is multifaceted as individuals can hold both positive and negative views of AI in the workplace (Koo et al., 2021; Sanjaya et al., 2025). There is currently limited research on AI's specific impact on employee well-being, but the current state of the literature

suggests the benefits of efficiency, productivity, and meaningful work outweigh the possible harms. For example, Giuntella et al. (2025) examined longitudinal survey data from German employees across a variety of occupations before, during, and after the widespread integration of AI and found no evidence of negative impacts on employee well-being or mental health. Ultimately, AI's association with a wide variety of positive benefits for employees exemplifies its potential as a job resource rather than a job demand.

AI as a Job Resource

The job demands-resources (JD-R) model outlines how job characteristics can be categorized as job demands or job resources which influence well-being outcomes (Demerouti et al., 2001; Bakker, 2011; Bakker & Demerouti, 2007). Job demands include physical, psychological, social, or organizational aspects of a job that are associated with physiological or psychological costs because of prolonged mental and/or physical effort (Bakker & Demerouti, 2007). For example, demands include challenging physical conditions, high work pressure, or client/customer interactions that are emotionally demanding (Bakker & Demerouti, 2007). Job resources are aspects that help employees achieve work goals, reduce job demands, and increase personal growth and development (Bakker & Demerouti, 2007). Examples include job autonomy, growth opportunities, and skill variety (Bakker & Demerouti, 2017). Additionally, personal resources like self-efficacy are proposed as having a similar role to job resources (Bakker & Demerouti, 2017). As employees collaborate with AI to reduce repetitive tasks, allowing them to focus on more value-adding work, it may function as a technological job resource. Pinho et al. (2026) found that employee-AI collaboration was positively related to work engagement, consistent with the motivational process outlined in the JD-R model, suggesting AI use at work functions as a resource that supports goal achievement.

The JD-R model has been previously used to relate job demands and job resources to the work-family interface. A primary assumption of the model is that job demands and resources can instigate an impairment process and a motivational process, respectively. For instance, burnout develops when job demands are high and job resources are limited, whereas engagement occurs when job resources are high and job demands are limited (Bakker & Demerouti, 2007). In addition to well-being at work, job demands and job resources can influence work-family outcomes. For example, Bakker et al. (2011) examined the relationship between high job demands, like workload and emotional demands, low job resources, such as autonomy or performance feedback, and work-family conflict in a sample of medical residents. Work-family conflict resulted from a combination of low job resources and high job demands, providing support for the impairment process.

Work-family conflict and work-family enrichment have important roles in shaping employee well-being and performance. Experiences of work-family conflict are negatively associated with outcomes such as job, life and family satisfaction, (Allen et al., 2020; Allen & French, 2023) and job performance (Hoobler et al., 2010). Conversely, work-family enrichment is positively related to job and family satisfaction, affective commitment, and physical and mental health (McNall et al., 2010). Given AI's potential as a resource, its use in the workplace may benefit one's roles in their family domain, mitigating work-family conflict and enhancing work-family enrichment.

AI Use at Work, Work-Family Conflict, and Work-Family Enrichment

One important factor of employee well-being is work-family conflict, defined as interrole conflict that occurs when demands from work and family are mutually incompatible (Greenhaus & Beutell, 1985). This conflict can occur in two directions, with work interfering with family

(WIF) or family interfering with work (FIW). Conflict can be time-based, strain-based, or behavior-based (Greenhaus & Beutell, 1985). Due to AI's capacity to enhance work efficiency, time-based conflict is important to the work-family interface as it occurs when time dedicated to responsibilities in one role (work/family) hinder the ability to meet responsibilities in another role (family/work). For time-based conflict to occur, time transferred from one domain, such as work, leaves demands there unmet (Edwards & Rothbard, 2000). Furthermore, time-based conflict can also occur if work pressures cause someone to be preoccupied with work even when attempting to fulfill the requirements of another role (Greenhaus & Beutell, 1985).

The JD-R model theorizes that a combination of low job resources and high job demands will be associated with work-family conflict. It also posits that demands have a direct positive relationship with strain-type variables like work-family conflict, with resources only acting as a buffer of this relationship (Bakker et al., 2011). However, previous meta-analyses have demonstrated how resources such as job autonomy and flexibility at work can have a direct negative relationship to work-family conflict (Liao et al., 2019). Accordingly, AI use as a resource may directly reduce job demands and mitigate time-based conflict. Balancing one's work and family roles entails decisions about how to allocate and reallocate one's limited time and energy, (Allen & French, 2023; Edwards & Rothbard, 2000) and improved efficiency with AI tools can help employees allocate less time and energy to work while achieving the same level of results. By reducing time spent on work tasks, employees may gain additional time for other role responsibilities and feel less overwhelmed, decreasing their hours spent at work and work-related preoccupation at home. For example, by using generative AI a software developer can complete all assigned tasks during regular working hours instead of staying late or bringing

work home. Based on the perspective that AI tools can serve as a resource that can improve efficiency, I will test the following hypothesis regarding how AI use at work is related to WIF.

Hypothesis 1: AI use at work will be negatively associated with WIF.

Meaningful work fostered by AI use may enhance positive affect, enriching employees' family lives and benefitting organizations. Work-family enrichment is defined as the extent to which experiences in one role contribute to improvements in another role, and like work-family conflict is bidirectional with work enriching family (WEF) and family enriching work (FEW) (Greenhaus & Powell, 2006). Greenhaus and Powell (2006) outline two theoretical pathways through which resources facilitate work-family enrichment, which I will review through the perspective of WEF. First, enrichment can occur through the instrumental path where resources are directly transferred from one's work role to their family role, improving performance in the family role. Second, the affective path outlines how work resources could be indirectly associated with improved performance in one's family role through positive affect, or the "positive moods and positive emotions derived from role experiences" (Greenhaus & Powell, 2006, p. 82).

The affective pathway provides the conceptual foundation for this study because although AI tools may not be directly transferred home, they can generate positive work experiences that subsequently enrich one's family life. Work-family enrichment builds on the concept of positive spillover as work experiences transfer home and result in improved affect or performance in one's family role (Carlson et al., 2006). Therefore, work-family enrichment may result from job resources like AI tools that foster meaningful work and generate positive affect at work. For instance, the software developer who experiences positive affect from using AI tools at work is likely to exhibit more positive responses to family members, enhancing both their affect at home

and their performance as a spouse/partner or parent (Carlson et al., 2006). Through this angle, I will test the following hypothesis on how AI use at work is related to WEF.

Hypothesis 2: AI use at work will have a positive relationship with WEF.

Based on the JD-R model and conceptual understandings of WEF and WIF, the resource pathway is more strongly associated with work-family enrichment whereas the demand pathway aligns more closely with work-family conflict. WEF involves acquiring work resources that can directly, or indirectly through positive affect, improve the quality of life in the family domain (Greenhaus & Powell, 2006). On the other hand, WIF occurs when work demands hinder performance in family roles, exemplified through the demand pathway (Greenhaus & Beutell, 1985). Meta-analyses have provided support for these propositions (Lapierre et al., 2018; Michel et al., 2011). Work resources like supervisor support exhibit stronger associations as antecedents of work-family enrichment compared to work-family conflict, whereas demands like job stressors demonstrate stronger associations as antecedents of work-family conflict compared to work-family enrichment (Lapierre et al., 2018; Michel et al., 2011). For instance, although resources like workplace social support and job autonomy have direct associations with work-family conflict, they ultimately have weaker effects than job demands (Kossek et al., 2011; Liao et al., 2019; Michel et al., 2011). Therefore, I will test the following hypothesis regarding a stronger relationship with WEF versus WIF for AI use at work.

Hypothesis 3: AI use at work will have a stronger relationship with WEF than WIF.

The Moderating Role of AI Resistance in the AI Use-WEF Relationship

Despite general positive attitudes toward AI's potential in the workplace, a number of employees remain resistant to its use for everyday tasks (Golgeci et al., 2025). This resistance may arise for a variety of reasons, including ethical (e.g., misalignment with one's values) and

practical concerns (e.g., skill obsolescence, job insecurity, accountability for generated outcomes) (Allen & Choudhury, 2022; Golgeci et al., 2025). Current research has emphasized the importance of transparency and employee voice throughout the process of AI implementation to reduce resistance (Nel and Van Niekerk, 2023; Valtonen and Holopainen, 2024), but it is also important to consider how resistance may relate to employee well-being outcomes. Although employees in AI-integrated workplaces must often engage with AI tools, those resistant to AI use, including those who hold both positive and negative views on its use, may not experience positive affect from its associated efficiency and productivity. Technological initiatives such as AI can introduce stressors, and resistance to these changes can amplify them (Valtonen & Holopainen, 2024), diminishing AI's value as a resource. For instance, a study by Rafferty and Jimmieson (2017) found that employee resistance to change was associated with lower psychological well-being and insomnia. However, its relation to the work-family interface has yet to be considered. Employees resistant to AI use may not view it as a resource, as such, they may not experience positive benefits that improve performance in their family role. Therefore, I will test the following hypothesis that AI resistance moderates the relationship between AI use at work and WEF.

Hypothesis 4: AI resistance will moderate the positive relationship between AI use at work and WEF, such that the relationship will be weaker for those higher in AI resistance.

AI Use at Work: Greater Benefits or Harms?

Prior research has investigated AI's impact on work outcomes (e.g. Brynjolfsson et al., 2025; Shao et al., 2024) but research on its relation to the work-nonwork interface is limited. One qualitative study based in an Indigenous region of Mexico found that although employees reported benefits from AI use at work such as stress reduction and improved work-life balance,

they also experienced negative outcomes including depersonalization of work (Ochoa, 2025). Additionally, another qualitative study by Solymosi et al. (2025) examining AI use and job crafting behaviors among a sample of Prolific employees in finance, retail, and insurance industries reported a common theme of time-spatial crafting where individuals used AI to change their workplace locations or hours to better suit their needs. This theme incorporated codes of improved well-being at work and improved work-life balance, although employees were only prompted to report benefits from AI use. Although both studies mention the work-nonwork interface, their research questions were not specific to employee well-being and did not capture other variables outside of work-life balance.

In addition to extending previous qualitative findings, using a mixed-method approach is beneficial as it allows for a comprehensive account of the phenomena of interest (Almalki, 2016). Current research on AI has focused on a small number of benefits and harms, but employee well-being across the work-nonwork interface may be impacted in a multitude of ways. For instance, some employees may experience only benefits at work, others only harms, and others may experience a combination of both. Similarly, there may be employees who experience benefits and/or harms to well-being in nonwork domains, and others who experience both. Therefore, I will take an exploratory approach to understanding both the possible benefits and harms to well-being associated with using AI at work. Specifically, I will address the following research questions to capture both the benefits and drawbacks of AI use at work related to employee well-being and experiences of WIF and WEF.

Research Question 1: In what ways do employees report using AI at work enhances their well-being (a) at work and (b) in nonwork domains?

Research Question 2: In what ways do employees report using AI at work harms their well-being (a) at work and (b) in nonwork domains?

Research Question 3: To what extent, and in what ways, does employee AI use at work affect WIF and WEF?

Method

Participant Sample and Procedure

Data were collected through the online survey platform Prolific, whose participants have been shown to demonstrate high data quality reflected through responses to measures of attention, comprehension, honesty, and reliability (Douglas et al., 2023; Peer et al., 2017, 2021). Participants had to be English-speaking, working with AI or AI tools at least once a week, using specific technology (e.g., software), living in the US, United Kingdom, Australia, New Zealand, or Canada, and working at least part-time to participate. I removed 16 participants from the initial sample who failed all three attention checks and two participants who selected all AI demographics in addition to “Not applicable.” The final sample included 584 participants ($M_{\text{age}} = 37.4$, $SD_{\text{age}} = 10.98$) who were working across a variety of industries, primarily in the United States (65.1%), United Kingdom (27.3%), Canada (7.0%), New Zealand (0.3%), and Australia (0.1%). Most participants were male (53.8%), followed by female (45.2%), non-binary (.9%), and transgender (.2%). Participants identified as White (64.9%), Black (21.4%), Asian (5.8%), mixed race (5.1%), or other (2.4%).

Regarding workplace demographics, the majority of individuals worked 31-40 hours per week (56.7%) followed by 41-50 hours (25.9%), 21-30 hours (11.7%), 51-60 hours (3.6%), and more than 60 hours (2.1%). The average organizational tenure was 7.57 years, ($SD = 7.20$). Participants worked in a variety of industries, with the highest percentages from finance and insurance (12.5%), information services and data processing (12.5%), health care and social assistance (11.0%), and manufacturing (5.3%). Participants used various types of AI at work, including generative AI (e.g., ChatGPT) (77.1%), general artificial intelligence (74.7%), chatbots

(57.9%), machine learning (34.1%), digital process automation (17.6%), intelligent character recognition (13.7%), natural language processing (12.7%), optical character recognition (12.5%), robotic process automation (12.0%), not applicable (3.1%), unsure (1.7%), and other (0.9%).

Measures

Artificial Intelligence Use

Participants responded to demographic questions on the type of AI used at their organization for their job as described above. I measured AI use at work using Tang et al.'s (2022) three-item scale. Participants rated the items on a 7-point scale (1 = *Strongly Disagree*; 2 = *Disagree*; 3 = *Somewhat Disagree*; 4 = *Neither Agree nor Disagree*; 5 = *Somewhat Agree*; 6 = *Agree*; 7 = *Strongly Agree*). Items were, "I used AI technology to carry out many of my job functions," "I spend a lot of my time working with artificial intelligence," and "I worked with AI technology to make important work decisions." Participants were prompted to report their experiences using AI technologies at work "In the past month." Cronbach's α for AI use scores was .85 and McDonald's ω was .85.

Artificial Intelligence Resistance

Resistance to AI was measured using an adapted version of Bhattacharjee and Hikmet's (2007) four-item scale on resistance to change. Computerized physician order entry (CPOE) was replaced with AI technology to align with the purpose of this study. For example, the phrase "change the way I order patient tests" was altered to say, "change the way I gather what I need for work" and "change the way I make clinical decisions" was altered to say, "change the way I make decisions." Therefore, the items were "I don't want AI technology to change the way I gather what I need for work," "I don't want AI technology to change the way I make decisions," "I don't want AI technology to change the way I interact with other people at my job," and

“Overall, I don’t want AI technology to change the way I currently work.” Participants rated these items on a 7-point scale (1 = *Strongly Disagree*; 2 = *Disagree*; 3 = *Somewhat Disagree*; 4 = *Neither Agree nor Disagree*; 5 = *Somewhat Agree*; 6 = *Agree*; 7 = *Strongly Agree*) and were prompted to report their experiences “In the past month.” Cronbach’s α for AI use scores was .90 and McDonald’s ω was .92.

Work Interfering with Family

I measured WIF using the work-to-family direction of the Work-Family Conflict Scale (Netemeyer et al., 1996). Employees responded to five items on a 7-point scale (1 = *Strongly Disagree*; 2 = *Disagree*; 3 = *Somewhat Disagree*; 4 = *Neither Agree nor Disagree*; 5 = *Somewhat Agree*; 6 = *Agree*; 7 = *Strongly Agree*). The items include, “The demands of my work interfere with my home and family life,” “The amount of time my job takes up makes it difficult to fulfill family responsibilities,” “Things I want to do at home do not get done because of the demands my job puts on me,” “My job produces strain that makes it difficult to fulfill family duties,” and “Due to work-related duties, I have to make changes to my plans for family activities.” All items were adapted to ask participants about their general work and family experiences “In the past month.” Cronbach’s α for WIF scores was .95 and McDonald’s ω was .95.

Work Enriching Family

I measured WEF using the three work-to-family items from the Shortened Work-Family Enrichment Scale (Kacmar et al., 2014) on a 7-point scale (1 = *Strongly Disagree*; 2 = *Disagree*; 3 = *Somewhat Disagree*; 4 = *Neither Agree nor Disagree*; 5 = *Somewhat Agree*; 6 = *Agree*; 7 = *Strongly Agree*). The items include, “My involvement in my work helps me to understand different viewpoints and this helps me to be a better family member,” “My involvement in my

work makes me feel happy and this helps me be a better family member,” and “My involvement in my work helps me feel personally fulfilled and this helps me be a better family member.”

Items were adapted to ask participants about their general work and family experiences “In the past month.” Cronbach’s α for WEF scores was .90 and McDonald’s ω was .90.

Artificial Intelligence Benefits and Harms to Well-being

Additionally, participants responded to four items developed specifically for this study involving how using AI for their job impacted their well-being across work-nonwork domains. The two items used to measure benefits were “Using AI technology enhanced my well-being at work” and “Using AI technology enhanced my well-being outside of work.” To measure the harms, the same items were presented using the word “harmed” instead of “enhanced.”

Participants responded to each of these four items on a 7-point scale (1 = *Strongly Disagree*; 2 = *Disagree*; 3 = *Somewhat Disagree*; 4 = *Neither Agree nor Disagree*; 5 = *Somewhat Agree*; 6 = *Agree*; 7 = *Strongly Agree*). If participants responded with a 4 or higher, they were then asked to describe how using the AI technology impacted them for each item. For instance, “Please describe how using AI technology enhanced your well-being at work.”

Data Analysis

All analyses were conducted in R, version 4.5.2 (R Core Team, 2025). Descriptive statistics and intercorrelations were analyzed using the *psych* package, version 2.5.3 (Revelle, 2025). Confirmatory factor analyses for AI use, AI resistance, WIF, and WEF scores were conducted using the weighted least squares mean and variance adjusted (WLSMV) estimator in *lavaan*, version 0.6-21, with factor variances fixed to 1.00 for model identification (Rosseel, 2012). A single-factor unidimensional model, a four-factor uncorrelated model, and a four-factor correlated model were compared using the Satorra-Bentler scaled chi-square difference test

(Satorra & Bentler, 2001). Model fit was assessed using several fit indices, including the χ^2 fit index, root mean square error of approximation (RMSEA), comparative fit index (CFI), Tucker-Lewis index (TLI), and standardized root mean square residual (SRMR). Models were determined to exhibit adequate fit if RMSEA and SRMR were less than or equal to 0.05 and 0.06 respectively, and CFI and TLI values were greater than .90 (Hu & Bentler, 1999).

Structural equation modeling was used to test *Hypotheses 1, 2, and 4* to account for the correlation between the outcome variables, WIF and WEF (Hoyle, 2023). The baseline model without the $WEF \times AI$ resistance interaction term was conducted directly in *lavaan* to examine traditional fit indices such as χ^2 , RMSEA, CFI, TLI, and SRMR. Then I used the *modsem* package (version 1.0.17), an extension of *lavaan*, with the latent moderated structural equations (LMS) approach to examine the moderating role of AI resistance in the relationship between AI use at work and WEF (Klein & Moosbrugger, 2000; Slupphaug et al., 2025). The LMS approach was used as it explicitly accounts for the non-normal distribution of the interaction term and the endogenous latent variable (Klein & Moosbrugger, 2000). The null hypothesis (H0) model without the interaction was compared with the alternative hypothesis (H1) model which included the interaction. When evaluating models with LMS, standard fit criteria such as RMSEA and SRMR are not applicable, so model fit was evaluated using the log-likelihood and Bayesian Information Criterion (BIC). To test *Hypothesis 3*, a Wald test was conducted to test the equality of two unstandardized regression coefficients, AI use at work to WIF and AI use at work to WEF, in *lavaan* (Klopp, 2020).

Qualitative Coding

There were 22 participants excluded from the qualitative data due to clear evidence of AI-generated responses, such as verbatim AI chatbot output and generic, impersonal

commentaries. Myself and two other trained industrial-organizational doctoral students used an iterative coding process to analyze responses through a bottom-up, constant comparison approach (Glaser, 1965). First, we separately developed an initial codebook for each of the four open-ended statements by coding batches of 20 participants. Then, two trained undergraduate research assistants independently reviewed and coded responses to these four open-ended items. Myself and the two other doctoral graduate students alternated reviewing these individual codes, and consensus meetings were held to resolve any disagreements. During these consensus meetings, previous codes were further developed, and new codes were created as they emerged.

Results

Table 1 presents descriptive statistics and intercorrelations for all study variables. The mean for WIF was slightly below the scale midpoint, with 55.3% of participant responses below the midpoint and the mean for WEF was slightly above the scale midpoint, with 84.6% of responses above the midpoint. In contrast to *Hypothesis 1*, AI use at work was positively correlated with WIF ($r = 0.13, p = 0.002$). The use of AI was positively correlated with WEF, ($r = 0.37, p < 0.001$) supporting *Hypothesis 2*.

I conducted a Confirmatory Factor Analysis (CFA) for each latent variable, which demonstrated good fit. In addition, a single-factor unidimensional model, a four-factor uncorrelated model, and a four-factor correlated model were compared. The four-factor correlated model fit significantly better than the single-factor unidimensional model, with a scaled χ^2 difference value of 2,371.30, $p < 0.001$. In addition, the four-factor correlated model fit significantly better than the four-factor uncorrelated model, with a scaled χ^2 difference value of 167.89, $p < 0.001$. Overall, the four-factor correlated model with all latent variables—AI use, AI

resistance, WIF, and WEF—demonstrated adequate fit, $\chi^2(84) = 131.66$, $\chi^2/df = 1.57$, RMSEA = 0.03 (95% CI upper = 0.04), CFI = 0.99, TLI = 0.99, SRMR = 0.04.

Hypotheses 1 and 2

The baseline model, shown in Figure 2, examined the hypothesized relationships between AI use at work, WIF, and WEF. In addition to AI use at work, AI resistance was added as a predictor of WEF. Correlations were added to account for the relationship between WIF and WEF and between AI use at work and AI resistance. Age, gender, hours worked per week, and organizational tenure were entered as covariates on all latent variables, including predictors. The model demonstrated adequate fit, $\chi^2(129) = 204.55$, $\chi^2/df = 1.59$, RMSEA = 0.01 (95% upper CI = 0.03), CFI = 1.00, TLI = 1.00, SRMR = 0.04. Consistent with the zero-order correlations, *Hypothesis 1* was not supported as AI use at work had a positive direct effect on WIF ($\beta = 0.12$, $p = 0.01$, 95% CI [0.03, 0.22]), rather than a negative effect. *Hypothesis 2* was supported as AI use at work had a positive direct effect on WEF ($\beta = 0.50$, $p < 0.001$, 95% CI [0.44, 0.59]).

Hypothesis 3

Hypothesis 3 posited that AI use at work would have a stronger relationship with WEF than WIF. A Wald test conducted on the baseline model indicated that the effect of AI use at work on WEF ($b = 0.52$) was stronger than the effect of AI use at work on WIF ($b = 0.12$), Wald $\chi^2(1) = 36.06$, $p < 0.001$ providing support for *Hypothesis 3*.

Hypothesis 4

Hypothesis 4 proposed that AI resistance would moderate the relationship between AI use at work and WEF. Results showed that the WEF $\times$ AI resistance interaction was not statistically significant ($\beta = -0.06$, $p = 0.141$) and the comparison with the alternative hypothesis model (log-likelihood = -18,773.73; BIC = 38,063.42) did not show a significant improvement in fit (log-

likelihood change = 1.13; and $D(1) = 2.26$, $p = 0.132$). Thus, *Hypothesis 4* was not supported.

Table 2 presents standardized and unstandardized estimates, confidence intervals, z-statistics, and p -values for the alternative hypothesis model, including covariates.

Qualitative Research Questions

Participants responded to four 7-point Likert items regarding AI use at work and its benefits and harms to their well-being. For benefits in work and nonwork domains, the means were above the scale midpoint, ($M = 4.94$, $SD = 1.68$, and $M = 4.82$, $SD = 1.61$, respectively). For harms in work and nonwork domains, the means were below the midpoint ($M = 2.58$, $SD = 1.88$, and $M = 2.49$, $SD = 1.84$, respectively). From the overall sample, 86.5% of participants responded to at least one of the four open-ended prompts, with 79.5% responding to the prompt about AI enhancing their well-being at work, and 40.2% responding to the prompt about AI enhancing their well-being outside of work. There were fewer participants who responded to the prompts about harms: only 22.2% addressed AI use at work harming their well-being at work and 17.3% addressed AI use at work harming their well-being outside of work. Furthermore, out of the total sample, 20.0% reported benefits and harms to their well-being at work, and 2.7% reported benefits and harms to their well-being outside of work. Overall, participants reported more positive than negative impacts of AI use at work across the work-nonwork interface.

Individual codes were generated separately within each prompt. These codes were grouped into four themes: two reflecting positive impacts (task facilitation and well-being benefits) and two reflecting negative impacts (task hindrance and well-being harms) from AI use at work. An overview of the codes falling under each theme, both at work and in nonwork domains, is presented in Table 3. The majority of participants had responses coded under either the theme of task facilitation/task hindrance or well-being benefits/harms. However, there were

some participants who reported how the benefits/harms of AI use for their work tasks directly impacted their well-being, connecting the two themes. For example, 36.2% of participants had responses that corresponded to both themes of task facilitation and well-being benefits at work and 25.1% had responses under of task facilitation and well-being benefits in nonwork domains. When discussing harms, 20.7% of participants fell under both task hindrance and well-being harms at work and 8.2% fell under task hindrance with harms to their well-being in nonwork domains. In the following sections, *Research Questions 1* and 2 will discuss the codes pertaining to these themes and provide examples of participants who reported instances relevant to either a task facilitation/hindrance or well-being theme as well as those who reported how task facilitation/hindrance directly benefitted/harmed their well-being.

Research Question 1

Research Question 1 asked about the ways in which employees reported using AI at work enhanced their well-being (a) at work and (b) in nonwork domains. As described above, the two themes of task facilitation and well-being benefits were identified from codes both in the responses to the prompt about (1) AI use at work and well-being at work and (2) AI use at work and well-being outside of work. The codes reflected how participants described the ways in which AI use facilitated task completion and/or how AI use positively influenced their well-being. Tables 4 and 5 provide definitions, example responses, and counts for all codes regarding AI's impact on well-being across the work-nonwork interface, respectively.

Task Facilitation and Benefits to Well-Being at Work. When discussing how AI was beneficial to the completion of work tasks, common codes and their frequencies included (1) enhances efficiency and productivity (41.3%), (2) enhances miscellaneous performance (15.2%), (3) enhances learning and development (4.2%) and (4) reduces reliance on others (1.0%).

Participants reported how AI enhances work by speeding up work tasks, freeing up time for other things and increasing the volume of tasks or deliverables accomplished. For example, one participant shared, “AI helped me save time by automating repetitive tasks that used to drain my focus.” Another common code involved AI enhancing one’s ability to perform their work outside of just efficiency and productivity. A participant shared, “I also use AI to help with my decision making and understand complex issues regarding my work.”

Regarding the well-being benefits of AI use at work, common codes and their frequencies included (1) reduces stress (14.7%), (2) makes work more meaningful (10.3%), (3) enhances general mental health (6.6%), (4) enhances self-efficacy/confidence (3.4%), (5) enhances work-life balance (2.1%), and (6) neutral (1.1%). Participants reported how AI alleviates psychological strain from work tasks. One example response is, “I didn’t have to overwork myself to the point that I stress about not getting things done.” AI was also commonly reported as assisting with and/or giving users more time to focus on higher-value activities, thus contributing to tasks or outputs that add value to their or the organization’s goals. Participants shared being able to “focus on higher value work” due to the time saved from AI tools.

Overall, 36.2% of participants responding to this prompt had responses coded under both themes of task facilitation and well-being benefits. These responses covered a variety of different codes. For instance, a participant shared, “Through encouragement and support, it has helped me be confident in my work, and reduced stress and pressure by making me more efficient in tasks.” This was coded as enhances self-efficacy/confidence, lowers stress, and enhances efficiency and productivity. Another participant stated, “When I have creative writing to complete, that I get into a cycle of constant re-wording, using AI helps to break that up and gives a different

perspective that greatly reduces the stress involved in creative writing,” which was coded as enhances miscellaneous performance and reduces stress.

Task Facilitation and Benefits to Well-Being in Nonwork Domains. When prompted to report how AI use at work enhanced well-being outside of work, participants continued to discuss how AI was beneficial to tasks completed during the workday. Common codes with their frequencies include (1) saves time (19.0%), (2) helps with learning and gathering information (13.5%), assists with general work tasks (11.2%), assists with planning and organizing (7.0%), and makes work easier (3.4%). AI assisting with work tasks saved users time throughout the workday, with one participant sharing, “It enhanced my well-being outside work by helping to source information and summarize it, information that I would have spent hours to get.” Furthermore, participants commonly reported AI assisting with finding, synthesizing, or understanding information, including supporting users in the acquisition of new knowledge or skills. A participant described how completing tasks was “Easier and quicker especially when trying to gather information that would take ages to search for before AI.”

When discussing how AI was beneficial to well-being in nonwork domains, common codes with their frequencies include (1) enhances general mental health (15.4%), (2) reduces work-life interference (14.3%), (3) reduces stress (8.3%), (4) neutral (4.7%), and (5) enhances work-life balance (3.1%). Regarding mental health, participants reported AI positively impacted their overall psychological well-being beyond stress reduction, including improvements to mood and energy level. One participant shared, “I have been feeling much more relaxed outside of work and have been able to really enjoy my off hours.” Additionally, another common code was AI reducing the extent to which work demands conflicted with the demands in one’s personal

life. One participant shared, “I stopped working overtime due to AI and so that really helps me to stay longer around my family to spend free time with them.”

Of these respondents, 25.1% had responses coded under both themes of task facilitation and benefits to well-being. For example, one participant said, “It enhanced my well-being outside work by helping to source information and summarize it, information that I would have spent hours to get. With this, I am able to spend more time with my family.” This was coded as AI helps with information gathering and learning, AI saves time, and reduces work-life interference. As another example, a participant shared, “AI helps me learn new things, which makes me feel good,” which was coded as AI helps with info gathering and learning and enhances mental health.

Overall Benefits to Well-Being in the Work-Nonwork Interface. As exemplified through these themes and underlying codes, participants shared how AI tools at work benefitted their well-being in the work-nonwork interface. In response to both prompts, participants discussed how AI was primarily beneficial through efficiency and productivity, which saved time on work tasks. Additionally, AI assisting with general tasks helped with performance and learning. These task benefits of AI were associated with, and for some participants directly influenced, well-being outcomes in codes such as enhances general mental health, reduces stress, and enhances work-life balance. However, there were also codes specific to well-being at work and in nonwork domains. Regarding benefits specific to work, participants highlighted how AI helped make work more meaningful by allowing them to focus on more value-adding work. Alternatively, a benefit distinct to nonwork experiences was reduced work-life interference, as participants reported how AI reduced the conflict between work and personal demands.

Research Question 2

In contrast to *Research Question 1* about benefits, *Research Question 2* asked about the ways in which using AI at work harmed well-being (a) at work and (b) in nonwork domains. In comparison to benefits of AI use at work, only 22.2% of participants reported ways in which AI harmed their well-being at work, and only 17.3% of participants reported ways in which AI was harmful to their well-being in nonwork domains. When addressing *Research Question 2*, the broad themes of task hindrance and well-being harms emerged from individual codes. The codes reflected how participants described the ways in which AI use at work hindered task completion and/or how AI use at work negatively influenced their well-being. Tables 6 and 7 provide definitions, example responses, and counts for all codes regarding AI's negative impact on well-being across the work-nonwork interface, respectively.

Task Hindrance and Harms to Well-being at Work. When discussing how AI was harmful to work tasks, participants shared the common codes of (1) AI dependency and skill decay (12.5%), (2) incorrect output (9.5%), (3) difficult learning curve (7.5%), (4) reduces social interactions (4.0%), (5) reduces productivity/efficiency (4.0%), and (6) reduces work quality (2.0%). Participants reported how AI fosters over-reliance, eroding their skills, knowledge, or ability to complete tasks independently. One participant described, "Relying on AI created a sense of dependency that made me question my own judgement," while another shared, "AI has limited my critical thinking ability." The other most commonly reported code under this theme was having a difficult learning curve, as AI tools required significant time, effort, or technical knowledge to learn and use effectively. For example, participants shared how they "Spent too much time learning how to make it work."

Participants reporting how AI harmed their well-being at work discussed codes including (1) neutral (17.5%), (2) job insecurity (13.0%), (3) adds pressure to produce (12.0%), (4) harms general mental health (9.0%), and (5) increases stress/anxiety (9.0%). Although there were many participants who felt neutral in response to this prompt, some discussed how using AI raised concerns about job displacement, leading to uncertainty about one's future employment. A participant responded by saying, "Now I feel like the job I had excelled at for many years is going to be replaced." Additionally, it was also mentioned how AI amplified work expectations to deliver outputs, increasing job demands. For instance, "I felt like I had to do things faster, and it was hard to keep up."

Overall, 20.7% of participants who responded to this prompt had replies coded under both themes of task hindrance and harms to well-being at work. For instance, one participant said, "I've maybe spent too much time learning how to make it work for me which has impacted my productivity. This in turn, makes me stressed." This response was coded as difficult learning curve, reduced productivity/efficiency, and increased stress/anxiety. Furthermore, another participant shared, "Using AI made me feel more stressed sometimes. I felt like I had to do things faster, and it was hard to keep up. I also worried about losing my job," which was coded as increased stress/anxiety, added pressure to produce, and job insecurity.

Task Hindrance and Harms to Well-Being in Nonwork Domains. When reflecting on how AI use at work harmed well-being in nonwork contexts, participants discussed codes including (1) AI dependency and skill decay (19.5%), (2) reduces social interactions (8.5%), (3) incorrect output (5.9%), and (4) reduces productivity/efficiency (5.9%). For example, participants discussed AI fostering over-reliance, eroding their skills, knowledge, or ability to complete tasks independently. Participants further emphasized their concerns of AI dependency

and skill decay, for example, “Using AI for all the little tasks can sometimes reduce my creativity.” Additionally, participants stated how AI tools were reducing opportunities for interpersonal communication and collaboration at work. For example, participants shared how AI “reduced face to face interactions.”

Regarding harms to well-being in nonwork domains, codes were (1) neutral (29.7%), (2) increases work-life interference (12.7%), (3) harms general mental health (5.9%), (4) job insecurity (6.8%), (5) digital fatigue (2.5%), and (6) fear of AI (2.5%). Similar to well-being harms at work, the most common code was neutral where participants shared how “AI has not been harmful” to their well-being in nonwork domains. However, some participants did note how AI use at work increased the extent to which work demands conflicted with the demands in their personal life. One participant described, “It has reduced my time which I use to interact and have a good time with my family.” Furthermore, AI negatively impacted mental health beyond increasing stress. A participant shared, “Sometimes, I feel like I’m not intelligent enough to handle anything without the use of AI.”

There were 8.2% of participants whose responses were coded as covering both task hindrance and harms. For instance, “I also have a lot of reservations and concerns about AI technology in our everyday lives too, it’s really alarming how quickly people are dumbing themselves down and abandoning their own capacities to learn and be imaginative. I think this could be really harmful.” This was coded as fear of AI and AI dependence and skill decay. Additionally, another participant responded, “I rely on it too much and end up overthinking decisions because of all the options it gives. It can also keep me on screens longer than I’d like. Sometimes it gives wrong information.” The response was coded as AI dependency and skill decay, decreased productivity/efficiency, digital fatigue, and incorrect output.

Overall Harms to Well-Being in the Work-Nonwork Interface. Participants shared overlapping perspectives on how AI use at work was harmful across the work-nonwork interface. In responses to both prompts about negative impacts to well-being, participants discussed how AI was harmful by facilitating dependency and skill decay, generating incorrect output, reducing social interactions, and reducing efficiency and productivity. These harms of AI use at work were associated with, and for some participants directly influenced, negative impacts to well-being both at work and after the workday. While some participants responded with neutral perspectives on AI, others reported concerns about job insecurity and harms to their general mental health. Specifically for experiences at work, participants reported how using AI tools also led to harms such as added pressure to produce and enhanced stress and anxiety, while in nonwork domains it increased work-life interference, digital fatigue, and fear of the implications AI use has for society.

Research Question 3

Research Question 3 asked about the extent, and in what ways AI use at work affects WIF and WEF. As particularly detailed in Tables 5 and 7, participants primarily reported how using AI was both beneficial and harmful to WIF through time-based and strain-based conflict. Additionally, 3.0% of participants discussed enhanced work-life balance when thinking about the well-being benefits of AI use at work, and 2.1% discussed work-life balance as a benefit to well-being outside of work. Impacts to WEF were very rarely discussed. In relation to WIF, 9.4% of participants reported reduced work-life interference whereas 2.3% of participants reported increased work-life interference. Although these participants who reported benefits to WIF may appear contradictory to the positive relationship I found between AI use at work and WIF, this may be related to differing types of conflict. The majority of individuals who had responses

coded as reduced work-life interference emphasized how AI use at work allowed them to spend more time with their family, and those with responses coded as increased work-life interference often described how they felt pressure to complete additional work outside of their traditional working hours.

Benefits to WIF and WEF. As exemplified above in *Research Question 1*, most participants under the code work-life interference discussed a reduction in time-based conflict, as AI decreased workloads and the need to work overtime. This decreased time on work tasks allowed them to spend more time with their family. In addition, a number of participants also discussed a reduction in strain-based conflict, for instance, “AI taking care of a lot at my job has freed up so much personal time and mental energy for my hobbies, family time, and most of all REST.” Regarding WEF, one participant shared, “It made my time at work more enjoyable which impacted my well-being outside work,” although this sentiment was not found in any other responses. To note, some participants also mentioned improvements to work-life balance without further context. Due to the difference in colloquial and academic definitions of work-life balance, it is unclear if these participants may have been experiencing a reduction in WIF or improvements to WEF.

Harms to WIF and WEF. When discussing harms to the work-family interface, participants primarily focused on AI use at work increasing WIF. As shared in Table 7, some participants had contrasting experiences on the impact of AI use at work in comparison to Table 5. There were participants who discussed how AI reduced the time they were able to spend with family, but most reported instances of how AI use at work increased strain-based conflict. For example, “AI hurt my well-being by making me spend too much time on my phone, feeling anxious about missing alerts,” or “AI technology sometimes pulls me back into work-related

thoughts or tasks during off-hours, making it harder to fully relax.” There were no participants who discussed harms to WEF.

Discussion

The purpose of the current study was to examine the relationship between AI use at work and its implications for the work-family interface, specifically WIF and WEF. Additionally, I assessed the moderating role of AI resistance in the relationship between AI use at work and WEF. Altogether, findings partially supported my hypotheses. Among a sample of 584 employees, SEM results indicated that the use of AI was positively associated with WEF, however AI resistance did not moderate this relationship. In addition, AI use at work was positively related to WIF contrary to what was hypothesized. Qualitative results demonstrate that employees primarily viewed AI as beneficial to task facilitation and their well-being, however various harms were also discussed. Together, this study adds to the limited current literature on AI in the workplace and its associations with employee well-being across work and nonwork domains.

Despite the prevalence of AI in the workplace, well-being and work-family considerations have been rarely investigated (Pereira et al., 2023). Based on reviews and qualitative research, AI has been posited as a tool that can benefit work-life balance from reduced time-based conflict (Ochoa, 2025; Rony et al., 2024; Solymosi et al., 2025) and improve well-being from positive affective experiences (Bankins et al., 2024). However, the positive finding between AI use at work and WIF aligns with research on AI use at work and strain-based conflict, as AI use at work has been associated with difficulties detaching from work (Shao et al., 2024; Yi & Kumar, 2026). Technological advancements can increase job demands, such as answering emails or working outside of designated work hours, which are positively associated with WIF (Ghislieri et al., 2017). Furthermore, this finding aligns with related research that

organizational investment in AI is associated with work-family conflict through the mediating role of job insecurity (Jeong & Jeong, 2024). To my knowledge, previous research has not tested the relationship between AI use at work and WEF. The positive relationship found between AI use at work and WEF provides support for AI's role in helping produce positive affective experiences at work, which may be associated with meaningfulness (Bankins & Formosa, 2023; Bankins et al., 2024). Additionally, this relationship was stronger than that between AI use at work and WIF, consistent with the resource pathway of the JD-R model as resources rather than demands have stronger associations as antecedents of WEF rather than WIF (Lapierre et al., 2018).

The current study did not find support for AI resistance as a moderator in the relationship between AI use at work and WEF, which diverges from other related studies. Resistance to change has been associated with lower psychological well-being at work (Rafferty & Jimmieson, 2017). Additionally, in a study regarding AI adoption in a sample of hotel employees, Yi and Kumar (2026) found that AI awareness, like AI resistance, was positively associated with work-family conflict through the mediator of psychological detachment. In contrast, I found the strength of the relationship between AI use at work and WEF did not differ for individuals high versus low on AI resistance. Although employees may be hesitant about AI's implications for work and society, it is possible that they still experienced benefits from AI use at work. Furthermore, I found that AI resistance was positively associated with WEF, which may indicate that some resistance to the implementation of AI tools may be beneficial. For example, resistance may reduce an employee's susceptibility to overuse AI tools and degrade their skills.

Participants responded to the open-ended prompts for benefits to well-being far more often than harms, both at work (79.5% vs. 22.2%) and outside of work (40.2% vs. 17.3%).

Common codes in relation to task benefits include enhanced efficiency and productivity and enhanced performance from AI use at work, while specific codes for well-being include AI perceived as reducing stress and making work more meaningful. This further supports the quantitative results between AI use at work and WEF and the proposition of AI making work more meaningful (Bankins & Formosa, 2023; Bankins et al., 2024). However, it is important to note that AI use at work was also perceived by some participants as harmful to their well-being across the work-nonwork interface. Specifically, codes such as incorrect output or AI dependency and skill decay formed part of the theme task hindrance, while job insecurity and increased work-life interference were perceived as harmful to well-being. There were also participants who had mixed views of AI, as 20.0% reported both benefits and harms to their well-being at work, and 2.7% reported both benefits and harms to their well-being in nonwork domains. Together, these qualitative results support previous findings that employees hold positive and negative attitudes toward AI in the workplace. In a mixed-method study by Koo et al. (2021), employees held a range of positive and negative attitudes toward the introduction of AI. Likewise, in the present study, participants viewed using AI at work as beneficial, harmful, or mixed, showing a range of outcomes experienced across different employees and even within some employees.

Specific to work-family outcomes, participants primarily discussed AI use at work as being beneficial as it reduced time-based conflict, although some participants did mention AI use at work as harmful due to an increase in time-based conflict. These responses were limited, with only 9.4% of participants reporting reduced work-life interference and 2.3% reported increased work-life interference. Responses related to WEF were very rarely mentioned. This experience

of strain-based conflict may explain why overall there was a positive association between AI use at work and WIF.

Theoretical Contributions

The current study makes several key contributions to the literature on AI, well-being, and the work-family interface. Primarily, this is one of the first studies to empirically examine the relationship between AI use at work and areas of the work-family interface, WIF and WEF. Current research on AI use at work and the work-nonwork interface has primarily been discussed in commentaries or reviews (e.g., Rony et al., 2024). Although there have been a handful of quantitative and qualitative studies that have discussed work-family variables in relation to AI (Ochoa et al., 2025; Solymosi et al., 2025; Yi & Kumar, 2026), there has yet to be an investigation of how employees themselves are engaging with AI tools with links to well-being. In addition to contributions of WIF, to my knowledge this is the first study to consider the relationship between AI use at work and WEF. By using a mixed-method design to investigate the relationship between AI use at work, WIF, WEF, and well-being, this study provides insights on how employees are viewing AI in the workplace and the impacts that it has to their lives at and outside of the workplace. Ultimately, as demonstrated in this study AI tools have implications for well-being at work that are also associated with success in the roles that employees hold in nonwork domains.

Although previous research has tended to view AI in either a positive or negative light, the results indicate that AI use at work is often perceived by employees as both a resource and a demand. This aligns with research emphasizing the double-edged nature of AI use at work in the workplace (Pinho et al., 2026; Yin et al., 2024). Using the JD-R framework, Pinho et al. (2026) examined employee-AI collaboration as a resource and AI awareness as a demand in the

workplace. Although AI was conceptualized as both a resource and a demand in this context, the results demonstrate that AI demands may shift from hindrance to challenge stressors under the availability of environments with many resources, demonstrating AI use at work as being double-edged.

Practical Implications

This research reveals several implications for organizations that are continuing to implement AI in work tasks, as AI can be a resource and a demand for employees. I found that AI use at work was positively related to WIF. Although some participants qualitatively reported that AI helped to reduce the conflict they experienced between work and their personal lives, others experienced the opposite. Based on the qualitative responses, AI use at work may be associated with an increase in strain-based conflict because of an added pressure to produce. Several participants noted that they felt expected to work outside of office hours, such as by answering emails, or continued to think about work while at home. As meta-analyses have shown that work-family conflict, specifically the direction of WIF, is related to negative work outcomes such as decreased job satisfaction, decreased organizational commitment, burnout, and absenteeism (Amstad et al., 2011), managers should actively work with employees to reduce strain-based conflict related to AI use at work. By building a culture where employees are not expected to produce even more with the help of AI, conflict between work and family will be mitigated. Organizations should also manage the demands of AI use at work, such as workload, to balance productivity goals with the well-being of employees. This would have positive implications for both employees and the organization, as well-being is linked to positive work outcomes like enhanced job performance (Sonnentag et al., 2023).

Although organizations need to be mindful of the potential harms of AI use at work, there are a variety of impactful benefits for employees. Using AI was viewed by most participants as benefitting task facilitation and well-being at work, which benefitted well-being in nonwork domains. Future research is needed on the mechanisms by which AI use at work relates to WEF. Based on some participant responses, it is plausible that AI may facilitate meaningful work and reduce some of the strain associated with work tasks. However, some participants did experience harms to their well-being from AI use at work. Organizations should make AI tools a high training priority to reduce the difficult learning curve, help employees manage incorrect AI outputs, and emphasize using AI in a way that does not promote skill decay. By emphasizing the benefits of AI use at work and addressing some of its job demands with training, the benefits of AI use can be maximized while mitigating harms.

AI resistance has been a topic of concern in the AI literature, especially regarding organizational outcomes during the process of AI implementation. However, AI resistance did not moderate the relationship between AI use at work and WEF. Although it was not a moderator here, organizations should continue to be transparent about AI implementation and encourage employee voice when making decisions about AI in employee tasks (Golgeci et al., 2025; Valtonen and Holopainen, 2024). Additionally, it should be considered that some level of resistance to AI technologies may help reduce AI dependency and skill decay, a point of concern for participants in this study.

Limitations and Future Directions

Although my study makes several contributions to the literature on AI use at work, employee well-being, and the work-family interface, I acknowledge a number of limitations. First, I cannot draw causal inferences from these findings as my study is cross-sectional.

Although previous longitudinal research has demonstrated that as a whole employees do not experience changes to their work-family conflict over time (Rantanen & Kokko, 2012), some participants discussed how AI use at work directly benefitted/harmed their well-being.

Therefore, it would be informative to implement daily diary studies or longitudinal designs to examine the relationship between AI use at work, WIF, and WEF over time. Second, this model is unidirectional and only explains the direction from AI use at work to family-based outcomes.

Although I believe this limitation to be justified as the focus of this study was to examine how AI use as a work resource may be associated with WIF and WEF, the constructs of work-family conflict and work-family enrichment are bidirectional. Future research should also consider how one's time at home could also influence the impact of using AI tools.

Third, the wording of the two qualitative prompts regarding benefits and harms to AI use at work and well-being outside of work could have been clarified further for participants. In the survey administered on Prolific, the section header instructed participants to answer a variety of questions regarding their experiences using AI technologies at work. The prompts, however, did not specify the use of AI at work. For example, participants were asked to describe how using AI technology enhanced/harmed their well-being outside of work. This likely led many participants to discuss personal uses of AI in the nonwork interface, such as for meal prepping or assistance with life concerns. Therefore, data from 240 out of 475 participants were removed from the responses about enhancements to well-being outside of work, and data from 44 out of 145 participants were removed from the responses about harms to well-being outside of work.

Prompts examining well-being outside of work should explicitly state where the AI technology is being used. Additionally, *Research Question 3* did not include prompts specifically addressing work-family experiences, rather, it was answered based on participant responses to general well-

being prompts. Future research should prompt individuals specifically about AI's impact on the work-family interface, rather than general perceptions of well-being.

Overall, AI use at work had a positive direct relationship with WIF, however there were participants who reported that AI was beneficial and allowed them to spend more time with family. Based on these conflicting results, it is evident that a person-centered approach could be beneficial when conducting research on AI on well-being, as participants have a variety of perspectives and experiences. Future research should consider incorporating methods such as latent profile analysis. For example, profiles could identify how employees differ on WIF and WEF based on different combinations of variables such as time engaging with AI tools, AI resistance, and experiencing meaningful work. Demographic variables such as age, gender, or number of children could also be important for profile membership, as previous research has demonstrated their role in influencing levels of work-family conflict and the probability of belonging to a specific profile (Lee, 2018).

An important note is that this mixed-method study should be viewed as a starting point for further in-depth research on AI use at work and well-being. One potential avenue for this involves a specific consideration of meaningful work as a mediator of the positive relationship between AI use at work and WEF. Bankins and Formosa (2023) posit that augmentation may enable employees to experience more meaningful work as they can focus more on value-adding tasks. This is exemplified in some of the qualitative results, as participants reported it as a benefit to their well-being at work. However, meaningful work and its three core dimensions of skill variety, task identity, and task significance should be considered to understand how AI tools for the purpose of augmentation or automation affect the work-nonwork interface. Other well-being outcomes involving perceived stress or positive affect could be explicitly considered.

Conclusion

Organizations are increasingly implementing AI into everyday work tasks, yet it is unclear how AI use at work may be associated with well-being at work as well as in family domains. This study examined the associations between AI use at work and the work-family interface, specifically WIF and WEF, and the moderating role of AI resistance between AI use at work and WEF. Additionally, qualitative responses were analyzed regarding how AI use at work was beneficial or harmful to employee well-being. I found that AI use at work was positively associated with WIF and WEF, though AI use as a moderator was not significant. Participants primarily viewed AI as being beneficial for the themes of task facilitation and their well-being across the work-nonwork interface, however harms were also noted for task hindrance and well-being. Overall, the use of AI at work is multifaceted, and organizations should continue to consider the positive and negative impacts its implementation has on employee well-being and the work-nonwork interface.

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Table 1*Descriptive Statistics and Intercorrelations of Study Variables*

Variable	<i>M</i>	<i>SD</i>	1	2	3	4	5	6	7	8
1. Age	37.35	10.98	—							
2. Gender	0.47	0.53	−.08	—						
3. Work Hours	1.27	0.79	.04	−.07	—					
4. Org. Tenure	7.57	7.20	.51***	−.07	.06	—				
5. AI Resistance	4.13	1.55	−.03	.07	−.08	−.03	(.85)			
6. AI Use	4.76	1.40	−.15***	.07	.01	−.02	−.15***	(.92)		
7. WEF	5.29	1.18	−.04	.06	−.10*	.04	.07	.37***	(.95)	
8. WIF	3.52	1.65	−.09*	−.10*	.09*	−.05	.01	.13**	−.21***	(.90)

Note. $N = 584$ participants. * $p < .05$, ** $p < .01$, and *** $p < .001$, two-tailed. WIF = work interference with family. WEF = work enriching family. Dummy codes: Gender (0 = *male*, 1 = *female*, 2 = *non-binary*, 3 = *transgender female*), work hours (0 = *21-30 hours per week*, 1 = *31-40 hours per week*, 2 = *41-50 hours per week*, 3 = *51-60 hours per week*, 4 = *More than 60 hours per week*). McDonald's omega for each measure is shown in parentheses on the diagonal.

Table 2*Summary of Results for the Hypothesized Structural Model in modsem*

Variable	<i>b</i> (<i>SE</i>)	[95% CI]	<i>z</i>	<i>p</i>	β
AI Use					
Age	−0.02 (0.01)	[−0.03, −0.01]	−3.79	< .001***	−0.20
Gender	0.15 (0.10)	[−0.03, 0.35]	1.61	0.107	0.07
Work Hours	0.03 (0.06)	[−0.10, 0.16]	0.48	0.632	0.02
Org. Tenure	0.01 (0.01)	[−0.10, 0.16]	1.59	0.112	0.08
AI Resist					
Age	−0.00 (0.01)	[−0.02, 0.01]	0.67	0.666	−0.02
Gender	0.21 (0.12)	[−0.03, 0.44]	1.70	0.088	0.07
Work Hours	−0.12 (0.08)	[−0.27, 0.04]	−1.50	0.131	−0.07
Org. Tenure	−0.00 (0.01)	[−0.02, 0.02]	−0.14	0.889	−0.01
WIF					
Age	−0.01 (0.01)	[−0.02, 0.01]	−1.18	0.237	−0.06
Gender	0.28 (0.13)	[0.02, 0.55]	2.11	0.035*	0.09
Work Hours	0.22 (0.09)	[0.04, 0.34]	0.02	0.015*	0.10
Org. Tenure	−0.00 (0.01)	[−0.03, 0.02]	−0.31	0.756	−0.02
AI Use	0.17 (0.07)	[−0.04, 0.30]	2.50	0.012*	0.12

WEF

Age	0.00 (0.00)	[−0.01, 0.01]	0.30	0.761	0.01
Gender	0.01 (0.08)	[−0.15, 0.16]	0.10	0.922	0.00
Work Hours	−0.14 (0.05)	[−.24, −0.04]	−2.74	0.006**	−0.11
Org. Tenure	0.01 (0.01)	[−0.01, 0.02]	1.03	0.303	0.05
AI Use	0.42 (0.05)	[0.33, 0.50]	9.26	<.001***	0.47
AI Resistance	0.11 (0.03)	[0.06, 0.17]	3.82	<.001***	0.19
AI Use X AI Resistance	−0.04 (0.03)	[−0.09, 0.01]	−1.47	0.141	−0.06

Note. $N = 574$. * $p < .05$, ** $p < .01$, and *** $p < .001$ (two-tailed). The boldface indicates significant predictors. WIF = work interference with family, WEF = work enriching family. Predictors are indented, dependent variables are not. β = standardized path coefficient; SE = standard error; CI = confidence interval.

Table 3

Qualitative Themes and Underlying Codes for Benefits and Harms of AI Use at Work in the Work-Nonwork Interface

Work-Domain Benefits	Work-Domain Harms	Nonwork-Domain Benefits	Nonwork-Domain Harms
Task facilitation • Enhances efficiency and productivity • Enhances miscellaneous performance • Enhances learning and development • Reduces reliance on others	Task hindrance • AI dependency and skill decay • Difficult learning curve • Incorrect output • Reduces social interactions • Reduces productivity/efficiency • Reduces work quality	Task facilitation • Saves time • Helps with gathering information and learning • Assists with general work tasks • Assists with planning and organizing • Makes work easier	Task hindrance • AI dependency and skill decay • Reduces social interactions • Incorrect output • Reduces productivity/efficiency
Well-being benefits • Reduces stress • Makes work more meaningful • Enhances general mental health • Enhances self-efficacy/confidence • Enhances work-life balance	Well-being harms • Job insecurity • Adds pressure to produce • Harms general mental health • Increases stress/anxiety	Well-being benefits • Enhances general mental health • Reduces work-life interference • Reduces stress • Enhances work-life balance	Well-being harms • Increases work-life interference • Harms general mental health • Job insecurity • Digital fatigue • Fear of AI

Note. Codes are presented in bullets under each theme for the benefits and harms of AI use at work in work and nonwork domains.

Table 4

Work-Domain Benefits of AI Use at Work: Themes, Definitions, and Example Responses

Theme	Code	Definition	Examples	Counts/Frequencies
Task facilitation	Enhances efficiency and productivity	AI enhances work by speeding up work tasks, freeing up time for other things, and increasing the volume of tasks or deliverables accomplished.	“The use of AI has made it easy to automate daily routine tasks and increase my productivity.” “AI helped me save time by automating repetitive tasks that used to drain my focus.”	336 (41.3%)
	Enhances miscellaneous performance	AI enhances one’s ability to perform their work outside of just efficiency and productivity.	“I also use AI to help with my decision making and understand complex issues regarding my work.” “It brought up new ideas that helped in developing strategies in the company.”	124 (15.2%)
	Enhances learning and development	AI enables or enhances one’s learning, including self and professional development at work.	“AI technology has been very useful in taking my existing skills to the next level.” “I’ve been able to expand my skillset and learn so many new things.”	34 (4.2%)

Well-being benefits	Reduces reliance on others	AI enables oneself to be less reliant on others for help and more self-sufficient or independent.	“This allows me to only ask my seniors when [I] really have a hard problem.” “Being able to ask questions immediately instead of waiting to find an answer or ask someone else.”	8 (1.0%)
	Reduces stress	AI alleviates psychological strain from work tasks.	“I didn’t have to overwork myself to the point that I stress about not getting things done.” “This makes the workloads light and lessens my anxiety and feelings of pressure at work. It makes me less stressed out on the job.”	120 (14.7%)
	Makes work more meaningful	AI assists with and/or gives users more time to focus on higher-value activities, thus contributing to tasks or outputs that add value to their or the organization’s goals.	“It has allowed me to explore another side of my job required research that I missed.” “Reduced my workload by automating routine tasks allowing me to focus on higher value work.”	84 (10.3%)
	Enhances general mental health	AI positively impacts one’s overall psychological well-being beyond stress reduction (e.g., improvements to mood and/or energy level).	“I feel much better completing projects that would normally have left me utterly exhausted.”	54 (6.6%)

		“It’s helped reduce burnout and made my workdays smoother.”	
Enhances self-efficacy/confidence	AI strengthens one’s belief in their ability to complete tasks or perform their role effectively.	“I am more confident that I can solve data related problems.” “The ability to automate certain processes and receive intelligent suggestions from AI platforms gives me greater confidence in the accuracy and timeliness of my work.”	28 (3.4%)
Enhances work-life balance	AI assisting with and/or giving more time towards one’s workload, or time spent on tasks, positively impacting users' work-life balance.	“Because of this, I am able to separate my work and personal life.” “Helped me maintain a better work-life balance.”	17 (2.1%)
N/A or neutral	AI use is not perceived as enhancing well-being at work.	“It didn’t really enhance nor detract from my well-being at work.” “It didn’t impact my well-being at work, positively or negatively.”	9 (1.1%)

Note. Total number of participant responses was 464, with a total of 814 coded items. Frequencies were calculated by dividing the number of code counts by the number of total coded items.

Table 5

Nonwork-Domain Benefits of AI Use at Work: Themes, Definitions, and Example Responses

Theme	Code	Definitions	Examples	Counts/Frequencies
Task facilitation	Saves time	AI reduces the amount of time needed to complete tasks or activities, allowing users to accomplish work more quickly.	“It enhanced my well-being outside work by helping to source information and summarize it, information that I would have spent hours to get.” “I use AI to research items, which saves me time and effort that would otherwise be spent looking things up manually.”	73 (19.0%)
	Helps with learning and gathering information	AI assists users in finding, synthesizing, or understanding information, including supporting them in the acquisition of new knowledge or skills.	“Easier and quicker especially when trying to gather information that would take ages to search for before AI.” “I use AI to help look up and teach me policies for my company.”	52 (13.5%)
	Assists with general work tasks	AI provides support across a broad range of everyday tasks.	“Improves my day to day tasks and how to carry out the functions.” “Helps simplify daily tasks, supporting healthier habits.”	43 (11.2%)

Well-being benefits	Assists with planning and organizing	AI assists users with prioritizing or coordinating work tasks, such as managing tasks, schedules, or projects.	“It has made me more organized with for example work and within day to day tasks.” “It has helped me organize thoughts or ideas to execute on plans that I’ve been trying to make more easily.”	27 (7.0%)
	Makes work easier	AI reduces the complexity or difficulty of various work tasks, making them more manageable and requiring less effort.	“This made it easier to balance responsibilities and enjoy more free time.” “Using AI technology has enhanced my well-being outside of work by making everyday tasks easier and more efficient.”	13 (3.4%)
	Enhances general mental health	AI positively impacts one’s overall psychological well- being beyond stress reduction (e.g., improvements to mood and/or energy level).	“I have been feeling much more relaxed outside of work and have been able to really enjoy my off hours.” “The associated freedom in time and deloading of tasks has led to improved mental health, and thus, a more positive outlook in life too.”	59 (15.4%)
	Reduces work-life interference	AI reduces the extent to which work demands conflict with demands in one’s personal life.	“I stopped working overtime due to AI and so that really helps me stay longer around	55 (14.3%)

		my family to spend free time with them.”	
		“It has firstly reduced my workload so I don’t need to come home and do work as much so I have time for my family.”	
Reduces stress	AI alleviates psychological strain from work tasks.	“I feel less stress because I know I have AI to help during working hours, to help with the burden.”	32 (8.3%)
		“Now I’m able to think less about work while I am at home, resulting in my stress levels to go down overall.”	
N/A or neutral	AI use is not perceived as enhancing well-being at work.	“It’s made no real difference, I’m possibly marginally less stressed about work, but it’s negligible.”	18 (4.7%)
		“Using the chatbot at work did absolutely nothing for my well-being outside of work. It was as good as forgotten by the time I had clocked out for the day.”	

Enhances work-life balance	AI assists with and/or gives more time towards reducing one's workload, or time spent on tasks, positively impacting users' work-life balance.	“AI hasn't changed my personal life much, but by making work more efficient, it's helped me have a better work-life balance.” “AI helps me maintain a better work-life balance by saving time during work hours.”	12 (3.1%)
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Note. Total number of participant responses was 235, with a total of 384 coded items. Frequencies were calculated by dividing the number of code counts by the number of total coded items.

Table 6

Work-Domain Harms of AI Use at Work: Themes, Definitions, and Example Responses

Theme	Code	Definitions	Examples	Counts/Frequencies
Task hindrance	AI dependency and skill decay	AI use fosters over-reliance, eroding users' skills, knowledge, or ability to complete tasks independently.	"AI has limited my critical thinking ability since I at times over rely on it to do tasks." "At times, relying on AI created a sense of dependency that made me question my own judgement."	25 (12.5%)
	Incorrect output	AI produces inaccurate, incomplete, or misleading results.	"AI systems can occasionally be annoying when they malfunction or issue excessive alerts." "Often gets things wrong...I have not had accurate results in several months."	19 (9.5%)
	Difficult learning curve	AI tools require significant time, effort, or technical knowledge to learn and use effectively.	"I've maybe spent too much time learning how to make it work for me." "AI technology provides much more information making it difficult for one to filter out hence being stressful."	15 (7.5%)

	Reduces social interactions	AI reduces opportunities for interpersonal communication and human collaboration at work.	“There are fewer opportunities for real conversations, brainstorming, or even simple human check-ins.” “It sometimes makes things feel less personal, especially when working with students or colleagues.”	8 (4.0%)
	Reduces productivity/efficiency	AI hinders one’s ability to complete tasks, resulting in tasks taking longer to accomplish.	“Required more work to fix AI systems that made mistakes.” “Reliance on AI outputs sometimes increased workload through revisions.”	8 (4.0%)
	Reduces work quality	AI contributes to outputs that are of a lower standard than what the user would have achieved independently, decreasing the quality.	“There were moments when I accepted AI-generated suggestions without enough critical review.” “I have sometimes created plans that taught material that was too complicated.”	4 (2.0%)
Well-being harms	N/A or neutral	AI use is not perceived as harming well-being at work.	“AI has not had any significant harm or damage to my well-being at work.” “AI has not been harmful to my well being at work.”	35 (17.5%)

Job insecurity	AI use raises concerns about displacement, leading to uncertainty about one's future employment.	“Now I feel like the job I had excelled at for many years is going to be replaced.” “AI has harmed my work by reducing workforce as many clinical settings have fired employees and replaced their tasks with AI.”	26 (13.0%)
Adds pressure to produce	AI amplifies work expectations to deliver more quickly, increasing users' job demands.	“I felt like I had to do things faster, and it was hard to keep up.” “At times, reliance on AI has created pressure to be more productive.”	24 (12.0%)
Harms general mental health	AI negatively impacts one's overall psychological well-being, beyond stress and anxiety, including adverse effects on mood and energy.	“At work, AI sometimes overwhelmed me with constant notifications.” “The automation of tasks may blur work-life boundaries, leading to pressure to respond quickly or do more with less.”	18 (9.0%)

Increases stress/anxiety	AI use contributes to enhanced psychological strain or anxiety.	“Using AI made me feel more stressed sometimes.” “Sometimes AI-generated alerts caused information overload, increasing my anxiety during shifts.”	18 (9.0%)
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Note. Total number of participant responses was 130, with a total of 200 coded items. Frequencies were calculated by dividing the number of code counts by the number of total coded items.

Table 7

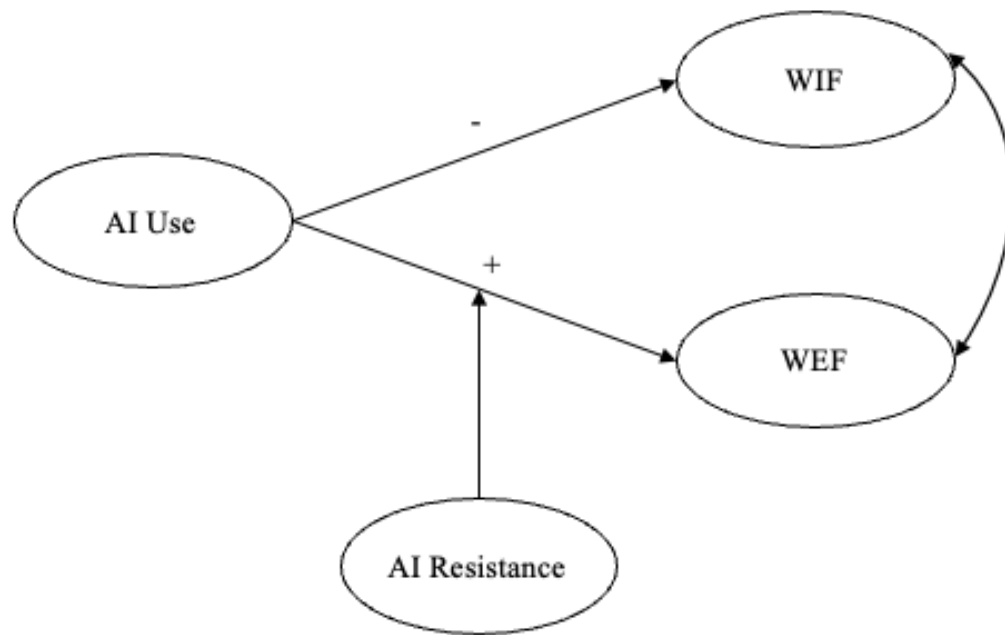
Nonwork-Domain Harms of AI Use at Work: Themes, Definitions, and Example Responses

Theme	Code	Definitions	Examples	Counts/Frequencies
Task hindrance	AI dependency and skill decay	AI use fosters over-reliance, eroding users' skills, knowledge, or ability to complete tasks independently.	"It has hindered my research skills by spoon feeding me with information during assignments." "Using AI for all the little tasks can sometimes reduce my creativity."	25 (20.5%)
	Reduces social interactions	AI reduces opportunities for interpersonal communication and collaboration at work.	"It occasionally made me feel disconnected from real human interaction." "Reduced face to face interactions."	10 (8.2%)
	Incorrect output	AI produces inaccurate, incomplete, or misleading results.	"It is sometimes known to the odd occasional error such as facts not completely being up to date." "It can give a false insight on what to expect."	8 (6.6%)
	Reduces productivity/efficiency	AI hinders one's ability to complete work tasks, decreasing the volume of	"Having to continue to iterate to get to the end result desired."	6 (4.9%)

		tasks or deliverables accomplished.	“I rely on it too much and end up overthinking decisions because of all the options it gives.”	
Well-being harms	N/A or neutral	AI use is not perceived as enhancing well-being at work.	“AI has not been harmful to my well-being outside of work.” “It didn’t do nothing to my well-being.”	36 (29.5%)
	Increases work-life interference	AI increases the extent to which work demands conflict with demands in one’s personal life.	“Using AI at work sometimes made me think about work even after hours, making it hard to fully relax at home.” “It has reduced my time which I use to interact and have a good time with my family.”	16 (13.1%)
	Harms general mental health	AI negatively impacts one’s overall psychological well-being beyond stress elevation (e.g., decreases in mood and/or energy level).	“...experiencing less downtime, which negatively affected rest and mental recovery.” “Sometimes, I feel like I’m not intelligent enough to handle anything without the use of AI.”	7 (5.7%)
	Job insecurity	AI use raises concerns about displacement, leading to uncertainty about one’s future employment.	“Everyone I talk to says that pretty much no one is hiring and it’s incredibly hard to find new positions.”	8 (6.6%)

		“It poses a threat to my job.”	
Digital fatigue	AI use contributes to psychological strain from prolonged screen time and excessive notifications.	“It can keep me on screens longer than I’d like.”	3 (2.5%)
		“AI has contributed to my digital overload.”	
Fear of AI	AI evokes apprehension or unease stemming from concerns about its broader implications for work and society.	“I have now read several articles from experts who state that AI will kill us all. That feels harmful.”	3 (2.5%)
		“I also have a lot of reservations and concerns about AI technology in our everyday lives too.”	

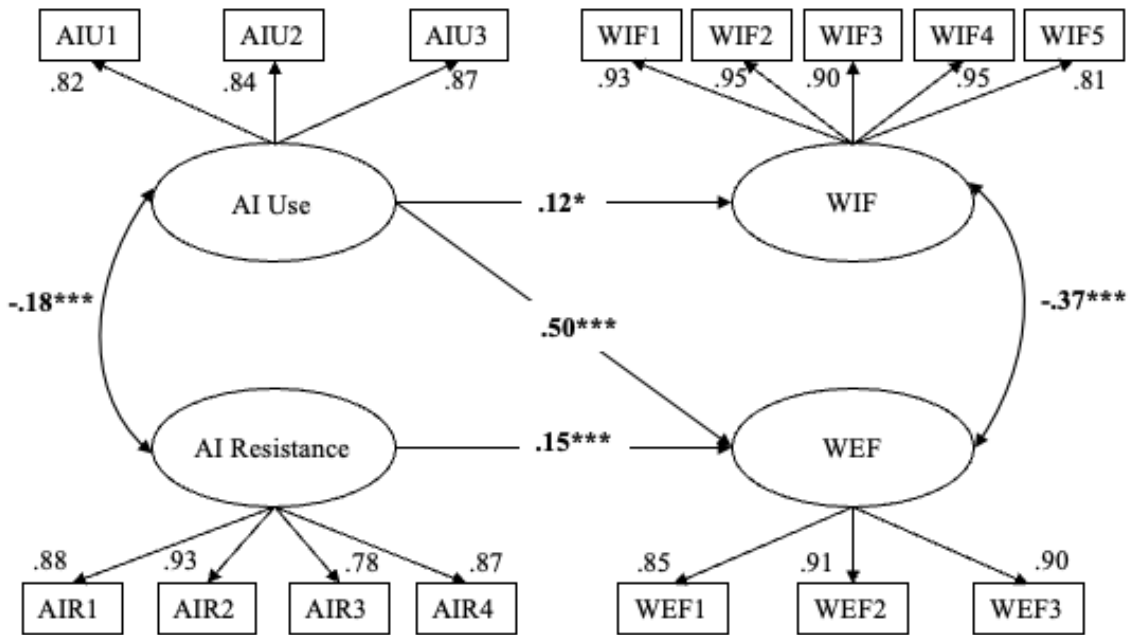
Note. Total number of participant responses was 101, with a total of 122 coded items. Frequencies were calculated by dividing the number of code counts by the number of total coded items.

Figure 1*Hypothesized Model*

Note. Hypothesized model with AI resistance moderating the relationship between AI use at work and work enriching family (WEF).

Figure 2

Summary of the Final Baseline Structural and Measurement Model in lavaan



Note. $N = 584$. * $p < .05$, ** $p < .01$, and *** $p < .001$ (two-tailed). Standardized path coefficients are reported. WEF = work enriching family, WIF = work interference with family. Age, gender, hours worked per week, and organizational tenure were entered as covariates, although not shown in this figure (See Table 2 for details). Due to the statistical non-significance of the interaction term, only the baseline model is presented. Fit of the structural model was adequate, $\chi^2(129) = 204.55$, $\chi^2/df = 1.59$, RMSEA = 0.01 (95% upper CI = 0.03), CFI = 1.00, TLI = 1.00, SRMR = 0.04. SEM = structural equation model, RMSEA = root-mean-square error of approximation, CI = confidence interval, CFI = comparative fit index, TLI = Tucker-Lewis Index, RMR = standardized root-mean-square residual.