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To my wonderful mentors and beautiful wife for supporting me along the way – thank you. I could never have done it without you.

The Relationship Between AI Use and Well-Being: Exploring the Roles of Frequency, Type, and Mediators

Abstract

This study investigates the nuanced impacts of Artificial Intelligence (AI) integration on workplace productivity, burnout, and employee well-being. Analyzing data from 151 professionals across diverse industries, our research reveals that AI's strategic application to core job functions significantly enhances productivity and supports employee well-being. However, our findings also caution against overreliance on AI, as excessive use contributes to diminishing returns. These results underscore the importance of a balanced, deliberate approach to AI deployment that prioritizes both organizational efficiency and employee health. By challenging the prevailing assumption that increased AI usage is universally beneficial, this study advances the conversation on AI's role in the workplace and provides a basis for developing policies that align technological innovation with the holistic needs of the workforce.

Key Words: Artificial Intelligence, Well-Being, Productivity, Burnout

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1 Introduction

1.1 Background

Artificial Intelligence (AI), defined as the simulation of human intelligence by machines, is at the forefront of a technological revolution that is reshaping workplaces and redefining employee well-being (Russel & Norvig, 2021). From machine learning and natural language processing to robotics, AI technologies are increasingly performing tasks traditionally requiring human cognition, driving significant changes in how work is executed.

The rise of Large Language Models (LLMs) like ChatGPT signifies a pivotal shift, with AI being heralded as the general-purpose technology of our time (Guszcza et al., 2022). The rapid and widespread adoption of these technologies, as evidenced by ChatGPT's unprecedented user growth (Heaven, 2024), highlights a profound transformation in work processes and employee roles. This integration underscores the need to examine not only the economic impacts of AI but also its implications on task execution, productivity, and employee well-being. As organizations increasingly embed AI into daily workflows, understanding these human factors becomes critical for leveraging AI's potential while maintaining a healthy and engaged workforce (Dwivedi et al., 2021; Brynjolfsson & McAfee, 2014).

1.2 Research Aims and Objectives

While AI promises to revolutionize productivity, it also introduces significant challenges, particularly in its impact on employee well-being. The widespread integration of AI into the workplace represents more than just a technological shift; it is fundamentally transforming the employee experience, raising critical questions about stress, burnout, and broader implications for mental health. This study rigorously examines the nuanced interplay between AI usage, productivity, burnout, and well-being, shedding light on these critical dynamics across diverse industries. By addressing these complexities, this research aims to bridge important gaps in the current understanding, offering a more sophisticated perspective on how AI can be strategically leveraged to enhance productivity without eroding employee well-being.

2 Literature Review

2.1 Brief Historical Evolution of AI in the Workplace

The evolution of AI has profoundly impacted the workplace over the past several decades. The conceptualization of AI as a distinct field emerged in the 1950s, with the 1956 Dartmouth Conference marking a seminal moment in establishing AI as a formal discipline (Buchanan, 2005). Initially, AI was primarily confined to theoretical exploration and experimental applications, but its practical utility has grown exponentially, particularly with advancements in computational power and algorithmic development (Howard, 2019).

In the 21st century, AI has moved from the periphery of organizational functions to become a central component of business operations. The rapid development of machine learning and big data analytics has enabled AI to transform various industries by automating routine tasks, optimizing workflows, and enhancing decision-making processes (Dwivedi et al., 2021). One example is the widespread access to AI-based digital tools, such as chatbots and virtual assistants. This application of AI technology has wiped out call centers and revolutionized businesses' ability to provide customer service, with chatbots' ability to provide better customer service help than humans at a fraction of the cost (Maedche et al., 2019).

Despite these advancements, the integration of AI into the workplace has been accompanied by significant challenges. The potential for job displacement due to automation and the growing demand for workforce reskilling and upskilling are critical concerns that continue to shape the discourse on AI's role in the modern workplace (Acemoglu & Pascual, 2019). These issues underscore the need for a balanced approach to AI adoption, one that maximizes its benefits while addressing its socio-economic implications. As AI continues to evolve, it brings with it not only technological advancements but also complex ethical considerations that must be addressed.

2.2 AI in the Workplace

AI is rapidly advancing across an array of sectors, reshaping the landscape of work and organizational practices. From manufacturing to healthcare, finance to transportation, AI redefines how tasks are executed, decisions are informed, and productivity is evaluated. The

widespread adoption of AI technologies presents both opportunities and challenges as organizations adapt to this technological evolution.

In healthcare, AI has facilitated significant advancements in patient care through predictive diagnostics and procedural efficiencies, enabling medical professionals to focus on more complex, patient-centered activities (Davenport & Kalakota, 2019). Similarly, in the finance sector, AI is revolutionizing data analysis and investment decision-making processes, leading to more accurate and efficient financial practices (Bahoo et al., 2024). In transportation, AI-powered autonomous vehicles are transforming the industry by improving safety and operational efficiency in both logistics and personal travel (Iyer, 2021).

In the industrial and manufacturing sectors, AI-powered robots are playing an increasingly critical role in automating routine and dangerous tasks traditionally reliant on manual labor. This automation not only frees workers from hazardous work but also stimulates innovation within companies that adopt these technologies (Liu et al., 2020). The educational sector is also realizing the benefits of AI, where both teachers and students gain from its integration. Students, particularly in low-income areas, can access individualized tutoring from large language models (LLMs), while teachers receive coaching from AI chatbots to enhance their effectiveness and tailor their teaching approaches (Zhang & Aslan, 2021).

However, the widespread integration of AI brings challenges, particularly concerning its impact on the workforce. Algorithmic management is on the rise, which is when AI-driven algorithms are used to manage employees, and companies employing this method have been shown to hurt employees' job satisfaction due to the lack of empathy within the models (Benlian et al., 2022). Also, as AI continues to automate tasks traditionally performed by humans, concerns about job displacement and the urgent need for upskilling have become more pronounced, causing stress to a great deal of employees (Acemoglu & Restrepo, 2019). Moreover, excessive reliance on AI, especially in areas beyond its current capabilities, can lead to suboptimal outcomes, sometimes worse than if AI had not been used at all (Dell'Acqua et al., 2023). Thus, while AI offers transformative potential, its integration into the workplace is complex, particularly from the user's perspective.

As AI continues to permeate organizational practices, it is imperative for firms to achieve a delicate balance in its deployment—one that optimizes productivity while preserving employee well-being. Strategic integration of AI should complement, rather than replace, human capabilities, fostering an environment where both technological innovation and employee health can thrive. The following section explores the intricate relationship between AI use and employee well-being, examining how AI can both support and challenge the mental and emotional health of the workforce.

2.3 AI and Well-Being

2.3.1 Workplace Well-Being

Workplace well-being, encompassing mental health, job satisfaction, and work-life balance, is a cornerstone of both employee satisfaction and organizational success (Harter et al., 2003). Research consistently demonstrates that when organizations prioritize well-being, they experience positive outcomes such as increased job performance, reduced turnover intentions, and a more engaged workforce (Guest, 2022; Krekel et al., 2019).

Central to this is the role of work-life balance, which has been shown to improve mental health outcomes, reduce stress, and enhance overall job satisfaction (Haar et al., 2014). Additionally, psychological well-being is closely tied to job performance, particularly when supported by positive coworker relationships and organizational initiatives such as Employee Assistance Programs (EAPs) (Wu et al., 2021). More recently, flexible work arrangements, including remote work options and flexible hours, have been found to further contributed to higher job and life satisfaction, although their impact on stress can vary (Ray & Cryan, 2021).

As AI becomes increasingly integrated into workplace practices, its influence on worker well-being has emerged as a critical area of exploration. The relationship between AI use and well-being is complex, offering both opportunities and challenges in balancing productivity with a healthy work environment.

2.3.2 Impact of AI on Workplace Well-Being

The integration of AI into workplace practices presents a multifaceted landscape with both positive and negative implications for employee well-being. While the productivity benefits of AI are well-documented, its influence on employee well-being is more nuanced, requiring a balanced approach to harnessing its potential without exacerbating risks.

AI technology has been shown to positively impact employees' mental health and well-being by automating repetitive tasks, reducing job-related stress, and increasing job satisfaction. For example, AI applications that streamline administrative tasks significantly reduce cognitive load, thereby enhancing overall well-being (Eziefule et al., 2022; Raya-Povedano et al., 2021). Additionally, AI-driven automation can improve work environments by optimizing conditions for comfort and safety, thereby reducing stress levels (Fisher, 2023). Moreover, AI's role in enhancing job satisfaction is evident when it allows employees to focus on more meaningful and creative tasks, as seen in industries where AI handles repetitive or mundane work (Bankins & Formosa, 2023).

However, the positive effects of AI are counterbalanced by potential challenges. One of the primary concerns is technostress—anxiety stemming from the continuous need to adapt to new technologies (Bondanini et al., 2020). This stress is likely exacerbated by the rapid pace of AI advancements, which often necessitates continuous upskilling and adaptation. Moreover, AI can contribute to job insecurity as employees fear displacement by AI systems capable of performing tasks traditionally done by humans (Acemoglu & Restrepo, 2019), leading to increased stress, anxiety, and a sense of devaluation.

Ethical considerations also play a crucial role in shaping the impact of AI on well-being. Bias in AI algorithms can lead to unfair treatment of employees, resulting in frustration and decreased morale (Kordzadeh & Ghasemaghaei, 2021). Furthermore, employees may experience discomfort and mistrust if they believe AI systems are continuously monitoring and evaluating their performance, raising privacy concerns and affecting their sense of autonomy and control at work (Benlian et al., 2022; Jarrahi et al., 2021). These ethical challenges underscore the need for careful and thoughtful AI integration to mitigate potential negative impacts on well-being.

Therefore, to fully harness the benefits of AI while mitigating its potential drawbacks, organizations must strategically integrate AI in a manner that supports, rather than overwhelms, their workforce. But by fostering this environment where AI complements and enhances human skills, organizations can enhance job satisfaction, reduce burnout, and promote overall well-being. This approach suggests that thoughtful AI integration could benefit employee outcomes, which leads us to the hypothesis that AI use is positively associated with worker well-being—a relationship that, if validated, could provide valuable insights for optimizing AI deployment in the workplace.

Hypothesis 1: There is a positive relationship between AI use and worker well-being.

Figure 1



2.4 AI and Productivity

The integration of AI into workplace practices has been widely recognized for its potential to significantly enhance productivity and output quality (Dell'Acqua et al., 2023). AI's capacity to automate routine tasks, generate data-driven insights, and support more informed decision-making allows human workers to focus on higher-order tasks requiring creativity and complex problem-solving skills (Deranty & Corbin, 2022). This augmentation is evident across various sectors; for instance, in customer service, AI chatbots efficiently manage routine inquiries, enabling human agents to address more complex issues, thereby improving overall service quality (Ferraro et al., 2024; Maedche et al., 2019).

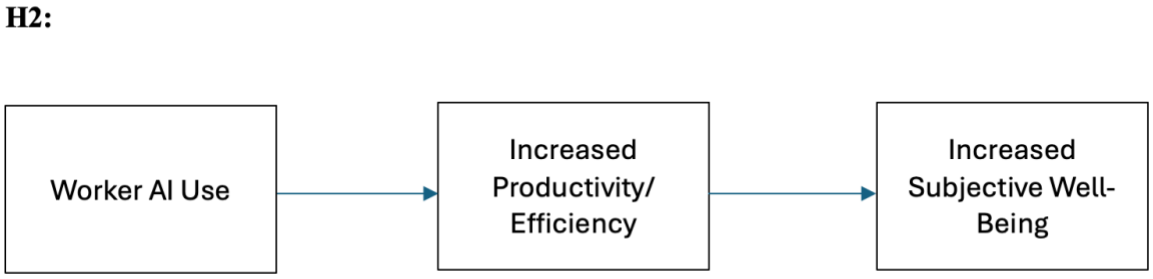
Moreover, AI plays a pivotal role in fostering psychological empowerment among employees. By equipping workers with tools that enhance their sense of control and autonomy, AI can lead to greater job satisfaction and improved performance (Nazareno & Schiff, 2021). In the manufacturing sector, AI's potential for driving productivity gains is particularly notable. AI technologies have been shown to optimize processes, reduce errors, and enhance operational efficiencies, leading to substantial improvements in productivity (Kehayov et al., 2022). Similarly, AI tools like ChatGPT have demonstrated their effectiveness in professional settings, significantly reducing task completion time by 40% and enhancing output quality by 18% (Noy & Zhang, 2023). These findings underscore AI's capacity to deliver consistent and significant productivity gains across various task and industries.

To fully realize the productivity benefits of AI, organizations must adopt a strategic approach to its integration. The concept of hybrid intelligence, which leverages the complementary strengths of humans and AI, is crucial for balancing efficiency with the necessary human oversight (Guszcza et al., 2022). This balance is vital for consistent productivity to be achieved because an overreliance on AI can result in a phenomenon termed "falling asleep at the wheel," where workers place undue trust in AI, neglecting necessary oversight (Dell' Acqua et al., 2023). Dell'Acqua et al. (2023) highlight this issue, showing that while AI-assisted consultants outperformed others in speed and perceived quality, they underperformed on tasks beyond the AI's capabilities because they continued to trust AI's outputs even when they should have known the AI was wrong. This finding underscores the importance of ensuring that human judgment remains integral to the decision-making process, preventing overreliance on AI, and ensuring that productivity gains are not achieved at the expense of quality.

While AI has the potential to significantly enhance productivity by automating routine tasks and improving decision-making processes, its integration into the workplace must be managed with careful consideration. However, when AI use and human oversight are balanced correctly, prior research suggests productivity gains will follow. We expect these productivity gains to translate into positive outcomes for workplace well-being. Therefore, we hypothesize that increased productivity mediates the relationship between AI use and higher levels of well-being.

Hypothesis 2: Increased productivity mediates the relationship between AI use and higher levels of well-being.

Figure 2



2.5 Type of AI Use

The integration of AI into workplace practices presents a complex landscape, with the nature of AI deployment shaping its impact on employees. Research on professionals such as consultants and lawyers highlights the effectiveness of AI in enhancing *Core Job Duties*, which we define as job duties central to a job role, such as legal research or data analysis in the context of these professions (Choi & Schwarcz, 2023; Dell'Acqua et al., 2023). These core tasks are fundamental to workers' professional identity and expertise, and AI's role in optimizing these duties has been linked to significant productivity gains.

In contrast, a growing body of literature underscores the value of AI in managing *Peripheral Job Duties*, which we define as tasks that, while essential, are not central to the worker's primary job function (Eziefule et al., 2022; Parycek et al., 2023). These peripheral tasks, which might include scheduling, administrative work, or routine data entry, are often seen as distractions from more meaningful work. By offloading these tasks to AI, employees are afforded more time and cognitive resources to devote to their core responsibilities, potentially enhancing both job satisfaction and overall performance.

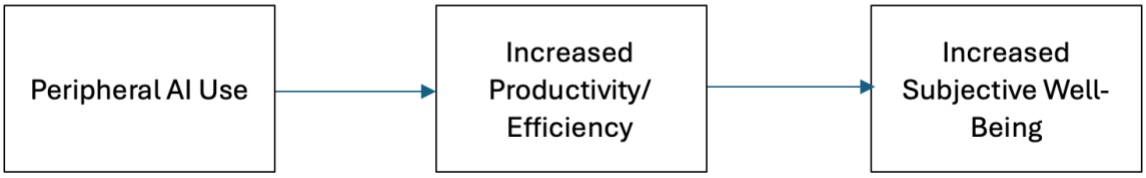
This distinction between core and peripheral AI use highlights a broader debate within the discourse on AI integration. Joanna Maciejewska's remark, "I want AI to do my laundry and dishes so that I can do art and writing, not for AI to do my art and writing so that I can do my laundry and dishes," succinctly encapsulates the underlying tensions (2024). While AI can be leveraged to relieve employees of peripheral tasks, the implications of using AI to undertake core responsibilities are more complex. Specifically, the potential erosion of job satisfaction and identity when AI encroaches on tasks central to one's professional role warrants careful examination (Brougham and Haar, 2018).

Understanding these nuances is crucial for organizations aiming to harness AI's potential while mitigating unintended consequences. If AI assumes control of tasks intrinsic to an employee's professional identity, it may diminish the sense of accomplishment and purpose derived from those duties (Brougham and Haar, 2018). Conversely, when AI manages peripheral activities, it can free workers to focus on the aspects of their jobs they find most fulfilling. Thus, the relationship between AI use and employee well-being is multifaceted, requiring a balanced approach considering both productivity gains and preserving job satisfaction and psychological health. This consideration forms the basis of our hypothesis that increased peripheral use of AI is positively associated with productivity, which, in turn, enhances worker well-being.

Hypothesis 3: Increased Peripheral Use of AI is positively associated with productivity, which leads to increased worker well-being.

Figure 3

H3:



2.6 Frequency of AI Use

The integration of AI into workplace practices has demonstrated significant potential in enhancing productivity, particularly when AI tools are used frequently. The frequency of AI use emerges as a critical factor in determining its impact on employees and their productivity, as studies consistently show that regular interaction with AI leads to productivity gains across various professional domains (Brynjolfsson et al., 2023; Noy & Zhang, 2023). For instance, Noy and Zhang (2023) found that professionals who frequently used generative AI tools like ChatGPT completed tasks 40% faster and produced outputs of 18% higher quality compared to those who did not use AI. Similarly, Dell'Acqua et al. (2023) reported that frequent AI use in knowledge-intensive tasks among consultants led to increased task completion speed and improved output quality, underscoring the effectiveness of AI in complex professional settings.

However, the benefits of frequent AI use come with potential downsides. Over-reliance on AI can lead to cognitive disengagement, where employees may become overly dependent on AI systems, resulting in a decline in their overall work quality (Dell'Acqua et al., 2023). Furthermore, as people use and become comfortable with AI's outputs, they tend to change their minds based on what the AI thinks is correct, even if they know the right answer (Passi & Vorvoreanu, 2022). While suboptimal outputs based on these reasons are likely to diminish as LLMs continue to advance in capability, it's important to consider the harmful effects of frequent AI use along with its benefits.

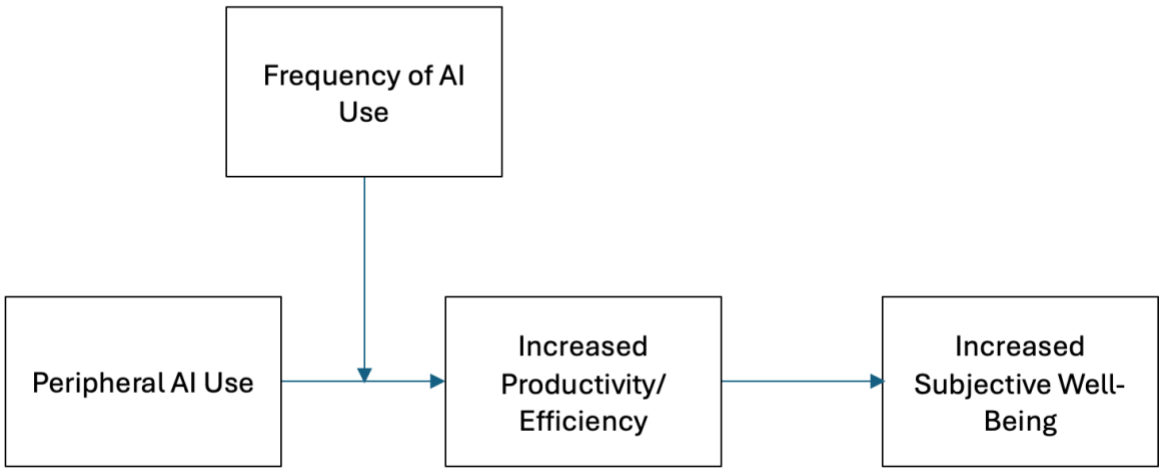
Thus, the relationship between frequent AI use and workplace outcomes is thus multifaceted and complex. While frequent use can drive significant productivity gains and enhance workplace

dynamics, it also introduces challenges that require careful management. Our research aims to further explore this intricate relationship, particularly how the frequency of AI use interacts with different types of AI applications to influence productivity and, ultimately, worker well-being. These considerations lead us to hypothesize that the positive relationship between peripheral AI use and productivity is especially pronounced when AI is used more frequently.

Hypothesis 4: The positive relationship between peripheral AI use and productivity is especially true when AI use is more frequent.

Figure 4

H4:



2.7 Burnout, Well-Being, and AI

Burnout and well-being are intrinsically linked, with well-being often serving as a protective buffer against the onset of burnout. When well-being is compromised, the likelihood of burnout increases, manifesting as emotional exhaustion, heightened stress, and diminished job satisfaction (Prentice et al., 2022). Studies by Prentice et al. (2022) and Bannon et al. (2022)

underscore this connection, demonstrating that positive psychological states and overall well-being are essential for preventing burnout. Maintaining high levels of well-being enables individuals to manage stress more effectively and remain engaged in their work, a dynamic that becomes increasingly important as workplaces integrate AI into their operations (Diener et al., 2020).

The integration of AI into the workplace introduces both promising opportunities and potential risks for managing burnout, a critical concern across various industries. Research suggests that AI can significantly mitigate burnout by reducing cognitive load and streamlining workflows, which allows employees to focus on more meaningful and satisfying tasks (Brynjolfsson et al., 2023; Eziefule et al., 2022). In high-stress environments such as healthcare, AI has been shown to enhance productivity and job satisfaction, thereby helping to alleviate burnout (Davenport & Kalakota, 2019).

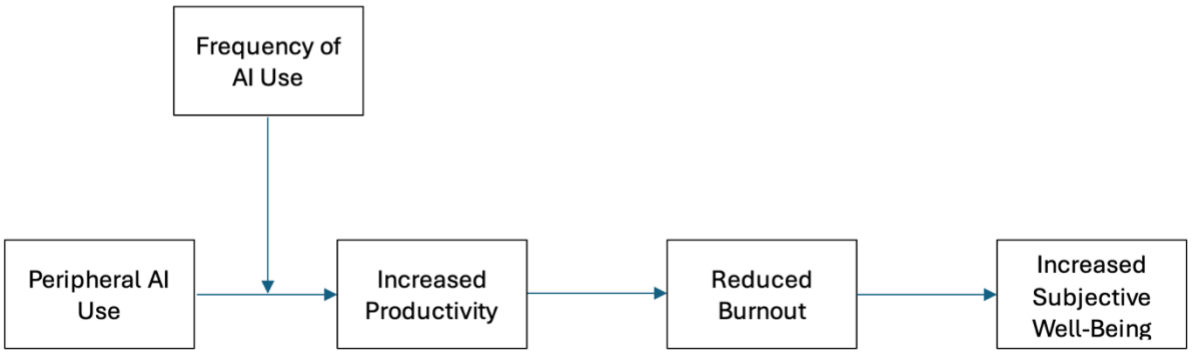
However, the benefits of AI are contingent on its thoughtful and strategic use. High frequencies of AI use can lead to technostress, characterized by the continuous pressure to adapt to new technologies, which may exacerbate burnout (Bondanini, 2020). This risk is particularly acute when AI encroaches on tasks that require human judgment and creativity, potentially leading to feelings of devaluation and job insecurity—key contributors to burnout (Bhargava et al., 2020).

Given the complex interplay between AI use, productivity, and burnout, we propose that AI can enhance worker well-being through a sequential process: increased productivity facilitated by AI reduces burnout, which in turn leads to improved well-being. This conceptual pathway leads to our hypothesis that AI use is positively related to worker well-being through serial mediation, where increased productivity leads to reduced burnout, ultimately enhancing worker well-being.

Hypothesis 5: AI use leads to worker well-being through serial mediation, where increased productivity leads to reduced burnout, which leads to increased worker well-being.

Figure 5

H5:


Frequency of AI Use
Peripheral AI Use
Increased Productivity
Reduced Burnout
Increased Subjective Well-Being

3 Methods

3.1 Sample and Data Collection

This study employed a cross-sectional survey methodology, targeting a diverse participant pool to examine the relationships among AI use frequency, AI use type, productivity, burnout, and well-being in professional contexts. 230 responses were collected, but 79 responses were discarded due to straight-lining and incomplete responses, bringing the valid total of responses to 151 participants. Data was collected through the London School of Economics and Political Science (LSE) Behavioral Lab and extended professional networks.

The participants represented a wide age range (18 to over 65), with the mean age falling within the 25-35 age group. The sample was predominantly female (74%) and included participants from various sectors such as hospitality, finance, healthcare, and education. Employment statuses were varied, encompassing full-time employees, part-time employees, self-employed individuals, and students, with 28% of respondents identifying as students. This diverse sample enabled a comprehensive analysis of AI's impact across different professional and educational environments.

3.2 Procedure

Participants were invited to complete an online survey hosted on Qualtrics. The survey was carefully structured to capture detailed data on AI usage and its subsequent impact on key workplace outcomes, minimizing potential priming effects by placing demographic questions at the end. The survey sequence began with questions on AI use frequency and type, followed by assessments of productivity, burnout, and well-being. This order was designed to ensure that responses were reflective of participants' experiences, rather than being influenced by earlier sections of the survey.

3.3 Measures

AI usage was assessed through two distinct dimensions: frequency and type. The frequency of AI use was measured on a continuous scale ranging from 0 (Never) to 100 (Every day),

capturing the varying intensities of participants' engagement with AI. Additionally, type of AI use was determined by asking participants to indicate their AI usage for core versus peripheral tasks on a slider scale from 0 (Peripheral Uses) to 100 (Core Uses). Core uses involved AI applications integral to primary job functions, while peripheral uses covered activities outside of these primary functions.

Productivity was assessed using a dual-item self-report measure, where participants rated their workplace productivity on a 5-point scale from 1 (Not productive at all) to 5 (Very productive). Additionally, participants provided a rating of how they believed others would evaluate their productivity. We calculated the average of these two ratings to derive the final productivity score. This dual approach, which captures both self-assessment and perceived external evaluation, was designed to mitigate potential biases in self-reporting and to offer a more comprehensive measure of productivity.

Burnout was measured using the 15-item Oldenburg Burnout Inventory (OLBI; Demerouti et al., 2003), which assesses emotional exhaustion and disengagement from work. Responses were recorded on a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). In this study, the OLBI demonstrated high internal consistency (Cronbach's $\alpha = .866$), ensuring its reliability for examining the hypothesized pathways involving burnout.

Well-being was assessed through two scales: the Scale of Positive and Negative Experience (SPANE) and the Flourishing Scale. The SPANE (Diener et al., 2010) is a 12-item scale measuring participants' positive and negative experiences over the past four weeks, with responses on a 5-point Likert scale. It showed excellent internal consistency (Cronbach's $\alpha = .916$). The Flourishing Scale, an 8-item measure also by Diener et al. (2010), assessed psychological flourishing, including aspects of purpose, social relationships, and self-esteem. This scale demonstrated high reliability (Cronbach's $\alpha = .907$.

Control Variables included age, a well-documented factor influencing technology adoption, productivity, and well-being outcomes (Lee & Coughlin, 2015). Age was controlled for in all analyses to isolate the effects of AI use on the outcomes of interest, ensuring a clearer understanding of the relationships being tested.

3.4 Data Analysis

Data were analyzed using IBM SPSS Statistics 27 and the PROCESS macro (Hayes and Rockwood, 2017), following a comprehensive analytical strategy. Descriptive statistics were first calculated for the key study variables. Pearson correlations were then conducted to examine the relationships among AI use frequency, AI use type, productivity, burnout, and well-being, providing a preliminary understanding of data distribution and initial patterns.

Mediation analyses were conducted using PROCESS Model 4 to test whether productivity mediated the relationship between AI use type and well-being outcomes (SPANE and Flourishing). This step was necessary for exploring the underlying mechanisms through which AI use affects well-being, particularly through productivity enhancement. To further investigate the complex pathways, serial mediation analyses were conducted using PROCESS Model 6, allowing the exploration of whether productivity and burnout sequentially mediated the relationship between AI use type and well-being outcomes.

Lastly, moderated mediation analyses, performed using PROCESS Model 83, examined whether the frequency of AI use moderated the indirect effects of AI use type on well-being through productivity and burnout.

4 Results

4.1 Descriptive Statistics and Correlations

Table 1 presents the descriptive statistics for the key variables in this study. The mean frequency of AI use was 49.03 (SD = 30.33), and the mean type of AI use was 43.88 (SD = 27.33). These figures suggest that AI utilization is fairly moderate, with considerable variation across the sample.

Table 1

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
TypeofAIUse	130	0	100	43.88	27.331
FrequencyofAIuse	151	0	100	49.03	30.326
Productivity	151	1.0	5.0	3.457	.7915
OLBI_M	151	1.13333333	4.46666667	2.97792494	.652413041
SPANE_M	151	1.08333333	4.91666667	3.37913907	.750104236
Flourishing_M	151	1.000	7.000	5.40066	1.018099
Valid N (listwise)	130				

The correlation analysis, shown in Table 2, indicated that the type of AI use was significantly and positively associated with productivity ($r = .295$, $p < .001$), implying that greater use of AI for core tasks is related to higher productivity levels. However, the correlation between the frequency of AI use and productivity was positive but did not reach statistical significance ($r = .129$, $p = .115$), suggesting that other factors may influence this relationship. Additionally, the frequency of AI use showed non-significant correlations with burnout (measured by OLBI_M, $r = -.085$, $p = .298$) and well-being measures, including SPANE ($r = .095$, $p = .246$) and Flourishing ($r = .083$, $p = .310$). These findings suggest that while the type of AI use positively impacts productivity, the frequency of AI use does not have a straightforward relationship with productivity, burnout, or well-being. These correlations underscore the necessity for further analysis, including mediation and moderated mediation, to fully understand these relationships.

Table 2

Correlations

		TypeofAIUse	FrequencyofAIuse	Productivity	OLBI_M	SPANE_M	Flourishing_M
TypeofAIUse	Pearson Correlation	1	.397**	.295**	-.024	.090	.105
	Sig. (2-tailed)		<.001	<.001	.788	.307	.235
	N	130	130	130	130	130	130
FrequencyofAIuse	Pearson Correlation	.397**	1	.129	-.085	.095	.083
	Sig. (2-tailed)	<.001		.115	.298	.246	.310
	N	130	151	151	151	151	151
Productivity	Pearson Correlation	.295**	.129	1	-.306**	.336**	.503**
	Sig. (2-tailed)	<.001	.115		<.001	<.001	<.001
	N	130	151	151	151	151	151
OLBI_M	Pearson Correlation	-.024	-.085	-.306**	1	-.652**	-.315**
	Sig. (2-tailed)	.788	.298	<.001		<.001	<.001
	N	130	151	151	151	151	151
SPANE_M	Pearson Correlation	.090	.095	.336**	-.652**	1	.575**
	Sig. (2-tailed)	.307	.246	<.001	<.001		<.001
	N	130	151	151	151	151	151
Flourishing_M	Pearson Correlation	.105	.083	.503**	-.315**	.575**	1
	Sig. (2-tailed)	.235	.310	<.001	<.001	<.001	
	N	130	151	151	151	151	151

**. Correlation is significant at the 0.01 level (2-tailed).

4.2 Mediation Analyses

Mediation analyses were conducted using PROCESS Model 4 to explore how AI use type affects well-being outcomes with productivity acting as a mediator. The analysis revealed that productivity significantly mediated the relationship between AI use type and well-being, as measured by SPANE and Flourishing. The direct effect of AI use type on SPANE was not significant (effect = 0.0006, p = .8166), but the indirect effect through productivity was significant (indirect effect = 0.0029, 95% CI [0.0008, 0.0053]), indicating that higher AI use for core tasks enhances well-being by increasing productivity. Similarly, for Flourishing, the direct effect of AI use type was not significant (effect = -0.0011, p = .6983), but the indirect effect through productivity was significant (indirect effect = 0.0050, 95% CI [0.0021, 0.0086]), further reinforcing the role of productivity as a critical mediator in translating AI use into improved well-being.

4.3 Serial Mediation Analyses

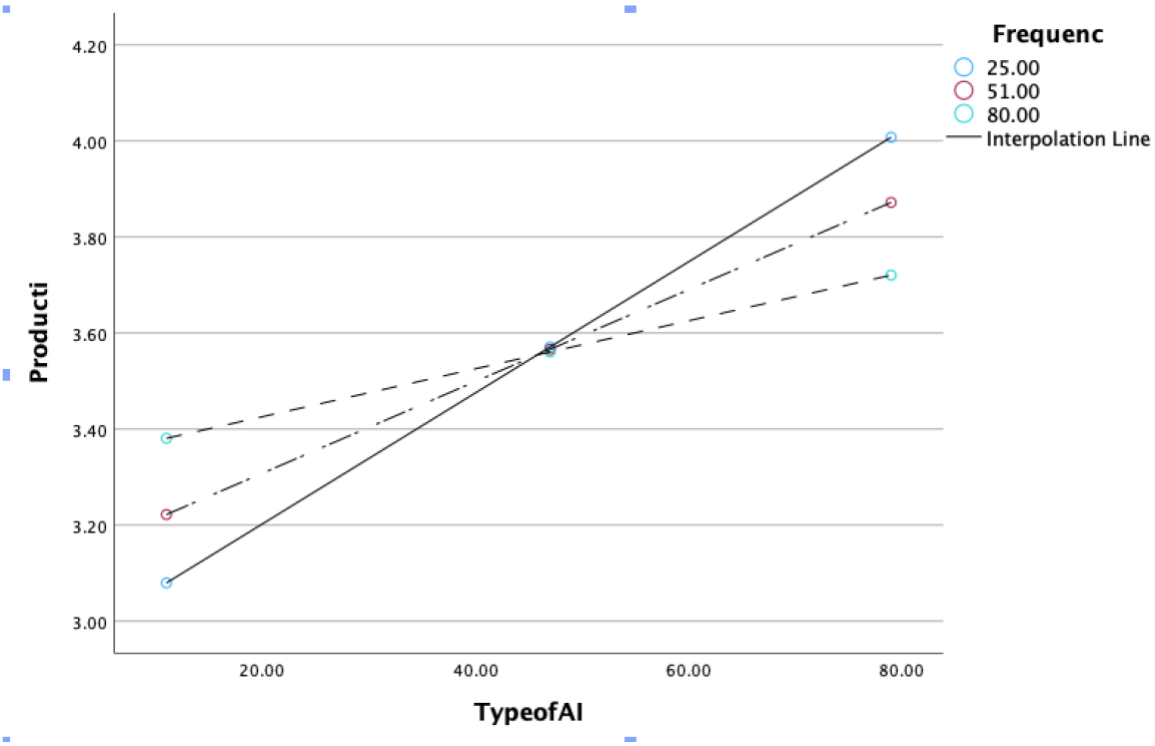
To delve deeper into the pathways linking AI use to well-being, serial mediation analyses were conducted using PROCESS Model 6, revealing that the relationship between AI use type and well-being is sequentially mediated by both productivity and burnout. For SPANE, the serial mediation analysis indicated a significant indirect effect of AI use type on well-being through productivity and burnout (indirect effect = 0.0017, 95% CI [0.0005, 0.0034]), suggesting that AI use enhances well-being by first increasing productivity, which subsequently reduces burnout. A similar pattern was observed for Flourishing, with a significant indirect effect through productivity and burnout (indirect effect = 0.0007, 95% CI [0.0001, 0.0019]). These results highlight the importance of considering both productivity and burnout in understanding how AI use affects well-being, providing a comprehensive view of the mechanisms involved.

4.4 Moderated Mediation Analyses

Moderated mediation analyses using PROCESS Model 83 further explored whether the frequency of AI use moderates the indirect effects of AI use type on well-being through productivity and burnout. The findings revealed significant moderated mediation effects, with the indirect effect of AI use type on SPANE through productivity and burnout being significant at lower (Frequency = 25; indirect effect = 0.0026, 95% CI [0.0009, 0.0050]) and moderate (Frequency = 51; indirect effect = 0.0018, 95% CI [0.0006, 0.0035]) levels of AI frequency. However, this effect became non-significant at higher frequencies of AI use (Frequency = 80; indirect effect = 0.0009, 95% CI [-0.0003, 0.0026]). A similar trend was observed for Flourishing, where the indirect effect was significant at lower and moderate AI frequencies (Frequency = 25; indirect effect = 0.0011, 95% CI [0.0001, 0.0027]; Frequency = 51; indirect effect = 0.0008, 95% CI [0.0001, 0.0019]), but not at the highest frequency (Frequency = 80; indirect effect = 0.0004, 95% CI [-0.0002, 0.0013]). These results suggest that the benefits of AI use on well-being are most pronounced at moderate levels of AI frequency and tend to diminish with excessive use. This pattern aligns with the concept of diminishing returns, indicating that while AI use can enhance well-being through increased productivity and reduced burnout, overuse may negate these benefits. Consequently, the findings support a nuanced approach to AI

integration, where optimal use is key to maximizing positive outcomes for employee well-being. Figure 6 visualizes this relationship.

Figure 6



5 Discussion

5.1 Overview

This study provides valuable insights into the complex relationship between AI usage, productivity, burnout, and well-being within contemporary work environments. Our findings contribute significantly to the growing body of literature on AI integration, challenging some of the prevailing assumptions about the benefits of AI in the workplace, particularly concerning the type and frequency of AI use.

5.1.1 AI Use and Productivity

One of the pivotal findings of our study contradicts Hypothesis 3, which posited that peripheral AI use would be more positively associated with productivity. Contrary to this hypothesis, our results revealed that core AI uses—applications directly related to essential job functions—are more strongly associated with increased productivity ($r = .295$, $p < .001$). This outcome aligns with the understanding of scholars who have explored the productivity benefits of AI use when integrated into core work tasks (Choi & Schwarcz, 2023; Dell'Acqua et al., 2023).

While it was hypothesized that peripheral uses of AI would be more beneficial for workers' perceived productivity gains, core uses being a predictor for worker productivity is an equally interesting finding. While the ethical implications of automating important human work are unclear, this finding opens new avenues for exploration into how AI can effectively be integrated into workers' core tasks while minimizing the negative effects associated with doing so. This finding also brings a new understanding that AI shouldn't just be used as our administrators and secretaries but as a co-intelligence working on our work's most essential tasks.

Furthermore, the moderation analysis of AI use frequency challenges Hypothesis 4, which suggested that peripheral AI use would have a stronger positive effect on productivity when used more frequently. Instead, we found that core AI uses lead to productivity increases most significantly at low and medium levels of use. While this finding was unexpected, it is a very interesting finding and has important implications for businesses implementing AI into their

workers' daily lives. Our data suggests that employees should use AI to assist with their core tasks, but tastefully and with caution.

This finding suggests that at low and medium levels of AI use, AI serves as an effective augmentation to human capabilities without overwhelming the user. However, as AI use frequency increases, productivity gains diminish. Managers and workers must think strategically about what types of work they should use AI for; because our findings suggest that all AI uses don't translate to productivity gains equally, nor does the frequency with which one uses it. Workers likely know the ways that AI helps them best, but further research should be done to establish what tasks lead to the most productivity gains and what type of working style best translates to, whether it is the cyborg or centaur approach (Dell'Acqua et al., 2023).

These results underscore the importance of a strategic approach to AI deployment within organizations. Rather than aiming constant AI integration, companies should focus on leveraging AI in key areas where it can most effectively complement human skills. Regular monitoring of AI's impact on productivity is essential to ensure that its use remains optimal, enhancing performance without leading to negative side effects.

5.1.2 AI Use and Burnout

The relationship between AI use and burnout is indeed multifaceted, as our findings highlight. Consistent with Hypothesis 5, which proposed that AI could reduce burnout by increasing productivity, we observed that AI-driven productivity gains can alleviate some of the workload pressures that typically lead to burnout. This aligns with existing literature, suggesting that AI's ability to streamline tasks and enhance efficiency allows employees to complete their work more quickly and with less effort, thereby reducing stress levels associated with high workloads (Brynjolfsson et al., 2023; Raya-Povedano, 2021).

However, the potential for AI to exacerbate burnout, as observed in certain contexts within our study, underscores the dual-edged nature of AI integration in the workplace. While AI can alleviate burnout by reducing workload, it can also contribute to it if used excessively. This aspect of our findings suggests that AI is always a solution to burnout, suggesting instead that the manner and frequency of AI integration are critical in determining its effects.

These findings emphasize the importance of organizational context in shaping the outcomes of AI use. Organizations must not only provide AI tools but also foster a supportive environment where AI is perceived as a resource that enhances the work process rather than a burden that adds to it. This might involve offering training programs that help employees manage their workload effectively with AI, promoting a balanced approach to AI use, and cultivating a workplace culture that prioritizes well-being alongside productivity.

To maximize the benefits of AI while mitigating its potential downsides, organizations should consider implementing AI in a way that supports, rather than overwhelms, employees. This may involve limiting the frequency of AI use in certain tasks, ensuring that AI serves as a complement to human skills rather than a replacement, and providing the necessary support to help employees adapt to AI-enhanced workflows.

5.1.3 AI Use and Well-Being

The relationship between AI use and well-being is complex, particularly when considering the indirect effects mediated by productivity and burnout. Our findings reveal that while the direct relationship between AI use and well-being—measured by SPANE (Scale of Positive and Negative Experience) and Flourishing—was not statistically significant, the indirect effects through productivity and burnout provided deeper insights. Specifically, Hypothesis 2 proposed that AI would enhance well-being through increased productivity, and Hypothesis 5 suggested a serial mediation effect where AI use would lead to increased productivity, subsequently reducing burnout, and ultimately improving well-being.

Our data partially supports these hypotheses, as the indirect effects indicate that AI's influence on well-being is primarily mediated by its impact on productivity and burnout. This suggests that AI does not directly enhance employees' subjective well-being but rather alters their work experience, which in turn affects how they perceive their overall well-being. When AI is used optimally to increase productivity, it can reduce burnout by alleviating workload pressures, indirectly contributing to more positive work experiences and better well-being.

The moderation analysis, particularly relevant to Hypothesis 4, underscores the critical role of AI use frequency in determining these outcomes. At moderate levels, core AI use appears to

optimize productivity and reduce burnout, both of which contribute positively to well-being. However, the benefits diminish at higher frequencies of AI use, supporting the concept of diminishing returns discussed earlier. Excessive AI use may lead to cognitive overload, reduced personal engagement with work, or even disengagement, thereby negating the positive effects on well-being that might otherwise occur.

These findings highlight the importance of balance in AI usage. For organizational leaders and managers, this suggests that AI implementation strategies should not merely focus on maximizing AI integration but rather on how AI can best complement their employees' abilities. By fostering environments where AI is used to support, rather than overwhelm, employees, organizations can enhance job satisfaction and well-being. Solutions may involve providing employees with the autonomy to determine the appropriate level of AI usage in their tasks, alongside targeted training to manage AI tools effectively, but future exploration is needed.

While AI has the potential to enhance well-being indirectly by improving productivity and reducing burnout, these benefits are contingent upon careful management of AI use frequency. For managers, this underscores the importance of creating a balanced AI strategy that optimizes productivity and well-being without leading to negative side effects.

5.1.4 Theoretical Contributions

This study offers significant theoretical contributions to the understanding of AI's role in the workplace by revealing the nuanced impacts of both the type and frequency of AI use on key employee outcomes. Our findings contribute to the literature on AI and productivity, particularly by introducing the concept of diminishing returns in AI usage as it relates to well-being. This insight—that more frequent AI use does not necessarily lead to better outcomes—adds a new dimension to the discourse on AI integration, emphasizing the importance of the context and quality of AI applications over mere frequency.

The results from Hypotheses 3 and 4 were instrumental in advancing this theoretical understanding. Contrary to Hypothesis 3, which suggested that peripheral AI use would be more positively associated with productivity, our findings indicate that core AI uses—those directly tied to essential job functions—had a stronger impact on productivity ($r = .295$, $p < .001$). This

result refines our understanding of AI's role in work processes, showing that the most substantial benefits are realized when AI supports tasks central to an employee's role and is used at a moderate level. This challenges the assumption that all AI applications equally enhance productivity, highlighting instead the importance of aligning AI use with core job functions to achieve optimal outcomes.

In the broader scheme, this study presents a novel pathway through which AI use leads to worker well-being, a significant new contribution to the literature. Our findings suggest that AI assistance with core work tasks, used at a moderate level, drives productivity gains and can reduce burnout, enhancing overall well-being. As AI is increasingly adopted by more companies, understanding this pathway has substantial implications. It highlights the importance of not just integrating AI but doing so in a way that maximizes positive employee outcomes, offering a roadmap for organizations to harness AI's potential while safeguarding and enhancing worker well-being. Additionally, the implications for future research are equally exciting, as this model opens new avenues for discovery. By exploring how different types of AI applications and varying levels of AI use interact with other organizational factors, researchers can further unravel the complexities of AI's impact on the workforce, leading to more targeted and effective strategies for AI integration.

5.2 Practical Implications

5.2.1 Strategic AI Deployment

The findings of this study underscore the critical importance of a strategic approach to AI deployment in the workplace, particularly when AI is utilized to enhance productivity in core tasks. Contrary to the prevailing assumption that increased AI usage invariably leads to better outcomes, our results highlight that the effectiveness of AI in boosting productivity is contingent upon both its application and the frequency of use. Specifically, AI delivers the most significant productivity benefits when integrated into core job functions in a moderated manner. This strategic deployment ensures that AI augments human capabilities rather than overwhelms them, thereby maximizing productivity without leading to cognitive overload or diminished employee engagement.

For practitioners, this means that organizations should avoid a one-size-fits-all approach to AI integration and instead focus on areas where AI can most effectively complement human skills. Leaders should conduct thorough job analyses to identify specific tasks where AI can enhance performance without undermining the critical thinking and problem-solving abilities of their workforce. This process should involve collaborating with employees to ensure that AI tools are aligned with the actual demands of their roles. Regular training sessions and updates on AI tools can also help employees stay informed and engaged, further enhancing the strategic value of AI deployment.

5.2.2 Balancing AI Use to Mitigate Burnout

The nuanced relationship between AI use and burnout, as revealed in this study, highlights the necessity of careful management of AI integration. While AI has the potential to alleviate burnout by reducing workload pressures, this benefit is closely linked to the frequency and manner of AI use. At moderate levels, core AI use can automate repetitive tasks, enabling employees to focus on more meaningful and engaging work, thereby reducing stress. However, as AI usage intensifies, the risk of burnout may increase, possibly due to the constant interaction with AI systems that could lead to increased stress or a sense of detachment from one's work.

To mitigate these risks, organizations should develop clear guidelines on AI usage that prioritize employee well-being. This includes setting limits on the frequency of AI use in daily tasks to prevent overreliance and potential burnout. Regular monitoring and feedback mechanisms are essential, allowing employees to voice their experiences and concerns regarding AI use. For instance, HR departments could implement periodic surveys or focus groups to assess the impact of AI on employee well-being and make necessary adjustments to AI usage protocols. Additionally, managers should be trained to recognize signs of burnout and take proactive steps to adjust AI workloads as needed.

5.2.3 Enhancing Well-Being Through Moderated AI Use

The study also emphasizes the importance of moderated AI use in fostering employee well-being. Although AI does not directly enhance well-being, it can indirectly contribute by

increasing productivity and reducing burnout. These benefits are most pronounced when AI is used judiciously. Overuse of AI, however, can lead to stress and disengagement, potentially negating the positive effects on well-being.

To leverage AI effectively, human resources and leadership teams should prioritize AI integration in a way that empowers employees to maintain control over their work processes. Providing targeted training programs that equip employees with the skills to manage AI tools effectively ensures that these tools are seen as enablers rather than burdens. Leadership should also work to create an organizational culture that views AI as a collaborative tool designed to assist rather than replace human workers. This cultural shift can help reduce anxiety and resistance, fostering a more positive attitude towards AI technologies. By positioning AI as a resource that enhances the employee experience, organizations can cultivate an environment where AI contributes to, rather than detracts from, overall well-being.

5.2.4 Tailoring AI Strategies to Organizational Contexts

The findings regarding the moderation effects of AI usage suggest that the optimal level of AI integration varies significantly depending on the organizational context and the nature of the tasks involved. In cognitively demanding roles, excessive AI use can exacerbate burnout and reduce job satisfaction, while in more routine or repetitive tasks, AI can be leveraged more heavily to improve efficiency and reduce workload.

Managers should tailor AI strategies to align with the specific needs and characteristics of their teams. This involves not only selecting the appropriate AI tools but also determining the right level of AI involvement in daily tasks. For example, in high-pressure environments, it might be beneficial to limit AI usage to assistive functions that reduce cognitive load, whereas in routine tasks, AI can be fully integrated to automate processes. By adopting a context-specific approach, organizations can achieve a balance between technological efficiency and employee satisfaction. Regular check-ins and assessments can help ensure that AI tools are being used optimally across different roles, preventing both underutilization and overburdening.

5.2.5 Continuous Monitoring and Adaptation

Given the dynamic and evolving nature of AI's impact on the workplace, it is imperative for organizations to engage in continuous monitoring and adaptation of their AI strategies. As AI technologies become more deeply embedded in organizational processes, their effects on productivity, burnout, and well-being are likely to evolve. Establishing regular feedback mechanisms and conducting periodic performance assessments can help organizations remain attuned to these changes, allowing for timely adjustments to AI strategies.

This proactive approach will enable organizations to maximize the benefits of AI while minimizing potential negative consequences. For example, organizations might consider implementing AI usage dashboards that track employee interactions with AI tools, combined with regular well-being check-ins. This data-driven approach would allow managers to identify trends and make informed decisions about when and how to adjust AI deployment. Additionally, organizations should foster a culture of flexibility, where employees feel empowered to provide input on AI usage and its impact on their work. By staying responsive to the changing landscape of AI use, organizations can foster a work environment that promotes both high performance and employee well-being, ensuring that AI continues to serve as a positive force within the organization.

5.3 Limitations and Future Research

5.3.1 Limitations

While this study provides valuable insights into the complex effects of AI usage on productivity, burnout, and well-being, several limitations must be acknowledged to contextualize our findings and inform future research directions.

A primary limitation of this research lies in its reliance on self-reported productivity measures. Although self-reports are a common methodological approach in social science, they remain inherently subjective and prone to biases. Respondents may unintentionally distort their responses due to personal perceptions, cognitive biases, or a desire to present themselves favorably (Jahedi and Méndez, 2014). This potential distortion could affect the observed

relationship between the frequency of AI use, the type of AI use productivity, and their relationships with other variables.

Another significant limitation is the demographic composition of the sample, which was predominantly female. While this focus offers important insights into how women experience AI integration in the workplace, it may not fully capture the experiences of the broader workforce. Gender dynamics are known to play a crucial role in technology adoption and interaction, and the overrepresentation of women in this sample could limit the generalizability of the findings (Gefen and Straub, 1997; Zhang et al., 2014). Future research should aim for a more gender-balanced sample to explore potential gender differences in AI usage patterns, perceptions, and outcomes.

Furthermore, the inclusion of students in the sample introduces an additional limitation. Students, who often face different expectations, stressors, and experiences compared to full-time professionals, might not fully reflect the dynamics present in more traditional employment settings. Thus the inclusion of students in this sample could skew the results, and the findings should be interpreted with caution (Peterson, 2001). To address this limitation, future studies should consider focusing on specific industries or targeting knowledge workers more broadly to obtain a more homogeneous and representative sample

Moreover, while our scale for measuring AI use frequency provided relevant insights into how often participants use AI, it was not without flaws. Specifically, the scale did not allow participants to specify how much they use AI throughout each day. The highest point on the scale indicated daily use but lacked the granularity needed to capture specific daily usage patterns. Future studies should collect more nuanced data, potentially through a second measure that captures the frequency and intensity of AI use throughout the workday. This would enable a more detailed analysis of how varying levels of AI interaction influence productivity, burnout, and well-being.

Additionally, while our study successfully grouped participants into core and peripheral AI uses, differences in job titles and daily tasks could influence how participants classify these categories. For instance, an executive might view scheduling a meeting as a peripheral task, while a secretary might consider it a core function. As a result, some tasks might be more challenging to

classify consistently across different roles. Therefore, while our classification of work tasks yielded valuable findings, future studies would benefit from developing more specific and standardized classifications of job duties. This could involve creating job-specific task lists that better capture the nuanced differences in AI use across various positions. Further, employing qualitative methods, such as interviews or focus groups, could provide richer context and understanding of how individuals perceive and classify AI use in their roles.

Lastly, a methodological shortfall of our study was not measuring the amount of non-AI technology each participant uses at work. Measuring this could be important due to the technology fatigue employees may already feel without using AI technology at work (Lee et al., 2016). Future work should focus on implementing this into our model for further nuance. By understanding the broader technological environment in which AI operates, researchers can better isolate the specific effects of AI on productivity and well-being, distinguishing them from the general impact of technology use.

5.3.2 Future Research Directions

Given these limitations, several promising avenues for future research emerge, each with the potential to deepen our understanding of AI's role in the workplace and its broader implications.

First, to address the limitation of subjective productivity measures, future research should incorporate both subjective and objective data. This could involve tracking real-time performance metrics, such as output quality, task completion rates, and efficiency, alongside self-reported productivity. By comparing and contrasting these measures, researchers could uncover discrepancies between perceived and actual productivity, offering a more nuanced view of AI's true impact on work performance. This dual approach would enhance the robustness of the findings and provide a clearer understanding of how AI influences both perceived and actual productivity outcomes.

In light of the gender imbalance observed in the current study, future research should strive to recruit a more gender-diverse sample. Understanding how different genders experience and influence AI use could reveal critical differences that inform more inclusive and effective AI implementation strategies. Such an approach would also explore whether the benefits or

drawbacks of AI use vary by gender, offering more insights into how AI technologies can be tailored to meet the needs of a diverse workforce.

To mitigate the influence of the student population on the findings, future studies could focus on specific industries or target a broader spectrum of knowledge workers. Narrowing the research focus to particular sectors or professional groups would enable a deeper exploration of the unique challenges and opportunities associated with AI integration in different contexts. Because specific industries are using AI differently, studies might uncover industry-specific factors that influence AI adoption and effectiveness, leading to more targeted and practical insights for business leaders and policymakers. For example, exploring AI use in high-stress industries, such as healthcare or finance, could reveal if AI continues to influence burnout and productivity and if specific sectors have pronounced effects.

Furthermore, our study found that core uses of AI lead to greater productivity than peripheral uses. This suggests a need to explore other smaller subsections of each category or entirely new categories. Future researchers might group AI tasks into creative versus non-creative categories or make other meaningful distinctions. Additionally, researchers should aim to break down these dyadic categories into smaller, more specific classifications to capture the nuances of how different, specific types of AI use impact productivity, burnout, and well-being. This could involve analyzing the cognitive demands of different tasks and how AI assists or hinders these processes.

Given that our study found core uses of AI lead to higher productivity, another valuable avenue for future research would be to explore how AI's automation of core duties affects employees' feelings of pride and ownership over their work. It is crucial to understand how this automation impacts employees' emotional connection to their work—a key predictor of workplace well-being (Kun & Gadanecz, 2019). Future researchers could examine whether the automation of core tasks diminishes or enhances employees' sense of pride, which in turn could influence their overall well-being and job satisfaction. This line of inquiry would provide deeper insights into the psychological effects of AI integration and help organizations balance productivity gains with maintaining a positive work environment.

Another intriguing area for future research lies in exploring the differential impact of AI on productivity across varying levels of expertise. A study by Logg and colleagues has indicated that experts tend to trust AI less than laypersons, which may limit the technology's effectiveness in expert-dominated fields (2019). This suggests that AI's productivity benefits might be more pronounced among non-experts. Therefore, future research should focus on measuring expertise levels, along with industry and job roles, to assess how trust in AI and subsequent productivity gains differ between experts and laypersons. Understanding these dynamics could lead to more nuanced AI integration strategies tailored to varying levels of expertise.

Finally, future research should consider adopting a longitudinal approach to explore the long-term effects of AI use on productivity, burnout, and well-being. While this study provides a valuable snapshot of these relationships, a longitudinal design would allow for the examination of how these dynamics evolve over time (Zeegers, 2001). Such research could offer important insights into the sustained impact of AI on employee outcomes and inform the development of adaptive strategies that organizations can employ to maximize the long-term benefits of AI while mitigating potential negative consequences. Understanding these temporal effects would be particularly valuable in guiding the ongoing integration of AI technologies in the workplace, ensuring that AI continues to enhance, rather than detract from, employee well-being and productivity over the long term.

6 Conclusion

This study offers significant contributions to our understanding of AI's multifaceted role in modern workplaces, particularly its nuanced influence on productivity, burnout, and well-being. By dissecting AI use into type and frequency, we demonstrated that AI can significantly enhance productivity when strategically integrated into core job functions. However, our findings also caution against the pitfalls of excessive AI use, which can lead to diminishing returns on productivity.

A key insight from our research is the indirect effect of core AI use on employee well-being, mediated by its effects on productivity and burnout. While AI has the potential to improve well-being by streamlining tasks and reducing stress, these benefits are contingent on careful management and balanced integration. Contrary to popular belief, higher frequencies of AI use do not necessarily yield better outcomes, underscoring the importance of a nuanced, strategic approach to AI deployment.

This study challenges the prevailing assumption that more AI is inherently better. Instead, it advocates for a thoughtful, optimized use of AI that enhances both performance and employee well-being. These findings have practical implications for organizations aiming to leverage AI technologies to foster a productive and healthy work environment.

Looking ahead, our research paves the way for future exploration into how AI can be harnessed to drive both organizational success and employee satisfaction. As AI technologies continue to evolve, their thoughtful integration will be crucial for realizing their full potential. The ongoing challenge will be to balance the benefits of AI with its potential downsides, ensuring that AI serves as a positive force within the workplace for the long term.

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Appendices

Appendix A – Scale Reliabilities

Scale: Burnout

Case Processing Summary

		N	%
Cases	Valid	151	99.3
	Excluded[a]	1	.7
	Total	152	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.866	15

Scale: SPANE

Case Processing Summary

		N	%
Cases	Valid	151	99.3
	Excluded[a]	1	.7
	Total	152	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.916	12

Scale: Flourishing

Case Processing Summary

		N	%
Cases	Valid	151	99.3
	Excluded[a]	1	.7
	Total	152	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.907	8

Appendix B – Full Report of Statistical Tests

Test #1

```
Run MATRIX procedure:


***************** PROCESS Procedure for SPSS Version 4.2
*****************

          Written by Andrew F. Hayes, Ph.D.
www.afhayes.com

    Documentation available in Hayes (2022).
www.guilford.com/p/hayes3


**************************************************************************
**********

Model  : 4

    Y  : SPANE_M

    X  : TypeofAI

    M  : Producti


Covariates:

 Age


Sample

Size:  130


**************************************************************************
**********

OUTCOME VARIABLE:

 Producti
```

```
Model Summary

          R       R-sq        MSE          F        df1
df2          p

      .3536      .1251      .4856     9.0763     2.0000
127.0000      .0002


Model

              coeff         se          t          p       LLCI
ULCI

constant     2.7400      .2069    13.2440      .0000     2.3306
3.1493

TypeofAI      .0091      .0023
3.9602      .0001      .0045      .0136

Age           .1093      .0466
2.3460      .0205      .0171      .2014


**************************************************************
**********

OUTCOME VARIABLE:

 SPANE_M


Model Summary

          R       R-sq        MSE          F        df1
df2          p

      .3529      .1246      .5019     5.9765     3.0000
126.0000      .0008


Model

              coeff         se          t          p       LLCI
ULCI
```

```
constant     2.0359      .3245     6.2733      .0000     1.3937
2.6782

TypeofAI      .0006      .0025      .2324      .8166
-.0043      .0055

Producti      .3179      .0902
3.5239      .0006      .1394      .4964

Age           .0639      .0484     1.3212      .1888
-.0318      .1596



****************** DIRECT AND INDIRECT EFFECTS OF X ON Y
*****************


Direct effect of X on Y

     Effect         se          t          p       LLCI
ULCI

      .0006      .0025      .2324      .8166
-.0043      .0055


Indirect effect(s) of X on Y:

             Effect     BootSE   BootLLCI   BootULCI

Producti      .0029      .0012      .0008      .0053


********************** ANALYSIS NOTES AND ERRORS
************************


Level of confidence for all confidence intervals in output:

  95.0000
```

Number of bootstrap samples for percentile bootstrap confidence intervals:

5000

WARNING: Variables names longer than eight characters can produce incorrect output

when some variables in the data file have the same first eight characters. Shorter

variable names are recommended. By using this output, you are accepting all risk

and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----

Test #2

Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

Written by Andrew F. Hayes, Ph.D. www.afhayes.com

Documentation available in Hayes (2022). www.guilford.com/p/hayes3

****

```
Model  : 4
    Y  : Flourish
    X  : TypeofAI
    M  : Producti

Covariates:
 Age

Sample
Size:  130

**************************************************************
**********
OUTCOME VARIABLE:
 Producti

Model Summary
          R       R-sq        MSE          F        df1
df2          p
      .3536      .1251      .4856     9.0763     2.0000
127.0000      .0002

Model
              coeff         se          t          p       LLCI
ULCI
constant     2.7400      .2069    13.2440      .0000     2.3306
3.1493
TypeofAI      .0091      .0023
3.9602      .0001      .0045      .0136
```

```
Age           .1093      .0466
2.3460      .0205      .0171      .2014

*************************************************************
**********

OUTCOME VARIABLE:

 Flourish


Model Summary

          R       R-sq        MSE          F        df1
df2          p

      .4292      .1842      .7203     9.4848     3.0000
126.0000      .0000


Model

              coeff         se          t          p       LLCI
ULCI

constant     3.6328      .3888     9.3438      .0000     2.8634
4.4022

TypeofAI     -.0011      .0030     -.3885      .6983
-.0070      .0047

Producti      .5554      .1081
5.1397      .0000      .3416      .7693

Age          -.0276      .0579     -.4764      .6346
-.1423      .0871



****************** DIRECT AND INDIRECT EFFECTS OF X ON Y
****************


Direct effect of X on Y
```

```
     Effect         se          t          p       LLCI
ULCI

     -.0011      .0030     -.3885      .6983
-.0070      .0047


Indirect effect(s) of X on Y:

             Effect     BootSE   BootLLCI   BootULCI

Producti      .0050      .0016      .0021      .0086


************************ ANALYSIS NOTES AND ERRORS
************************

Level of confidence for all confidence intervals in output:

  95.0000


Number of bootstrap samples for percentile bootstrap confidence
intervals:

  5000


WARNING: Variables names longer than eight characters can
produce incorrect output

when some variables in the data file have the same first eight
characters. Shorter

variable names are recommended. By using this output, you are
accepting all risk

and consequences of interpreting or reporting results that may
be incorrect.


------ END MATRIX -----
```

Test #3

```
Run MATRIX procedure:


***************** PROCESS Procedure for SPSS Version 4.2
*****************

          Written by Andrew F. Hayes, Ph.D.
www.afhayes.com

    Documentation available in Hayes (2022).
www.guilford.com/p/hayes3


**************************************************************************
**********

Model  : 6

    Y  : Flourish

    X  : TypeofAI

   M1  : Producti

   M2  : OLBI_M


Covariates:

 Age


Sample

Size:  130


**************************************************************************
**********

OUTCOME VARIABLE:
```

```
 Producti


Model Summary

          R       R-sq        MSE          F        df1
df2          p

      .3536      .1251      .4856     9.0763     2.0000
127.0000      .0002


Model

              coeff         se          t          p       LLCI
ULCI

constant     2.7400      .2069    13.2440      .0000     2.3306
3.1493

TypeofAI      .0091      .0023
3.9602      .0001      .0045      .0136

Age           .1093      .0466
2.3460      .0205      .0171      .2014


**************************************************************
**********

OUTCOME VARIABLE:

 OLBI_M


Model Summary

          R       R-sq        MSE          F        df1
df2          p

      .3396      .1153      .3690     5.4762     3.0000
126.0000      .0014


Model
```

```
              coeff         se          t          p       LLCI
ULCI

constant     4.0280      .2783    14.4740      .0000     3.4772
4.5787

TypeofAI      .0012      .0021      .5857      .5591
-.0030      .0054

Producti     -.2794      .0774    -3.6126      .0004     -.4325
-.1264

Age          -.0432      .0415    -1.0414      .2997
-.1253      .0389


**************************************************************
**********

OUTCOME VARIABLE:

 Flourish


Model Summary

          R       R-sq        MSE          F        df1
df2          p

      .4667      .2179      .6961     8.7042     4.0000
125.0000      .0000


Model

              coeff         se          t          p       LLCI
ULCI

constant     4.7753      .6237     7.6566      .0000     3.5410
6.0097

TypeofAI     -.0008      .0029     -.2738      .7847
-.0066      .0050

Producti      .4762      .1116
4.2666      .0000      .2553      .6971
```

```
OLBI_M       -.2837      .1224    -2.3183      .0221     -.5258
-.0415

Age          -.0399      .0572     -.6967      .4873
-.1531      .0734


****************** DIRECT AND INDIRECT EFFECTS OF X ON Y
*****************


Direct effect of X on Y

     Effect         se          t          p       LLCI
ULCI

     -.0008      .0029     -.2738      .7847
-.0066      .0050


Indirect effect(s) of X on Y:

          Effect     BootSE   BootLLCI   BootULCI

TOTAL      .0047      .0018      .0014      .0083

Ind1       .0043      .0015      .0016      .0075

Ind2      -.0004      .0007     -.0019      .0009

Ind3       .0007      .0005      .0001      .0019


Indirect effect key:

Ind1 TypeofAI    ->    Producti    ->    Flourish

Ind2 TypeofAI    ->    OLBI_M      ->    Flourish

Ind3 TypeofAI    ->    Producti    ->    OLBI_M      ->
Flourish


********************** ANALYSIS NOTES AND ERRORS
************************
```

Level of confidence for all confidence intervals in output:

  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

  5000

WARNING: Variables names longer than eight characters can produce incorrect output

when some variables in the data file have the same first eight characters. Shorter

variable names are recommended. By using this output, you are accepting all risk

and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----

Test #4

Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.
www.afhayes.com

    Documentation available in Hayes (2022).
www.guilford.com/p/hayes3

```
**************************************************************************
**********
Model  : 6
    Y  : SPANE_M
    X  : TypeofAI
   M1  : Producti
   M2  : OLBI_M

Covariates:
 Age

Sample
Size:  130

**************************************************************************
**********
OUTCOME VARIABLE:
 Producti

Model Summary
          R       R-sq        MSE          F        df1
df2          p
      .3536      .1251      .4856     9.0763     2.0000
127.0000      .0002

Model
              coeff         se          t          p       LLCI
ULCI
```

```
constant     2.7400      .2069    13.2440      .0000     2.3306
3.1493

TypeofAI      .0091      .0023
3.9602      .0001      .0045      .0136

Age           .1093      .0466
2.3460      .0205      .0171      .2014


**************************************************************
**********

OUTCOME VARIABLE:

 OLBI_M


Model Summary

          R       R-sq        MSE          F        df1
df2          p

      .3396      .1153      .3690     5.4762     3.0000
126.0000      .0014


Model

              coeff         se          t          p       LLCI
ULCI

constant     4.0280      .2783    14.4740      .0000     3.4772
4.5787

TypeofAI      .0012      .0021      .5857      .5591
-.0030      .0054

Producti     -.2794      .0774    -3.6126      .0004     -.4325
-.1264

Age          -.0432      .0415    -1.0414      .2997
-.1253      .0389
```

```
**************************************************************************
**********

OUTCOME VARIABLE:

 SPANE_M


Model Summary

          R       R-sq        MSE          F        df1
df2          p

      .6464      .4179      .3364    22.4333     4.0000
125.0000      .0000


Model

              coeff         se          t          p       LLCI
ULCI

constant     4.7549      .4336    10.9671      .0000     3.8969
5.6130

TypeofAI      .0014      .0020      .6970      .4871
-.0026      .0054

Producti      .1293      .0776     1.6660      .0982
-.0243      .2828

OLBI_M       -.6750      .0851    -7.9362      .0000     -.8434
-.5067

Age           .0347      .0398      .8738      .3839
-.0440      .1134



****************** DIRECT AND INDIRECT EFFECTS OF X ON Y
*****************


Direct effect of X on Y
```

```
     Effect         se          t          p       LLCI
ULCI

      .0014      .0020      .6970      .4871
-.0026      .0054


Indirect effect(s) of X on Y:

          Effect     BootSE   BootLLCI   BootULCI

TOTAL      .0020      .0018     -.0015      .0054

Ind1       .0012      .0008     -.0004      .0027

Ind2      -.0008      .0014     -.0036      .0018

Ind3       .0017      .0007      .0005      .0034


Indirect effect key:

Ind1 TypeofAI    ->    Producti    ->    SPANE_M

Ind2 TypeofAI    ->    OLBI_M      ->    SPANE_M

Ind3 TypeofAI    ->    Producti    ->    OLBI_M      ->
SPANE_M


************************ ANALYSIS NOTES AND ERRORS
************************


Level of confidence for all confidence intervals in output:

  95.0000


Number of bootstrap samples for percentile bootstrap confidence
intervals:

  5000
```

```
WARNING: Variables names longer than eight characters can
produce incorrect output

when some variables in the data file have the same first eight
characters. Shorter

variable names are recommended. By using this output, you are
accepting all risk

and consequences of interpreting or reporting results that may
be incorrect.


------ END MATRIX -----
```

Test #5

```
Run MATRIX procedure:


***************** PROCESS Procedure for SPSS Version 4.2
*****************


          Written by Andrew F. Hayes, Ph.D.
www.afhayes.com

    Documentation available in Hayes (2022).
www.guilford.com/p/hayes3


**************************************************************
**********

Model  : 83

    Y  : SPANE_M
```

```
    X  : TypeofAI
   M1  : Producti
   M2  : OLBI_M
    W  : Frequenc

Covariates:
 Age

Sample
Size:  130

************************************************************
**********
OUTCOME VARIABLE:
 Producti

Model Summary
          R       R-sq        MSE          F        df1
df2          p
      .3934      .1548      .4767     5.7217     4.0000
125.0000      .0003

Model
              coeff         se          t          p       LLCI
ULCI
constant     2.3432      .2943     7.9621      .0000     1.7607
2.9256
TypeofAI      .0176      .0049
3.5809      .0005      .0079      .0273
```

```
Frequenc       .0072       .0040      1.8165       .0717
-.0006       .0151

Int_1          -.0002       .0001     -2.0682       .0407
-.0003       .0000

Age             .1254       .0471
2.6601       .0088       .0321       .2187


Product terms key:

 Int_1    :         TypeofAI x         Frequenc


Test(s) of highest order unconditional interaction(s):

       R2-chng           F         df1         df2           p

X*W       .0289     4.2775     1.0000   125.0000       .0407

----------

    Focal predict: TypeofAI (X)

          Mod var: Frequenc (W)


Conditional effects of the focal predictor at values of the
moderator(s):


   Frequenc     Effect          se           t           p
LLCI       ULCI

    25.0000       .0136       .0034
4.0196       .0001       .0069       .0204

    51.0000       .0096       .0025
3.8631       .0002       .0047       .0145

    80.0000       .0050       .0031      1.6369       .1042
-.0010       .0110
```

```
**************************************************************************
**********

OUTCOME VARIABLE:

 OLBI_M


Model Summary

          R       R-sq        MSE          F        df1
df2          p

      .3396      .1153      .3690     5.4762     3.0000
126.0000      .0014


Model

              coeff         se          t          p       LLCI
ULCI

constant     4.0280      .2783    14.4740      .0000     3.4772
4.5787

TypeofAI      .0012      .0021      .5857      .5591
-.0030      .0054

Producti     -.2794      .0774    -3.6126      .0004     -.4325
-.1264

Age          -.0432      .0415    -1.0414      .2997
-.1253      .0389


**************************************************************************
**********

OUTCOME VARIABLE:

 SPANE_M


Model Summary

          R       R-sq        MSE          F        df1
df2          p
```

```
      .6464      .4179      .3364    22.4333     4.0000
125.0000      .0000


Model

              coeff         se          t          p       LLCI
ULCI

constant     4.7549      .4336    10.9671      .0000     3.8969
5.6130

TypeofAI      .0014      .0020      .6970      .4871
-.0026      .0054

Producti      .1293      .0776     1.6660      .0982
-.0243      .2828

OLBI_M       -.6750      .0851    -7.9362      .0000     -.8434
-.5067

Age           .0347      .0398      .8738      .3839
-.0440      .1134



****************** DIRECT AND INDIRECT EFFECTS OF X ON Y
*****************


Direct effect of X on Y

     Effect         se          t          p       LLCI
ULCI

      .0014      .0020      .6970      .4871
-.0026      .0054


Conditional and unconditional indirect effects of X on Y:


INDIRECT EFFECT:

 TypeofAI    ->    Producti    ->    SPANE_M
```

Frequenc	Effect	BootSE	BootLLCI	BootULCI
25.0000	.0018	.0013	-.0007	.0044
51.0000	.0012	.0009	-.0005	.0030
80.0000	.0006	.0007	-.0005	.0020

Index of moderated mediation:

	Index	BootSE	BootLLCI	BootULCI
Frequenc	.0000	.0000	-.0001	.0000

INDIRECT EFFECT:

TypeofAI -> OLBI_M -> SPANE_M

Effect	BootSE	BootLLCI	BootULCI
-.0008	.0014	-.0035	.0020

INDIRECT EFFECT:

TypeofAI -> Producti -> OLBI_M -> SPANE_M

Frequenc	Effect	BootSE	BootLLCI	BootULCI
25.0000	.0026	.0011	.0009	.0050
51.0000	.0018	.0008	.0006	.0036
80.0000	.0009	.0007	-.0004	.0025

Index of moderated mediation:

	Index	BootSE	BootLLCI	BootULCI
Frequenc	.0000	.0000	-.0001	.0000

```
************************ ANALYSIS NOTES AND ERRORS
************************

Level of confidence for all confidence intervals in output:

  95.0000

Number of bootstrap samples for percentile bootstrap confidence
intervals:

  5000

W values in conditional tables are the 16th, 50th, and 84th
percentiles.

WARNING: Variables names longer than eight characters can
produce incorrect output

when some variables in the data file have the same first eight
characters. Shorter

variable names are recommended. By using this output, you are
accepting all risk

and consequences of interpreting or reporting results that may
be incorrect.

------ END MATRIX -----
```

Test #6

```
Run MATRIX procedure:
```

```
***************** PROCESS Procedure for SPSS Version 4.2
*****************

          Written by Andrew F. Hayes, Ph.D.
www.afhayes.com

    Documentation available in Hayes (2022).
www.guilford.com/p/hayes3

**************************************************************************
**********

Model  : 83

    Y  : Flourish

    X  : TypeofAI

   M1  : Producti

   M2  : OLBI_M

    W  : Frequenc

Covariates:

 Age

Sample

Size:  130

**************************************************************************
**********

OUTCOME VARIABLE:

 Producti

Model Summary
```

```
          R       R-sq        MSE          F        df1
df2          p

      .3934      .1548      .4767     5.7217     4.0000
125.0000      .0003


Model

              coeff         se          t          p       LLCI
ULCI

constant     2.3432      .2943     7.9621      .0000     1.7607
2.9256

TypeofAI      .0176      .0049
3.5809      .0005      .0079      .0273

Frequenc      .0072      .0040     1.8165      .0717
-.0006      .0151

Int_1        -.0002      .0001    -2.0682      .0407
-.0003      .0000

Age           .1254      .0471
2.6601      .0088      .0321      .2187


Product terms key:

 Int_1    :        TypeofAI x        Frequenc


Test(s) of highest order unconditional interaction(s):

       R2-chng          F        df1        df2          p

X*W      .0289     4.2775     1.0000   125.0000      .0407

----------

    Focal predict: TypeofAI (X)

          Mod var: Frequenc (W)
```

Conditional effects of the focal predictor at values of the moderator(s):

Frequenc	Effect	se	t	p	LLCI	ULCI
25.0000	.0136	.0034			4.0196	.0001 .0069 .0204
51.0000	.0096	.0025			3.8631	.0002 .0047 .0145
80.0000	.0050	.0031	1.6369	.1042	-.0010	.0110

****

OUTCOME VARIABLE:

OLBI_M

Model Summary

R	R-sq	MSE	F	df1	df2	p
.3396	.1153	.3690	5.4762	3.0000	126.0000	.0014

Model

	coeff	se	t	p	LLCI	ULCI
constant	4.0280	.2783	14.4740	.0000	3.4772	4.5787
TypeofAI	.0012	.0021	.5857	.5591	-.0030	.0054

```
Producti      -.2794       .0774    -3.6126       .0004      -.4325
-.1264

Age           -.0432       .0415    -1.0414       .2997
-.1253       .0389

**************************************************************
**********

OUTCOME VARIABLE:

 Flourish


Model Summary

          R       R-sq        MSE          F        df1
df2          p

      .4667       .2179       .6961     8.7042     4.0000
125.0000       .0000


Model

              coeff         se          t          p       LLCI
ULCI

constant      4.7753       .6237     7.6566       .0000     3.5410
6.0097

TypeofAI      -.0008       .0029     -.2738       .7847
-.0066       .0050

Producti       .4762       .1116
4.2666       .0000       .2553       .6971

OLBI_M        -.2837       .1224    -2.3183       .0221      -.5258
-.0415

Age           -.0399       .0572     -.6967       .4873
-.1531       .0734
```

```
****************** DIRECT AND INDIRECT EFFECTS OF X ON Y
*****************

Direct effect of X on Y

     Effect         se          t          p       LLCI
ULCI

     -.0008      .0029     -.2738      .7847
-.0066      .0050

Conditional and unconditional indirect effects of X on Y:

INDIRECT EFFECT:

 TypeofAI    ->    Producti    ->    Flourish

   Frequenc     Effect     BootSE   BootLLCI   BootULCI

    25.0000      .0065      .0022      .0029      .0115

    51.0000      .0046      .0016      .0018      .0081

    80.0000      .0024      .0018     -.0009      .0061

      Index of moderated mediation:

              Index     BootSE   BootLLCI   BootULCI
Frequenc     -.0001      .0000     -.0002      .0000

INDIRECT EFFECT:

 TypeofAI    ->    OLBI_M      ->    Flourish

     Effect     BootSE   BootLLCI   BootULCI

     -.0004      .0007     -.0018      .0009
```

INDIRECT EFFECT:

TypeofAI -> Producti -> OLBI_M -> Flourish

	Effect	BootSE	BootLLCI	BootULCI
Frequenc 25.0000	.0011	.0007	.0001	.0028
51.0000	.0008	.0005	.0000	.0020
80.0000	.0004	.0004	-.0002	.0013

Index of moderated mediation:

	Index	BootSE	BootLLCI	BootULCI
Frequenc	.0000	.0000	.0000	.0000

********** ANALYSIS NOTES AND ERRORS **********

Level of confidence for all confidence intervals in output:

95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

5000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

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and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----

Appendix C – Informed Consent & Survey

Survey:

AI and Wellbeing

Start of Block: Informed Consent

Page Break

My name is Hayden Sliger. I am a Masters student at the London School of Economics and Political Science (LSE). I would like to invite you to take part in my dissertation research, which examines the how frequent AI use affects subjective well-being.

If you agree to take part, you will be asked to complete a short 8 to 10 minute survey. Your participation is voluntary. You may stop taking part in the study at any time.

The information that you provide will remain anonymous; I will not ask for your name at any time. Furthermore, the information collected will remain confidential as only I and my dissertation supervisor, Professor Nicole Abi-Esber, will have access to it. The data from this survey will be analysed for broad patterns and it will not be possible to identify any individual responses.

If you have any questions about the research, please contact me at H.Sliger@lse.ac.uk

If you agree to participate, please indicate below.

If you were recuited via the LSE Behavioural Lab, please input your 5-digit SONA ID in the text box below the agreement option

○ I agree, I consent to my data being collected. (1)

_____

Page Break

Please select the option that best describes your frequency of AI use.

	Never	Once a month	Weekly	Most days	Every day
		0		100	
How often do you use AI technology? ()					

Page Break

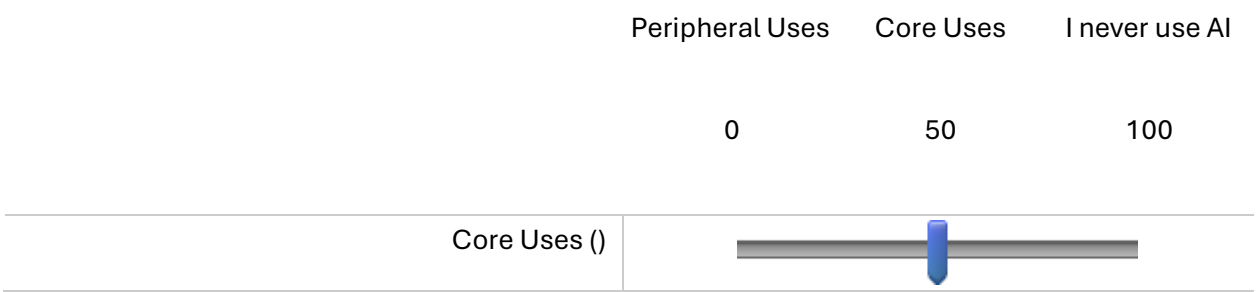
Please move the slider to the area that best represents your use of AI technology. For example if you only use AI for Core Uses, you would move the slider all to the way right (100). And if you only use AI for Peripheral Uses, you would move the slider all the way to the left (0). If you use AI for Core and Peripheral Uses equally, you would move the slider to the middle (50).

If you are a student, please define your job as being a student.

Core Uses: Core uses of AI are use cases where you use AI to assist with or automate the main duties of your job. An example would be if you are a writer, and you use AI technology to write for you.

Peripheral Uses: Peripheral Uses of AI are use cases where you use AI to assist or automate tasks that are outside of your main job duties. An example would be if you are a writer, and you use AI technology to manage your calendar.

I never use AI: Please select this option if you never use AI.



Please write one or two sentences specifying how you typically use AI technology.

If you've never used AI technology, write "N/A".

_____

Page Break

Below are eight questions regarding your working environment. Using the scale below, indicate their frequency by indicating a response for each statement.

	Never (1)	Rarely (2)	Sometimes (3)	Often (4)	Always (5)
Do you have to work fast? (1)	○	○	○	○	○
Do you have too much work to do? (2)	○	○	○	○	○
Do you have to work extra hard to finish a task? (3)	○	○	○	○	○
Do you work under time pressure? (4)	○	○	○	○	○
Can you do your work in comfort? (5)	○	○	○	○	○
Do you have to deal with a backlog at work? (6)	○	○	○	○	○
Do you have problems with the pace of work? (7)	○	○	○	○	○
Do you have problems with your workload? (8)	○	○	○	○	○

Page Break

Below are four statements with which you may agree or disagree with. Using the scale below, indicate your agreement with each item by indicating a response for each statement.

	Never (1)	Rarely (2)	About half the time (3)	Most of the time (4)	Always (5)
At times I am overwhelmed by all the work I have to do (1)	○	○	○	○	○
I could deliver better work products if I had more time (2)	○	○	○	○	○
I am able to cope with an increased workload (3)	○	○	○	○	○
I have trouble handling my workload (4)	○	○	○	○	○

Page Break

Below are ten statements with which you may agree or disagree. Using the scale below, indicate your agreement with each item by indicating a response for each statement.

	Strongly disagre (1)	Disagree (2)	Somewhat Disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Using AI would improve my performance at work (1)	○	○	○	○	○	○	○
Using AI would increase my productivity at work (2)	○	○	○	○	○	○	○
Using AI technology would enhance my effectiveness at work (3)	○	○	○	○	○	○	○
I would find AI technology useful in my work (4)	○	○	○	○	○	○	○
Using AI would help me work more quickly (5)	○	○	○	○	○	○	○
Using AI technology would make my job easier (6)	○	○	○	○	○	○	○
AI technology would be easy to learn (7)	○	○	○	○	○	○	○

It would be helpful to become skillful at using AI technology (8)	○	○	○	○	○	○	○
It would be easy to use AI technology (9)	○	○	○	○	○	○	○
I feel that I would be in control while using AI technology (10)	○	○	○	○	○	○	○

Page Break

Please write 1 or 2 sentences about what accomplishing tasks at work looks like on a typical day.

_____

Page Break

In the past month, how productive were you at work?

	Not productive at all (1)	Below average productivity (2)	Productive (3)	Above average productivity (4)	Very productive (5)
How productive were you? (1)	○	○	○	○	○

Page Break

In the past month, how would others rate your productivity at work?

	Not productive at all (1)	Below average productivity (2)	Productive (3)	Above average productivity (4)	Very productive (5)
How productive would others rate you as? (1)	○	○	○	○	○

Page Break

Below are fifteen statements with which you may agree or disagree. Using the scale below, indicate your agreement with each item by indicating a response for each statement.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I always find new and interesting aspects in my work (1)	○	○	○	○	○
There are days when I feel tired before I arrive at work (2)	○	○	○	○	○
It happens more and more often that I talk about my work in a negative way (3)	○	○	○	○	○
After work, I tend to need more time than in the past in order to relax and feel better (4)	○	○	○	○	○
I can tolerate the pressure of my work very well (5)	○	○	○	○	○
Lately, I tend to think less at work and do my job almost mechanically (6)	○	○	○	○	○
I find my work to be a positive challenge (7)	○	○	○	○	○

During my work, I often feel emotionally drained (8)	○	○	○	○	○
Over time, I can become disconnected from this type of work (9)	○	○	○	○	○
After working, I have enough energy for my leisure activities (10)	○	○	○	○	○
Sometimes I feel sickened by my work tasks (11)	○	○	○	○	○
After my work, I usually feel worn out and weary (12)	○	○	○	○	○
This is the only type of work that I can imagine myself doing (13)	○	○	○	○	○
I feel more and more engaged in my work (14)	○	○	○	○	○
When I work, I usually feel energized (15)	○	○	○	○	○

Page Break

Please think about what you have been doing and experiencing during the past 4 weeks. Then report how much you experienced each of the following feelings, using the scale below.

	Very rarely (1)	Rarely (2)	Sometimes (3)	Often (4)	Very often (5)
Positive (1)	○	○	○	○	○
Negative (2)	○	○	○	○	○
Good (3)	○	○	○	○	○
Bad (4)	○	○	○	○	○
Pleasant (5)	○	○	○	○	○
Unpleasant (6)	○	○	○	○	○
Happy (7)	○	○	○	○	○
Sad (8)	○	○	○	○	○
Afraid (9)	○	○	○	○	○
Joyful (10)	○	○	○	○	○
Angry (11)	○	○	○	○	○
Contented (12)	○	○	○	○	○

Page Break

Below are eight statements with which you may agree or disagree. Using the scale below, indicate your agreement with each item by indicating a response for each statement.

	Strongly disagree (1)	Disagree (2)	Slightly disagree (3)	Neither agree nor disagree (4)	Slightly agree (5)	Agree (6)	Strongly agree (7)
I lead a purposeful and meaningful life (1)	○	○	○	○	○	○	○
My social relationships are supportive and rewarding (2)	○	○	○	○	○	○	○
I am engaged and interested in my daily activities (3)	○	○	○	○	○	○	○
I actively contribute to the happiness and well-being of others (4)	○	○	○	○	○	○	○
I am competent and capable in the activities that are important to me (5)	○	○	○	○	○	○	○
I am a good person and live a good life (6)	○	○	○	○	○	○	○
I am optimistic about my future (7)	○	○	○	○	○	○	○

People respect me (8)	○	○	○	○	○	○	○

Page Break

How old are you?

- ○ Under 18 (1)
- ○ 18-24 years old (2)
- ○ 25-34 years old (3)
- ○ 35-44 years old (4)
- ○ 45-54 years old (5)
- ○ 55-64 years old (6)
- ○ 65+ years old (7)

How do you describe yourself?

- ○ Male (1)
- ○ Female (2)
- ○ Non-binary / third gender (3)
- ○ Prefer to self-describe (4) _____
- ○ Prefer not to say (5)

What best describes your employment status over the last three months?

- ○ Working full-time (1)
- ○ Working part-time (2)
- ○ Unemployed and looking for work (3)
- ○ A homemaker or stay-at-home parent (4)
- ○ Student (5)
- ○ Retired (6)
- ○ Other (7)

What industry do you work in?

- ○ Agriculture (1)
- ○ Utilities (2)
- ○ Finance (3)
- ○ Entertainment (4)
- ○ Education (5)
- ○ Health care (6)
- ○ Information services (7)
- ○ Data processing (8)
- ○ Food services (9)
- ○ Hotel services (10)
- ○ Human Resources (17)
- ○ Legal services (11)
- ○ Publishing (12)
- ○ Law Enforcement (13)
- ○ Military (14)
- ○ Other (Please fill in) (15) _____
- ○ Prefer not to say (16)

What is the highest level of school you have completed or the highest degree you have received?

- ○ Less than high school degree (1)
- ○ High school graduate (high school diploma or equivalent including GED) (2)
- ○ Some college but no degree (3)
- ○ Associate degree in college (2-year) (4)
- ○ Bachelor's degree in college (4-year) (5)
- ○ Master's degree (6)
- ○ Doctoral degree (7)
- ○ Professional degree (JD, MD) (8)

Choose one or more races that you consider yourself to be:

- [ ] White (1)
- [ ] Black or African American (2)
- [ ] American Indian or Alaska Native (3)
- [ ] Asian (4)
- [ ] Native Hawaiian or Pacific Islander (5)
- [ ] Hispanic Or Latino (6)
- [ ] Other (7) _____

End of Block: Informed Consent