Artificial Intelligence at Work: Balancing Engagement and Health Harms in the Digital Workplace

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Abstract. This research examines the dual influence of artificial intelligence (AI) on employee outcomes, specifically its impact on work engagement and health detriment in the context of Indonesian workplaces. This study aims to investigate the dual role of AI as a motivational resource and a source of strain, and its subsequent impact on employee well-being and engagement. A quantitative design was utilized to collect data from 150 office workers in Greater Jakarta through purposive sampling. The data were analyzed using structural equation modeling (SmartPLS 3.2.9) to examine the direct and mediating relationships among AI utilization, health harm, and engagement. The findings indicate that AI enhances engagement through skill development and the reduction of repetitive tasks; however, it also contributes to health issues such as stress, fatigue, and work-life imbalance, which adversely impact engagement. This study uniquely contributes by empirically validating the simultaneous presence of resource-enhancing and strain-inducing pathways of AI adoption in an emerging economy, thereby extending dual-pathway models of organizational behavior. The findings hold significant implications for managers and policymakers, highlighting the necessity for balanced AI strategies that optimize productivity while protecting employee well-being to facilitate sustainable digital transformation.

1 Introduction

The rapid growth of industry has increased the speed of workplaces, prompting organizations to enhance value for stakeholders by fostering closer integration between technology and human resources [1]. In this context, artificial intelligence (AI) serves as a crucial instrument for augmenting employee capabilities, optimizing operations, facilitating decision-making,

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and enhancing overall organizational productivity [2]. The growing dependence on AI illustrates its significant impact on contemporary work dynamics [2].

AI's ability to reinforce business models and maintain competitiveness. The findings highlight AI's potential to transform operations and its impact on employee outcomes, establishing AI as a key element in human resource strategies across various industries [3]. The influence of AI extends beyond mere efficiency and productivity improvements, also impacting employee well-being. Studies indicate that artificial intelligence can alleviate workloads, enhance cognitive performance, and promote favorable mental conditions [4]. AI-enabled environments reduce demands on employees, which subsequently improves engagement and job satisfaction [5]. Evidence suggests that AI indirectly enhances workplace well-being by promoting healthier work rhythms and aiding employees in more effectively managing their responsibilities [6].

AI adoption presents certain risks, despite its benefits. Although it can enhance job satisfaction and minimize routine tasks, it may also present health-related challenges. [7] warned that cognitive overload, job insecurity, and increased surveillance may arise as adverse effects of AI implementation. The effects, referred to as "health harm," include psychological and physical strains, such as stress, fatigue, and disrupted work–life balance [8]. Organizations must evaluate the benefits of AI-driven efficiency in relation to its potential negative impacts on employee well-being. This study investigates the relationship between AI technology, health risks, and work engagement [9]. This research examines the dynamics of AI utilization in organizations, aiming to elucidate how it can enhance productivity while promoting a healthier and more engaged workforce [10]. This study seeks to improve the existing discourse on technology-enabled human resource management and its future implications for work [11], [12].

Studies on artificial intelligence in the workplace demonstrate that intelligent systems transform value creation and capture, resulting in quantifiable impacts on organizational performance and employee experience [9], [13]. Foundational research illustrates the role of AI in enhancing process optimization and forecasting, thereby improving productivity and decision quality [14]. This technical shift has implications for individuals: digital tools modify task design and cognitive load, which may allow for greater focus on higher-value work while also influencing perceptions of competence, autonomy, and fairness [15].

Employee outcomes provide evidence of this duality. Research indicates that the integration of AI is positively associated with engagement when technologies enhance skills, broaden learning opportunities, and are incorporated within supportive talent-management frameworks[5]. Simultaneously, recent findings underscore potential risks: Awareness of AI can increase anxiety and emotional fatigue, particularly in contexts of low perceived organizational support. Enhanced monitoring and automation may exacerbate job insecurity and technostresss [7]. The identified strains, characterized as "health harm" encompassing both psychological and physical symptoms, are consistently linked to reduced engagement and safety-related behaviors [16].

Recent research synthesizes these elements to evaluate pathway mechanisms. In the context of service and hospitality, the advantages of AI for engagement diminish as health risks increase, suggesting that strain processes may partially mediate the relationship between technology and engagement [9], [17]. Business research indicates that the absence of proactive health safeguards may negate the efficiency gains of AI due to stress-related disengagement [11]. In contrast, when organizations prioritize support and capability building, AI can improve engagement through resource acquisition and learning [18]. Previous research supports the investigation of a mediated model in which AI technology influences work engagement via health harm, elucidating the conditions under which digital transformation enhances rather than undermines human sustainability in the workplace [17].

Prior research has established the transformative role of artificial intelligence in enhancing organizational productivity and reshaping work design; however, significant gaps persist in understanding its effects on employee well-being and engagement. Research indicates that AI can enhance efficiency, decision-making, and employee satisfaction when utilized as a supportive tool [19]. Simultaneously, increasing evidence indicates its unintended consequences, including technostress, job insecurity, and surveillance-induced anxiety, which adversely affect health and diminish engagement [9], [12]. This duality presents an incomplete understanding of AI's role in the workplace, characterized by the simultaneous presence of positive and negative outcomes.

Existing literature frequently examines these outcomes in isolation, with specific studies concentrating on productivity and engagement advantages, while others highlight the potential risks to mental health and well-being [20]. Moreover, research is predominantly focused on technologically advanced contexts, resulting in a scarcity of insights regarding the impact of AI adoption on employee outcomes in emerging economies characterized by unique cultural and organizational dynamics. Furthermore, a significant portion of the existing evidence is either conceptual or exploratory, lacking adequate empirical validation of models that encompass both the enabling and constraining effects of AI. This restricts the capacity to offer practical recommendations for organizations aiming to reconcile technological advancement with sustainable human resource practices. This study addresses existing gaps by exploring the relationship between AI usage, health harm, and work engagement, particularly within the framework of modern workplace dynamics.

2 Hypothesis Development

2.1 The Relationship between AI Utilization and Work Engagement

Artificial intelligence has emerged as a fundamental element in contemporary organizations, providing innovative methods to optimize operations, improve decision-making, and foster more adaptable work environments [21]. AI enhances employee productivity by automating routine tasks and augmenting capabilities, allowing a focus on higher-value activities, which improves individual and organizational outcomes [22]. Empirical evidence substantiates this perspective, with research indicating that AI-enabled workplaces can reduce cognitive strain and enhance job satisfaction [23], while promoting adaptability and commitment [5]. This reasoning suggests that AI usage improves engagement.

H1: The utilization of artificial intelligence has a significant influence on work engagement.

2.2 The Relationship between AI Utilization and Health Harm

The implementation of AI presents challenges, despite its potential benefits. Job displacement, increased surveillance, and cognitive overload are recognized as emerging risks linked to AI adoption [7]. Such experiences can increase stress and insecurity, resulting in what is termed "health harm," which includes both psychological and physical strains, such as fatigue and disrupted work–life balance [12]. AI may not only serve as a supportive resource but also function as a job demand that increases strain, consequently compromising well-being. This perspective indicates that the use of AI may correlate with increased health risks.

H2: The utilization of artificial intelligence has a significant influence on health harm.

2.3 The Relationship between Health Harm and Work Engagement

Employee engagement is significantly influenced by both psychological and physical well-being. Employee stress and fatigue reduce their ability to maintain vigor, dedication, and absorption in their work [24]. Research indicates that factors like technostress and burnout diminish motivation, job satisfaction, and proactive behaviors [16]. Health harm diminishes employees' cognitive and emotional resources, thereby obstructing full engagement [25].

H3: Health harm has a significant influence on work engagement.

3 Methodology

3.1 Research Design and Approaches

This research utilizes a quantitative design to examine the relationships among artificial intelligence (AI) technology, health harm, and work engagement in office workers in Greater Jakarta. A quantitative approach was chosen due to its capacity for hypothesis testing and statistical modeling of latent constructs, providing empirical evidence to support theoretical assumptions [26]. This design is suitable considering the study's aim to examine both direct and mediating effects within a structural framework. The research framework is shown in Figure 1.

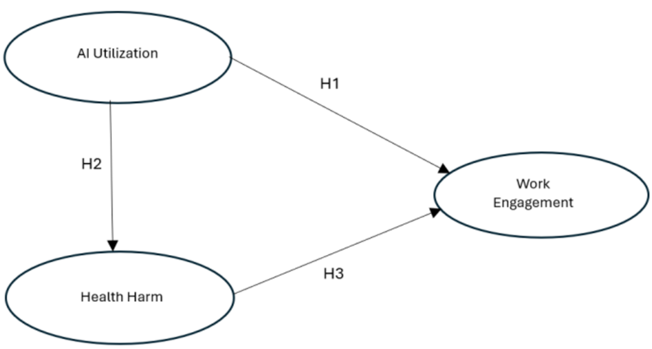

Fig. 1. Research Framework

3.2 Data Collection

The sampling method employed was non-probability judgmental sampling and purposive sampling. This approach was selected due to the unavailability of precise data regarding the population size and distribution of employees utilizing AI in workplace environments indicates that purposive sampling is suitable when the researcher utilizes professional judgment to select respondents capable of offering pertinent insights [26]. Data were collected using online questionnaires distributed through Google Forms, facilitating efficient access to participants in Jakarta, Bogor, Depok, Tangerang, and Bekasi. This method was especially effective for accessing dispersed respondents in a cost- and time-efficient way [26]. Data were collected between August and December 2024, providing insights into workplace dynamics during this period.

A total of 150 responses were collected, which meets the minimum sample size requirements for structural equation modeling (SEM) [27]. The required minimum sample size for this study was calculated to be between 115 and 230 respondents, using the formula $N = 5 \times$ indicators to $N = 10 \times$ indicators. This range is consistent with guidelines for structural equation modeling, recommending a sample size of at least five to ten times the number of observed indicators to achieve reliable parameter estimation and robust statistical analysis [28], [29].

3.3 Research Instrument

The questionnaire comprised three primary constructs: AI technology, health harm, and work engagement. All items were assessed using a five-point Likert scale, with responses ranging from strongly disagree (1) to strongly agree (5), facilitating interval-level measurement suitable for SEM analysis. Items related to AI technology were adapted from [9], [30], addressing aspects of productivity, efficiency, skill development, and perceived risks, including job displacement. Items were adapted from [8], [31] to assess health harm, focusing on psychological strain, fatigue, work–life imbalance, and physical well-being. Work Engagement, adopted from [32], [33], was utilized to measure work engagement. This instrument measures three dimensions: vigor, dedication, and absorption.

3.4 Data Analysis

The data analysis was conducted utilizing structural equation modeling (SEM) through SmartPLS version 3.2.9. SEM was considered suitable for this study because it facilitates the simultaneous estimation of intricate relationships among constructs, including the assessment of mediation effects within a unified model [28], [29]. Several evaluation criteria were applied to ensure the robustness of the measurement model. Reliability was evaluated using Cronbach's alpha and composite reliability (CR), with values above 0.70 deemed acceptable indicators of internal consistency [28], [29]. The structural model was evaluated through the analysis of path coefficients, t-statistics, and p-values to test the proposed relationships. Additionally, R^2 values were utilized to assess the model's explanatory power regarding the variance in the endogenous variables [28], [29].

4 Result and Discussion

The demographic characteristics of the respondents are essential for contextualizing the study's findings. The gender distribution was balanced, comprising 53 percent male and 47 percent female respondents, indicative of a diverse workforce composition. Most respondents (61.7%) were aged between 21 and 30 years, suggesting that the sample predominantly consisted of young professionals engaged in the dynamics of technology adoption in the workplace.

The analysis of work tenure indicated a predominance of early career employees, with 69.8 percent possessing less than five years of work experience. This shows that many respondents are in the early stages of their professional development, where exposure to artificial intelligence could significantly influence skill acquisition and perceptions of job security. Most respondents held staff-level positions (45%), followed by supervisory, managerial, and higher-level roles, with 4 percent identifying as directors. This distribution indicates that, although the sample encompasses various organizational levels.

4.1 Measurement Model Analysis

The measurement model analysis (Table 3) demonstrated the measurement model was assessed to evaluate indicator reliability, internal consistency, convergent validity, and multicollinearity, following the guidelines established by [28], [29]. The reliability of indicators was assessed via factor loadings, with values exceeding 0.70 deemed acceptable.

Table 3. Validity and Reliability Results.

Item	Loading Factor (> 0.7)	VIF (<5.0)	Cronbach's Alpha (> 0.6)	Composite Reliability (≥ 0.6)	AVE (≥ 0.5)	Remarks
AI1	0.838	1.598	0.695	0.831	0.625	Valid and Reliable
AI2	0.859	1.640				
AI3	0.659	1.179				
HH1	0.874	3.794	0.887	0.908	0.561	Valid and Reliable
HH2	0.873	3.593				
HH3	0.853	3.090				
HH4	0.842	3.308				
HH5	0.581	1.700				
HH6	0.570	2.048				
HH7	0.653	1.574				
HH8	0.658	1.731				
WE1	0.668	1.886	0.921	0.932	0.536	Valid and Reliable
WE2	0.745	2.771				
WE3	0.779	2.694				
WE4	0.700	2.756				
WE5	0.868	3.963				
WE6	0.739	2.185				
WE7	0.765	2.933				
WE8	0.731	2.307				
WE9	0.759	2.966				
WE10	0.587	1.674				
WE11	0.665	1.726				

Table 3. Validity and Reliability Results.

Item	Loading Factor (> 0.7)	VIF (<5.0)	Cronbach's Alpha (> 0.6)	Composite Reliability (≥ 0.6)	AVE (≥ 0.5)	Remarks
WE12	0.744	2.118				

Notes: HH: Health Harm; AIU: AI Utilization; WE: Work Engagement

Multicollinearity was evaluated through variance inflation factor (VIF) values, all of which fell below the suggested threshold of 5.0, signifying the absence of significant multicollinearity concerns among the indicators. Internal consistency reliability was assessed through Cronbach's alpha and composite reliability (CR). The Cronbach's alpha values for AI (0.695), health harm (0.887), and work engagement (0.921) surpassed the minimum acceptable threshold of 0.60, indicating satisfactory reliability. The CR values of 0.831 (AI), 0.908 (health harm), and 0.932 (work engagement) exceeded the recommended threshold of 0.70, indicating robust internal consistency among the constructs.

Convergent validity was evaluated through the calculation of average variance extracted (AVE). All constructs demonstrated AVE values exceeding the 0.50 threshold, with AI at 0.625, health harm at 0.561, and work engagement at 0.536. The findings indicate that the constructs accounted for over 50 percent of the variance in their indicators, thus confirming convergent validity. The validity and reliability tests reveal that the measurement model meets the criteria established by [28], [29]. Although certain items exhibited weaker loadings, the constructs collectively displayed strong internal consistency, sufficient convergent validity, and no multicollinearity issues, thereby supporting the retention of indicators for subsequent structural analysis.

4.2 R-Square Value Analysis

The R-square value (Table 4) represents the proportion of variance in the dependent variables explained by the independent variables in the model. In this study, the R^2 value for health harm was 0.128, whereas work engagement exhibited an R^2 of 0.070 [28], [29]. R^2 values of 0.75, 0.50, and 0.25 as substantial, moderate, and weak, respectively; however, the acceptable level of R^2 is contingent upon the research context and model complexity [28], [29]. The R^2 value of 0.128 for health harm indicates a weak explanatory power, signifying that approximately 12.8 percent of the variance in health harm is accounted for by the exogenous variable(s). The R^2 value of 0.070 for work engagement signifies that merely 7 percent of its variance is accounted for, indicating a limited predictive capacity [28], [29]. The findings suggest that although artificial intelligence technology helps in identifying health harm and work engagement, other substantial factors not included in the existing model likely also affect these outcomes. The findings indicate a necessity for future research to enhance the model by integrating additional predictors, including leadership style, organizational support, or individual psychological resources, to augment its explanatory power.

Table 4. R-Square Value.

Variable	R-Square
Health Harm	0.128
Work Engagement	0.070

4.3 Hypothesis Testing

The structural model analysis (Table 5) indicates that the structural model analysis validated all three proposed hypotheses, highlighting the dual role of AI in influencing employee outcomes.

The analysis revealed a positive and statistically significant relationship between AI utilization and health harm (β = 0.371, t = 2.262, p = .012), thereby supporting hypothesis H1. This finding aligns with previous studies that warned of the unintended consequences associated with AI adoption, such as technostress, surveillance pressures, and job insecurity [7], [9]. The findings support the health impairment perspective, suggesting that although AI serves as a performance enhancer, it concurrently acts as a job demand that heightens strain and undermines well-being.

Secondly, the use of AI showed a positive and significant impact on work engagement (β = 0.283, t = 1.725, p = .042), thereby supporting hypothesis H2. This aligns with previous research indicating that effective AI implementation decreases cognitive load and liberates employees from repetitive tasks, consequently improving vigor, dedication, and absorption [5], [11]. The findings support the resource-based pathway, indicating that AI adoption enhances engagement by broadening opportunities for skill development, decision-making, and meaningful work.

Table 5. Hypothesis Testing.

Hypothesis	**Original Sample (O)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	***p* Values**	**Remarks**
AIU → HH	0.371	0.164	2.262	0.012	H1 supported
AIU → WE	0.283	0.164	1.725	0.042	H2 supported
HH → WE	-0.253	0.148	1.712	0.044	H3 supported

Notes: HH: Health Harm; AIU: AI Utilization; WE: Work Engagement

Third, health harm exhibited a negative association with work engagement (β = −0.253, t = 1.712, p = .044), thereby supporting H3. This finding supports previous research that associates psychological and physical strain with decreased motivation, satisfaction, and proactive behaviors [8]. The findings underscore the health impairment pathway, confirming that employee well-being is essential for ongoing engagement [32], [33].

These findings indicate that AI adoption provides resource-enhancing benefits that promote engagement; however, if not managed properly, its concurrent strain-inducing effects may undermine these advantages. The findings extend the dual-pathway models outlined in the hypothesis development section, illustrating that AI functions as both a resource and a demand, with outcomes dependent on the balance organizations maintain between these competing dynamics.

4.4 Discussion

This study presents empirical evidence regarding the dual nature of artificial intelligence in the workplace, demonstrating that AI both enhances work engagement and poses health risks. The findings indicate that the adoption of AI significantly enhances engagement by enabling employees to concentrate on higher-value tasks, acquire new skills, and utilize automated decision-support systems. The study concurrently demonstrated a positive correlation between AI exposure and health harm. This underscores the idea that AI serves both as a resource and as a job demand that may negatively impact employee well-being. The negative correlation between health harm and engagement reinforces the health impairment pathway, indicating that psychological and physical strain reduces employees' capacity to maintain vigor, dedication, and absorption. These results enhance the dual-pathway perspective by demonstrating that AI adoption cannot be assessed solely through the lens of efficiency or productivity. The outcomes of AI are contingent upon the equilibrium between its resource-enhancing and strain-inducing characteristics. This nuance enhances the literature on organizational behavior and HRM by framing AI as a dual-faceted construct—potentially motivating or depleting employees based on its implementation and management.

This research contributes to theoretical development in multiple aspects. This study enhances the existing literature on artificial intelligence in human resource management by incorporating health harm into the discourse surrounding employee engagement. However, this study illustrates their concurrent existence within a shared context. The study empirically validates both pathways, thereby reinforcing dual-pathway models that conceptualize AI as a resource and a demand.

The findings underscore the necessity for more refined frameworks that consider boundary conditions. The lack of robust mediation via health harm suggests that alternative mechanisms, such as psychological empowerment, digital trust, or learning opportunities, may explain how AI affects engagement. Moderators, including leadership style, organizational culture, and employee digital literacy, may influence the extent of AI's effects. Future theoretical models must incorporate these variables to reflect the complexity of technology-enabled work dynamics accurately.

This study contributes to the contextualization of AI research within emerging economies by focusing on young professionals in Greater Jakarta. This research illustrates how employees in rapidly developing economies encounter both the benefits and challenges of AI adoption, contrasting with the predominantly technologically advanced contexts found in existing literature. This enhances the cross-cultural significance of AI research and highlights the necessity of incorporating local contexts in theoretical development.

The findings highlight the necessity for balanced strategies in AI adoption from a managerial standpoint. The correlation between AI and engagement suggests that organizations should leverage AI to augment, rather than replace, human capabilities. Managers can improve this outcome by ensuring that AI systems minimize repetitive tasks and facilitate skill development, allowing employees to concentrate on high-value, meaningful work.

The positive correlation between AI and health harm highlights the risks associated with overlooking employee well-being. Clear communication regarding AI implementation, inclusive decision-making processes, and training initiatives aimed at enhancing digital literacy may mitigate feelings of insecurity and surveillance. Organizations should invest in proactive health and wellness initiatives, such as stress management programs, workload monitoring, and flexible work arrangements, to mitigate the strain associated with AI utilization.

These insights hold significant relevance for firms in emerging economies, where aggressive pursuit of digital transformation is essential for maintaining competitiveness. Adopting a human-centered approach to AI implementation enables organizations to enhance productivity and safeguard employee well-being, thereby ensuring that technological advancements lead to sustainable performance.

5 Conclusion

This research examined the dual influence of artificial intelligence (AI) on employee outcomes, specifically its effects on work engagement and health detriment. The findings indicate that AI has a dual impact in the workplace: it increases engagement by alleviating employees from monotonous tasks and facilitating learning opportunities, while simultaneously exacerbating psychological and physical stress that detracts from overall well-being. The detrimental impact of health harm on engagement highlights the necessity for technological advancements to be accompanied by intentional measures to preserve employee resources.

This research is significant as it transcends simplistic narratives that categorize AI solely as a driver of efficiency or a source of risk. The study illustrates that AI functions both as a resource and a demand, generating concurrent benefits and costs within organizational contexts. This duality enhances theoretical models of employee engagement by incorporating technology-driven resource gains alongside strain-induced health impairment pathways, thus offering a more comprehensive framework for understanding digital transformation in the workplace.

The findings indicate that organizations should not depend exclusively on technological adoption to enhance motivation and productivity. To maximize the potential of AI, organizations must ensure employee well-being by fostering transparent communication, engaging in participatory implementation, providing digital literacy training, and initiating proactive wellness programs. Organizations can attain sustainable AI integration by balancing engagement gains with protective measures, thereby enhancing both performance and human sustainability.

This study enhances the discourse on AI-enabled work by elucidating its complex and occasionally contradictory effects on employees. The findings, although specific to the Indonesian context, align with international discussions regarding the future of work. As organizations globally adopt AI, the challenge lies in effectively utilizing technology for efficiency while simultaneously designing workplaces that safeguard and promote human well-being. Meeting this challenge is essential for ensuring that digital transformation supports not just organizational competitiveness but also the broader goals of sustainable and inclusive work.

This study presents significant contributions; however, several limitations require consideration. The application of purposive sampling in Greater Jakarta restricts the generalizability of findings across various industries and regions. Future research should utilize probability sampling and larger, more diverse datasets to improve external validity. The cross-sectional design limits the ability to draw causal inferences. Longitudinal or experimental designs would yield more profound insights into the temporal dynamics of AI adoption, health harm, and engagement. Examining employee adaptation to AI over time may indicate whether strain effects lessen with increased familiarity or whether they remain as persistent challenges.

This study did not consider cultural factors that may influence employee perceptions of AI. Comparative research on collectivist versus individualist societies, as well as developed versus emerging economies, may yield significant insights into the ways cultural values influence the relationship between AI adoption, health outcomes, and engagement. Employing mixed-method approaches that integrate quantitative modeling with qualitative interviews can provide deeper insights into employees' lived experiences in AI-enabled workplaces.

Authors' Contributions and Data Availability

MGH lead the research, overseeing conceptualization, methodology, software, writing (including the original draft preparation), and final review. **KI** prepare the literature review and discussion and is responsible for writing, proofreading, and editing. **MGH, RH, and KI** handle data collection and prepare the literature review. They are responsible for writing, proofreading, and editing.
Data availability
https://zenodo.org/records/17391062/files/Open%20Data%20ID%20162.xlsx?download=1

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