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To cite this article: Hassan Hessari, Ali Bai & Fatemeh Daneshmandi (25 Oct 2024): Generative AI: Boosting Adaptability and Reducing Workplace Overload, Journal of Computer Information Systems, DOI: [10.1080/08874417.2024.2417672](https://doi.org/10.1080/08874417.2024.2417672)

To link to this article: <https://doi.org/10.1080/08874417.2024.2417672>



Published online: 25 Oct 2024.



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Generative AI: Boosting Adaptability and Reducing Workplace Overload

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ABSTRACT

In the evolving digital work environment, the rising prevalence of generative AI tools presents a complex challenge for practitioners: deciding whether to allow or restrict their use in organizational settings. Our research contributes to expanding the broaden-and-build theory and the job demands-resources model (JD-R) within the context of generative AI tools usage. This study investigates the impact of generative AI tools on employees' perceived work overload, focusing on the mediating role of employee adaptability. Utilizing a survey of 307 employees and Structural Equation Modeling (SEM) techniques, findings show that generative AI tools usage by employees not only directly reduces perceived work overload but also significantly boosts employee adaptability, further decreasing perceived work overload. This highlights the dual benefits of generative AI tools in the workplace, offering valuable insights for managers on consciously integrating these technologies to enhance adaptability and reduce workload stress.

KEYWORDS

Generative artificial intelligence (AI); employee adaptability; perceived work overload; the job demands-resources model (JD-R); the broaden-and-build theory; large language models (LLMs)

Introduction

The rise of generative AI marks a significant shift in professional contexts, transforming how tasks are performed and concepts are developed, from text and images to music.¹ Technologies like ChatGPT exemplify how AI enables employees to automate repetitive tasks and focus on strategic, innovative activities.^{2,3} Our research mainly aims to understand how and whether these tools can impact employee adaptability and perceived work overload.

Generative AI is reshaping corporate environments by driving innovation and productivity across industries.^{4,5} Organizations use these tools to streamline operations and boost creativity, although concerns about misuse remain.⁶ The increasing adoption of AI has significant implications for automation and data management,⁷ and poses managerial challenges, including changing workforce roles and the need for adaptive leadership.⁸ As AI tools become integral to workplace dynamics, leaders must restructure teams and develop leadership capable of managing AI integration effectively.⁹

Experts stress the need for comprehensive studies on AI's effects on companies and employees, as highlighted in *The Wall Street Journal*, *Forbes*, and *Harvard Business Review*. Alavi and Westerman¹⁰ argue that AI can revolutionize knowledge work by easing cognitive load and enhancing learning. Chui et al.⁴ emphasize the need for swift action to manage AI's risks and harness its

potential, while Fowler¹¹ predicts AI will drive enterprise efficiency and innovation. Gupta¹² calls for strategic deployment, and Needleman¹³ highlights AI's transformative impact on digital behavior, especially in online searches and shopping. These insights collectively emphasize the necessity of a prudent, forward-thinking approach to AI integration, aiming to maximize its benefits while addressing its challenges.

Using Structural Equation Modeling (SEM), this study investigates the relationship between generative AI tools, employee adaptability, and workplace overload. It expands the theoretical foundations of the broaden-and-build theory and the job demands-resources model, applying them to AI-driven workplace evolution.^{14,15} Central to this research is the role of generative AI in boosting employee adaptability and reducing work overload. The findings provide practical, evidence-based strategies for organizations, highlighting AI's potential to create work environments where human and technological potential blend to foster productivity and well-being. This research advocates for a future where AI and human adaptability merge, enhancing productivity and employee well-being.

Theoretical development

In the following section, we outline the theoretical frameworks that underpin this study. Specifically, we draw

on key concepts from the broaden-and-build theory and the Job Demands-Resources (JD-R) model to explore how generative AI tools influence employee adaptability and perceived work overload.

Broaden-and-build theory

The broaden-and-build theory, developed by Fredrickson, highlights the role of positive emotions in expanding cognitive frameworks and strengthening personal resources across various fields, including information systems.^{15,16} In the workplace, this theory helps explain how technology, particularly generative AI tools, can affect users' psychological states and work outcomes. While AI can provoke fears related to job replacement,¹⁷ studies suggest that generative AI tools often foster positive emotions by enhancing task efficiency.^{18,19} For instance, Joskowicz and Slomovitz²⁰ found that professionals widely use AI tools, leading to positive perceptions of their workplace impact. Many are increasingly optimistic about the role of generative AI.^{3,21}

Research has applied this theory to show how positive cognitive frameworks improve stress management, resilience, and job performance.^{22–25} While our study did not directly measure emotions, the cognitive mechanisms of the broaden-and-build theory are relevant. Generative AI tools promote positive cognitive states by automating routine tasks and improving decision-making, aligning with the theory's principles.^{26–28} This theory provides a robust framework for understanding AI's dual role in reducing work overload and enhancing adaptability.

In our study, generative AI tools are seen as assets that streamline tasks and evoke positive emotions, which broaden cognitive capacities and foster adaptability. This adaptability helps employees deal with challenges and reduce feelings of work overload, consistent with the core tenets of the broaden-and-build theory.¹⁶ By nurturing positive emotions, generative AI tools can improve psychological well-being, creativity, and openness to change. As employees become more adaptable and resourceful, they are better equipped to handle complex tasks, decreasing their perception of work overload. Generative AI tools thus help create a more agile and positive workplace where employees can thrive.

Job Demands-Resources (JD-R) model

The Job Demands-Resources (JD-R) model, widely used in occupational health psychology, explores the balance

between job demands, which lead to strain, and job resources, which foster growth and reduce stress.²⁹ Job resources, such as autonomy and feedback, are linked to higher engagement, while job demands, like work overload, increase stress.³⁰ Recent studies emphasize that job resources significantly alleviate work demands and enhance performance.^{31,32}

In information systems, the JD-R model has been expanded to account for digital demands and resources. Technological disruptions often introduce job demands, adding strain as employees adapt to new systems, increasing cognitive load and stress.^{33,34} However, once familiar with these tools, employees can experience generative AI as valuable job resources. Generative AI tools like ChatGPT can automate routine tasks and support decision-making, thus improving efficiency.³⁵ Studies show that generative AI tools adoption has led to positive perceptions and improved workplace outcomes, particularly in skill development and learning.^{20,36}

We view generative AI tools as significant job resources that reduce job demand-induced stress by automating repetitive tasks and streamlining decision-making, in line with the JD-R model.¹⁴ Recent research affirms this perspective, demonstrating AI's ability to enhance productivity, creativity, and job satisfaction across skill levels.^{37,38} These tools allow employees to focus on more complex work, boosting overall performance and engagement.³⁹ Moreover, generative AI tools' ability to handle structured and unstructured tasks leads to significant organizational shifts and more human-like interactions.^{40,41}

In our study, generative AI tools are seen as key resources that mitigate job demands and reduce perceived work overload. By enhancing efficiency and productivity, these tools foster employee well-being and satisfaction. This aligns with both the broaden-and-build theory and the JD-R model, offering a framework for understanding generative AI tools' transformative impact on workplace dynamics by reducing stress and enhancing adaptability.

Hypothesis development

Work overload is a common challenge in modern workplaces, arising when job demands exceed an employee's capacity to cope.^{14,42} It often results from excessive assignments, tight deadlines, or cognitively demanding tasks.⁴³ Factors such as rapid technological changes, competitive pressures, and high productivity expectations contribute to this issue.⁴⁴ The consequences of chronic work overload include burnout, stress, and reduced job satisfaction, ultimately lowering job

performance and negatively impacting mental and physical health.^{45–48}

Work overload also harms organizational performance, as overwhelmed employees struggle to maintain quality, leading to errors and reduced customer satisfaction.^{49,50} High turnover due to burnout increases recruitment and training costs.⁵¹ To mitigate these issues, organizations must reassess workloads, set achievable goals, and manage fatigue.⁵² Emerging technologies, like generative AI, offer valuable tools to help employees manage these challenges.

Generative AI is transforming workplaces by automating routine tasks such as e-mail drafting, meeting scheduling, and content creation.^{27,28} By shifting focus away from mundane tasks, AI enables employees to engage in more strategic, creative work, fostering innovation and productivity.^{1,53} These tools also support learning and development by offering personalized tutoring and instant feedback, helping employees adapt to new roles and technologies.^{54,55} Generative AI improves decision-making through rapid insights from data analysis, enhances efficiency, and introduces fresh solutions, promoting a dynamic and innovative work environment.^{19,56} Its integration into routine operations strengthens data-driven decision-making and accelerates innovation cycles through rapid prototyping.^{57,58} Based on these insights, the following hypotheses are proposed:

H1: Using AI-generative tools mitigates perceived workload among employees.

Employee adaptability plays a crucial role in today's evolving workplace, allowing individuals to manage technological advancements and market shifts while seizing new opportunities.⁵⁹ Research highlights that adaptability is essential for maintaining productivity and fostering innovation in dynamic environments.⁶⁰ Adaptable employees can quickly learn new technologies, adjust workflows, and embrace changing strategies, which is critical for driving organizational success and staying competitive.^{61,62} AI tools, particularly those that support decision-making and continuous learning, can enhance employee adaptability by facilitating rapid adjustments to new processes.⁶³ Thus, we propose the following:

H2: Using AI-generative tools enhances employee adaptability.

As technological advancements and market fluctuations transform the professional landscape, the ability to adjust, learn, and grow has become

indispensable.⁶⁴ Adaptability fosters resilience, continuous improvement, and innovation, benefiting both individual performance and organizational agility.⁶⁵ By embracing change and updating their skills, adaptable employees help organizations navigate the complexities of modern business.⁶⁶

Adaptability goes beyond technical skills; it represents a proactive, resilient mind-set that embraces change and fosters a culture of innovation and flexibility.⁶⁷ Highly adaptable employees don't just cope with change—they excel, contributing to their career growth and organizational success.⁶⁸ Based on this, we propose:

H3: Employee adaptability diminishes perceived workload amongst employees.

We further propose that adaptability mediates the relationship between AI tool use and perceived workload. Employees using AI tools may develop higher adaptability, enabling them to better manage their workloads. Therefore, we hypothesize:

H4: Employee adaptability mediates the relationships between using AI-generative tools and perceived workload.

Research indicates that factors such as age, gender, education, and work experience influence perceptions of work overload.⁶⁹ Older employees may experience more overload due to slower adaptation to technology,⁷⁰ while gender differences in workload stem from varying role expectations and work-life balance pressures.⁷¹ Higher education and experience typically improve problem-solving and workload management, though increased responsibilities can also raise perceptions of overload.⁷² Including these control variables strengthens the robustness of our findings, ensuring that the effects of generative AI tools and adaptability on perceived workload are not confounded by these factors (see [Figure 1](#)).

Methodology

In the upcoming section, we describe the research methodology used in this study, including the data collection process, participant selection, and analytical techniques. We also detail the ethical considerations and statistical methods applied to validate the research findings.

Participants and data collection

This study examines the impact of generative AI tools on employees' perceived work overload, focusing on

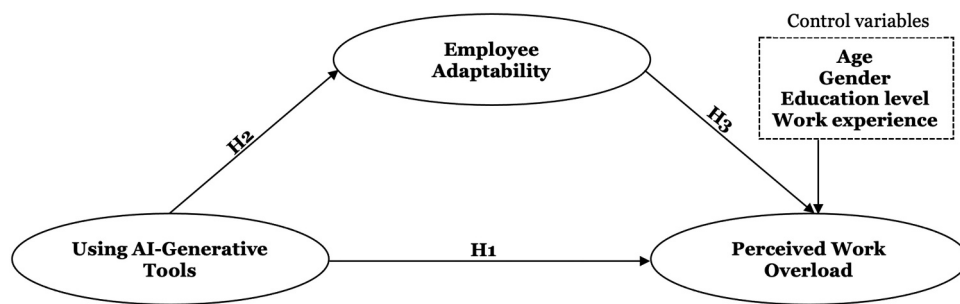


Figure 1. Conceptual framework.

adaptability. In Iran, where internet access has grown, employees often bypass government restrictions using VPNs.^{73,74} The research targeted full-time employees from various Iranian organizations with internet access, particularly in less restricted environments.⁷⁵ Given the increasing use of generative AI tools in Iran,^{76,77} this setting offers valuable insights into the tools' effects on workload perception and adaptability.

Ethical approval was obtained by distributing questionnaires to organizational managers with a cover letter outlining the study's objectives. Senior management granted permission, ensuring compliance with ethical standards.⁷⁸ Data collection occurred via an online platform, allowing for convenient employee access, a common practice in survey-based research.⁷⁹ Each participant received a unique survey link.

To minimize social desirability bias and improve data quality, the survey was conducted in two phases.⁸⁰ In the first phase, participants responded to control and independent variables, with confidentiality and anonymity assured. Participants were assigned unique codes for the second wave, which focused on dependent variables.⁸¹ A lucky draw incentivized participation, with gift cards as prizes, and only one response per individual was allowed, following best research practices.⁸²

For the translation of scales from English to Persian, two translators—one familiar with the scales and one unfamiliar—were employed.⁸³ Back-translation confirmed accuracy, with input from three expert translators⁸⁴ and a pilot test involving 25 bilingual participants.⁸⁵ Cronbach's alpha was used to assess reliability, resulting in a well-validated questionnaire.⁸⁶

To address non-response bias, two reminders were sent for each survey phase.⁸⁷ Of the initial 610 participants, 112 were excluded for not meeting sampling criteria, and 174 were disqualified for failing attention checks or completing the survey too quickly, leaving 324 for the second wave. After further exclusions, 307 employees completed the survey, achieving a 50.3% response rate, consistent with similar studies.⁸⁸

Measures

The questionnaire items, derived from established scales, are detailed in the [Appendix](#) with their respective sources. Perceived work overload was measured using Moore⁸⁹ self-rating scale, which has been widely applied in studies such as Ahuja et al.⁹⁰ Employee adaptability was assessed using Griffin et al.⁹¹ scale, which evaluates the ability to adjust thoughts, behaviors, and strategies in response to changing workplace conditions. To measure generative AI tool usage, we adapted a question from Venkatesh et al.⁸⁸ focused on technology adoption. Participants were instructed to reflect solely on their professional use of generative AI tools, and examples like ChatGPT, Claude, and Gemini were provided to ensure clarity. This ensured responses were specifically related to workplace applications of generative AI tools.

Our model utilized first-order constructs, as perceived work overload, employee adaptability, and generative AI tools usage have no sub-dimensions. Likert scales, based on previous studies,^{88,90} were used, with a seven-point range from "strongly disagree" to "strongly agree." Control variables included age, education, work experience, and gender.⁹² Age and work experience were measured in years, gender was coded as binary (0 for female), and education was categorized into five levels.

Data analysis and results

To ensure the reliability and validity of our data, we employed descriptive statistics, a correlation matrix, and Confirmatory Factor Analysis (CFA) to examine the dimensionality of the scales and assess model quality. Structural Equation Modeling (SEM) was then used to test our hypotheses.

CFA verifies whether observed variables can be explained by a smaller number of latent constructs based on the theoretical model.⁹³ We applied CFA within Covariance-Based Structural Equation Modeling (CB-SEM), which is effective for well-established theories with precise measurements.⁹⁴

CB-SEM evaluates complex relationships among variables by comparing observed and predicted covariance matrices, making it particularly valuable in fields like social sciences and business where high multicollinearity is present.⁹⁵

In information systems research, recognizing the nature of constructs is essential. Our constructs are reflective, meaning they are shaped by the latent variable.⁹⁶ SEM, ideal for questionnaire-based data, was key to testing our hypotheses.⁹⁷ For the analysis, we used the *lavaan*, *semTools*, *psych*, and *tidyverse* packages in R Studio.^{98,99}

Descriptive statistics

In our research, we analyzed 307 fully completed responses. The demographic composition of our sample revealed that a significant majority, 58%, were male. Additionally, a substantial portion of participants, 45.2%, possessed a master's degree. Age-wise, 43.9% of our respondents fell within the 26–33 years bracket. In terms of professional experience, 42.6% reported having 1–6 years of work experience. For a comprehensive overview of these demographic details, refer to Table 1.

Table 1. The demographic characteristics.

Category		Frequency	Percentage
Gender	Male	178	58%
	Female	129	42%
Educational level	PhD	13	4.3%
	Masters	139	45.2%
	Bachelors	124	40.4%
	Associate degree	27	8.8%
	High school	4	1.3%
Age	18–25	38	12.3%
	26–33	135	43.9%
	34–41	83	27%
	42–48	28	9.1%
	49–56	23	7.7%
	57–64	10	3.2%
Work Experience	1–6 Years	131	42.6%
	7–13 Years	95	31%
	14–20 Years	42	13.7%
	21–27 Years	24	7.8%
	More than 28 Years	15	4.9%

Preliminary analyses

In our study, the *psych* and *tidyverse* packages in R Studio were used for preliminary analyses. Questionnaire reliability, which refers to the consistency of responses across different samples and over time, was evaluated using Cronbach's alpha, with a target value above 0.70 for each variable.^{86,100,101} Construct reliability, essential for ensuring stable and accurate measurements, was assessed through Composite Reliability (CR) and Average Variance Extracted (AVE). According to established standards, CR values should exceed 0.7, and AVE should be above 0.5, with the square root of AVE being greater than the correlations for each construct.¹⁰² Our results met these criteria (see Tables 2 and 3). Normal distribution is fundamental for statistical analysis, aiding in data interpretation and hypothesis testing.¹⁰³ In our study, skewness values between –0.8 and 0.8, and kurtosis values between –2 and 2, confirmed a satisfactory level of normal distribution¹⁰⁴ (see Table 3).

Discriminant validity measures the extent to which a construct is distinct from other unrelated constructs, ensuring that each measure captures a unique concept.¹⁰⁵ It is crucial to avoid conflating related constructs, as this could lead to inaccurate conclusions.¹⁰⁶ In our study, the correlations between constructs showed satisfactory discriminant validity. We also used the heterotrait-monotrait ratio of correlations (HTMT) via *semTools* in R Studio. HTMT values below 0.85 are considered acceptable for covariance-based models,^{107,108} and our results met this standard (see Table 4).

Common method bias (CMB) occurs when the same measurement method is used across variables, potentially leading to spurious associations and skewed results.¹⁰⁹ To address CMB in our study, we applied two techniques outlined by Podsakoff et al.¹⁰⁹ First, Harman's single-factor test showed that a single factor accounted for only 32.4% of the variance, well within acceptable limits.¹¹⁰ We then used the correlation matrix approach recommended by Pavlou et al.,¹¹¹ which identified no excessively high correlations ($r > 0.90$), indicating that CMB is not a significant concern in our data.¹⁰⁹ The relevant correlations are detailed in Table 3.

Table 2. Confirmatory factor loadings range of items, Cronbach's alpha.

Constructs	Items	Confirmatory factor loadings	Reliability (alpha) α
Generative AI tools usage	1	0.900	0.92
	2	0.897	
	3	0.882	
Perceived work overload	1	0.856	0.91
	2	0.863	
	3	0.881	
	4	0.797	
Employee adaptability	1	0.860	0.84
	2	0.723	
	3	0.815	

Table 3. Correlation matrix, means, standard deviations, reliability, and square root of AVE.

Constructs	1	2	3	Kurtosis (skew)	CR	AVE	Mean	SD
Generative AI tools usage	0.893			−1.42 (0.24)	0.922	0.798	3.78	1.90
Perceived work overload	−0.438**	0.851		−0.92 (−0.56)	0.914	0.724	4.66	1.60
Employee adaptability	0.533**	−0.338**	0.806	−0.85 (−0.26)	0.844	0.649	4.23	1.49

Significant: ** $p < .001$, * $p < .05$, Not significant: ns.

SD = standard deviation, CR = composite reliability, AVE = Average variance extracted.

Diagonal lines rendered in boldface show the square root of the AVE of each construct.

Table 4. Discriminant validity (HTMT ratios).

	Generative AI tools usage	Perceived work overload	Employee adaptability
Generative AI tools usage			
Perceived work overload	0.476		
Employee adaptability	0.602	0.367	

Measurement model

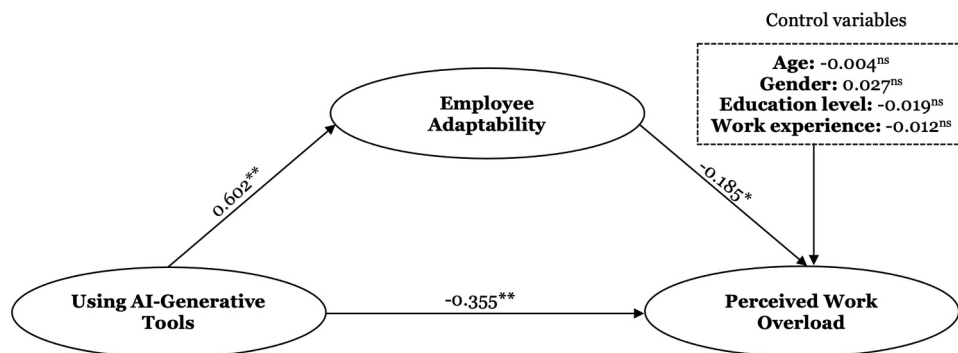
We conducted confirmatory factor analysis (CFA) using the *lavaan* package in R Studio, a widely adopted method in social sciences and Information Systems research due to its robustness in validating theoretical models.^{93,112} CFA assesses how well the gathered data aligns with a pre-established theoretical framework, which is critical for validating constructs and hypotheses. Several key fit indices were used to evaluate model performance. The Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Goodness-of-Fit Index (GFI) should ideally exceed 0.9 for a model to be considered a good fit.¹¹³ The Normed Fit Index (NFI) and Non-Normed Fit Index (NNFI) should also be above 0.8 and 0.9, respectively.¹¹⁴ Additionally, we used the Standardized Root Mean Square Residual (SRMR) and Root Mean Square Error of Approximation (RMSEA) to assess residuals, with optimal values for these indices being below 0.08.¹¹⁵

Our CFA results confirmed the robustness of our model. The CFI was 0.979, NFI was 0.964, and both

the TLI and NNFI were 0.97, indicating strong alignment with the data. The SRMR at 0.041 and RMSEA at 0.068 demonstrated a good fit with minimal error. The GFI at 0.951 further validated the model's effectiveness in capturing the data structure. Collectively, these indices support the model's statistical validity and theoretical soundness.

Structural equation modeling results

We conducted Structural Equation Modeling (SEM) using the *lavaan* package in R Studio to analyze the structural equation of our model, incorporating various control variables. Model fitness was evaluated using established indices, all of which indicated a satisfactory fit. The Comparative Fit Index (CFI) was 0.981, Tucker-Lewis Index (TLI) 0.976, Normed Fit Index (NFI) 0.951, Non-Normed Fit Index (NNFI) 0.976, and Goodness-of-Fit Index (GFI) 0.933, meeting criteria set by leading scholars.^{116,117} Additionally, the Standardized Root Mean Square Residual (SRMR) was 0.053, and the Root Mean Square Error of Approximation (RMSEA) was 0.044, both aligning with benchmarks for a well-fitting model.¹¹⁵ The relative chi-square value (chi-square/degrees of freedom) was 1.5, which falls within the acceptable range for good model fit.¹¹⁸ These indices confirm that our model demonstrates a strong fit with the data. The SEM results and model visualization can be found in Figure 2.

**Figure 2.** Structural models with standardized estimates.

Hypotheses testing

Our analysis provided valuable insights into the proposed hypotheses. The use of generative AI tools significantly reduced perceived work overload, with a standardized estimate of -0.355 ($p < .001$), supporting Hypothesis 1 (H1). Hypothesis 2 (H2) was also confirmed, showing a positive correlation between generative AI usage and employee adaptability (standardized estimate of 0.602 , $p < .001$). Hypothesis 3 (H3) was validated with a standardized estimate of -0.185 ($p < .05$), demonstrating that employee adaptability reduces perceived work overload. Control variables did not show significant associations with perceived work overload. For further details and implications, see Table 5.

Mediating analysis

We used Structural Equation Modeling (SEM) to analyze the mediating variables, a method known for its robustness in mediation analysis.¹¹⁹ The *lavaan* package in R Studio was employed for this purpose,⁹⁹ and bootstrapping with 5000 samples was implemented to estimate indirect effects reliably, a standard practice in complex models.¹²⁰ Our analysis focused on the indirect and total impacts of key concepts. The results showed that generative AI tools indirectly reduce perceived work overload through employee adaptability, with an impact coefficient of -0.111 ($p < .05$). The indirect effect was calculated as follows:

Indirect effect calculation: Indirect effect = $0.602 * (-0.185) = -0.111$.

Overall, generative AI usage had a significant negative impact on perceived work overload, with an impact coefficient of -0.467 ($p < .001$), considering its direct effect of -0.355 ($p < .001$). Employee adaptability serves

as a partial mediator in this relationship.¹²¹ Detailed results can be found in Table 6.

Discussion

Generative AI tools are gaining global attention, with applications spanning beyond text generation to include music and images. Despite their appeal, research gaps remain regarding their impacts on organizational structures, workforce dynamics, and employee well-being.²⁰ Al Naqbi et al.¹²² emphasize the need for comprehensive evaluations of AI tools, particularly their effects on labor productivity, cost savings, and labor markets, highlighting job displacement and creation. Jo and Park¹²³ stress the importance of designing policies that maximize the benefits of generative AI while addressing human-AI interaction challenges. Ooi et al.³⁹ call for deeper research into AI adoption strategies across different organizational contexts to enhance productivity, learning, and engagement. These findings point to the need for targeted research to optimize AI's benefits while mitigating its potential drawbacks.

Our study contributes to this growing body of literature by examining how generative AI tools influence perceived work overload, focusing on the mediating role of employee adaptability. The findings reveal that using AI tools significantly reduces perceived work overload, both directly and indirectly through increased adaptability. This dual effect highlights AI's ability to lower workload while enhancing employee adaptability, emphasizing the tools' potential to alleviate work-related stress.

Our study highlights the significant relationship between employees' use of generative AI tools and a decrease in perceived workload. These tools not only directly reduce work overload but also indirectly alleviate it by enhancing employee adaptability.

Table 5. Hypothesis testing.

Hypothesis	Factors	Standardized coefficient	Standard error	p value	Supported
H1	Generative AI tools usage > Perceived work overload	-0.355	0.063	.000**	YES
H2	Generative AI tools usage > Employee adaptability	0.602	0.050	.000**	YES
H3	Employee adaptability > Perceived work overload	-0.185	0.076	.016*	YES
Control variable	Age > Perceived work overload	-0.004	0.092	.949 ^{ns}	
Control variable	Gender > Perceived work overload	0.027	0.167	.617 ^{ns}	
Control variable	Educational level > Perceived work overload	-0.019	0.109	.721 ^{ns}	
Control variable	Work experience > Perceived work overload	-0.012	0.085	.850 ^{ns}	

Significant: ** $p < .001$, * $p < .05$, Not significant: ns.

Table 6. Mediating testing.

Hypothesis	Path	Mediator	Direct	Indirect	Total	Hypothesis	Supported
H4	Generative AI tools usage > Perceived work overload	Employee adaptability	-0.355^{**}	-0.111^{*}	-0.467^{**}	H4	Yes

Significant: ** $p < .001$, * $p < .05$, Not significant: ns.

Although research on generative AI tools in the workplace is still emerging, recent studies underscore the positive impact of these tools. Bilgram and Laarmann⁵⁷ show how generative AI fosters innovation within organizations, with human teams successfully integrating AI into their workflows. Similarly, Jaskowicz and Slomovitz²⁰ report that employees using AI tools experience increased productivity and a positive attitude toward their adoption. These findings align with our results, reinforcing the benefits of generative AI adoption.

Our research also reveals that generative AI tools significantly improve employee adaptability. Noy and Zhang¹²⁴ note that AI users achieve greater productivity, particularly benefiting employees with lower skill levels by automating routine tasks. They highlight the potential of AI to boost job satisfaction and streamline workflows. Ooi et al.³⁹ add that AI assists employees by quickly generating concise, actionable information, especially in customer service contexts. Siderska et al.¹²⁵ further emphasize that generative AI tools usage allows employees to focus on more meaningful work. Our findings echo these studies, confirming the dual benefits of generative AI tools in reducing workload stress and enhancing adaptability, thereby transforming workplace dynamics.

Our research reveals a significant inverse correlation between employee adaptability and perceived work overload, showing that greater adaptability is linked to reduced feelings of work-related stress. Nakra and Kashyap¹²⁶ confirm that adaptability enhances psychological well-being, helping employees manage workplace challenges more effectively. Similarly, Shin and Lee¹²⁷ note that adaptability improves task management and self-regulation. Gong et al.¹²⁸ add that adaptable employees tend to be more innovative and open to learning, which fosters both personal and professional growth. These findings support our results, reinforcing the critical role adaptability plays in reducing perceived workload.

Within the frameworks of the job demands-resources (JD-R) model and the broaden-and-build theory, generative AI tools emerge as key resources that foster positive psychological outcomes and enhance adaptability.^{15,29} Our findings align with these models, suggesting that generative AI significantly reshapes workplace dynamics by reducing work demands and mitigating perceived overload. While control variables like age, gender, education, and work experience were considered, none showed significant correlations with perceived work overload, implying that other factors may play a more influential role.

Our study advances the understanding of how generative AI tools reduce perceived work overload and enhance adaptability. By automating routine tasks, these tools allow employees to focus on strategic, innovative work, improving productivity and efficiency.¹²⁹ However, generative AI also presents challenges, such as job displacement and ethical concerns regarding privacy and transparency.^{130,131} The risks associated with data misuse and AI decision-making biases highlight the need for ethical guidelines and transparency in AI algorithms. Additionally, the growing difficulty in distinguishing between human and AI-generated content raises concerns about trust and authenticity.^{132,133} Addressing these issues requires a balanced approach, including robust privacy protections, ethical standards, and strategies for retraining workers displaced by AI.¹³⁴ This approach underscores the transformative potential of AI in reshaping business processes, paving the way for future research to optimize AI deployment strategies.

Contributions for theory

Our research contributes to the understanding of human-AI dynamics in organizational behavior, technology management, and technology adoption. By examining how employees' use of generative AI tools influences their perceived work overload and adaptability, we address a gap in the literature concerning the practical implications of generative AI tools for employee well-being and efficiency. This study provides empirical insights into the effects of generative AI in professional settings. Additionally, our research explores the link between employee adaptability and perceived work overload. By analyzing how adaptability helps mitigate feelings of overwhelm in high-demand environments, we contribute to theories of workplace resilience and adaptability, revealing how individual resilience, technology use, and job demands interact.

Our work also extends the broaden-and-build theory by showing how using of generative AI tools foster positive emotions and adaptability, offering a fresh perspective on the role of technology in enhancing psychological well-being and emotional resilience at work. Finally, our study advances the job demands-resources (JD-R) model by positioning generative AI tools usage as an organizational resource that helps address job demands and reduce perceived overload. This highlights the transformative potential of AI in workload management and employee engagement, paving the way for future research on optimizing AI deployment for improved organizational performance and employee satisfaction.

Contributions for policy

Organization-Level Contributions

Generative AI tools offer profound opportunities for organizations to enhance operational efficiency, foster innovation, and streamline decision-making. By automating routine tasks and optimizing workflows, organizations can redirect their focus toward more strategic and creative initiatives. Furthermore, these tools help address concerns related to security and privacy by improving data handling processes. To maximize these benefits, organizations must develop comprehensive policies that clearly define the scope of generative AI tools usage, ensure data privacy, and create frameworks for continuous monitoring to prevent potential misuse. Additionally, organizations should invest in employee training to ensure that the workforce is equipped to leverage AI tools effectively, thereby fostering an adaptive and resilient organizational culture.

Employee-Level Contributions

For employees, the integration of generative AI tools reduces the burden of repetitive tasks, allowing them to focus on high-impact, strategic activities. This not only enhances job satisfaction but also provides opportunities for professional growth through continuous learning facilitated by AI-powered personalized learning platforms. As employees become more adaptable, they are better able to manage job demands, improving their productivity and psychological well-being. Organizations should encourage the use of AI tools as a resource to support employees in achieving work-life balance, reducing stress, and fostering long-term career development. Clear guidelines on the responsible use of AI tools are also crucial to ensure that employees are not overwhelmed by technological changes and can fully realize the benefits of these innovations.

Limitations and further research

While our study offers valuable insights, several limitations should be acknowledged. First, the data was collected solely in Iran, where the socio-political context may affect the use and perception of generative AI tools, limiting the generalizability of our findings to other regions or cultures. Future research should explore cross-cultural comparisons to assess the impact of generative AI tools in different settings. Additionally, since our study involved employees from various organizations, the results may not apply directly to specific groups or industries. Future studies could conduct

sector-specific analyses to uncover industry-specific implications of AI tools.

Our theoretical foundation relied on the broaden-and-build theory and the job demands-resources (JD-R) model. Future research could benefit from alternative frameworks, such as the Stressor-Strain-Outcome (SSO) model or Organizational Culture Theory. While we focused on employee adaptability as a mediating factor, future studies could explore other constructs and outcomes related to AI tool usage. Additionally, our research centered on perceived work overload, but future work could investigate other positive effects or potential drawbacks of AI adoption in the workplace. Lastly, we did not analyze specific features or tools, leaving room for further investigation into how particular AI characteristics impact employee and organizational outcomes.

Conclusion

Our research advances the understanding of generative AI tools' impact on workplace dynamics, focusing on reducing perceived work overload and enhancing employee adaptability. The key findings reveal that AI tools not only directly reduce work overload but also increase adaptability, which further alleviates overload. This dual benefit highlights the potential of generative AI tools to create more efficient and adaptable work environments. Building on the broaden-and-build theory and the job demands-resources (JD-R) model, our study shows how AI tools serve as resources that foster positive psychological outcomes and adaptability. These results align with previous research, showcasing the innovation and productivity benefits of generative AI in professional settings.^{20,57} Additionally, the broader implications of AI integration in the workplace are clear. By automating routine tasks and enhancing adaptability, generative AI tools not only improve employee performance but also contribute to organizational efficiency and well-being. This research underscores AI's transformative potential in reshaping business processes and employee experiences, paving the way for future studies to optimize AI deployment strategies. In summary, our findings offer valuable insights for managers and policymakers aiming to leverage generative AI tools for workforce productivity and adaptability. The study advocates for strategic AI integration to maximize benefits while addressing challenges, fostering a more dynamic, resilient, and innovative work environment.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

The datasets generated during the current study are not publicly available due to privacy concerns but are available from the corresponding author on reasonable request.

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Appendix. Measures and operationalization of constructs

Table A1. Measures and operationalization of constructs.

Perceived Work Overload ^{89,90}	(1) I feel that the number of requests, problems, or complaints I deal with is more than expected. (2) I feel that the amount of work I do interferes with how well it is done. (3) I feel busy or rushed. (4) I feel pressured.
Employee adaptability ⁹¹	(1) I can adapt well to changes in core tasks. (2) I can cope with changes to the way you must do your core tasks. (3) I can learn new skills to help you adapt to changes in your core tasks.
Generative AI tools usage ⁸⁸	(1) I find generative AI tools useful in my work-related tasks. (2) Using generative AI tools helps me accomplish work-related tasks more quickly. (3) Using generative AI tools increases my productivity.