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GENERATIVE ARTIFICIAL INTELLIGENCE USE AND EMPLOYEE OUTCOMES: THE MEDIATING ROLE OF COGNITIVE OVERLOAD AND THE MODERATING ROLE OF AI GOVERNANCE CLARITY, (BANKING SECTOR SURVEY)

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ABSTRACT
With the emergence of generative artificial intelligence (GenAI) spreading quickly into organizational settings, concerns emerge regarding the overall effect it has on employee experience, performance, and their fair access to benefits. Based on the theory of Conservation of Resources, the paper will explore the cognitive processes by which the use of GenAI affects job performance and job satisfaction and the way AI governance transparency moderates such interactions. Based on survey data of 300 employees based on Partial Least Squares Structural Equation Modeling (PLS-SEM), it was found that the use of GenAI is positively related to job performance and job satisfaction, but also has a major impact on cognitive overload. Cognitive overload, in its turn, has negative implications on the outcomes and partially mediates the relationships between GenAI use and employee outcomes. More importantly, AI governance clarity moderates the connection between GenAI use and cognitive overload, with clarity of governance having a significant negative effect on cognitive strain. These results indicate that, although GenAI can positively impact the workplace outcome, the positive effect is partly neutralized by the augmented cognitive load. Transparent and evident forms of governance turn out to be a major organizational asset to curb negative cognitive consequences and renew more inclusive and accommodating GenAI adoption conditions. The research study makes contributions to the theory by connecting the cognitive processes to governance situations in AI research, and provides practical information to organizations interested in implementing the GenAI tools in a responsible and equitable environment.

Keywords: Generative artificial intelligence; Cognitive overload; Job performance; Job satisfaction; AI governance clarity.

1. INTRODUCTION

Generative Artificial Intelligence (GenAI) has rapidly become embedded in contemporary organizational environments. Tools such as large language models and generative systems are increasingly used to assist employees with writing, analysis, problem solving, and decision-making tasks. Organizations adopt these tools with the expectation that they will enhance efficiency, creativity, and employee productivity (Liu, 2025; Zhang, 2025).

Despite these anticipated benefits, recent studies suggest that the integration of GenAI into everyday work may also introduce new challenges for employees. Unlike traditional automation technologies, GenAI requires continuous human interaction, including prompt formulation, evaluation of outputs, and accountability for AI-supported decisions (Hai, 2025). These requirements may increase employees' cognitive effort rather than reduce it.

Cognitive overload has emerged as a critical concept for understanding the psychological consequences of advanced workplace technologies. When the cognitive demands associated with technology use exceed an individual's processing capacity, performance and well-being may deteriorate (Sweller, 1988). At the same time, organizations differ substantially in how clearly they define and communicate rules, responsibilities, and ethical boundaries related

to AI use. AI governance clarity may therefore play a crucial role in shaping how employees experience GenAI-related demands (Weill & Ross, 2004; IBM, 2025).

Regardless of the fast organizational implementation of generative artificial intelligence (GenAI), employees become more and more cognitively challenged due to the daily contact with AI systems, including the necessity to check the results, deal with the responsibility, and respond to new expectations of AI usage. These issues provoke the concerns regarding the impact of GenAI usage on the cognitive resources of the employees and their work performance and job satisfaction. Meanwhile, as organizations regularly focus on AI governance at policy level, employees tend to have no clear and specific high-level instructions on how to use GenAI, which creates a problem of uncertainty about whether governance mechanisms reduce or increase cognitive strain. As a result, organizations have minimal empirical data to inform the development of GenAI practices that can improve employee performance without their unintended cognitive load.

Although prior research has examined AI use, technostress, and employee outcomes, limited empirical work integrates these elements into a single explanatory framework. In particular, the mediating role of cognitive overload and the moderating role of AI governance clarity remain underexplored in GenAI contexts. Addressing this gap, the present study develops and tests a moderated mediation model grounded in Conservation of Resources theory.

2. LITERATURE REVIEW

2.1 Generative Artificial Intelligence Use

Generative Artificial Intelligence Generative AI systems can generate new content like text, code, images, and analytic summaries according to the patterns observed in extensive data (Liu, 2025). GenAI is becoming an essential tool that assists knowledge workers in organizational contexts, such as writing reports, creating ideas, interacting with customers, and performing analytical procedures (Zhang, 2025).

According to empirically found studies, AI-assisted employees can also be more efficient in their tasks and improve the quality of their work, especially when AI is implemented as an aiding tool instead of a substitute to human judgment (Zang, 2025). There is also research based on the technology acceptance and use theories, which suggest that consistent and successful usage of the innovative digital tools may promote the work results (Venkatesh et al., 2012).

Nevertheless, new data points to the fact that the application of GenAI is qualitatively dissimilar to the previous technologies at the workplace. Workers will have to continuously check the output of AI, determine its correctness, and address ethical or organizational risks linked to the use of AI (Hai, 2025). Consequently, the use of GenAI could be a performance-promoting tool and a cause of cognitive load at the same time (Filippelli, 2026).

2.2 Job Performance

Job performance is the level of effective functioning of the employees with their formal job duties and the accomplishment of work-related objectives (Williams and Anderson, 1991). Previous studies have indicated that the use of superior digital tools can enhance performance due to a rapidness, precision, and quality of decision-making (Koopmans et al., 2014).

According to recent reports on AI-assisted work, AI tools have the potential to improve the performance of employees by offering them real-time feedback, analytical support, and decision assistance (Zhang, 2025). Workers who apply AI in their professional activities are also more prone to a sense of increased performance, especially in positions that require high cognitive abilities (Liu, 2025).

Nevertheless, the benefits of AI usage in terms of performance are not predetermined. The information overload and technostress literature predicts that overcognitive load may cause poor performance by dissecting attention and exerting greater mental fatigue (Karr-Wisniewski and Lu, 2010). Such contradictory results indicate the need to investigate intermediate factors like cognitive overload to discover the performance implications of using GenAI.

Based on the Conservation of Resources theory, the conceptualization of GenAI use defines it as a technology-based job demand that has the potential to drain the finite cognitive resources of employees and thus cause a cognitive overload, which in turn results to a change in job performance and job satisfaction (Hobfoll, 1989; Sweller, 1988).

2.3 Job Satisfaction

Job satisfaction is an affective assessment that an employee has towards his job and work experiences (Cammann et al., 1983). Organizational studies have shown that job satisfaction is usually related to supportive technology and autonomy promoting tools (Bakker and Demerouti, 2007).

GenAI could bring employees more satisfaction as AI tools can help decrease the number of monotonous tasks and work on creative or analytical problems (Liu, 2025). Nevertheless, the outcomes of satisfaction might be harmed in cases when the use of AI leads to the emergence of uncertainty, pressure to monitor, or higher workload (Högemann et al., 2025).

Research related to technostress and AI-related stress factors suggests that job satisfaction may decrease due to mental overload, and continuous adjustment to new technologies, although the performance may be good (Sapkota, 2025).

The results indicate that the outcomes of job satisfaction through the use of GenAI relies on the cognitive experiences of the employees.

2.4 Cognitive Overload

Cognitive over load is the situation where the cognitive processing capacity of a task is greater than the mental requirements of the task (Sweller, 1988). Which is why in digital workplaces, overload is commonly linked with the abundance of information, multitasking, and engagement with the system all the time (Karr-Wisniewski and Lu, 2010).

Under GenAI, cognitive overload can be caused by ongoing prompt-output interactions, the uncertainty of the AI-generated information, and the need to justify AI-assisted choices (Hoegemann et al., 2025). In recent studies, these experiences are operationalized to be of the nature of AI-stressors which expand the conventional technostress models (Sapkota, 2025).

In empirical research, the connection between cognitive overload and poor job performance, emotional burnout, and low job satisfaction is always found (Roetzel, 2019). Cognitive overload, therefore, is a key process of stating the adverse outcomes of using GenAI.

2.5 Mediating Role of Cognitive Overload

The studies of workplace technologies show that the impact that they have on employee performance is usually indirect and follows psychological processes like stress and overload (Karr-Wisniewski and Lu, 2010). Conservation of Resources theory assumes that once cognitive resources get exhausted people feel strained and this affects their performance and well-being (Hobfoll, 1989).

Employees under GenAI conditions are also still responsible in the decisions made using AI, and this might increase mental loads and cause depletion of resources (Hai, 2025). Recent empirical works indicate that AI-related cognitive strain mediates the connection between AI use and employee outcomes partly (Filippelli, 2026).

Nevertheless, very little research has specifically tested cognitive overload as an intermediate between GenAI usage and various employee outcomes in one empirical framework, which is a major literature gap.

2.6 AI Governance Clarity

The term AI governance clarity is used to describe how well rules, policies, and responsibilities of using AI are defined and communicated within an organization (Weill and Ross, 2004). The clarity of governance gives the employees direction on what is acceptable in the use of AI and accountability as well as ethical limits (IBM, 2025).

In line with policy-oriented and practitioner studies, transparent frameworks of AI governance can create uncertainty and perceived risk in relation to AI adoption (ISACA, 2025; ASEAN, 2025). Governance clarity can also serve as a contextual resource that minimizes ambiguity and cognitive load to an employee.

2.7 Moderating Role of AI Governance Clarity

According to the Job Demands Resources model, the contextual resources have the capacity to mitigate the adverse effects of job demands in the results of employees (Bakker and Demerouti, 2007). In GenAI-assisted work, the clarity of AI governance could help minimize the connection between GenAI application and cognitive overload by diminishing uncertainty and decision ambiguity.

AI governance clarity is specified as a first-stage moderator because it primarily shapes employees' appraisal and processing demand during GenAI use (guidance, accountability, permitted practices), thereby weakening the GenAI use → cognitive overload relationship; extending moderation to downstream paths would be less theoretically diagnostic and would reduce parsimony.

2.8 Research Gap and Model Justification

This paper is based on the Conservation of Resources theory which views GenAI use as a technology-based job demand that can occupy the few cognitive resources of employees resulting in cognitive overload, and consequently in job performance and job satisfaction changes (Hobfoll, 1989; Sweller, 1988). Although previous studies have investigated the independent relationships between AI use and employee outcomes the current study is unusual in that it incorporates multiple employee outcomes alongside GenAI use and cognitive overload on the same explanatory model.

AI governance clarity is added as a contextual moderator since governance mechanism is the key factor of how employees understand, regulate, and think about the application of GenAI. Unambiguous governance principles, response frameworks, and delimitations minimize ambiguity and uncertainty, which undermine the correlation between GenAI usage and cognitive loads. According to methodological advice on the conditional process modeling, moderation is identified on the path between use and cognitive overload and not on outcome paths, since this approach provides increased theoretical accuracy and model sparsity (Hayes, 2018; Papagiannidis et al., 2024). The research proposes the model tested with the help of PLS-SEM because it is appropriate in the case of complex mediated moderation models and predictive research aims.

Although the impact of AI or digital technologies on employee outcomes has been studied in the past, these associations have been mostly explored separately. In the current research, the use of GenAI, cognitive overload, job performance, and job satisfaction are put together in one framework to achieve a more comprehensive explanation of how GenAI influences employees at both cognitive and outcome levels, as a result of recent calls to integrate AI

research into the field of organizations in an integrative and theoretically driven manner (Chuang, 2025; Papagiannidis et al., 2024).

3. CONCEPTUAL FRAMEWORK AND HYPOTHESES

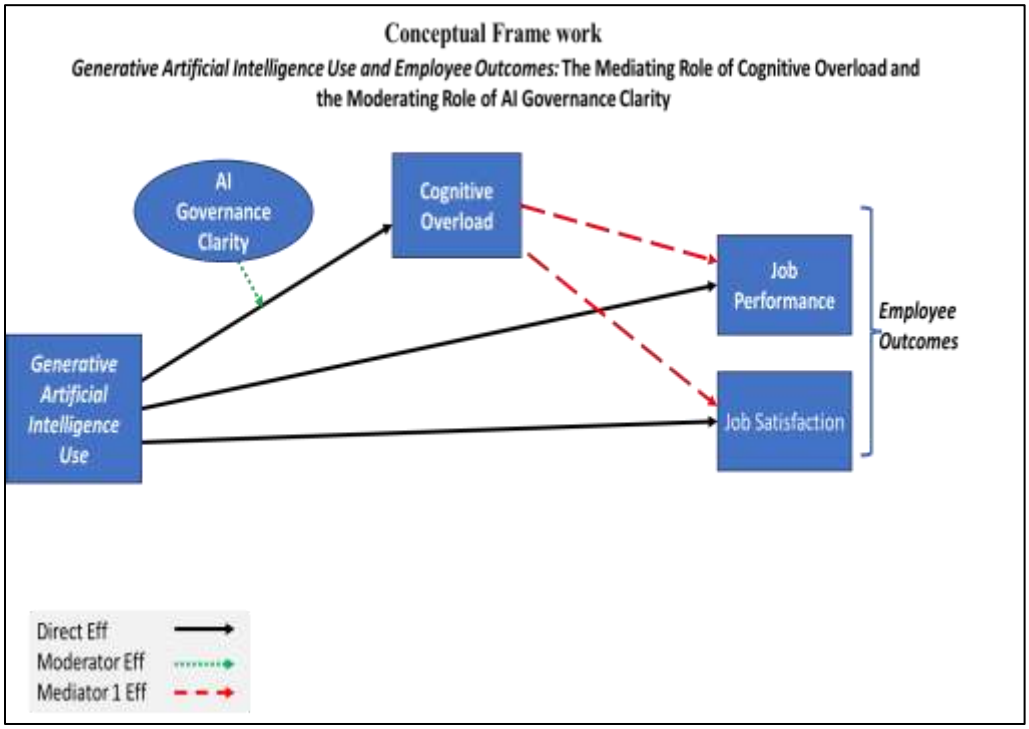

Figure 1. Conceptual Framework of the Study

Hypotheses

H1a: Generative AI use is positively related to job performance.
H1b: Generative AI use is positively related to job satisfaction.
H2: Generative AI use is positively related to cognitive overload.
H3a: Cognitive overload is negatively related to job performance.
H3b: Cognitive overload is negatively related to job satisfaction.
H4a: Cognitive overload mediates the relationship between generative AI use and job performance.
H4b: Cognitive overload mediates the relationship between generative AI use and job satisfaction.
H5: AI governance clarity moderates the relationship between generative AI use and cognitive overload such that the relationship is weaker when governance clarity is high.

Only Mediation path was taken for moderation as AI governance clarity is modeled as a first-stage moderator on the relationship between GenAI use and cognitive overload because governance mechanisms primarily influence employees' interpretation, regulation, and cognitive processing of GenAI use, rather than directly shaping how cognitive overload translates into job performance or job satisfaction. Extending moderation to the dependent variable paths would be theoretically less precise and would reduce model parsimony without a clear conceptual rationale (Hayes, 2018; Papagiannidis et al., 2024).

4. METHODOLOGY

4.1 Research Design

This research was a quantitative research design to investigate how the use of generative artificial intelligence affects the results of the employees. The use of cross-sectional survey methodology helped to gather information regarding the employees who are employed in the organizations which actively use the generative AI tools in the working process. Quantitative design was viewed as fitting, which can be used to test the hypothesis and analyze the relationships between two or more variables at the same time.

4.2 Sample and Data Collection

The structured questionnaire was used to gather data on 300 employees. The respondents were identified based on companies where the use of generative AI tools is conducted in the context of work, including the development of

content, analysis, and decision support. The involvement was voluntary and the respondent's assured anonymity and confidentiality. Partial Least Squares Structural Equation Modeling (PLS-SEM) was sufficient in the final sample size.

4.3 Measurement of Variables

All the variables were observed through already tested scales modified to the generative AI environment. The answers were put down in a five-point Likert scale where 1 wasn't strongly disagree but rather strongly agree.

GenAI use scale was based on the previous technology use and AI use scales used in organizational systems and information systems research (Venkatesh et al., 2012; Chuang, 2025). Though the previous research concentrated mainly on the general AI or use of digital tools, the items were modified to match GenAI-specific workplace tasks, including content generation, decision support, and task augmentation, in line with recent GenAI work-related research (Högemann et al., 2025).

Measurements of cognitive overload were made with the help of modified items of known information and techno-overload scales (Karr-Wisniewski and Lu, 2010; Rasool et al., 2022). These scales are very much validated in the organizational technology settings and are theoretically consistent with the COR theory. The latest GenAI studies point to the same cognitive requirements, such as augmented monitoring, substantiation, and cognitive workload, which prove the contextual relevance of the construct in GenAI contexts (Högemann et al., 2025).

The self-reported performance scale created by Williams and Anderson (1991), which has been widely applied in technology, AI, and technostress research studies, was used to measure job performance (Saleem et al., 2023). The scale will be appropriate in the current research since it entails in-role performance behaviors that depend directly on the availability of cognitive resources.

The items applied in the evaluation of job satisfaction were based on the modified Michigan Organizational Assessment Questionnaire (Cammann et al., 1983) which is a well-known scale in organizational studies. This scale has been used with success in earlier research on the use of technology and technostress, and thus it can be used in GenAI-powered workplaces (Mansuroğlu, 2026).

The concept of AI governance clarity was operationalized through accommodating the items used in previous studies of IT governance, role clarity, and AI transparency frameworks (Weill and Ross, 2004; Papagiannidis et al., 2024). Despite the lack of empirical uses of AI governance clarity in the employee level, the recent literature highlights the necessity to convert the governance structures into unambiguous and practical instructions to the employees, thus confirming the relevance and applicability of the construct to the study (Batool, 2025).

Measuring Generative Artificial Intelligence Use was done using six items that represent the level to which employees use generative AI tools to aid in their work activities. Cognitive Overload was quantified in a seven-item scale that investigated the perceived physical exertment and information processing requirement among the employees when using AI tools.

The level of Job Performance was evaluated based on five questions that indicated how employees believed they were performing their official job duties. Job Satisfaction was described on three measures that measured general job satisfaction of the employees. The measure of AI Governance Clarity was done based on six items that assess how well the organizational rules and guidelines concerning the use of AI are well defined and communicated.

4.4 Data Analysis Technique

Data were analyzed using Structural Equation Modeling, Partial Least Squares (PLS-SEM) and obtained the descriptive statistics of SPSS. The SmartPLS 4 was used to analyze data. The two step analysis was applied. The first was the measurement model, whose reliability and validity were determined. Second, structural model was tested to determine the relationships that are hypothesized as well as mediation and moderation effects. To identify the significance of the path coefficients, bootstrapping was done by employing 5,000 subsamples.

4.5 Measurement Instruments

All constructs were measured using **multi-item reflective scales** adapted from established studies and modified to suit the generative AI context. Responses were recorded on a **five-point Likert scale** ranging from 1 (strongly disagree) to 5 (strongly agree).

- **Generative Artificial Intelligence Use** was measured using six items adapted from technology use and acceptance literature, focusing on the frequency and extent of GenAI use in work tasks (Venkatesh et al., 2012; Zhang, 2025).
- **Cognitive Overload** was measured using seven items adapted from cognitive load and information overload research, capturing employees' perceptions of excessive mental effort and information processing demands when using AI tools (Sweller, 1988; Karr-Wisniewski & Lu, 2010).
- **Job Performance** was measured using five items adapted from Williams and Anderson (1991), reflecting employees' self-assessed effectiveness in fulfilling in-role job responsibilities.
- **Job Satisfaction** was measured using three items adapted from the Michigan Organizational Assessment Questionnaire (Cammann et al., 1983), capturing employees' overall affective evaluation of their job.

- **AI Governance Clarity** was measured using six items adapted from IT governance and organizational policy clarity literature, assessing the extent to which AI-related rules, responsibilities, and guidelines are clearly defined and communicated (Weill & Ross, 2004; IBM, 2025).

5. RESULTS

5.1 Measurement Model Results

The measurement model was assessed to evaluate the reliability and validity of the constructs prior to testing the structural relationships. Internal consistency reliability, convergent validity, and discriminant validity were examined following established PLS-SEM guidelines.

Descriptive Statistics

Table 2 presents the descriptive statistics for the study variables. The mean values indicate moderate levels of generative AI use, cognitive overload, job performance, job satisfaction, and AI governance clarity among respondents. The standard deviation values suggest sufficient variability in the responses.

Table 2. Descriptive Statistics

Construct	N	Minimum	Maximum	Mean	SD
Generative AI Use (GAIU)	300	1.00	5.00	2.998	1.157
Cognitive Overload (CO)	300	1.00	5.00	2.997	1.128
Job Performance (JP)	300	1.00	5.00	3.027	1.151
Job Satisfaction (JS)	300	1.00	5.00	3.014	1.193
AI Governance Clarity (AIGC)	300	1.00	5.00	3.012	1.166

5.1.1 Reliability and Convergent Validity

Internal consistency reliability was assessed using Cronbach's alpha and composite reliability (CR). Convergent validity was evaluated using average variance extracted (AVE). The results are presented in Table 3.

Table 3. Reliability and Convergent Validity

Construct	Cronbach's α	Composite Reliability (CR)	AVE
Generative AI Use	0.892	0.918	0.651
Cognitive Overload	0.910	0.929	0.650
Job Performance	0.870	0.906	0.659
Job Satisfaction	0.801	0.882	0.714
AI Governance Clarity	0.885	0.920	0.743

As shown in Table 3, all Cronbach's alpha and composite reliability values exceed the recommended threshold of 0.70, indicating satisfactory internal consistency reliability. In addition, all AVE values are greater than 0.50, confirming adequate convergent validity.

5.1.2 Discriminant Validity

Discriminant validity was assessed using the Fornell–Larcker criterion. The results are reported in Table 4.

Table 4 Discriminant Validity (Fornell–Larcker Criterion)

Construct	AIGC	CO	GAIU	JP	JS
AIGC	**0.862**				
CO	0.112	**0.806**			
GAIU	0.306	0.356	**0.807**		
JP	0.128	−0.066	0.253	**0.812**	
JS	0.053	−0.270	0.056	0.148	**0.845**

Note: Diagonal values represent the square root of AVE.

The results show that the square root of the AVE for each construct is greater than its correlations with other constructs, satisfying the Fornell–Larcker criterion and confirming discriminant validity. HTMT values (not tabulated) were all below 0.85, providing further support for discriminant validity.

5.2 Structural Model Results

The structural model was assessed to test the proposed hypotheses. Bootstrapping with 5,000 resamples was employed to examine the significance of the structural paths.

5.2.1 Direct Effects

The results of the direct effects among the constructs are presented in **Table 5.**

Table 5 Structural Model Results (Direct Effects)

Hypothesis	Structural Path	β	t-value	p-value	Decision
H1a	Generative AI Use → Job Performance	0.316	5.747	< .001	Supported
H1b	Generative AI Use → Job Satisfaction	0.174	3.110	.002	Supported
H2	Generative AI Use → Cognitive Overload	0.349	6.346	< .001	Supported
H3a	Cognitive Overload → Job Performance	−0.178	2.928	.003	Supported
H3b	Cognitive Overload → Job Satisfaction	−0.332	5.726	< .001	Supported

As shown in Table 5, generative AI use has a significant positive effect on job performance and job satisfaction. Generative AI use also has a significant positive effect on cognitive overload. Cognitive overload has a significant negative effect on both job performance and job satisfaction.

5.2.2 Coefficient of Determination

The explanatory power of the structural model was assessed using the coefficient of determination (R^2).

- Cognitive Overload: $R^2 = 0.31$
- Job Performance: $R^2 = 0.27$
- Job Satisfaction: $R^2 = 0.29$

These values indicate that the model explains a moderate proportion of variance in the endogenous constructs.

5.3 Mediation Analysis

The mediating role of cognitive overload in the relationship between generative AI use and employee outcomes was examined using the bootstrapping procedure with 5,000 resamples. The indirect effects are reported in Table 6.

Table 6 Mediation Analysis Results

Hypothesis	Indirect Path	β	t-value	p-value	Mediation
H4a	GAIU → CO → JP	−0.062	2.582	.010	Partial
H4b	GAIU → CO → JS	−0.116	3.960	< .001	Partial

The indirect effects are statistically significant. Since the direct effects also remain significant, cognitive overload partially mediates the relationships between generative AI use and both employee outcomes.

5.4 Moderation Analysis

The moderating role of AI governance clarity was examined by testing the interaction effect between generative AI use and AI governance clarity on cognitive overload. The results are presented in Table 7.

Table 7 Moderation Analysis Results

Hypothesis	Interaction Path	β	t-value	p-value	Decision
H5	GAIU × AIGC → Cognitive Overload	−0.215	3.755	< .001	Supported

The results indicate that AI governance clarity significantly weakens the positive relationship between generative AI use and cognitive overload.

6. DISCUSSION

This paper investigated the impact of generative artificial intelligence application on both job performance and job satisfaction where cognitive overload was a mediating variable and AI governance clarity was a moderating factor. The results give empirical evidence of a proposed moderated mediation model.

The findings show that the use of generative AI has a positive effect on job performance and job satisfaction. This implies that workers are driven to find generative AI tools as useful in accomplishing work-related tasks and improving work experience in general. The results are in line with the previous research that reveals the performance-improving promise of AI-assisted work.

Meanwhile, the use of generative AI causes cognitive overload to an even greater extent. This observation is corroborated by recent studies indicating that GenAI imposes new cognitive tasks, including development of timely decisions, verification of outputs and responsibility of AI-assisted decisions. The adverse consequences of mental overload on job performance and job satisfaction serve as a further confirmation of the fact that cognitive overload and extreme mental demand may impair the results of the workers.

The outcomes of mediation indicate that cognitive overload is a partial factor that determines the impact of using generative AI on employee outcomes. The overall improvement in performance and satisfaction with the use of generative AI is also partially nullified by the rise in cognitive overload. This observation underscores the two-sidedness of generative AI as a source and a need at the working place.

Moreover, the moderation findings determine that AI governance transparency undermines the association between the use of generative AI and cognitive overload. Employees who have well-defined organizational regulations, duties, and principles surrounding the use of AI in their work have reduced mental burden due to generative AI applications. This explains the role of organizational context in the experiences that employees have with AI technologies.

7. Implications

7.1 Theoretical Implications

The proposed study will add to the body of work on artificial intelligence in the workplace by combining the use of generative AI, cognitive overload, and outcomes of employees into one empirical model. Through the application of the Conservation of Resources theory, the study proves that generative AI uses and consumes cognitive resources at the same time. The fact that the AI governance clarity is introduced as a moderator is a continuation of the current literature because it emphasizes the importance of organizational governance as a situational resource that helps to reduce cognitive strain.

7.2 Practical Implications

The results have a number of viable implications towards organizations that have adopted generative AI technologies. First, organizations must understand that the adoption of generative AI is not only a technical problem but also a cognitive and managerial problem. Second, AI governance frameworks must be established and clarified to minimize uncertainties and cognitive overloads in employees. Third, the training programs must not only be aimed at the technical skills, but also effective use of AI and management of cognitive workload.

8. LIMITATIONS AND FUTURE RESEARCH

This study has a few limitations even though it has contributed to it. This study is cross-sectional and therefore prohibits inference of causality and the use of self-reported data is likely to cause common method bias. Future studies may use longitudinal designs or objective measures of performance to cause or build on causality.

Also, further research can examine other mediating variables, including emotional exhaustion or AI-related anxiety, and other moderators, including AI literacy, leadership support, or organizational culture.

9. CONCLUSION

This research comes to the conclusion that the use of generative artificial intelligence positively affects job performance and job satisfaction, but these positive aspects are balanced to some extent by cognitive overload. AI governance transparency is a significant moderating factor because it removes cognitive load linked to the use of generative AI. All in all, the results underscore the significance of sound AI governance and cognitively sensible implementation plans in the most efficient realization of the advantages of generative AI without jeopardizing employee performance.

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