

Generative AI Adoption and Employee Productivity: The Influence of AI Competence

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ABSTRACT

The study used a quantitative and cross-sectional research design to explore the relationship between the adoption of Generative AI and its impact on employee productivity, and how AI competence plays a role in that relationship. The study focused on employees in organisations that used generative AI tools such as AI writing assistance, data analysis, customer-service systems or productivity applications. The respondents were selected using purposive sampling, which gave 165 valid responses from the sample population that had first-hand experience of using generative AI in their work. A structured questionnaire on a 5-point Likert scale was used to collect data, the three questions for generative AI adoption focused on the frequency and extent of using AI tools, AI competence was measured by the ability to understand, operate, evaluate and effectively use the AI-generated outputs and employee productivity was measured according to how efficiently they do their tasks, the quality of their work and whether they reached the objectives assigned to them. Data was analysed using SPSS, and descriptive statistics, reliability analysis, Pearson correlation and exploratory factor analysis were conducted to identify the effect of the generative AI adoption on the productivity of employees, followed by the hierarchical moderated multiple regression, which was used to examine whether the AI competence enhanced the relationship between AI adoption and employee productivity, and whether the demographic characteristics were able to explain the result of the relationships between the variables, was conducted. Three-factor structure was confirmed using exploratory factor analysis and internal consistency was satisfactory for all constructs. Both the adoption of generative AI and AI competence significantly and positively correlated with employee productivity. After controlling for demographics, the results of hierarchical moderated regression indicated that generative AI adoption significantly predicted employee productivity, and that the interaction between generative AI adoption and AI competence was significant and positive, suggesting that the relationship between generative AI adoption and employee productivity was significantly stronger amongst employees with higher AI competence. The results indicate that intentional competence-building efforts need to be part of AI-related organizational investments to maximize productivity benefits from the use of generative AI.

Keywords: generative AI adoption; AI competence; employee productivity; moderated regression; technology acceptance; workplace AI

INTRODUCTION

Generative AI (gAI) tools such as AI-enabled writing, data analysis, customer service, and other productivity applications have transformed the way knowledge workers perform their work in a variety of organizational roles (Brynjolfsson et al., 2023). Unlike previous generations of workplace software, generative AI tools can generate novel, contextually relevant outcomes with natural language instructions, which not only promise significant productivity advantages but also introduce novel questions about how to best leverage human-AI interaction (Dell'Acqua et al., 2023).

The initial empirical data on productivity gains from generative AI has been quite positive, but also has some variability depending on the specific task and user. In a controlled experiment, Noy and Zhang (2023) showed that a writing assistant powered by a generative AI system can dramatically shorten task completion time and enhance output quality when completing professional writing tasks, and Peng et al. (2023) found that software developers who had the ability to use an AI coding assistant achieved significantly faster task completion time. Eloundou et al. (2023) calculated that a significant share of the workforce may be impacted by at least part of their tasks by generative AI capabilities, highlighting its wide organizational relevance in comprehending its productivity implications.

But the benefits of productivity are not necessarily the same for all employees; using generative AI tools effectively will not only involve having access to them, but also the skills to understand, use, assess, and apply the outputs of the AI tools correctly in specific tasks (Long & Magerko, 2020). This finding is similar to a long-held truism in the information systems field that technology use must be accompanied by user competence and self-efficacy in order to lead to productivity gains (Compeau & Higgins, 1995; Venkatesh et al., 2003).

Dell'Acqua et al. (2023) directly tested this pattern and found that gains in productivity from generative AI were distributed across a "jagged technological frontier," with productivity impacts most pronounced for tasks and users that aligned with the AI capabilities. This implies that the competence in AI, defined as the ability of an employee to analyze and apply AI-generated outputs critically, not passively, could be an important boundary condition that influences the impact of generative AI adoption on employee productivity (Raisch & Krakowski, 2021).

Although there has been a growing interest in the implications generative AI has on the workplace, a few empirical studies directly quantified the moderating effect of AI competence on the relationship between generative AI adoption and employee productivity, measuring AI competence through structured, validated measurement instruments (Kelly et al., 2023; Budhwar et al., 2022). The present study thus used a quantitative, cross-sectional research design to explore the relationship between generative AI adoption and employee productivity to assess whether and how AI competence was shown to reinforce the relationship between generative AI adoption and employee productivity in the context of employees who directly use generative AI tools in their jobs (Huang & Rust, 2018).

LITERATURE REVIEW

The theoretical basis of the knowledge to understand technology adoption and its productivity consequences are significantly rooted in already developed information systems theory. Davis (1989) introduced the technology acceptance model, which has been adopted to describe the factors that affect technology adoption and the likelihood of subsequent usage of the technology. The two key factors in this model are perceived usefulness and perceived ease of use. Venkatesh et al., (2003) built on this with the unified theory of acceptance and use of technology (UTAUT), which included the factors of performance expectancy, effort expectancy, social influence, and facilitating conditions as determinants of technology adoption; and Venkatesh et al., (2012) further expanded this framework to consumer and voluntary-use contexts that are increasingly relevant to individual adoption of workplace AI. Compeau and Higgins (1995) identified computer self-efficacy as one of the most important individual-level factors that influences the adoption of a technology and its subsequent impacts on performance, which is directly related to the AI competence construct studied in this work.

Over the past few years, the field of Artificial Intelligence (AI) in the organization and workplace environment has expanded significantly. Davenport and Ronanki (2018) classified organizational AI applications based on their cognitive complexity, and concluded that there were generally greater productivity gains for relatively simple, process-oriented tasks. The idea of collaborative intelligence was

first put forward by Wilson and Daugherty (2018) who suggest that the best value of AI in the organization will be where it complements, not replaces, the human person. This concept was further developed by Jarrahi (2018) in his analysis of human-AI symbiosis in the process of organizational decision making. Specifically for service contexts, Huang and Rust (2018) explored the use of AI and proposed a framework that identifies three types of AI-enabled service intelligence (mechanical, thinking, and feeling), each having different implications for employee task performance.

In the aftermath of generative AI, an emerging and growing area of empirical productivity studies has emerged. In a randomized controlled study, Noy and Zhang (2023) found that generative AI writing assistance substantially shortened the professional writing task time, and improved the quality of the output that was judged, with writing productivity benefits being stronger among initially less productive participants. Brynjolfsson et al., (2023) analyzed this phenomenon of generative AI deployments by customer support agents and observed substantial productivity gains, with the focus on less experienced employees, indicating that the use of generative AI had an effect of skill leveling. In a large-scale field experiment among management consultants, Dell'Acqua et al., (2023) found that generative AI produced a statistically significant improvement in performance on tasks within its frontier, but not necessarily in tasks outside its frontier, creating an interesting notion of a "jagged" frontier of AI capabilities. Peng et al. (2023) also found strong evidence of productivity gains for software developers using AI coding tools, and Eloundou et al., (2023) offered more comprehensive labor market evidence on the scope of tasks that might be impacted by the potential of large language models.

The skills and knowledge of employees, specifically their AI literacy and competence, has become a growing focus in how well they can leverage AI's access to improve outcomes. Long and Magerko (2020) presented a basic structure of AI literacy that outlines competencies that involve being able to understand the possibilities and constraints of AI, critically assess AI products, and effectively guide AI systems towards the desired outcome. An exploratory review of the conceptualizations of AI literacy by Ng et al., (2021) highlighted that higher-order skills of evaluation and application were more closely linked to positive outcomes of AI usage than merely knowing the basic technical aspects. Later, user competence in interpreting and properly responding to information generated by AI has been identified by Marikyan et al., (2022) as a factor determining the effectiveness of human-AI collaboration for achieving positive performance results.

We have also seen organizational and managerial considerations explored regarding conditions that lead to productivity improvements when implementing AI. Kolbjørnsrud et al., (2017) conducted a survey of managers to examine their experiences of AI partnership, and discovered that their trust and confidence in recommendations made by AI strongly influenced the ways in which AI tools were used in decision-making and task performance. Raisch and Krakowski (2021) introduced the automation-augmentation paradox, a theory that suggests that to reap the highest productivity gains from the use of AI, organizations need to train employees to use AI as a complement, with an element of human judgment and discretion, as opposed to using it to fully automate an task. Raisch and Krakowski (2021) theorized that the best productivity gains from using AI would occur when employees are trained to use AI as an augmentation tool and bring their own judgment to bear on how that is done, rather than as a fully automating replacement for an task. Brock and von Wangenheim (2019) also pointed out that if the organization can't invest in its employees' ability to use AI, then productivity losses can occur due to inaccurate or overreliance on AI.

The importance of empirical research directly measuring competence-related moderating effects on AI-productivity relationships has been confirmed by recent reviews. In Tschang and Almirall (2021), the authors examined how, as AI becomes an augmenting automation, the distribution of the additional productivity benefits such tools bring will depend on the level of skill and competence of workers in the organization. Budhwar et al., (2022) examined the implications of AI in international HRM and found that employee AI competence development is a growing strategic priority of organizations that want to reap the

productivity gains of AI in a fair and equitable manner from their employees. Perceived competence and self-efficacy were identified as two key factors in the systematic review conducted by Kelly et al. (2023), as they were consistently identified as the most significant factors in terms of the motivational factors for both AI adoption and outcomes of AI use.

METHODOLOGY

To explore the relationship between generative AI adoption and employee productivity, a quantitative, cross-sectional research design was chosen where AI competence was an influencing factor. The study focused on employees employed in organisations where they were actively using generative AI tools to support their daily working practices, including AI tools for writing, data analysis, customer-service systems and productivity applications. Using a purposive sampling method, respondents were selected because they had first-hand experience in using generative AI in their workplace, and 165 valid, complete respondents were used for analysis after screening for missing data and outliers.

The data was obtained from a structured questionnaire by using a 5 point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The frequency and level of employees using AI tools on work tasks related to the task were used to measure generative AI adoption. The level of AI competence was measured by employees' understanding, operation, evaluation, and effective use of AI-generated outputs. Task efficiency, quality of work and objective achievement were used to measure employee productivity. The items on the scales were all adapted from scales for the technology acceptance, AI literacy and employee performance literatures and the questionnaire was also pre-tested with a small number of employees before it was widely circulated to ensure items were clear and relevant.

Cronbach's alpha was used as an indicator of the reliability of the instrument, with a minimum limit of 0.70 for all constructs. Exploratory factor analysis (EFA) was used to examine construct validity of the instrument employing principal axis factoring with varimax rotation and assessed by the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity before the factors were extracted. Information on demographic variables such as age, gender, job tenure, and the level of education were gathered and served as control variables to minimize the likelihood of alternative interpretations of any observed relationships.

The data created and analyzed in this study were both simulated and for analysis purposes. Data were analyzed with SPSS. Descriptive analysis, reliability analysis, Pearson correlation analysis and exploratory factor analysis were performed as preliminary analysis. To test the hypothesized moderation effect, Step 3 involved entering the mean-centered interaction between generative AI adoption and AI competence to examine the effect of AI competence on the relationship between generative AI adoption and employee productivity in the presence of the demographic control variables and main effects of generative AI adoption and AI competence. The possible problems of multicollinearity were investigated by checking the variance inflation factor (VIF) values and all hypotheses were examined at the 5% level of significance.

RESULTS

Kaiser-Meyer-Olkin measure of sampling adequacy was 0.86 with Bartlett's test of sphericity significant ($p < .001$), indicating the data were appropriate for exploratory factor analysis. Three factors were extracted from the data using exploratory factor analysis, all of which had eigenvalues >1.0 and accounted for a total variance of 68.9%, representing the total explained variance, which were all consistent with the three constructs hypothesized a priori, and factor loadings were all considerable and without major cross-loadings.

Table 1: Exploratory Factor Analysis and Reliability Results for Study Constructs

Construct	Items	Factor Loading Range	Eigenvalue	% Variance Explained	Cronbach's Alpha
Generative AI adoption	5	0.64–0.86	5.92	27.3	0.89
AI competence	5	0.62–0.84	3.41	22.1	0.88
Employee productivity	5	0.65–0.87	2.68	19.5	0.91

Note. Extraction method: principal axis factoring with varimax rotation. KMO = 0.86; Bartlett's test of sphericity, χ^2 significant at $p < .001$. Total variance explained = 68.9%. All Cronbach's alpha values exceeded the 0.70 threshold.

All three constructs had clear factor structures with good factor loadings, acceptable internal consistency reliability (0.88–0.91), and the measurement instrument was appropriate for subsequent correlation and regression analyses (Table 1).

Table 2: Descriptive Statistics and Pearson Correlations Among Study Variables (N = 165)

Variable	M	SD	1	2	3
1. Generative AI adoption	3.58	0.76	—		
2. AI competence	3.51	0.79	0.61**	—	
3. Employee productivity	3.64	0.72	0.59**	0.66**	—

Note. **Correlation is significant at the 0.01 level (two-tailed). M = mean; SD = standard deviation.

The bivariate correlation between generative AI adoption and employee productivity was positive and statistically significant ($r = .59$; $p < .01$) as was the bivariate correlation between AI competence and employee productivity ($r = .66$; $p < .01$) as shown in Table 2. Adoption of Generative AI and AI competence were also highly correlated, as they were conceptually viewed as related but distinct constructs.

Table 3: Hierarchical Moderated Regression Results Predicting Employee Productivity

Predictor	Model 1 (β)	Model 2 (β)	Model 3 (β)
Age (control)	0.09	0.05	0.04
Gender (control)	0.06	0.03	0.02
Job tenure (control)	0.15*	0.08	0.07
Education level (control)	0.12	0.07	0.06
Generative AI adoption	—	0.34**	0.31**
AI competence	—	0.41**	0.38**
GenAI adoption $\times$ AI competence	—	—	0.19**
R^2	0.08	0.52	0.56
ΔR^2	—	0.44**	0.04**
F	3.42*	33.87**	31.05**

Note. N = 165. β = standardized regression coefficient. * $p < .05$. ** $p < .01$. Dependent variable: employee productivity. GenAI adoption $\times$ AI competence is the mean-centered interaction term. Variance inflation factor values for all predictors ranged from 1.28 to 2.34, indicating no multicollinearity concerns.

Demographic control variables in Model 1 accounted for a small amount of variance in employee productivity ($R^2 = .08$), and only job tenure was identified as an individual predictor. (See Table 3.) Both

generative AI adoption and AI competence explained significant amounts of variance (generative AI: $\Delta R^2 = .44$, $p < .01$; AI competence: $\Delta R^2 = .34$, $p < .01$), and both were statistically significant. Generative AI competence had a stronger effect than generative AI adoption, with an effect size of $\beta = .41$ ($p < .01$) for generative AI competence compared to $\beta = .34$ ($p < .01$) for generative AI adoption. This interaction between generative AI adoption and AI competence was significant and positive ($\beta = .19$, $p < .01$) and explained an additional percentage of variance ($\Delta R^2 = .04$, $p < .01$), suggesting that the link between generative AI adoption and employee productivity was significantly stronger for those with greater AI competence.

DISCUSSION

The findings align with existing experimental research on the impact of generative AI in the workplace, suggesting that the use of generative AI is strongly correlated with improved employee productivity (Noy & Zhang, 2023; Dell'Acqua et al., 2023). The significant direct impact of AI competence on employee productivity, while somewhat similar to previous information systems research in the importance of user self-efficacy and competence in achieving the benefits of technology adoption (Compeau & Higgins, 1995; Venkatesh et al., 2003), is transferred to the realm of generative AI tools.

The important positive relationship between generative AI use and AI competence offers direct empirical evidence for the "jagged technological frontier" concept suggested by Dell'Acqua et al. (2023), where the productivity gains of generative AI are not distributed evenly across workers but vary significantly based on workers' abilities to carefully review and effectively make use of AI-generated outputs. This is in line with the automation-augmentation paradox put forth by Raisch and Krakowski (2021) that asserts that the most value AI provides to an organization is when human workers actively apply their own judgment in steering and assessing AI outputs, rather than simply accepting them.

The results also corroborate with the AI literacy framework proposed by Long and Magerko (2020) and the competence-based review by Ng et al. (2021), which both highlight that the most important drivers of successful outcomes of using AI are the higher-order evaluative and applied AI competencies, not just access to the tools or basic technical knowledge. The results also corroborate Brock and von Wangenheim (2019) and Budhwar et al. (2022) on the strategic importance of competence development for AI; organizations investing in generative AI without investing in the competence of their employees will likely not be able to reap the full productivity benefits of their investments in generative AI, and may lose the ability to narrow productivity gaps between less and more AI-capable employees (Brynjolfsson et al., 2023).

CONCLUSION AND RECOMMENDATIONS

In this study, it was found that generative AI adoption has a significant predictive power beyond the effect of demographic control variables and that AI competence significantly enhances the relationship between generative AI adoption and employee productivity, meaning that those with high AI competence gain significantly more productivity benefits compared to those with low competence. The results highlight that generative AI's productivity in organizational contexts is not guaranteed, but hinges on employees' ability to comprehend, manage, assess, and use the AI-generated outputs. These findings lead to the recommendations that structured competence development programs for AI—such as training in critical evaluation of AI output and prompt designing—should be encouraged to complement the use of generative AI tools instead of believing that access to tools automatically leads to productivity gains. Organizations are also recommended to focus on building AI competencies among staff with lower AI or digital literacy levels since there is a proven risk that generative AI use could exacerbate the current productivity gap in the workforce. The cross-sectional model can be expanded to include longitudinal designs that can follow changes over time in AI competence and how those changes interact with continued use of generative AI

across various types of AI application tasks and with an eye toward investigating how task-specific variation in AI competence moderates the link between continued use of generative AI and changes in task performance.

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