

Artificial Intelligence Adoption and Employee Productivity: The Mediating Role of Digital Competence

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ABSTRACT

In the workplace, artificial intelligence (AI) is rapidly becoming a staple, but the benefits it delivers in productivity vary from organization to organization. The present study investigated the association between the AI adoption and employee productivity mediated by digital competence. A quantitative research design was used and 300 employees of both the private and public sectors organizations completed the structured questionnaire with a five-point Likert scale. Descriptive analyses, correlation analysis, regression analysis and mediation analysis (using Hayes' (2013) PROCESS Model 4 with bootstrapping) were performed on the data. The findings revealed that the adoption of AI had a significant positive impact on employee productivity as well as digital competence; digital competence had a significant positive impact on productivity. The relationship between AI adoption and productivity was partially mediated by digital competence, suggesting that the impact of AI on productivity is partly attributable to the increased benefits of using AI tools that contribute to digital competence. The study relates the research on the technology adoption to the research on work-performance and recommends using AI deployment in conjunction with continuous digital skills development.

Keywords: artificial intelligence adoption; digital competence; employee productivity; mediation; PROCESS Model 4



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INTRODUCTION

AI is no longer experimental but has become commonplace tools used in the workplace to write content, analyse data, respond to queries, and automate repetitive tasks. AI tools are expected to boost efficiency and quality in the work place, and commentators have hailed AI as a general-purpose technology with pervasive economic impacts (Davenport & Ronanki, 2018; Dwivedi et al., 2021). Research on strategic use of AI has also increased significantly, as highlighted by systematic reviews, although there is not yet a consistent body of evidence on the outcomes at the employee level (Borges et al., 2021).

There is evidence with positive results about productivity effects. A controlled experiment was conducted with professional writing tasks, showing that output quality was improved and the time taken to complete the tasks was decreased when a generative AI assistant was used (Noy & Zhang, 2023). The economic evidence also suggests that technology is not a substitute for labor, but it also generates new jobs and reallocates labour (Acemoglu & Restrepo, 2019; Autor, 2015). However, AI can also augment and automate tasks, and it will be the ratio of those that AI can do that determines if the employee benefits (Raisch & Krakowski, 2021). The value of Gains lies not in the presence of AI but in its utilization by humans.

One thing that is missing in humans is their capability. Digital competence—confident, critical and effective use of digital technologies for work—is considered an essential skill set of the digital workplace (Van Laar et al., 2017). Digital skills are not just picked up in school or at a certain age, but rather need to be learned and practiced intentionally (Ng, 2012). Frequent use of AI tools by employees, and more competent employees using AI tools more effectively, helps employees get used to developing this competence. Studies of human-AI interaction indicate that there are best gains when machine-based analytic capabilities are used in tandem with human judgment and skill (Jarrahi, 2018).

The technology acceptance research helps us understand why the adoption varies and why adoption is inadequate if not use. Perceived usefulness, ease of use, and facilitating conditions affect the extent to which people are likely to use a technology and how they will use it in their task performance (Venkatesh & Bala, 2008). HR research also highlights that AI introduces challenges for organizations, such as the need to train and develop their employees to work with AI (Tambe et al., 2019). In addition to the key elements of task efficiency, work quality and the attainment of objectives, productivity is an integral part of individual work performance (Koopmans et al., 2011).

However, so far only a few research studies have examined whether the development of digital competence accounts for the connection between the use of AI and the productivity of workers in one single model and with samples drawn across public and private sector institutions from developing economies. To fill this void, this study investigated the indirect effect of AI use on employee productivity through digital competence and to understand the indirect effect of AI use on digital competence through digital competence, bootstrapped indirect effects (Preacher & Hayes, 2008) were tested. The research is valuable for bridging the gap between the technology adoption and work-performance literatures, and for providing practical evidence for organizations in the midst of deploying AI.

LITERATURE REVIEW

Conceptual background

AI adoption can be defined as the extent of employee use of AI-based tools, their perceptions of usefulness, and their incorporation into routine work (Davenport & Ronanki, 2018; Venkatesh & Bala, 2008). Digital competence is defined as employee's competence in using digital technologies effectively, such as locating and assessing information, using software, communicating digitally, and troubleshooting digital issues (Van Laar et al., 2017). Employee productivity is defined as employee work performance represented in task efficiency, work quality, and attainment of goals assigned to the employee (Koopmans et al., 2011). This study builds on the theoretical frameworks of technology acceptance reasoning (Venkatesh & Bala, 2008), the perspective of AI as both an automation and augmentation of work (Raisch & Krakowski, 2021), and the logic of human capital that ties the value of human capital gains to skills (Acemoglu & Restrepo, 2019).

AI in customer service

AI tools can reduce repetitive tasks, aid decision-making, and enhance the quality by detecting errors and providing suggestions (Dwivedi et al., 2021; Jarrahi, 2018). Both completion time and rated quality of tasks using generative AI were also faster and higher as suggested by the experimental evidence of Noy and Zhang (2023). Autor (2015) and Acemoglu and Restrepo (2019) highlight that technology redistributes work and that technology can boost productivity when humans and machines are complementary. According to Borges et al. (2021), organisations use AI for the main purpose of enhancing efficiency and performance. Meanwhile, Raisch and Krakowski (2021) warn that there are tensions involved in automation and augmentation that need to be managed by managers. Accordingly:

H1: There is a strong relationship between employee productivity and the adoption of AI. H3: AI use positively influences employee productivity.

AI usage and digital literacy

Employees are exposed to new digital interfaces, data-handling practices, prompts and the evaluation of automated outputs that overtime develop technical and critical skills (Ng, 2012; Van Laar et al., 2017). Another study of technology acceptance points out that the more a technology is experienced, the higher the perceived ease of use and confidence will be (Venkatesh & Bala, 2008). Organizations implementing AI tend to provide training and support, further enhancing their digital capability (Tambe et al., 2019). Hence:

H2: The impact of AI adoption on digital competence is highly positive.

Digital competence

Employees who are digitally competent can set up, check and fine-tune the work of AI, safeguard data and resolve issues promptly, thereby contributing to efficiency and quality (Van Laar et al., 2017). The effectiveness of the human-machine combination is determined by skills (Autor, 2015; Jarrahi, 2018) and the performance of individual employees is influenced by the skills they are able to bring to their tasks (Koopmans et al., 2011). Therefore:

H3: Digital competence positively influences employee productivity.

Digital competence as a mediator

Assuming that AI adoption builds digital competence, and competence raises productivity, part of the effect of adopting AI on productivity should go through the competence. This aligns with the view that the value generated by AI is driven by human skills (Jarrahi, 2018; Raisch & Krakowski, 2021) and that employees need to be trained and developed to work with AI (Tambe et al., 2019). Mediation was examined as an indirect effect in the PROCESS program (Hayes, 2018; Preacher & Hayes, 2008), which is based on bootstrapped confidence intervals and requires two coefficients, and the resulting sampling distribution to be asymmetric. Thus:

H4: Digital competence mediates between AI adoption and employee productivity.

Conceptual framework

The conceptual model states that the independent variable is the adoption of AI, the dependent variable is the productivity of employees and digital competence is the mediator between the independent variable and the dependent variable (PROCESS Model 4).

METHODOLOGY

Research design

This study used a quantitative research design to explore the relationship between AI adoption and employee productivity, using digital competence as a mediating variable. The study used a quantitative approach because testable hypotheses were desired and estimates of the magnitude and significance of direct and indirect effects were sought. The design was cross sectional (all variables measured at one time).

A structured questionnaire was used to gather data from 300 employees employed in public and private sector organisations. The addition of both sectors was designed to represent a range of technology use in different types of organizations. All participants were asked to participate voluntarily, and all respondents were assured of anonymity, while only employees who used digital tools in their regular work was included. The number of samples was greater than the three variables used in regression analysis (Hair et al., 2019).

Instrument and measurement

A five-point Likert scale (1 = strongly disagree to 5 = strongly agree) was used in the questionnaire. Measuring the adoption of AI involved assessing the use of AI-based tools, how useful employees found the system, and the extent to which they used AI in their daily tasks. Digital competence evaluated staff's effectiveness in the use of digital technologies. Task efficiency, quality of work, and the attainment of tasks' targets were used to measure employee productivity. The following demographic information was gathered to describe the sample: Gender, age, education, sector, and work experience. Scales were subjected to a pilot test with a small subset of workers prior to the main survey and ambiguous items were restated.

Cronbach's alpha was used to compare the reliability of the instruments, and the values obtained were considered acceptable if they were above 0.70 (Tavakol & Dennick, 2011). All variables were self-reported by the same respondents, which was a limitation and resulted in procedural remedies being implemented within the questionnaire, such as anonymity, clear wording, and separating the predictor and outcome items (Podsakoff, et al., 2012).

Data analysis

Descriptive statistics, correlation analysis, regression analysis and mediation analysis (Hayes' PROCESS Model 4) were used to analyze the collected data. Sample descriptive statistics and frequencies were used to provide summary data for the sample and the variables in the study, while Pearson correlations were used to explore bivariate relationships. The key assumptions in the regression model were tested prior to interpretation: linearity, normality of residuals, homoscedasticity and multicollinearity (Hair et al., 2019). Mediation was tested using PROCESS Model 4 that estimates the total effect (path c), direct effect (path c'), the effect of AI adoption on digital competence (path a), and the effect of digital competence on productivity controlling for AI adoption (path b). The indirect effect ($a \times b$) was computed with the 5,000

bootstrap samples and 95% bias-corrected confidence intervals, and was considered significant if it did not contain zero (Hayes, 2018; Preacher & Hayes, 2008).

ANALYSIS AND RESULTS

Demographic profile

The characteristics of the 300 respondents are summarized in table 1. The sample consisted of employees in the public and private sectors, by age and experience, with most having a bachelor's degree or higher.

Table 1. Demographic profile of respondents (N = 300)

Characteristic	Category	Frequency	Percentage
Gender	Male	171	57.0
Gender	Female	129	43.0
Age	Under 30 years	96	32.0
Age	30–39 years	118	39.3
Age	40 years and above	86	28.7
Education	Bachelor's or below	162	54.0
Education	Master's	109	36.3
Education	MPhil/PhD	29	9.7
Sector	Private	172	57.3
Sector	Public	128	42.7
Experience	Less than 5 years	88	29.3
Experience	5–10 years	122	40.7
Experience	More than 10 years	90	30.0

Reliability and descriptive statistics

The reliability of the data and descriptive statistics will be discussed. The number of items, means, standard deviations, and Cronbach's alpha values for each scale are presented in Table 2. The internal consistencies (alpha values) are acceptable and all values were > 0.70 (Tavakol & Dennick, 2011). The mean scores were above the middle point of the scale indicating moderate to high level of AI use, digital competence, and perceived productivity.

Table 2. Reliability and descriptive statistics

Variable	Items	Mean	SD	Cronbach's α
AI adoption	8	3.71	0.66	0.89
Digital competence	8	3.84	0.60	0.88
Employee productivity	9	3.79	0.58	0.90

Correlation analysis

Pearson correlations are shown in Table 3. All three variables were positively and significantly related with each other and the highest relationship was found between digital competence and productivity. The correlations were not high (less than 0.80) and so there was no concern of multicollinearity.

Table 3. Pearson correlations among study variables

Variable	1	2	3
1. AI adoption	1		
2. Digital competence	0.52**	1	
3. Employee productivity	0.50**	0.58**	1

Note. N = 300. ** $p < .01$ (two-tailed).

Regression and mediation analysis

The results of the PROCESS Model 4 are shown in Table 4. The use of AI was also positively associated with digital competence with a relatively high effect size ($a = 0.47$, $p < .001$; $R^2 = .27$), supporting H2. Digital competence ($b = 0.42$; $p < .001$) was a significant positive predictor of productivity in the model, which confirms H3, while AI adoption retained a significant direct effect ($c' = 0.24$; $p < .001$). AI adoption had a significant overall product impact ($c = 0.44$, $p < .001$) confirming H1. The indirect effect via digital competence was 0.20 (95% BC [0.14, 0.26] not containing zero) in favour of H4. The direct effect remained significant, so the relationship between the first two constructs was partially mediated by the direct effect, with approximately 45% of the total effect being accounted for.

Table 4. PROCESS Model 4 results (unstandardized coefficients; 5,000 bootstrap samples)

Path	B	SE	t	p	LLCI	ULCI
AI adoption → Digital competence (a)	0.47	0.04	11.80	< .001	0.39	0.55

Path	B	SE	t	p	LLCI	ULCI
Digital competence → Productivity (b)	0.42	0.05	8.40	< .001	0.32	0.52
AI adoption → Productivity, direct (c')	0.24	0.05	4.80	< .001	0.14	0.34
AI adoption → Productivity, total (c)	0.44	0.04	11.00	< .001	0.36	0.52
Indirect effect (a × b)	0.20	0.03			0.14	0.26

Note. $R^2 = .27$ (digital competence model); $R^2 = .39$ (productivity model with mediator); $R^2 = .25$ (total-effect model). LLCI and ULCI are lower and upper limits of the 95% confidence interval.

DISCUSSION

The findings showed that there is a positive correlation between the use of AI and employee productivity. This aligns with empirical findings that AI support enhances speed and quality (Noy & Zhang, 2023), and that technology can boost productivity by complementing human effort (Acemoglu & Restrepo, 2019; Autor, 2015). AI-based tools that are used by employees, considered useful, and incorporated into their workflows seem to be more efficient in getting work done, creating better work, and achieving goals more consistently. The discovery further corroborates the reviews which have efficiency and performance as key drivers for the adoption of AI (Borges et al., 2021; Dwivedi et al., 2021).

Digital competence also improved significantly following the adoption of AI, consistent with the perspective that using digital technologies in practice contributes to the development of digital competence (Ng, 2012; Van Laar et al., 2017) and with evidence of technology acceptance that experience increases the perceived ease of use and confidence in the use of digital technologies (Venkatesh & Bala, 2008). The positive effect of digital competence on productivity matches arguments that human capability determines how well people can work with intelligent systems (Jarrahi, 2018) and the importance of individual abilities for work performance (Koopmans et al., 2011).

The partial mediation shows that digital competence is a crucial but not the single channel. Some of the advantage of AI comes inbuilt, such as automated mundane activities which don't need much more skill. Another portion comes from competency: workers who develop and utilize digital abilities, using AI, are better off. This is reminiscent of the automation – augmentation split (Raisch & Krakowski, 2021) and the need to prepare employees for working with AI (Tambe et al., 2019). It implies that someone who is more digitally capable might get more productivity out of the same two workers using the same AI tool. It suggests that more digitally capable workers may be able to get more productivity out of the same two workers using the same AI tool.

CONCLUSION AND RECOMMENDATIONS

The study investigated the relationship between AI adoption and employee productivity, along with the mediation effect between the electronic competence of the employees of private organizations and public-

sector organizations. The evidence demonstrated positive impacts of AI adoption on productivity, both directly and indirectly, as well as its ability to enhance digital competence, and the partial transfer of digital competence to productivity. This study adds value by combining technology adoption research with work-performance research and by elucidating a human-capability mechanism by which AI generates value.

Based on these results, organizations are encouraged to think of adopting AI as a broader value proposition, rather than just a technical solution. As AI tools are introduced, managers must ensure that staff receive systematic training, peer-to-peer learning, and ample opportunities for practice to cultivate digital skills for verifying and refining AI-generated outputs. They should also embed AI in their regular processes; establish guidelines around data usage and data security; and track efficiency and quality to ensure progress is not compromising accuracy. To complement these efforts, policymakers and sector regulators can provide funding for digital skills training for public sector employees, encourage the adoption of national digital competence frameworks and foster public-private partnerships to ensure that smaller organisations have access to digital skills training.

There are a number of caveats to be noted. While the cross-sectional study design does constrain causal inferences, it is possible that more productive workers are more likely to use AI and are more likely to become more proficient with digital skills. Common method bias effects may still be present despite procedural controls applied in the one source of self-reported measures (Podsakoff et al., 2012) and productivity was judged by perception of output, not by actual output measures. Future studies may employ a longitudinal design or an experimental design, incorporate both self-reports and supervisor ratings or system-based productivity measures, and investigate moderators like sector, age, type of job, organizational support, or trust in AI.

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