Adoption of Generative Artificial Intelligence Tools Among Supervisors in the Second Half of Their Working Life: A Qualitative Study

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Additional material is published online only. To view please visit the journal online.

Cite this as: Bashir F and Priyanga T. Adoption of Generative Artificial Intelligence Tools Among Supervisors in the Second Half of Their Working Life: A Qualitative Study. Premier Journal of Science 2025;15:100124

DOI: https://doi.org/10.70389/PJS.100124

Peer Review
Received: 14 August 2025
Last revised: 22 September 2025
Accepted: 29 September 2025
Version accepted: 3
Published: 16 October 2025

Ethical approval: N/a
Consent: N/a
Funding: No industry funding
Conflicts of interest: N/a
Author contribution: Firdaus Bashir – Conceptualization, Writing – original draft, Writing – review and editing
Priyanga Tamilselvan – Data curation, Formal Analysis, Investigation, Methodology, Validation
Guarantor: Firdaus Bashir
Provenance and peer-review: Unsolicited and externally peer-reviewed
Data availability statement: N/a

ABSTRACT

The adoption of generative artificial intelligence tools into the workspace is an inevitable advancement which is revolutionising the way an organisation function. Hence, it is essential for employees, particularly supervisors, to prepare themselves to accept and integrate it into their daily tasks. The present study examines the impact of socio-demographic variables, including age group, gender, educational qualification, and years of experience, on the adoption of generative artificial intelligence tools among supervisors in the second half of their working life. The technology acceptance model was considered as the underpinning theory, and the four components of this model, including perceived ease of use, perceived usefulness, expectancy outcome and training availability in the organisation, were considered for the study. Data was collected through a survey method by distributing a structured questionnaire to supervisors of three textile manufacturing organisations using a purposive sampling technique. The reliability of the questionnaire was ensured using confirmatory factor analysis. The final data was then processed for percentage analysis, chi-square, regression and the correlation coefficient test. The socio-demographic factors analysed for the study were found to be statistically significant with the perceived ease of use, expectancy outcome and the availability of training in the organisation. Neither age nor gender showed a significant relationship, whereas years of experience and educational qualification demonstrated a significant association with the perceived usefulness of the integrated tools.

Keywords: Middle-aged supervisors, Generative AI adoption, Technology acceptance model, Socio-demographic factors, Textile manufacturing sector

Introduction

Generative Artificial Intelligence (GenAI) is a remarkable advancement in the realm of artificial intelligence. GenAI tools, which are the practical embodiments of this technology, are highly proficient as their competency is way beyond just generating responses to the prompt that has been fed. It is capable of generating distinct and original content, which consists of images, text code, audio, and video.[1] They are prominent in identifying patterns in large data sets and generating understandable information of high significance in everyday use.[2] Some of these tools that have exemplary transformative potential are ChatGPT, DALL·E, Codex, and Jasper AI.[3] ChatGPT and Jasper AI are content generation platforms, Codex is an AI-powered coding solution, and DALL·E provides advanced solutions for customised visuals. These tools are of great importance for reshaping the practices followed by supervisors from various departments in an organisation to streamline tasks which are performed regularly. Past literature has evidenced the revolution made by Gen AI Technology in the workplace by reshaping responsibilities of various functional strategies.[4] Organisations are continuously looking forward to optimising performance by integrating advanced tools into their workstream. For which training programs are obligatory to avoid any sort of mismatch in the skills required with the existing competencies available to perform a job. Usually, younger employees come across as digital natives. They generally exhibit an inclination towards learning a new technology and are willing to undergo training.[5]

Organisations are keen on customising training to reskill older employees who might at times come across as averse to adopting a new technology.[6] Middle-aged employees ranging from 40 to 55 years of age, possessing experience and leadership capabilities, are often overlooked. They face barriers while trying to adopt advanced tools, while their organisation is trying to integrate. The present study focuses on addressing this gap by exploring the impact that socio-demographic variables have on the adoption of Gen AI tools. Middle-aged supervisors are the focus of the present study as they play a prominent role in the organisation in empowering their teammates to adopt a new technological tool. For instance, a supervisor employed in the human resource department can take the aid of ChatGPT to automate the tasks of screening resumes by mapping them to the skill sets required for the job vacancy.[7] DALL·E can be appealing to supervisors who are willing to convert complex context to images.[8] Thus, they serve as a crucial mediator connecting wider organisational objectives with team performance by continuously monitoring and inspiring employees under their supervision.[9]

Theoretical Underpinning and Review of Literature

Theoretical Underpinning

The Technology Acceptance Model (TAM)[10] has been employed as the underlying theory of the study. The two prominent aspects of the model are Perceived Ease of Use as well as Perceived Usefulness. Perceived ease of use indicates that the user perceives the integrated technology to be simple and easy to use. Hence, fewer efforts are required from the user to operate it. While perceived usefulness indicates that by using it, one can enhance one's productivity. The two components aid in developing either a positive or a negative attitude towards accepting and using the newly integrated Gen AI tool. The TAM model has undergone refinement over time, and other models, namely TAM2, TAM3, Unified Theory of Acceptance and Use of Technology (UTAUT), have evolved.[11] TAM has been chosen over other models because of its flexibility and being well-suited for research with smaller sample sizes,[12] and allows for concentrating on a specific area of interest.

This theory explains how various social demographic factors, such as age group, gender, educational qualification, and years of experience, impact acceptance of GenAI tools. Using TAM as a framework, one past study found that older employees had more difficulty integrating new technology than younger ones.[13] In contrast, higher educational qualifications and more years of experience generated a favourable perception of the usefulness of new technology.[14]

Review of Literature

Since work requirements are ever-changing and intensifying, the adoption of these tools enables an organisation to maintain higher standards. Employees can use it for diverse purposes such as generating human-like texts, providing innovative solutions, analysing extensive data sets, doing repetitive work, producing formal and detailed reports, and evaluating employee feedback. Besides, supervisors are frontline managers[15] who concentrate heavily on daily operational activities and ensure that their entire team meets daily targets;[16] therefore, the intention to adopt it enriches their work profile. Nevertheless, integrating a technology can pose both opportunities and challenges. Literature points out that middle-aged individuals generally adopt technology when it enables them to meet deadlines,[17] decrease workloads or improve their task management skills.[18] If they fail to familiarise themselves quickly, then the issue of job security crops up.[19]

User-friendly features of technology increase the level of acceptance[20] due to the ease of operation, as completing an assigned task requires minimal effort.[21] Furthermore, employees believe it is practical when the effort required is minimal.[22,23] Organisations can provide sufficient practical training to assist employees in incorporating technology into their tasks for improved outcomes.[24] This offers numerous advantages, such as accomplishing more tasks in a shorter duration, obtaining a promotion or salary increase, and enhancing one's competency level.[25]

Age as a variable requires deeper examination to understand the nuances of its influences on technology adoption in various workplaces across industries. A previous study has highlighted that younger supervisors adopt GenAI tools faster than older ones.[26] Similarly, research on the usage of ChatGPT at work revealed that age has a significant impact.[27] Advancing age correlates with diminished acceptance of technology due to decreased self-efficacy or a propensity to resist change.[13] However, older adults may not inherently resist technology if they receive adequate support, such as training tailored to their specific requirements.[28] They readily adopt technology when they recognise personal or professional advantages.[29]

Gender differences play a vital part in forming an adoption intention. Computer self-efficacy and ease of use enhance women employees' confidence, but for men, it is the tangible usefulness of the technology adopted.[30] It is interesting to note that employees with lower educational qualifications have come across as hesitant due to limited digital literacy.[31] Besides it is evidenced that years of experience help in aligning oneself with technology adoption.[32] The present study intends to examine the influence that socio-demographic variables have on the adoption of Gen AI tools. The research questions framed for the study (RQs) are:

1. RQ1: Do socio-demographic variables, including age, gender, educational qualification, and years of experience of supervisors, have a bearing on the perceived ease of use while adopting Gen AI tools into their work?
2. RQ2: To what extent do the socio-demographic variables of supervisors who are in the second half of working life affect the perceived usefulness of the Gen AI tools?
3. RQ3: Can these variables impact the expectancy outcome while adopting Gen AI tools?
4. RQ4: Do these factors have an impact on the availability of training in the organisation?

Research Methodology, Measures and Tools

A formal cover letter clearly stating the purpose of the study was distributed among the top management. Ethical clearance for the study was obtained at the outset, with prior approval secured from the institutional management. Following this, all potential participants were thoroughly briefed regarding the purpose and scope of the research. Participation was entirely voluntary, and respondents were informed of their right to decline or withdraw without any consequences. Informed consent was obtained before data collection, and assurances were provided that all responses would remain confidential and be utilised strictly for academic and research purposes. This enabled in building trust, collecting honest reviews and gaining the support of management. A structured questionnaire, both in Tamil and English, was circulated to collect data. Two bilingual experts were chosen to independently translate the questionnaire from English into Tamil. These translations were then compared and combined into a single version after resolving discrepancies. To ensure that the meaning was consistent, it was then translated into English by two different experts unfamiliar with the original questionnaire. An expert committee panel reviewed all versions to confirm accuracy. Select supervisors who were in the second half of their working life were given an option to choose between the two different languages to record their responses. The study was conducted across three textile manufacturing organisations, each operating for more than a decade. These firms serve both domestic and international markets, producing a range of blended fabrics and finished garments. Over time, their operations have evolved from conventional practices to increasingly digitized systems. Notably, the adoption of AI-powered tools has gained momentum, with supervisors utilising applications such as

ChatGPT for preparing shift reports and DALL·E for generating visual safety instructions. The selected textile manufacturing companies had 200 supervisors in total, 70 of them from the first organisation, 65 from the second, and 65 from the third. A post-hoc power analysis was performed using G*Power software to determine whether the final sample size was sufficient to detect medium effect sizes (Cohen's d = 0.5) at a 0.05 significance level. The statistical power of 0.82, which exceeded the widely accepted criterion of 0.80, showed that the sample size was sufficient for further statistical analysis to determine meaningful correlations between variables. The three textile manufacturing companies were purposefully chosen based on the supervisors on staff who were required to actively interact and integrate AI tools into their everyday work operations. These supervisors were assigned to a variety of operational divisions, including production, quality control, operations, and human resources. The purposive sample technique enabled the capture of the practical nuances of AI adoption in ordinary supervisory activities.

A pilot study was initially conducted with 15 respondents, and the data from this phase was excluded from the final analysis. Insights from the pilot exercise informed minor revisions in the questionnaire to enhance clarity and comprehension. The revised structured questionnaire was then administered to 141 supervisors, of which 130 complete responses were retained for statistical analysis using the Statistical Package for the Social Sciences (SPSS, version 28). Incomplete questionnaires were excluded from the dataset. A purposive sampling technique was employed to ensure the inclusion of mid-level supervisors who were actively engaged in integrating digital technologies into their daily work practices. To identify suitable respondents, the researcher sought inputs from managers, assistant managers, and administrative heads, guided by predetermined selection criteria. Specifically, respondents were required to be between 40 and 55 years of age and hold at least a diploma-level qualification.

The total years of experience a supervisor had within their respective organisation was taken as a variable; hence, a minimum of three years in the current organisation was established as the baseline criterion. Department type was considered as the control variable since supervisors from different work areas, like production, quality control, administration, and human resources, were included in the study.

The data met the normality criterion as skewness and kurtosis values fell within ±2, linearity and equal variance were validated, supporting the use of Pearson correlation. The final selected data, after being tested for missing values and errors, were assigned numerical codes and organised into a data frame. Percentage analysis was employed to describe the socio-demographic variables, and thereafter, the mean score of various dimensions of technology acceptance was estimated. The relationship of categorical variables with the adoption of Gen AI tools was determined by a non-parametric chi-square test. P-value measures were estimated, and they had to be less than or equal to 0.05 for statistically significant consideration. To evaluate the relationship between the variables chosen for the study and their direction of association, the correlation coefficient was calculated. There were four constructs identified to measures adoption of technology I) Perceived ease of use which specifies the extent Gen AI tools is believed to be useful, easy and flexible by the employees, ii) Perceived usefulness reflecting the ability to streamline tasks and increase efficiency, thus boosting overall productivity, iii) Expectancy- outcome, which depicts whether the tools will aid in completing tasks effectively, leading to career progression and iv) Availability of adequate training which implies the presence of sufficient hands-on training programs for employees to ensure proficiency. These indicators were derived from past literature, which has been outlined in Table 1.

Table 1 | Indicators used to measure the selected variables

S. No	Measuring the Select Variables		
	Construct	Indicators	Study
1.	Perceived Ease of Use	• The technology adopted is easy to use. • The technology incorporated is flexible • It can do what is required to be done. • Operation of the technology is easy. • I can be skilled at it.	[10]
2.	Perceived Usefulness	• With this technology, I can accomplish tasks faster. • It improves my performance. • It enhances productivity at the job. • Doing the job is easier with its integration. • The technology is useful for the task at hand.	[10], [33], [34]
3	Expectancy - Outcome	• Less time will be spent on routine work. • Quantity of work for the same amount of time will be increased. • Chances of promotion are better. • Chances of a raise in pay are more • The chances of being a competent worker are high.	[35], [36]
4	Training Availability	• Adequate training opportunities are provided by the management. • Hands-on training is provided. • The training provided is informative. • The training provided is useful. • It enables adoption of new technology.	[34], [37]

Table 2 | Percentage distribution of the employee age group

S. No.	Age	Number of Employees	Percentage (%)
1	40 years to 44 years	67	51.5
2	45 years to 49 years	47	36.2
3	50 years to 54 years	16	12.3
	Total	130	100

Source: Primary data.

Results of the Study

Percentage analysis was performed on the selected socio-demographic variables chosen for the study. The age of supervisors who are in the second half of their careers is depicted in Table 2.

Table 2 denotes those 67 employees, amounting to 51.5% of the total sample belonged to the age category of 40–44 years, 47 employees representing 36.2% of the total sample belonged to 45–49 years and 16 employees representing 12.3% percentage of the total

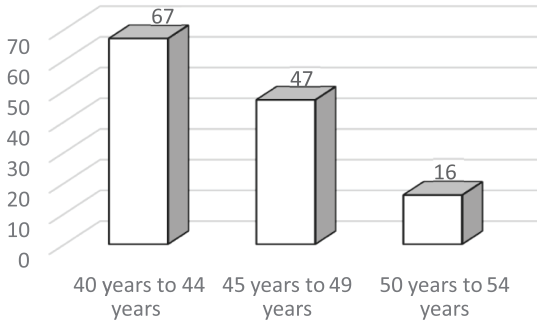

Fig 1 | Bar graph indicating number of employees in different age group

Table 3 | Gender of the employees in their second half of working life

S. No.	Gender	Number of Employees	Percentage (%)
1	Men	80	61.5
2	Women	50	38.5
	Total	130	100

Source: Primary data.

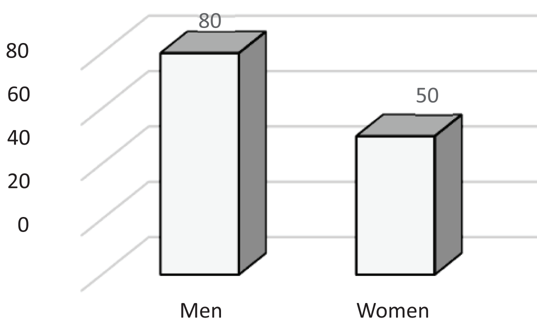

Fig 2 | Bar graph indicating gender of employees in different age

Table 4 | Educational qualification of the employees who are in their second half of working life

S. No.	Educational Qualification	Number of Employees	Percentage (%)
1	Post Graduate	25	19.2
2	Graduate	63	48.5
3	Diploma	42	32.3
	Total	130	100

Source: Primary data.

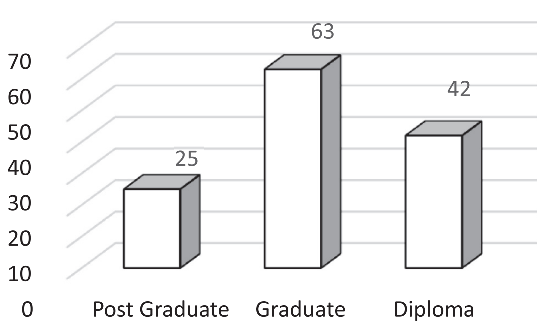

Fig 3 | Bar graph indicating the educational qualification of employees

Table 5 | Employee's years of experience who are in their second half of working life

S. No.	Years of Experience	Number of Respondents	Percentage
1	3–6 years	43	33.0
2	7–10 years	71	54.6
3	11–14 years	16	12.4
	Total	130	100

Source: Primary data.

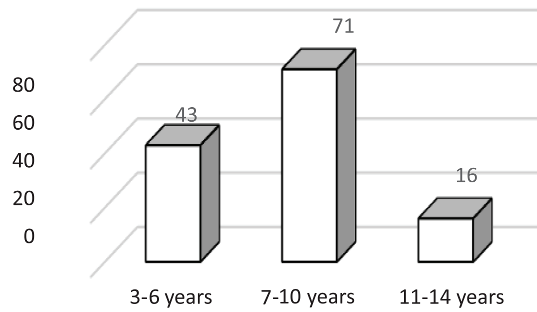

Fig 4 | Bar graph indicating the years of experience of employees

Table 6 | Mean score estimated for the dimensions of technology acceptance

Dimensions	Mean Score
Perceived Ease of Use	3.973
Perceived usefulness	2.982
Expectancy-Outcome	3.761
Training Availability	3.028

Source: Primary data.

sample belonged to 50–54 years, which is a graphical representation in Figure 1.

Table 3 outlines the gender distribution of the respondents. It shows that 80 employees, accounting for 61.5% of the sample, were men and 50 employees, representing 38.5% of the sample, were women. The graphical representation is given in Figure 2. The result indicates that most of the study respondents were male.

Table 4 outlines that 25 employees, equating to 19.2 % of the sample, had completed postgraduation, 63 employees equating to 48.5 % were graduates, and the remaining 42 employees, equating to 32.3% were diploma holders. The majority of respondents were graduates, as represented in Figure 3.

Table 5 represents the years of experience of 130 employees. 43 employees had 3 to 6 years of experience in the organisation, totalling 33.0 %, 71 of them had work experience ranging from 7 to 10 years, accounting for 54.6 %, 16 out of the total had 11 to 14 years of experience, which was in the minority, accounting for 12.4 %. This data has been illustrated as a bar diagram in Figure 4.

Mean score for different dimensions of technology acceptance by supervisors employed in the textile manufacturing sector is represented in Table 6. The mean

Table 7 | Reliability analysis for the dimensions of technology acceptance

	Factor Loading Value	Cronbach's Alpha	AVE	Composite Reliability
PU1	0.87	0.75	0.64	0.77
PU2	0.61			
PU3	0.70			
PU4	0.97			
PEOU1	0.85	0.80	0.61	0.80
PEOU2	0.72			
PEOU3	0.76			
PEOU4	0.79			
ATT1	0.86	0.84	0.76	0.84
ATT2	0.87			
ATT3	0.87			
BI1	0.81	0.77	0.68	0.77
BI2	0.86			
BI3	0.80			

Source: Primary data.

Table 8 | Socio-demographic variables and perceived ease of use

S. No.	Chi Square value	Calculated Value	*P*-Value	Result
1	Age Group	23.783	0.000*	Significant
2	Gender	21.875	0.001*	Significant
3	Educational qualification	18.790	0.001*	Significant
4	Years of employee experience	20.761	0.001*	Significant

Source: Primary data, *- 5% significant level.

Table 9 | Socio-demographic variables and perceived usefulness of the technology

S. No.	Chi Square value	Calculated Value	*P*-Value	Result
1	Age Group	1.653	0.510	Not Significant
2	Gender	1.783	0.175	Not Significant
3	Educational qualification	17.832	0.001*	Significant
4	Years of employee experience	18.531	0.001*	Significant

Source: Primary data, *- 5% significant level.

Table 10 | Socio-demographic variables and expectancy-outcome

S. No.	Chi Square Value	Calculated Value	*P*-Value	Result
1	Age Group	20.683	0.001*	Significant
2	Gender	12.367	0.002*	Significant
3	Educational qualification	23.084	0.002*	Significant
4	Years of employee experience	22.653	0.001*	Significant

Source: Primary data, *- 5% significant level

Table 11 | Socio-demographic variables and training availability

S. No.	Chi Square value	Calculated Value	*P*-Value	Result
1	Age Group	17.904	0.001*	Significant
2	Gender	16.541	0.001*	Significant
3	Educational qualification	18.294	0.001*	Significant
4	Years of employee experience	20.593	0.002*	Significant

Source: Primary data, *- 5% significant level.

score of perceived ease in using the new technology integrated was 3.973, which indicates that employees could perform better with user-friendly features of Gen AI tools. The mean score of perceived usefulness was 2.982, which appears to be modest. This could likely be due to inadequate training on how to frame effective prompts or a lack of understanding about the friendly features of each tool that can be effortlessly applied in daily tasks. Providing printed materials detailing the features of the adopted tools, along with customised knowledge sharing sessions on framing prompts, can positively impact how users perceive the usefulness of these tools. The value for expectancy-outcome was (3.761) and training availability was (3.028). To improve the mean score of training availability, organisations should further invest in structured and accessible training programs to upgrade supervisors' skillsets.

To test the reliability of the TAM constructs, Factor loading values, Cronbach's Alpha, Average Variance Extracted (AVE) and Composite Reliability values were tabulated under Table 7. From the results, it was evident that all the values fell within the range of 0.6 to 0.95, and hence, the research instrument used for the study is highly reliable. The chi-square test was employed to estimate the influence of socio-demographic variables on the acceptance of new GenAI tools among supervisors who were in the second half of their working lives.

The chi-square value for age is estimated at 23.783 in Table 8, with a *p*-value of 0.000, indicating that the impact of the perception of ease of use regarding GenAI tools integrated across is statistically significant at the 5% significance level. The chi-square value of 21.875, with a p-value of 0.001, signifies that gender both men and women had a noteworthy impact, chi-square value of 18.790, with a *p*-value of 0.001, indicates that the supervisor's level of educational qualification encompassing of diploma holder, graduate even postgraduate significantly impacts perceived ease of use, the chi-square value of 20.761, with a *p*-value of 0.001 indicates that years of experience influence the perceived ease of use all of which at a 5% significant level.

Age group with a chi-square value of 1.653 and a *p*-value of 0.510, and gender measured with a chi-square value of 1.783 and a *p*-value of 0.173, does not significantly impact the perceived usefulness of GenAI tools at a 5% significance level, as denoted in Table 9. On the contrary, educational qualification with an estimated chi-square value of 17.832 with a p-value of 0.001, and the chi-square value of employee experience at 18.531 with a *p*-value of 0.001 were considered significant. Supervisors with technically driven educational backgrounds may perceive GenAI tools as valuable resources to work productively, while others with non-technical educational backgrounds might display apprehension owing to their limited exposure.

Table 10 represents that the chi-square value for age group was estimated at 20.683 with a *p*-value of 0.001, the chi-square value of gender was estimated at 12.367 with a *p*-value of 0.002, educational qualification at 23.084 with a *p*-value of 0.002 and years of experience at 22.653 with a *p*-value of 0.001 at a 5% significant level and were found statistically significant.

Table 11 indicates that the socio-demographic variables had a considerable impact on training availability. Age group had the chi-square value measured at 17.904 with a *p*-value of 0.001, the chi-square value of gender was 16.541 with a *p*-value of 0.001, the chi-square value

Table 12 | Correlation co-efficient and technology acceptance among employees

	Perceived Ease of Use	Perceived Usefulness SS	Expectancy-Outcome	Availability of the Training
Perceived Ease of Use	1			
Perceived usefulness	0.912**	1		
Expectancy-Outcome	0.631	0.752*	1	
Availability of the Training	0.813*	0.736**	0.671*	1

Source: Primary data, **- 1% significant level and *- 5% significant level.

Table 13 | Regression analysis

S. No.	Socio-Demographic Factors	*P*-Value			
		Perceived Usefulness	Perceived Ease of Use	Availability of the Training	Expectancy - Outcome
1	Age Group	0.156	0.215	0.002	0.001
2	Gender	0.165	0.001	0.002	0.227
3	Educational qualification	0.002	0.198	0.001	0.096
4	Years of employee experience	0.002	0.003	0.003	0.001

Source: Primary data.

for educational qualification was valued at 18.291 with a *p*-value of 0.001, and years of experience had the chi-square measured at 20.593 with a *p*-value of 0.002 which were found significant at a 5% significance level.

The correlation tool was used to determine the association between the four dimensions adapted for Gen AI technology acceptance among supervisors in the second half of their working life. According to Table 12, the perception of ease of use has a strong positive association with the perceived usefulness of the GenAI tools at a 1% significance level, where correlation coefficient (r = 0.912) closer to 1. This implies that the perception of easiness in using the tool augments its perceived usefulness. Supervisors when given adequate hands-on training become comfortable in handling the tools, thus this association revealed a strong correlation (r = 0.813) at a 5% significance level. The tools are perceived useful when it is easy to handle. At 5% significance level, the perceived usefulness of the tool has a favourable relationship with the expectancy outcome (r = 0.752). Training can boost supervisors' perception of usefulness (r = 0.736) at a 1% significance level. A positive association between expectancy outcome and availability of training at a 5% significance level (r = 0.673) was denoted.

The regression analysis tabulated under Table 13 indicates that socio-demographic factors exert varied levels of influence on the adoption of technology. Years of work experience emerged as the most decisive factor, showing significant effects on all four constructs. This finding highlights that employees with longer experience not only recognise the system as more valuable and easier to operate but are also more attentive to training opportunities and develop stronger expectations about its outcomes. Educational qualification was also found to be an important determinant, significantly influencing perceived usefulness and training availability. This suggests that higher educational attainment shapes employees' ability to recognise the benefits of technology while also encouraging their participation in training programs. Gender differences were evident in relation to perceived ease of use and training access, reflecting variations in how male and female supervisors interact with technology and engage with supportive resources. Age, meanwhile, did not appear to affect perceived usefulness or ease of use but had a significant impact on training availability and expectancy outcome, pointing to generational differences in how employees approach learning opportunities and form expectations from technology adoption. Overall, these results emphasize the need to consider demographic diversity, particularly work experience, when developing strategies for digital integration in the workplace. Overall, these findings highlight the importance of considering demographic differences, particularly employee experience, when implementing and promoting new technologies in the workplace.

Discussion

The findings of this study indicate that supervisors, regardless of age, share a consistent perception regarding the usefulness of AI tools in the workplace. This uniformity may be attributed to the standardised availability of such tools across age groups, coupled with the task-oriented nature of supervisory roles that largely focus on monitoring, coordination, and reporting. The integration of technology enhances these functions, while organizational support systems and structured training help to narrow potential age-related differences in technology adoption.

Gender, however, emerged as a significant differentiator, particularly in perceptions of the ease of using generative AI tools. This outcome is consistent with prior research,[39] suggesting that variations in digital literacy levels, as well as the nature and extent of prior work experience, may explain the differences observed between male and female supervisors.

Female employees prefer to retain their positions and aspire to demonstrate equal competence to men in technology utilisation technology.[40] Although Perceived Ease of Use (PEOU) is an important factor influencing the adoption of generative AI, women tend to attach greater importance to this dimension.[13] They often favour technologies with intuitive and user-friendly features that enhance comfort and confidence,[41] whereas men are generally more willing to engage with higher levels of technological complexity. The findings of this study reinforce that, for both age and gender, the primary driver of adoption is the ease with which the technology can be used, rather than its perceived usefulness.

Supervisors possessing educational qualifications and technological exposure found adoption more accessible than those lacking such opportunities.[42] Individuals with substantial work experience favour technology that is effortlessly adaptable and user-friendly, a conclusion supported by previous literature.[43] Experienced professionals necessitate minimal disruptions in their routines and established work status. They anticipate finishing their task promptly with minimal deviations.

 DOI: https://doi.org/10.70389/PJS.100124 | Premier Journal of Science 2025;15:100124

Training programs should be customised to accommodate supervisors' different learning styles and levels of tool experience.Individuals who can swiftly adapt may engage in accelerated training that specifically emphasizes advanced features, while those with limited technical experience can participate in repetitive or foundational training programsAssigning individuals to work with technologically proficient colleagues during their sessions can promote mutual learning and cooperation.Peer support facilitates the seamless and efficient integration of technology across diverse functional domains.

This study contrasts manual task completion with processes supported by generative AI tools, offering valuable insights into efficiency and workflow transformation. When tasks are performed manually, supervisors typically spend considerable time conceptualizing, drafting, and repeatedly revising reports to achieve the desired quality. In contrast, the use of tools such as ChatGPT, Black Box AI, and DALL·E significantly reduces both the time and effort required. Leveraging natural language processing, these systems not only generate coherent and contextually appropriate text but also handle grammatical refinements with ease. Moreover, they enable the creation of well-structured paragraphs and allow reports to be summarised or reformatted in styles tailored to organisational requirements, thereby minimising human effort while maintaining consistency and accuracy.

GenAI tools assist with brainstorming, but in manual processes, supervisors often experience decision-making fatigue, which slows down content preparation. Using these tools improves time management and task accuracy and enables faster decision-making, streamlining workflows and contributing to better supervisory performance.

Implication of the Study

Supervisors, regardless of the stage of their career, play a vital role in contributing to organizational growth. However, those in the latter half of their careers are often undervalued, making it essential for management and policymakers to design strategies that encourage continuous learning and skill enhancement among this group. This study contributes to the relatively limited body of literature by exploring the influence of socio-demographic factors on key dimensions of technology adoption, with a particular focus on middle-aged supervisors—a segment that remains underexamined. The findings emphasize the importance of ensuring ease of use when introducing new generative AI tools, as usability strongly determines acceptance.

Given that the quality of prompts directly impacts the accuracy of AI-generated outputs, targeted training should equip supervisors with the ability to formulate effective prompts. Moreover, adequate training opportunities can help bridge the gap between existing skills and those required for effective technology use. These insights extend to AI tool developers as well, who are encouraged to design systems with intuitive, user-friendly features capable of delivering high-quality outcomes while reducing time and effort. Since technology integration is a continuous process,[44] it becomes imperative to strengthen employee readiness to facilitate smoother adoption and enhance overall user experience.

Limitations and Future Directions

This study is a cross-sectional design as it captures data at a single point in time; therefore, a longitudinal study can be undertaken as an extension of this work. The findings of the study may not be fully generalised to all employees across various sectors, as the purposive sampling technique applied can introduce selection bias, making the results context-specific to the participating firm. Besides, it is a single-region focus; therefore, future studies can concentrate on multi-regional approaches. Supervisors in various locations may undergo diverse experiences with GenAI tools. While this study focuses on the textile manufacturing sector, future research could be extended to other rapidly evolving industries such as healthcare, education, or retail. Comparative analyses across different organizational levels including managers, administrators, and other employee groups, could provide richer insights. Future research may focus on understanding how supervisors, and managers shape their teams' willingness to adopt generative AI tools, particularly through strategies that reduce resistance to change. Examining the design and effectiveness of customised training programs tailored to the specific needs of various employee groups would further illuminate how these tools can be seamlessly integrated into workplace practices.

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