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Technology adoption trends: generative AI among indian it employees across different generations and genders

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Abstract
The rapid advancement and integration of Generative AI technologies into various sectors have significant implications for technology adoption across different demographics in India's working population, particularly among IT employees. This surge in AI adoption is driving the need to understand the relation between propensity to adopt new technology and both gender and generation-related individual differences within the Indian workforce. The examination of Gen-AI adoption propensity is done based on dimensions such as optimism, proficiency, dependence, and vulnerability. A cross-sectional survey design is planned for this study with a sample of 330 using quota sampling on a population including professionals aging 22 to 54 and working in Delhi NCR. The Shapiro-Wilk and Kolmogorov-Smirnov test, Mann-Whitney U test, Kruskal-Wallis test are applied to test the hypotheses. The findings of the study show that Gen Z shows higher optimism and dependability for Gen-AI while Gen Y shows the highest proficiency in Gen-AI technology. In addition, the results also indicate optimism, vulnerability and dependence to be higher for women. It is expected that by comprehensively analysing these factors, the study can guide policymakers, educators, and technology developers to tailor their approaches, ensuring inclusive dissemination of Gen-AI technologies.

Keywords AI adoption, Gender influence, Generation influence, Generative AI

Introduction

Generative AI has transformed the ways of working and processes across industries and an increasing number of employees are using it for their functional tasks at the workplace (Marak et al., 2025; Ortiz-Ospino et al., 2025). Deloitte (2024) report on Generative Artificial Intelligence has ranked India in the first position where 27% of IT-based organisations are utilising the technology to their professional benefit. The 20th edition of the State of the Developer Nation Report states the existence of 24.3 million software developers in China with 7 million followed by India with 5.8 million. The third position is held by the USA with 4.4 million of them (LinkedIn, 2023). With an exponential rise of software developing business opportunities, many developers have resorted to Generative AI tools for their operational IT-related tasks leading to a higher efficiency output for them (Capgemini, 2023; Rubin & Callaghan, 2020). The enhanced use of Generative AI tools can be well understood by the US data where organisations have enhanced their usage of tools with the highest place being taken by Marketing and IT followed by Consulting.

Capgemini (2023) report states that the adoption of generative AI for software engineering is still in its infancy. Currently, 27% of organisations actively explore its potential through pilot projects, while 11% have already begun integrating generative AI into their software functions. It has also been studied that 63% of professionals still use unauthorised tools for Generative AI that can be a threat for security breaches, functional errors and even legal implications. Mckinsey's (2024) report discusses the increasing use of tools which has seen a sudden spike in the last 2–3 years leading to a change in the organisation's strategic perspective towards adoption of such measures at a larger scale. The report also analyses these trends and factors responsible for the enhanced usage while also stating the roles and profiles of employees using it (Mckinsey, 2024). This can be further correlated with the functional level division of employees among both genders. Certain functions have a higher involvement in AI adoption based on the tasks that are undertaken and how they get enhanced through the usage of Generative AI. Verticals like IT, marketing, product development, and personalised marketing seem to have adopted more Generative AI content as compared to other functions.

The women are participating more in conferences, seminars, and workshops as the IT companies are paving their way towards diversity and inclusion measures. But, reports by Deloitte (2024), state the fact that male dominance is high in the IT and software sector even when women's participation is increasing over the years. According to Zippia (2024), 28.7% of software programmers are women, while 71.3% are men. With an increase in the number of women in the IT sector, it is important to study the adoption of Generative AI by them. Besides, since the current usage is majorly attributed to men as 70% of the IT sector is dominated by them it is important to study their adoption pattern as well. This led to our first research question, i.e., *RQ1: What role does gender play in shaping the propensity to adopt Gen-AI among Indian IT professionals?* For developing future Generative AI content, it is thus important to understand the usage by both genders and whether the propensity to adopt is different for different genders. In future, it is expected that women's participation will further increase in the IT sector, which entails the importance of the study even more. This may help to also understand the factors affecting both genders in Generative AI leading to better productivity.

According to the Pulse report (2023) released in its 23rd Developer Nation global survey, when it comes to age, the ages between 25 and 34 are the ones with more active developers, with 34.9% being part of this group. Following is the age bracket between 18 and 24 with 29.5%. With seniority, there's a drop of only 19.7% of developers in the 35–44 age. The age bracket between 45 and 54 only has 9.11% of developers (Accenture, 2024). Accenture (2024) suggests the existence of generational differences among people and their adoption of generative AI. This has been connected with the concept of the digital natives' segment who have been born and brought up with the internet and smartphones and to what extent they were responsive enough to adopt the new technology tools like Generative AI. This brings on our second research question, i.e., *RQ2: How* *do generational differences among Indian IT professionals influence their propensity to adopt Gen-AI technologies?* The paper thus tries to first understand the adoption of Generative AI in Indian IT professionals and then focuses on the analysis based on gender and generation. The exploration of the above two research questions prompts the third one, i.e., *RQ3: How can understanding the generational and gender dynamics influence their propensity to adopt Gen-AI to improve training and policy-making in the Indian IT sector?*

The IT sector is one of the pioneers in using Gen AI and has the maximum adoption that provides a concrete foundation for the research rationale. The analysis of the genders and generations would provide an understanding linked to the reasons for their adoption, the benefits and challenges they face, impact of dimensions like proficiency, optimism, dependence and vulnerability that would bring more clarity about the propensity to adopt technology further.

Literature review

Being a new concept, Generative AI development is still underway through analysing user content demands and integrating it with the technology (Fosso Wamba et al., 2024). The basis of Generative AI is natural language processing, automated content creation, intelligent data analysis, etc. that is provided to the end user in a manner to facilitate professional working. Ooi et al. (2023) suggest the use of Generative AI in every sector that focuses on the improvement of the working processes while also enhancing productivity. According to Jovanovic and Campbell (2022), Generative AI adoption has increased exponentially with more industries utilising it for developing text, images, video or even audio based on the nature of the business (Farrelly & Baker, 2023). As it is a subpart of deep learning, it has found its adoption in many human-driven intelligence systems of education, banking, IT, media, social media, retail, etc., creating a widespread adoption globally (Fosso Wamba et al., 2024; Granić & Marangunić, 2019). The machine learning algorithms used by the Gen AI technology have provided new data structures to professionals while also creating new possibilities for more inputs. Budhwar et al. (2023) discuss the basis of the adoption of Gen AI that emphasises the transformation based on deep neural networks and other large language models (LLM) that enabled the exponential boom since the 2020s leading to its usage in all verticals. Gen AI has found its usage in almost all sectors with variety which is creating a huge business potential for technology companies like Microsoft, Google, Open AI, etc. The most common type of Gen AI used are chatbots like ChatGPT, Gemini, Claude, CoPilot, etc. being offered by IT companies around the world (Feuerriegel et al., 2024). The technology also involves many intelligent image processing platforms like Stable Diffusion, Midjourney, etc. that also help in image-to-video and text-to-video AI services (Wach et al., 2023). It emphasizes the variety of adoption methods creating a higher level of potential for the IT sector where software development, coding, and writing programs form the basis of the business model. The higher rate of adoption is both strategic and integrated deeply in technology advancement (Budhwar et al., 2023). Farrelly and Baker (2023) state the usage of Gen AI has increased exponentially but so have the threats linked to it for society and also certain crucial sectors like media, journalism, financial, politics, etc. as security breaches, deepfake incidents, privacy concerns and security of data along with job losses have become a major concern of the industries (Noy & Zhang, 2023).

The adoption of Gen AI is determined by many factors that are both market-driven and technology-related. According to Kanbach et al. (2024), crucial factors impacting the adoption of Gen AI are the user beliefs and perceived usefulness of the technology for self and professional tasks. Even the model given by Davis et al. (1989) termed as Technology Acceptance Model places ease of use and to be able to provide some tangible benefits are core for the adoption of new technologies. A study by Murray (2024) also states the general acceptability of new technology like Gen AI to the cultural fitment of the user and how open they are to innovation adoption. Ajibade (2018) discusses the impact of behavioural intentions when people are exposed to new technology and how they have adopted that into their work thereby increasing the use if the earlier usage leads to benefits. According to a study undertaken by Vartiainen & Tedre (2023), the role of technology in enhancing job performance, especially the roles and tasks employees find difficult is as important as the adoption factor for them. The importance of actual contribution in making the job performance better might differ among employees based on their age and gender. Studies have not emphasized the role of age, gender and generation leading to a better understanding of the IT workforce both globally and in India (Doulani, 2018).

Noy and Zhang (2023) discussed the growing contribution of women in the IT sector leading to equality in the gender distribution in the workforce. This also throws light on the usage of Gen AI by both genders and it does not portray any difference in the usage (Kanbach et al., 2024). It is also impacted by a range of factors, including interests, needs, professional fields, and social dynamics. A report by Accenture (2024) states that women now contribute around 30% of the IT workforce and engage in many of the Gen AI usage for software and business communication purposes. However, there is a lack of specific studies or research on the impact of gender on the usage of Gen AI. The main functions in an IT setup that may use Generative AI for creative applications such as digital art, fashion design, content creation, and social media (Murray, 2024) are undertaken by both genders as it is technical skill-based. Based on the skillset, it involves all kinds of technical applications such as software development, gaming, and engineering, where Generative AI is used for code generation, game design, or creating simulations (Dwivedi et al., 2023). Working in an IT setup may require the help of Gen AI for many purposes like the development of codes or even for operational tasks, but how both genders differ in this is not clear. There is a lack of research even on how they use the input provided. Vartiainen and Tedre (2023) suggest that the psychometric profile of both men and women is different and so should their adoption of technology and also its uses. It is well documented that personality, opinions, qualities, perceptions and communication methods among both genders through earlier research in psychology (Dwivedi et al., 2023). The application of gender differences needs to be studied in more detail for the technology adoption and technology readiness index.

Besides, generational differences among people belonging to Gen X, Gen Y and Gen Z also pose a logical rationale for the study as the evolution of technology has taken place differently for different generations (Ebert & Louridas, 2023). The demographic divide also bases itself on the generational divide leading to the evaluation of the eagerness or readiness for technology adoption (Ellingrud et al., 2023). Generations also may differ in their innovation adoption drive that forms the basis for other new technological advancements acceptance (Ellingrud et al., 2023). The Table 1 defines the age group of all the generations thus helping in better analysis.

With the age gap between each generation in the range of 15 years, digital evolution and adoption have varied with their growth in time. Since the technology and internet revolution happened after 2000, the speed of advancements has exponentially advanced (Fui-Hoon Nah et al., 2023). The quickest of them all have been Gen Z who have grown up with technology and are also called the 'digital natives (Pramudita et al., 2023). The same needs to be also analysed for the usage and adoption of Gen AI platforms for both personal and professional work and how comfortable they are with them. Spanjol and Noble (2023) explain that generations not only differ in age but also the cohort similarities, preferences, opinions, attitudes towards technology, tastes, state of mind, perceptions, etc. creating a need to also study their technology adoption (Spanjol & Noble, 2023, Hussein, 2017).

Recent literature review on technology adoption in emerging economies highlights both similarities and differences in comparison to Indian context (Lai, 2017; Ajzen, 2020; Awa et al., 2017). For instance, in China, the AI adoption has been accelerated by robust governmental initiatives and expansive digital ecosystems. In addition, young professionals tend to exhibit greater optimism and proficiency, whereas older workers demonstrate greater vulnerability to automation risks (Zhang et al., 2022). In Brazil, it has been noted that gender that gender disparities standout, with women indicating both a higher reliance on AI-based tools for completing routine tasks, and a heightened worry about data privacy and exploitation (Silva & Gomes, 2021). A stark generational divide in digital skills is also found in South Africa, where younger 'Gen Z' worker lead in adoption, and Baby Boomer' employees face difficulties in training and adjustment (Nkosi, 2020). When considering these nations, India strikes a particular note as it combines having a large IT workforce, rapid AI adoption, and the struggles to overcome generational and gender-based digital skill gaps and access issues. Comparing the Indian experience with these other emerging economies broadens the lens, revealing shared hurdles like intergenerational gaps and susceptibility, along with distinct possibilities, such as making the most of India's demographic edge- a young, technology-oriented workforce.

While global research on Generative AI adoption provides helpful framework, the issues in India require a more focused perspective. Considerable growth in AI adoption has been seen across Indian workforce (Mani, 2025; Ghai, 2025; Sareen, 2025; Johny, 2025). An Emeritus study shows 96% of Indian professionals use AI and generative AI tools in their daily tasks, surpassing both US (81%) and UK (84%) (Azeem, 2025). This study also highlights that 94% of Indian professional feel AI skills are essential for career growth. Similarly, BCG reports that 92% of Indian professionals use Generative AI tools on a near-daily basis, representing one of the highest adoption rates in the world (Sarkar, 2025). Combining these local observations with cross-country comparative trends has

Table 1 Generation cohorts

Generation title	Year range
Traditionalists	1925–1945
Baby Boomers	1946–1964
Generation X	1965–1980
Generation Y or Millennials	1981–2000
Generation Z	2001–2010
Generation Alpha	2010–2025

not only provided a basic understanding of how technology is adopted but also the factors that might play an inhibiting role or an enhancing role along with the lack of studies to realise the impact of age, gender and generation. Most of the studies are either based on the rising adoption of Gen AI or are very sector-specific. Research is needed to specifically evaluate the impact on IT professionals while also studying the impact of age, gender and generation to make future research more meaningful.

Research gap

The above review of literature on the adoption of Gen AI and factors impacting the same, clearly provides a research gap of studying differences between gender and generations for the same. The reports on the adoption of IT in the Indian context proves the increasing presence of women in the IT workforce that makes the basis for studying the differences among how both the genders use gen AI for their work. The research clearly showcases a gap in this context and would add value to the current research rationale for undertaking such study for developing features to Gen AI platforms.

The research gap also exists as there are no studies to showcase the differences in the way different generations use Gen AI with special focus on Gen X, Gen Y and Gen Z who have witnessed the technology revolution. Such research is very much relevant in the current situation as many organisations are innovating with new platforms and technologies to cater to the working needs of different sectors. The Gen AI tools are here to stay and much deeper research is needed on people from various sectors to evaluate the new innovations that should be added to the Gen AI platforms. The gap can be studied better by understanding the adoption of Gen AI adoption among different generations. These gaps lead to the following hypothesis that would help in analysing data further:

H1 There is a relation between Gen-AI adoption propensity and gender.

H2 There is a relation between Gen-AI adoption propensity and generation (age cohort).

Research methods

The study investigates the relationship between employees' propensity to adopt new technology (Technology adoption propensity (TAP) and gender and generation-related individual differences in a sample of Indian professionals (Celik & Aybas, 2024; Kalasa & Annuar, 2019). A cross-sectional survey design is used to determine whether there are gender and generational differences in Technology adoption propensity. The research methodology included: identifying relevant construct, preliminary test, data collection, confirmatory factor analysis (CFA) for testing the constructs' reliability and validity and hypotheses testing. The Shapiro-Wilk and Kolmogorov-Smirnov test, Mann-Whitney U test, Kruskal-Wallis test are applied to test the hypotheses.

Participants and procedure

This study applies a quota sampling method to represent employees from all generations and both genders. In the first step, the population is divided into distinct subgroups and then the respondents were selected from different subgroups based on its proportion in the entire population. The exact sample size is computed separately for three generational subgroups i.e., Generation X, Generation Y, and Generation Z. In addition, gender proportion is also taken into consideration while selecting samples from the population. Data is gathered using a structured questionnaire from IT professionals with more than 3 years of experience in a software company or IT based job profile. Sampling frame is selected from multiple sources like directory of IT firms in Delhi NCR region, website of the company and personal networks. In all 1000 professionals were contacted and received 336 responses. Six responses with missing values were deleted. The respondents in the 330 sample included professionals aged between 22 and 54, working in Delhi NCR. Following statistical reports were referred for sample selection. According to Galan (2025), nearly 30% of IT professionals in India are females. Also, according to a survey by Pulse (2023), more than 34% of technology professionals fall between 25 and 34 years of age; more than 29% follow between 18 and 24 age brackets. Another research shows that approximately 73% of IT employees are between 18 and 34 years of age. Besides, the Pulse report (2023) also indicates that there are more than 9% IT professionals falling in the 45–54 age bracket and 29% in the 35–54 age bracket. The detailed sample structure is presented in Table 2. The population figures presented in the Table 2 are derived from secondary industry reports and surveys, including (Galan, 2025), which provide estimates on gender distribution and generational composition of IT professionals in India. These sources were used to estimate generational and gender proportions within the IT workforce. Based on these distributions, quota sampling was used to maintain representation by generations and genders. Sample sizes for each subgroup were proportionately determined and then scaled down to the actualized sample of 330 valid responses from IT professionals within the Delhi NCR area. Although the numbers are a decent approximation, they are not exact census figures; therefore, they must be understood as representative proportions based on accessible industry data.

Measures

The data collection is done using a structured questionnaire. The 'Technology adoption propensity (TAP) index' developed by Ratchford and Barnhart (2012) which measures consumers' belief and attitudes towards a wide range of new technology, was modified to suit the present research requirement. The scale was validated by a nationwide survey with 567 (first round) plus 356 (second round) US participants. Ratchford and Barnhart (2012) version of 'Technology adoption propensity (TAP) index' comprise four factors i.e. optimism, proficiency, dependence, vulnerability; with Chronbach's Alpha value of 0.87, 0.87, 0.78, 0.73 respectively. Given that a Chronbach's Alpha value of more than 0.7 is found for all dimensions, Ratchford and Barnhart (2012) reached respondents from the age of 20–55 in both females and males. The adapted questionnaire comprised six

Table 2 Sample design

Generation		Male			Female		
		Population	Sample	Proportion (%)	Population	Sample	Proportion (%)
Generation X	34 (10%)	1372	22	7	252	12	3
Generation Y	95 (29%)	3978	68	20.3	7308	27	8.7
Generation Z	201 (61%)	10,015	140	51.1	1839	61	21.9
Total tech. professional- 28,000	330	19,600	230	70	8400	100	30

Source Galan, (2025)

items on age, gender, experience, company, designation, and sector. Besides, a total of 14 items in four dimensions of TAP are developed and measured on a five-point Likert scale with anchors of '1-never' and '5- always'.

From the four factors, factor one, Optimism, measures aspects of perceived usefulness of Gen-AI to make work easier. The items describing this factor are: 'Gen-AI gives me control over my work', 'It helps me in making required changes in my work', 'It allows me to accomplish the things easily during the times I want to do them', 'Gen-AI makes my life easier'. Factor two, Proficiency, measures technical competence or one's abilities to learn Gen-AI quickly and easily. The items included are: 'I can understand the new features of Gen-AI without anybody's help', 'I seem to face less problems while using Gen-AI in comparison to others', 'People take my help on Gen-AI', and 'I enjoy exploring Gen-AI for work'. The factor dependence depicts a feeling of over dependence on Gen-AI. The items developed to measure the factor are: 'I am controlled by Gen-AI for work more than I control it', 'I feel I am overly dependent on Gen-AI for work', and 'I am increasingly dependent on Gen-AI for work as I am using it'. In addition, vulnerability factor measures the belief that Gen-AI enhances chances of being manipulated because of wrong information. It depicts the distrust or scepticism about Gen-AI. The items are: 'I should be careful while using Gen-AI for work', 'Individuals and institutions are using Gen-AI for invading people's privacy', and 'Technology companies are exaggerating Gen-AI work applications for us'.

Results

Validity and reliability

The reliabilities of research factors are examined using Cronbach's alpha coefficients and composite reliability (CR) values. The TAP scale items, their mean, standard deviation, factor loadings, average variance extracted (AVE) and reliability values are compiled in Table 3.

Table 3 depicts that all CR and Cronbach's alpha values are higher than the desired 0.7 value and proves the reliability of the items. Convergent validity is checked by item reliabilities, composite reliabilities of the constructs and AVE as suggested by Fornell and Larcker (1981) criteria. In addition, all factor loadings are significant and AVE values greater than 0.5. This confirms convergent validity. Table 4 depicts the examination of

Table 3 AVE, CR, CA, item mean, standard deviation and factor loading values of the dimensions

Variable	AVE	CR	Alpha	Item	Item mean	SD	Factor loading
Optimism	0.761	0.927	0.895	OP1	3.78	1.046	0.866
				OP2	3.67	1.009	0.875
				OP3	3.70	1.013	0.881
				OP4	3.81	1.018	0.868
Proficiency	0.823	0.949	0.928	PF1	3.19	1.212	0.893
				PF2	3.18	1.158	0.881
				PF3	3.24	1.144	0.945
				PF4	3.21	0.984	0.91
Dependence	0.787	0.917	0.865	DP1	3.95	0.842	0.883
				DP2	3.98	0.850	0.898
				DP3	3.95	0.853	0.88
Vulnerability	0.697	0.873	0.782	VUL1	3.23	1.030	0.846
				VUL2	3.25	0.996	0.853
				VUL3	3.22	1.000	0.804

Table 4 Factor correlation values

Variable	OP	PF	DP	VUL
OP	**-0.872**	0.074	0.043	0.307
PF	0.074	**-0.907**	-0.023	0.317
DP	0.043	-0.023	**-0.887**	0.045
VUL	0.307	0.317	0.045	**-0.835**

Table 5 Test of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
OP	0.160	330	0.000	0.922	330	0.000
PF	0.135	330	0.000	0.963	330	0.000
VL	0.136	330	0.000	0.938	330	0.000
DP	0.138	330	0.000	0.964	330	0.000

a. Lilliefors Significance Correction

Table 6 Gen-AI technology adoption among men and women

Variables	*p*	Mann-Whitney U	Mean rank	
			Women	Men
OP	0.024	9720.0	183.30	157.76
PF	0.008	9407.0	144.57	174.60
VL	0.018	9645.0	184.05	157.43
DP	0.000	5245.0	228.05	138.30

discriminant validity by verifying the square root of the AVE values of each construct and its cross-correlation with other constructs. All squared correlation values between the constructs are less than AVE.

Hypothesis testing

In order to select the appropriate statistical test, a test of basic assumption is conducted. The Shapiro-Wilk and Kolmogorov-Smirnov test is conducted to investigate the normality of the data. Table 5 depicts the results that all significance values lesser than 0.05 (refer Table 5). This shows that the data collected is not normally distributed. Therefore, Mann-Whitney U test, a non-parametric test is applied to examine the role of gender in Gen-AI adoption by professionals. Besides, Kruskal-Wallis test is also applied to compare Gen-AI adoption among three generation professionals i.e. Generation X, Generation Y, and Generation Z. The complete analysis is conducted using the 23.0 version of SPSS at <0.05 significant (p) values.

The results of the Man-Whitney U test confirm the difference in the Gen-AI adoption by men and women. As shown in Table 6, p values of all four dimensions of Gen-AI technology adoption are less than 0.05. The results justify partial acceptance of H1, that there is a relation between Gen-AI adoption propensity and gender. Mean values of three dimensions i.e. optimism, vulnerability and dependence are higher for women.

For testing the second hypothesis, Kruskal-Wallis test is performed. The results in Table 7 show significant p values for three dimensions i.e. optimism, proficiency and dependence. The results justify partial acceptance of H2, that there is a relation between Gen-AI adoption propensity and generations. Significant differences in terms of Gen-AI adoption among professionals of different generations is found. Results show that Gen

Table 7 Gen-AI technology adoption among generations

Dimensions	*p*	Kruskal-Wallis H	Mean rank		
			Gen X	Gen Y	Gen Z
OP	0.019	7.923	179.28	154.22	193.68
PF	0.006	10.100	166.45	173.19	117.38
VL	0.057	5.744	176.28	156.09	190.97
DP	0.000	44.164	193.06	139.84	240.22

Z shows higher optimism and dependability for Gen-AI (Mean Rank = 193.68, $p = 0.019$ and Mean Rank = 240.22, $p = 0.00$ respectively) than others. Besides, Gen Y shows the highest proficiency in Gen-AI technology.

Discussions

While evaluating the results, a clear indication is provided regarding the differences in how both the genders use Gen AI in their professional field. The differences can be due to the basic differences between men and women towards their orientation for technology adoption. This can be the result of differences in personality, opinions, technical proficiency, skillset, job enrichment creating a higher level of propensity for women mainly towards optimism, vulnerability and dependence. This supports the first hypothesis of having relation between the adoption of Gen AI and gender. The findings also relate to the review of literature where it was discussed that as women are now an important percentage of the IT workforce, their adoption of emerging technology would differ. The difference in the mean values of dependence, vulnerability and optimism is higher for women as compared to men explaining on proficiency being the main variable where men have scored higher. The underlying reasons may vary for both the genders including job profiles, stage of career, generation cohort, team project, etc. which have led to 3 factors having higher scores for women. Even within IT, women tend to be grouped in roles with varying task mixes (e.g., client servicing, QA, documentation, product support) compared to men in more coding/engineering track tasks (Xiong et al., 2020). Where work is communication-centric, compliance oriented, it is overrepresented by women in certain settings. They will have a tendency to use AI tools as productivity enhancers. Gendered technology adoption and Indian applicants for digital access literature also reveals structural and socialization components (availability of access, training possibilities, and initial exposure) depressing women's self-efficacy and enhancing dependence on aids (Russo et al., 2025).

Moreover, the observed pattern- women scoring higher on vulnerability and dependence while men score higher on proficiency- can be interpreted through established constructs in gender and organizational psychology (Todman, 2006). A large body of work links higher technology-related anxiety and lower computer self-efficacy among women to greater perceived vulnerability when new systems are introduced; women often report more AI/computer anxiety which reduces confidence and increases reliance on tools or on colleagues for decision support. This dynamic plausibly explains why female respondents report both greater vulnerability (feeling at risk from AI errors or privacy issues) and greater dependence (using AI to compensate for lower self-reported technical confidence).

While discussing the second hypothesis, it is proved that there is a relation between the generation and the propensity towards technology adoption. The results show that

Gen Z who have been born between 2001 and 2020 have higher propensity to use Gen with a higher score on dependence and optimism towards Gen AI as they relate more towards the younger population and have seen the technology revolution. Their greater reliance and optimism are consistent with being a digitally native generation comfortable with pervasive AI-facilitated processes; they pick up and use tools readily. Whereas Gen Y has seen a higher score for proficiency as they belong to the year between 1981 and 2000 who are more in the middle management cadre looking at adoption of Gen AI within companies at strategic level. The propensity towards technology adoption is not just a function of age or job profile but a complete mix of attitude, perception, learning and motivation to use it in their jobs while seeking to enhance productivity. At a decision-making level, such emerging technology would provide the support to both Gen Y and Gen Z even when there are different management levels within the IT firm (Choudhary et al., 2024). This is further supported by earlier studies that raised the same question of how generations differ in their technology adoption proving that there is relation between them leading to partial acceptance of H2. Integrating these outputs suggests several deeper interpretations that move beyond descriptive differences. Psychological mechanism such as technology anxiety, self-efficacy, risk aversion, seem to mediate the gender -AI adoption relationship. Interventions that alleviate anxiety and increase self-efficacy like focused training, mentoring, experiential labs should decrease perceived vulnerability and unhealthy dependence. Second, organizational design features such as role design, upskilling access, strategic AI task exposure influence generational proficiency which in turn will encourage rotation assignments and role enrichment among younger workers (Chan, 2023).

Theoretical and practical implications

The outcomes of this study offer academic worth as well as practical recommendations for fostering an even more inclusive and result-oriented AI workplace AI workplace in India. This research adds to the body of literature on TAP model by looking at generational and gender-based items and hence providing an improved perception on how optimism, expertise, reliance and exposure are some factors influencing AI adoption (Calvo-Porral & Pesqueira-Sanchez, 2020; Santini et al., 2019). Specifically, this study is among the first to integrate gender and generational differences simultaneously within the TAP model in the Indian IT sector (Berényi et al., 2021). Prior global studies (Ma et al., 2024; Setälä et al., 2025) mainly examine technology adoption drivers like perceived usefulness and ease of use but do not account for India's distinct workforce profile. This study adds India-specific dimensions- generational cohort differences, sectoral distribution, and digital skill preparedness-capturing both enthusiasm for AI tools and the challenge of uneven access to upskilling. Thus, it can inform future research on issues related to the divide between digital and physical spaces indicating that age as well as gender could affect technology adoption especially in rapidly changing sectors like IT.

The IT companies may use the findings of this study to design custom-made training and upskilling programs that are aimed at the needs of different generations and genders. For benefit from taking basic AI classes in order to fill any skill gaps. The insights derived from this can enable firms creating AI instruments to customise their products and promotional approaches so they align more closely with different user demographics demands and levels of comfort.

Limitations

This research has some limitations that need to be taken into account. To begin with, the geographical domain is confined to IT professionals operating in the Delhi NCR area of India, which could restrict generalizability of results to other parts of India or to international settings, where organizational dynamics and AI readiness for adoption could be different. Second, the research concentrates solely on IT professionals and thus precludes insights from other sectors like healthcare, finance, or manufacturing whose generative AI adoption patterns could be very different. Third, a cross-sectional study design captures attitudes at one point in time but now how views about. Generative AI could change as individuals advance in their careers or as technology improves. Lastly, although this research points to generational and gender variations, it does not take into account other factors that could impact optimism and exposure to AI adoption such as educational background, socio-economic class, occupational positions, or organizational rank, which could influence the two. These gaps limit the explanatory breadth of the results and indicate precaution against overgeneralizing.

Future scope

Basing on the above constraint, future studies can widen in a number of ways. Firstly, widening the scope to capture various sectors other than IT would enable comparison of adoption drivers and inhibitors across various industries. Secondly, taking a longitudinal approach would offer more insights into how gender and generational perceptions of AI change over time, especially as AI usage is increasingly integrated into organizational operations. Subsequent research should also examine psychological and behavioural moderators such as digital anxiety, openness to change, technology self-efficacy, and risk aversion that can potentially explain why some employees are more vulnerable or reliant than others. Investigation of such factors would not only enrich theory-based contributions to technology acceptance research but also yield actionable recommendations for organizations to develop focused interventions, training initiatives, and policies to encourage fair AI uptake across gender and age-based cohorts.

Conclusions

This research aimed to investigate generational and gender differences in AI skills, dependency, and vulnerability, conceptualizing a model of explaining these differences. The results contribute to theory by applying existing theoretical models of technological adoption and digital literacy to the new frontier of Generative AI, thereby incorporating socio-demographic factors into models of technology acceptance. The implications are also profound. As Generative AI grows in popularity, the need for such professionals eith the ability to utilize such technologies has been on the rise. The suggested model provides a framework for empirical studies that investigate skill acquisition, labor adaptability, and educational approaches across age and gender boundaries. All these lessons can be used by policymakers, educators, and corporate trainers to develop interventions that bridge gaps and facilitate rapid AI readiness. At a societal level, the research points to challenges and opportunities in developing a technologically capable citizenry. Narrowing the gaps in AI capability and constructing equal opportunities for skill acquisition can help advance India's digital transformation agenda and propel inclusive economic development. The theoretical contribution and practical relevance therefore align towards developing a framework that not only enriches academic insight but also helps construct a future-proof workforce that is capable of negotiating the AI-driven economy.

Author contributions
AA Conceived and planned the study, research design, methodology, Collected Data. reviewed and corrected the manuscript. KK Wrote literature review, discussions, implications. Both authors read and proof read the entire manuscript.

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Data availability
The data that support the findings of the study are available from the corresponding author upon reasonable request.

Declarations

Ethical approval and consent to participate
The study does not require any ethical approval considering the topic of study as it does not involve any sensitive issue. Also, the participants of the study are adults, and were informed about the purpose of the study. Their anonymity is ensured. Dataset of the study can be shared with them if asked. Consent to participatehas been taken from the respondents while collecting data.

Consent to publish
Consent to publish has been obtained from the participants confirming data sharing and publishing the outcomes of the data collected. Anonymity of the participants is ensured.

Conmpeting interest
No potential conflict of interest was reported by the authors.

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References
Accenture, & Gen, A. I. (2024). Challenge, retrieved from: https://www.accenture.com/us-en/insights/high-tech/gen-ai-challenge (Accessed on 10th August 2024).
Ajibade, P. (2018). Technology acceptance model limitations and criticisms: Exploring the practical applications and use in technology-related studies, mixed-method, and qualitative researches. *Library Philosophy and Practice*, *9*.
Ajzen, I. (2020). The theory of planned behavior: Frequently asked questions. *Human Behavior and Emerging Technologies*, *2*(4), 314–324.
Awa, H. O., Ojiabo, O. U., & Orokor, L. E. (2017). Integrated technology-organization-environment (TOE) taxonomies for technology adoption. *Journal of Enterprise Information Management*, *30*(6), 893–921.
Azeem, S. (2025). 96% of India's professionals using AI tools, outpacing US, UK: Emeritus. *Fortune India*, https://www.fortuneindia.com/macro/96-of-indias-professionals-using-ai-tools-outpacing-us-uk-emeritus/120368? (Accessed 30 August 2025).
Berényi, L., Deutsch, N., Pintér, É., Bagó, P., & Nagy-Borsy, V. (2021). Technology Adoption Propensity Among Hungarian Business Students. *European Scientific Journal*, *17*(32), 1–21. https://doi.org/10.19044/esj.2021.v17n32p1.
Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., & Varma, A. (2023). Human resource management in the age of generative artificial intelligence: Perspectives and research directions on ChatGPT. *Human Resource Management Journal*, *33*(3), 606–659.
Calvo-Porral, C., & Pesqueira-Sanchez, R. (2020). Generational differences in technology behaviour: Comparing millennials and Generation X. *Kybernetes*, *49*(11), 2755–2772. https://doi.org/10.1108/K-09-2019-0598.
Capgemini (2023). Software organizations in IT, retrieved from: https://www.capgemini.com/insights/research-library/gen-ai-in-software/#:~:text=The%20adoption%20of%20generative%20AI%20for%20software%20engineering,begun%20integrating%20generative%20AI%20into%20their%20software%20functions. (Accessed on 2nd August 2024).
Celik, H., & Aybas, M. (2024). Psychometric evaluation of Technology Adoption Propensity (TAP) index within independent samples of Turkish individuals. *American Journal of Business*, *40*(1), 43–63. https://doi.org/10.1108/AJB-10-2023-0181.
Chan, C. K. Y., & Lee, K. K. W. (2023). The AI generation gap: Are gen Z students more interested in adopting generative AI such as ChatGPT in teaching and learning than their gen X and millennial generation teachers? *Smart Learn Environ*, *10*, 60. https://doi.org/10.1186/s40561-023-00269-3.
Choudhary, R., Shaik, Y. A., Yadav, P., & Rashid, A. (2024). Generational differences in technology behavior: A systematic literature review. *Journal of Infrastructure Policy and Development*, *8*(9), 6755.
Davis, F. D., Bagozzi, R. P. & Warshaw, P.R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982.
Deloitte (2024). State of generative AI in enterprises, retrieved from: https://www2.deloitte.com/us/en/pages/consulting/articles/state-of-generative-ai-in-enterprise.html (Accessed on 15th August 2024).
Doulani, A. (2018). An assessment of effective factors in technology acceptance model: A meta-analysis study. *J Sci Res*, *7*(3), 153–166.
Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., & Wright, R. (2023). Opinion Paper:So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, *71*, 102642.

Ebert, C., & Louridas, P. (2023). Generative AI for software practitioners. *IEEE Software*, *40*(4), 30–38.

Ellingrud, K., Sanghvi, S., Madgavkar, A., Dandona, G. S., Chui, M., White, O., & Hasebe, P. (2023). Generative AI and the future of work in America. McKinsey Global Institute. https://www.mckinsey.com/mgi/our-research/generative-ai-and-the-future-of-work-in-america. (Accessed 30 August 2025).

Farrelly, T., & Baker, N. (2023). Generative artificial intelligence: Implications and considerations for higher education practice. *Education Sciences*, *13*(11), 1109.

Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative ai. *Business & Information Systems Engineering*, *66*(1), 111–126.

Fornell, C., & Larcker, D. (1981). Structural equation models with unob- servable variables and measurement error. *Journal of Marketing Research*, *18*, 39–50. https://doi.org/10.2307/3150980.

Fosso Wamba, S., Guthrie, C., Queiroz, M. M., & Minner, S. (2024). ChatGPT and generative artificial intelligence: An exploratory study of key benefits and challenges in operations and supply chain management. *International Journal of Production Research*, *62*(16), 5676–5696.

Fui-Hoon Nah, F., Zheng, R., Cai, J., Siau, K., & Chen, L. (2023). Generative AI and ChatGPT: Applications, challenges, and AI-human collaboration. *Journal of Information Technology Case and Application Research*, *25*(3), 277–304.

Galan, S. (2025). Global estimated population 2024–2030, be generation. *Statista*, https://www.statista.com/statistics/1607121/estimated-population-of-the-world-by-generation/ (Accessed 30 July 2025).

Ghai, N. (2025). India's gen-AI boom faces talent drought. *The Economic Times*, https://economictimes.indiatimes.com/news/company/corporate-trends/indias-genai-boom-faces-talent-drought/articleshow/123550091.cms? (Accessed 30 August 2025).

Granić, A., & Marangunić, N. (2019). Technology acceptance model in educational context: A systematic literature review. *British Journal of Educational Technology*, *50*(5), 2572–2593.

Hussein, Z. (2017). Leading to intention: The role of attitude in relation to technology acceptance model in e-learning. *Procedia Computer Science*, *105*, 159–164.

Johny, A. K. (2025). India beats global average in employees using AI: Report. *The Times of India*, https://economictimes.indiatimes.com/tech/artificial-intelligence/india-beats-global-average-in-employees-using-ai-report/articleshow/122095005.cms? (Accessed 30 August 2025).

Jovanovic, M., & Campbell, M. (2022). Generative artificial intelligence: Trends and prospects. *Computer*, *55*(10), 107–112.

Kalasa, A. A., & Annuar, S. N. S. (2019). The relationship between service quality and customer satisfaction among millennials in the hospitality industry: Technology adoption propensity (tap) as moderating factor. *The Business & Management Review*, *10*(3), 75–84.

Kanbach, D. K., Heiduk, L., Blueher, G., Schreiter, M., & Lahmann, A. (2024). The GenAI is out of the bottle: Generative artificial intelligence from a business model innovation perspective. *Review of Managerial Science*, *18*(4), 1189–1220.

Lai, P. C. (2017). The literature review of technology adoption models and theories for the novelty technology. *JISTEM-Journal of Information Systems and Technology Management*, *14*(1), 21–38.

LinkedIn (2023). Software developers India, UK, Germany, retrieved from: https://www.linkedin.com/pulse/comparison-software-developers-india-us-uk-germany-entire-agarwal (Accessed on 4th August 2024).

Ma, L., Chen, Y., & Xu, J. (2024). Exploring AI adoption in digital economies: An extended technology acceptance model. *Technological Forecasting and Social Change*, *198*, 122971. https://doi.org/10.1016/j.techfore.2023.122971.

Mani, V. (2025). AI to augment jobs, not take them away: HCLTech chair Roshni Nadar. *The Times of India*, https://timesofindia.indiatimes.com/city/bengaluru/ai-to-augment-jobs-not-take-them-away-hcltech-chair-roshni-nadar/articleshow/123533194.cms? (Accessed 30 August 2025).

Marak, Z. R., Pahari, S., Shekhar, R., et al. (2025). Factors affecting chatbots in banking services: The UTAUT2 and innovation resistance theory perspective. *J Innov Entrep*, *14*, 47. https://doi.org/10.1186/s13731-025-00514-8.

Mckinsey (2024). The state of AI, retrieved from: https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai (Accessed on 6th August 2024).

Murray, M. D. (2024). Tools do not create: Human authorship in the use of generative artificial intelligence. *Case W Res JL Tech & Internet*, *15*, 76.

Nkosi, P. (2020). Generational differences in digital proficiency and workplace technology adoption in South Africa. *South African Journal of Human Resource Management*, *18*(1), a1273. https://doi.org/10.4102/sajhrm.v18i0.1273.

Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science*, *381*(6654), 187–192.

Ooi, K. B., Tan, G. W. H., Al-Emran, M., Al-Sharafi, M. A., Capatina, A., Chakraborty, A., & Wong, L. W. (2023). The potential of generative artificial intelligence across disciplines: Perspectives and future directions. *Journal of Computer Information Systems*, 1–32.

Ortiz-Ospino, L., González-Sarmiento, E., & Roa-Perez, J. (2025). Technology trends in the creative and cultural industries sector: A systematic literature review. *Journal of Innovation and Entrepreneurship*, *14*, 39. https://doi.org/10.1186/s13731-025-00497-6.

Pramudita, E., Achmadi, H., & Nurhaida, H. (2023). Determinants of behavioral intention toward telemedicine services among Indonesian Gen-Z and Millenials: A PLS–SEM study on Alodokter application. *Journal of Innovation and Entrepreneurship*, *12*, 68. https://doi.org/10.1186/s13731-023-00336-6.

Pulse report (2023). Slash data's developer nation survey. *Developer Nation*, https://www.developernation.net/developer-reports/dn23/ (Accessed 18 August 2024).

Ratchford, M., & Barnhart, M. (2012). *Technology Adoption Propensity Index* [(Database record]). APA PsycTests. https://doi.org/10.1037/t40481-000.

Rubin, A., & Callaghan, C. W. (2020). Propensity to adopt new technologies and research productivity in a developing country context. *International Journal of Business Innovation and Research*, *22*(4), 546–568.

Russo, C., Romano, L., Clemente, D., Locovone, L., Gladwin, T. E., & Panno, A. (2025). Gender differences in artificial intelligence: The role of artificial intelligence anxiety. *Frontiers*, *16*(1), 1559457.

Santini, F., de Ladeira, O., Sampaio, W. J., Perin, C. H., M. G., & Dolci, P. C. (2019). Propensity for technological adoption: An analysis of effects size in the banking sector. *Behaviour & Information Technology*, *39*(12), 1341–1355. https://doi.org/10.1080/0144929X.2019.1667441.

Sareen, L. (2025). For every 10 AI roles, there is 1 engineer: India's skills crises explained. *The Times of India*, https://timesofindia.indiatimes.com/education/news/for-every-10-ai-roles-there-is-1-engineer-indias-skills-crisis-explained/articleshow/123614584.cms? (Accessed 30 August 2025).

Sarkar, B. (2025). Nine in 10 Indian employees embracing genAI tools, well ahead of global average: Report. *The Economic Times*, https://economictimes.indiatimes.com/jobs/hr-policies-trends/nine-in-10-indian-employees-embracing-genai-tools-well-ahead-of-global-average-report/articleshow/122091405.cms? (Accessed 30 August 2025).

Setälä, M., Rantanen, T., & Hänninen, K. (2025). Generational differences in AI technology adoption: Evidence from global survey data. *Journal of Innovation & Knowledge*, *10*(1), 15–27. https://doi.org/10.1016/j.jik.2024.100430.

Silva, M., & Gomes, R. (2021). Gendered dimensions of artificial intelligence adoption: Evidence from Brazilian service industries. *Information Systems Frontiers*, *23*(6), 1567–1582. https://doi.org/10.1007/s10796-021-10121-5.

Spanjol, J., & Noble, C. H. (2023). From the Editors: Engaging with generative artificial intelligence technologies in innovation management research—Some answers and more questions. *Journal of Product Innovation Management*, *40*(4).

Todman, J. (2006). Computer anxiety: The role of psychological gender. *Computers in Human Behavior*, *22*(5), 856–869.

Vartiainen, H., & Tedre, M. (2023). Using artificial intelligence in craft education: Crafting with text-to-image generative models. *Digital Creativity*, *34*(1), 1–21.

Wach, K., Duong, C. D., Ejdys, J., Kazlauskaitė, R., Korzynski, P., Mazurek, G., & Ziemba, E. (2023). The dark side of generative artificial intelligence: A critical analysis of controversies and risks of ChatGPT. *Entrepreneurial Business and Economics Review*, *11*(2), 7–30.

Xiong, C., Ye, B., Mihailidis, A., Cameron, J., Astell, A., Nalder, E., & Colantonio, A. (2020). Sex and gender differences in technology needs and prefernces among informal caregivers of persons with dementia. *Bmc Geriatrics*, *20*(1), 176.

Zhang, L., Chen, H., & Wu, J. (2022). Government policy, digital ecosystems, and AI adoption: Evidence from China's technology sector. *Technological Forecasting and Social Change*, *180*, 121680. https://doi.org/10.1016/j.techfore.2022.121680.

Zippia (2024). Software programmer demographics and statistics in the US. *Zippia, The Career Expert*, https://www.zippia.com/software-programmer-jobs/demographics/ (Accessed 18 August 2024).

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