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Factors Affecting the Adoption of Generative AI Tools Among Information Technology Employees: A UTAUT3, TTF, and SOR Perspective

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Abstract: This empirical study examined the components that affect the adoption and actual use of generative AI tools among information technology (IT) employees in Hyderabad. This study also attempted to unravel the SOR, UTAUT3, and TTF models by integrating them for practical application in industry and by IT sector employees. Data were gathered from 470 employees working in several IT industries in Hyderabad by adopting a quantitative method for this investigation. IBM-AMOS was used to test the hypotheses. Thirty-six variables were used to measure the following 10 reflective constructs: optimism, innovativeness, trust, performance expectancy, effort expectancy, hedonic motivation, social influence, task–technology fit, adoption intentions toward generative AI tools, and actual use of generative AI tools. EFA and CFA analyses were conducted to unravel the structural relationships between constructs, and hypotheses were tested using SEM. A 12% variance in the adoption intention of generative AI tools by IT industry employees was explained by optimism, innovativeness, trust, performance expectancy, effort expectancy, hedonic motivation, social influence, and task–technology fit, and a 5% variance in the actual use of generative AI tools was explained by the adoption intentions. The construct trust fully mediated the nexus between adoption intentions to use generative AI tools and actual use. All constructs, except hedonic motivation, statistically significantly influenced the adoption intentions of generative AI tools. In turn, adoption intentions to use generative AI tools influenced the actual use of generative AI tools. A study involving Hyderabad IT industry employees revealed that they could adopt useful technology to improve performance.

Keywords: generative AI tools, social influence, trust, effort expectancy, optimism

1. Introduction

Generative AI tools are gaining attention in the information technology (IT) industry because of their potential to revolutionize automation, data analysis, and software development processes. The three famous models that researchers have applied to dissect the components that influence generative AI technologies are the unified theory of acceptance and use of technology (UTAUT), task–technology fit (TTF), and stimulus–organism–response (SOR) models. We investigated how these models comprehended the adoption of generative AI tools by IT sector employees.

The main reason for transforming employees' attitudes from diligence to astute work in the IT sector is the significant advancements made in artificial intelligence and machine learning. Generative AI tools, including OpenAI, ChatGPT, Google Gemini, Microsoft's Copilot, and Bing AI, are utilized by IT businesses, academics, IT specialists, and companies. AI tools such as SlidesAI, Wepik, and Tome have significantly transformed presentation development, content creation, image creation, and video generation industries [1, 2]. ChatGPT, an AI tool, is frequently utilized by IT professionals worldwide for letter and report drafting and text generation [3]. Immediate explanations for queries and explanation-based solutions are possible with the AI-based virtual assistant ChatGPT. ChatGPT provides solutions to queries, enhancing accessibility, performance, and engagement [4].

Instant, human-like responses are possible using generative AI technologies for performance improvement and productivity through the automation of repetitive tasks with personalized assistance [5]. Chatbots aid employees in timely work completion, but generative AI tools and their use are novel in higher education, healthcare, engineering, and management, with limited research on adoption intentions [6–8] and the hospitality and tourism industry [3, 9]. A reliable methodology for modeling factors influencing adoption intentions and the actual use of generative AI tools for enhancing employee performance and engagement is needed. This study aimed to understand IT industry employees' use of generative AI technologies by integrating the UTAUT3, TTF, and SOR models. The UTAUT3

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model is a comprehensive framework that considers various factors influencing the adoption and utilization of generative AI tools [10].

This study addresses the lacuna of past studies that use single- or dual-theory models, investigating user acceptance and behavioral intentions concerning the adoption of generative AI technologies in design through an integrated theoretical model analysis that combines three theoretical models to investigate the user intentions and driving factors that influence adoption intentions of generative AI among IT employees. The current study examines a broad process, specifically actual usage–intention to use–recommendation, and integrates the SOR, UTAUT3, and TTF models with knowledge regarding users' behavioral intentions to adopt and use generative AI and to create a novel research model. The SOR, UTAUT, and TTF models were integrated to unravel the factors that affect the adoption of generative AI tools by IT employees.

1.1. Research gap

The IT industry has extensive AI literature. However, the application of generative AI across various sectors is not explored, as with most studies focusing on a single tool. Trust dynamics are crucial for generative AI adoption in the IT sector and are influenced by various factors, necessitating further investigation and strategy development for wider adoption. This study emphasizes the importance of perceived usefulness, ease of use, and ethical considerations in fostering trust and promoting adoption. The IT industry must address trust issues in generative AI through transparent practices, ethical guidelines, and comprehensive AI education programs to fully utilize its potential. Trust is crucial for generative AI adoption in industry settings and requires transparency, ethical considerations, and user empowerment. This study explores the influence of trust on IT sector employees, providing practical and theoretical insights. Despite growing interest in generative AI, the available literature is scarce because few studies have been conducted on its adoption in industry, particularly in the IT sector. Previous studies mainly focus on ChatGPT's general applications in education or workplaces, neglecting the unique challenges and opportunities of generative AI. Trust plays a crucial role in technology adoption, but its mediating role in the relationship between AI adoption and actual use by IT industry employees is not fully researched.

2. Review of Literature and Hypotheses Development

Integrating technology in the context of the IT industry has immensely helped employees learn, interact, and engage with knowledge systems. Technological advancements have made generative AI a remarkable innovation with significant effects on professional work. These technology and systems can produce content similar to human-made creations, covering text, images, audio, and simulations through advanced machine learning algorithms. For IT professionals, tools such as ChatGPT, DALL-E, and similar platforms offer new ways for enhancing creativity, efficiency, and analytical ability. This is necessary to prepare them for leadership roles in the technology-driven environment of the universe.

2.1. Generative AI in the IT industry

IT businesses often emphasize analytical rigor, strategic thinking, and decision-making skills. The emergence of generative AI technology aligns smoothly with these goals. This tool helps employees address complex problems, discover new ideas, and effectively acquire important insights. For example, generative AI aids in conducting SWOT analyses, creating case study solutions, simulating market scenarios, and improving the learning experience of staff. The transformative potential of generative AI also introduces challenges that need thoughtful evaluation. A significant distinction between generative AI and conventional IT is its ability to make decisions independently. Gefen et al. [11] noted that generative AI addresses results that lack transparency or reliability. These concerns highlight the importance of trust, which is a psychological state that involves the expectation that technology will work as intended without malicious intent or preconceived ideas.

2.2. Trust in technology adoption

Trust is widely acknowledged as the foundation of technology, as demonstrated by the technology evaluation model [12] and unified technology evaluation and usage theory [13]. Research has identified perceived usefulness, perceived ease of use, and trust as important influencing factors of courtship behavior. However, in relation to generative AI, trust is a vital component due to the inherent complexity of technology and potential risks, and issues such as ethical concerns arise. Data privacy and incorrect information have intensified only the skepticism surrounding generative AI and turned trust into an important intermediary in the adoption process.

For IT industry employees, trust in generative IA spans multiple dimensions. This includes trust in the algorithm's ability (i.e., accuracy and relevance of results), integrity (i.e., unbiased and ethical performance), and predictability (i.e., consistent and reliable results). Greater trust or lack of trust can lead to resistance to technology adoption. Regardless of the perceived benefits, trust is not only a passive influence but also an intermediary that plays a role in shaping the interaction among technological features and user behavior. The adoption of generative AI in industry, particularly among IT industry employees, is influenced by various factors, with trust playing a pivotal role. This study examines the acceptance of generative AI and its related effects on employees working in the IT industry. The mediating effects of trust on the nexus between the intention to use and actual use were also investigated.

This study explored the effectiveness of AI in collaborative learning environments [14] and reported how generative AI tools can help in group discussions and provide problem-solving strategies. Trust and reliability are essential factors of generative AI adoption by humans. Thus, there is a need to build trust in the adoption of these technologies.

To understand and unravel generative AI adoption, this study integrated the UTAUT, TTF, and SOR models. UTAUT explains the acceptance process. Task compatibility focuses on the TTF, and emotional and cognitive responses are examined using SOR. The integration of these models helps in comprehending how adoption decisions are influenced by cognitive factors such as perceived usefulness and emotional reactions (such as fear of AI).

The UTAUT model, developed by Venkatesh et al. [13], explains the four key components, namely, performance expectancy, effort expectancy, social influence, and facilitating conditions, that significantly influence technology adoption.

Performance expectancy: A systems' effectiveness in improving job performance is influenced by an individual's perception of its benefits. Generative AI technology adoption is closely related to its perceived value or usefulness. When IT professionals believe that generative AI can enhance their productivity, performance, and overall work quality, they are more enthusiastic regarding adopting technology. Enhancing decision-making skills, automating repetitive tasks, and encouraging creativity are key motivators for IT employees to adopt generative AI.

Effort expectancy: The term "ease" is the level of comfort or ease when using a system. If the technology is simple, users are more inclined toward its adoption. Although the deployment of generative AI tools in the IT industry initially created some difficulties, employees will try to embrace these technologies sooner or later. However, related training and clear and straightforward documentation are needed [13].

Social influence: It is an individual's perception of the belief that others should adopt a new system [13]. Social influence affects individuals' ability to use technologies if their colleagues reap benefits. IT employees are influenced by peers' and colleagues' opinions and are motivated to use generative AI tools [15].

The UTAUT model, enhanced by Venkatesh et al. [16], incorporated the components hedonic motivation, price value, and habit to understand technology adoption intentions and user enjoyment.

Therefore, the following hypotheses are proposed:

H1: Performance expectancy significantly affects the adoption of generative AI.
H2: Effort expectancy significant affects the adoption of generative AI.
H3: Hedonic motivation has a positive effect on generative AI adoption.
H4: Social influence significantly affects adoption intention.

2.3. TTF model

The TTF model emphasizes the importance of aligning a technology's capabilities with its intended tasks to improve performance and satisfaction. TTF in IT professionals depends on how AI tools align with daily responsibilities, addressing work-related challenges such as coding efficiency, automating repetitive tasks, and facilitating decision-making processes [17]. The research on the IT sector indicates that the successful and seamless adoption of AI tools is most effective when tailored to specific job functions such as software development, system administration, and data analysis [12, 18]. The perception of generative AI tools in office settings is influenced by task complexity, with structured tasks benefiting more and creative tasks posing challenges and aligning with work performance goals.

Studies on the TAM highlight the importance of the total time frame (TTF) in assessing the effectiveness of a technology in facilitating task completion [17]. This study reveals a positive correlation between total time spent (TTF) and online interaction behavior and performance among IT personnel.

H5: TTF significantly influences the adoption intentions of generative AI tools.

Technology adoption will be increased if users perceive positive emotions toward the use of the system, and the user will adopt and use the technology. There is a close association between attitudes toward technology and behavior in a certain way [12]. Thus, the hypothesis formulated is as follows:

H6: The actual usage of generative AI tools is positively influenced by attitudes toward their use and adoption intentions.

2.4. Trust in AI systems

Trust is an important factor for technology adoption. Trust is the intention to be vulnerable to someone else's actions on the basis of positive expectations, honesty, and goodwill, ensuring trustworthiness. To adopt the technology, it should be transparent and reliable. Hoff and Bashir [19] emphasized the importance of consistent performance and clear results in fostering trust in automated systems, especially in generative AI. The survey reported by La-Rosa Barrolleta and Sandoval-Martín [20] revealed that transparency in algorithms and ethical factors such as fairness and bias reduction significantly enhance user trust in generative AI tools. Trust in technology is affected by factors such as security, privacy, and data safety, which are dynamic and stable with frequent use and experience of generative AI tools.

2.4.1. Mediating role of trust in generative AI adoption

The relationship between generative AI tools and user adoption can be influenced by trust. Trust can help in alleviating the intricacies and risks related with the use of generative AI tools and can gradually increase adoption intentions and adoption rates [21]. Trust in generative AI in the IT industry can enhance employees' perceptions of its ease of use and usefulness by reducing misunderstandings and biases. McGehee [22] studied the adoption of generative AI by educators in classrooms. Moreover, confidence use and adoption of generative AI have a significant effect on their willingness. The reliability and consistency of IA ethics and outcomes can be integrated into teaching. This emphasizes the importance of fostering trust not only among employees but also among HR managers. This often serves as a key influencer of adoption decisions.

H7: Trust mediates the nexus between adoption intentions and the actual use of generative AI tools.

2.5. SOR model

The SOR model, developed by Russell and Mehrabian [23], emphasizes how external stimuli influence internal factors, such as attitudes, emotions, and perceptions, leading to adoption behavior in technology adoption research.

2.5.1. Stimulus

External factors such as exposure to new AI technologies, organizational announcements, and marketing efforts can influence the adoption of generative AI. The perception and attitudes of IT employees toward generative AI can be influenced by internal communications, industry conferences, or vendor demonstrations [24].

2.5.2. Organism (internal state)

The SOR model reflects individuals' internal states, including attitudes, emotions, and cognitive evaluations, such as IT employees' reactions to generative AI adoption, including ease of use, risk, trust, and emotions [23, 25]. An employee's fear of automation replacing their job might hinder adoption, and excitement regarding staying ahead of the curve could encourage it.

2.5.3. Response

The response to generative AI tools, influenced by positive emotional responses such as enthusiasm, can significantly affect adoption rates, whereas negative emotions such as fear or resistance can hinder adoption [25].

2.6. Integration of UTAUT, TTF, and SOR in generative AI adoption

This study integrated three models to attain a comprehensive understanding of the recent surge in generative AI adoption. The UTAUT framework focuses on AI adoption acceptance, TTF emphasizes task compatibility, and SOR offers insights into emotional and cognitive responses. Thus, two new components, namely, optimism and innovativeness, were introduced. The integration of these three frameworks clearly reveals cognitive dimensions. Jha and Singh [18] reported that performance expectancy and TTF are key predictors of generative AI adoption among IT professionals, with emotional reactions mediating the process of decision-making.

This study underscores the significance of comprehending task relevance and emotional responses within organizations for the successful implementation of generative AI tools. This study employs models such as UTAUT, TTF, and SOR to clarify acceptance behaviors and alignment between tasks and AI technology, emphasizing the need for a comprehensive strategy. Thus, hypotheses 8 and 9 are formulated as follows:

H8: Optimism affects the adoption intentions of generative AI tools and is statistically significant.
H9: Innovativeness affects the adoption intentions of generative AI tools and is statistically significant.

2.7. Research objectives

Identifying factors influencing generative AI adoption: Examine the technological, individual, and contextual factors that drive the adoption of generative AI tools among IT industry employees.

Explore trust as a mediator: Investigate how trust mediates the nexus among the relationships between the perceived attributes of generative AI (e.g., performance expectancy and effort expectancy) and adoption behavior.

Recommendations: Develop actionable strategies for fostering trust and increasing the responsible adoption of generative AI by IT industry employees.

By taking care of these aspects, this study aims to bridge the gap between technological innovation and human-centered adoption frameworks, ensuring that the potential of generative AI is fully realized in nurturing the next generation of business leaders. These findings yield novel insights into the theory of user behavior, charting a course for the refinement of generative AI design tools. The purpose of such improvements is to encourage broader adoption and utilization of these tools in relevant areas. To achieve this, it is important to refine their functionality and accuracy.

2.8. Theoretical framework

The authors integrated the TAM, TRI, and SOR frameworks. Following the model reported by Prasad and De [26] as well as Almusawi and Durugbo [27], this study created a model that replaces the TRI with a TTF model. Generative AI enables users to produce, improve, and condense unstructured data into valuable and meaningful results. The UTAUT model [13] and its two constructs—performance expectancy and effort expectancy—form the basis of the theoretical framework [13]. In the recent past, three new constructs—cost/perceived value, habit, and hedonic motive—have been added to UTAUT2. These constructs affect how people utilize technology, and these effects are modulated by age, gender, and experience. According to Venkatesh et al. [16], hedonic motivation is the enjoyment of using technology, which significantly influences its acceptance and use.

Therefore, the integrated UTAUT, TTF, and SOR theoretical frameworks, which are founded on the three discussed models, are presented in Figure 1 and adopted from Prasad and De [26].

3. Methodology

A questionnaire was designed to gather the data to measure 10 reflective constructs on the basis of the TTF–UTAUT–SOR models. Data were gathered using a seven-point Likert-type scale, where 1 means strong disagreement and 7 indicates strong agreement. Three experts in management, with expertise in the use of generative AI tools, examined the questionnaire content. A pretest with 100 IT industry employees was carried out. Nonprobability sampling (convenience sampling) was used to collect the data from the respondents who fulfilled the study sample characteristics. The data were gathered from several IT industries with diverse cultural backgrounds from Hyderabad to avoid sample bias and to have that sample represent the population. The data were gathered from April to September 2024, the questionnaire was published on Google Forms, and a link was shared through WhatsApp and email with the respondents, the employees of the IT industry who actively use generative AI tools regularly for their routine office tasks. A total of 502 responses were received. However, 32 responses were not considered for analysis because they are incomplete. Therefore, 470 valid responses were considered for the analysis. The details of the study sample are provided in Table 1.

Convenience sampling is an affordable and easy method of gathering information through social media, public spaces, or emails. Convenience samples can help in addressing unsatisfactory customer experiences by preserving anonymity and offering incentives such as gift cards, allowing individuals to share their experiences anonymously and turn negative emotions into positive ones. Convenience sampling allows for quick, personalized feedback on specific topics, enabling quick data collection and tailoring of surveys to provide demographic details for future generalizations, and its saves time and resources. The research process is easier, and the data are immediately available.

The data sources are employees working in the IT industry in Hyderabad and Indian Metro, which hosts more than 500 IT companies.

Figure 1
Theoretical framework

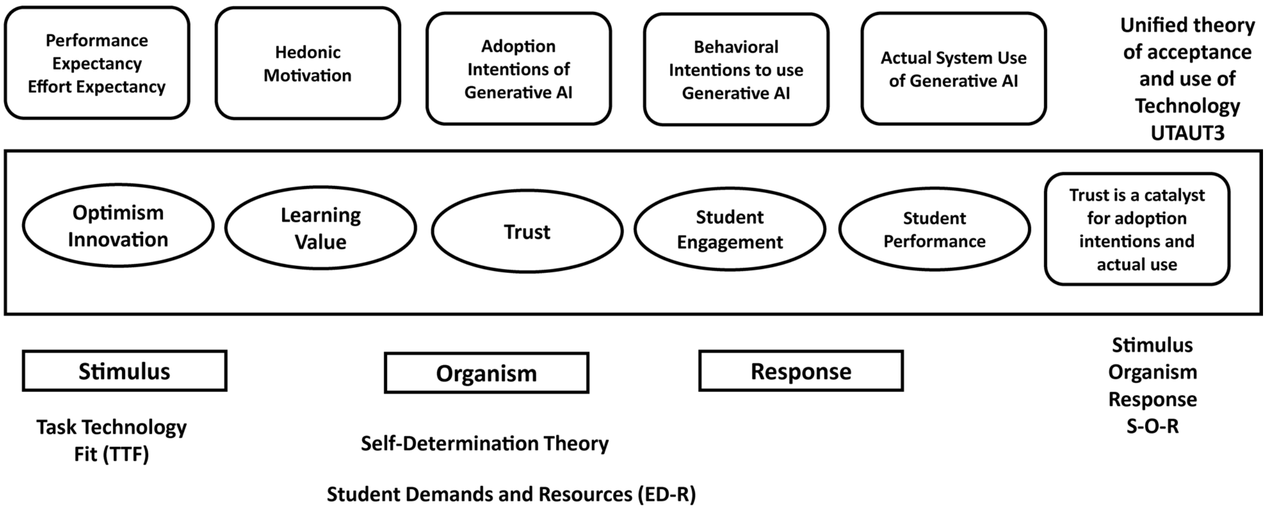

Table 1
Demographic characteristics of the study sample

	Number	Percentage
“Gender”		
“Male”	240	52.0
“Female”	230	48.0
Age (years)		
20–25	175	37.23
26–30	85	18.10
31–35	90	19.14
36–40	82	17.43
>40	38	8.10
Education		
Graduate	160	34.04
Postgraduate	210	44.68
Others	100	21.28
Student/scholars		
Software engineers	140	29.79
Team leader	87	18.51
Technical head	65	13.83
Project manager	85	18.09
Others	93	19.79
Generative AI		
ChatGPT	201	42.77
Quillbot	105	22.34
AI tools for image generation (DALL-E 3, Canva AI, Craiyon, Midjourney, and others)	101	21.49
Text generation tools such as GPT-4, PaLM, and any other AI tools	51	10.85
AI tools, if any other	12	2.55
AI tool use frequency		
Extensively, every day	206	43.83
Twice or thrice a day	75	15.96
Twice a week	110	23.40
Based on the requirement	50	10.64
Sometimes in a week	29	6.17

The email information of the IT industry employees was procured from a third party. The respondents were asked to fill the questionnaire only if they are actively using generative AI in their routine work.

Sampling representativeness was protected by collecting data from employees who are actively using generative AI tools for their routine activities in the IT industry and who are from diverse educational, cultural, and social backgrounds. Furthermore, data were gathered from multiple sources, i.e., several IT companies to avoid bias and to have diversity in the sample.

3.1. Justification of the sample size

For SEM with the maximum likelihood measure and multivariate normal data, a sample size of 200–400 is advised, with a 5:1 ratio, which means that five individuals are needed for each question or statement. According to Cochran [28], 386 is the sample size required for an unknown population. As a result, 470 is a much larger sample size than necessary for validity [29].

3.2. Measures

The literature review aimed to create a model outlining the factors influencing the adoption and utilization of generative AI technologies by IT employees. Nevertheless, few studies on generative AI tools exist, and those that do exist focus on ChatGPT rather than the TTF–UTAUT–SOR framework.

To supplement the available literature, the authors present the theoretical framework and research model in Figure 1 [26] and Figure 2, respectively. The notions of optimism and innovativeness were operationalized on the basis of previous studies [30, 31]. The constructs have three and four items, respectively. Following the UTAUT3 model, four constructs, namely, performance expectancy, effort expectancy, social influence, and hedonic motivation, were modeled [13]. The trust construct has four items and is modeled based on the theories of Glikson and Woolley [32]. This empirical study included four items for the TTF and used items from several research studies [33, 34]. Using the evaluation instruments reported by Venkatesh et al. [16] and Farooq et al. [35], the adoption intention of generative AI tools and actual usage of generative tools were measured. The items, along with their factor loadings, are shown in Table 2.

4. Data Analysis and Results

To unearth the underlying structures in a set of observed variables, EFA was conducted using SPSS 29. Exploratory factor analysis extracted 36 items into 10 constructs based on their shared variance. All factor loadings were >0.5, and the 10 components explained a total variance of 76.0%, which was far greater than the benchmark value of 0.50. The KMO measure of 0.840 indicated that the data were adequate. Because the correlation matrix was not discernible according to Bartlett's test of the sphericity value (<0.001), additional analysis was performed. Table 2 describes the study variables and factor loadings.

The SEM analysis consists of a measurement model to determine correlations between constructs and indicators, and a structural model to investigate anticipated links among them [36]. The third study employs a mediation model to assess the mediating role of trust in the

Figure 2
Authors' research model

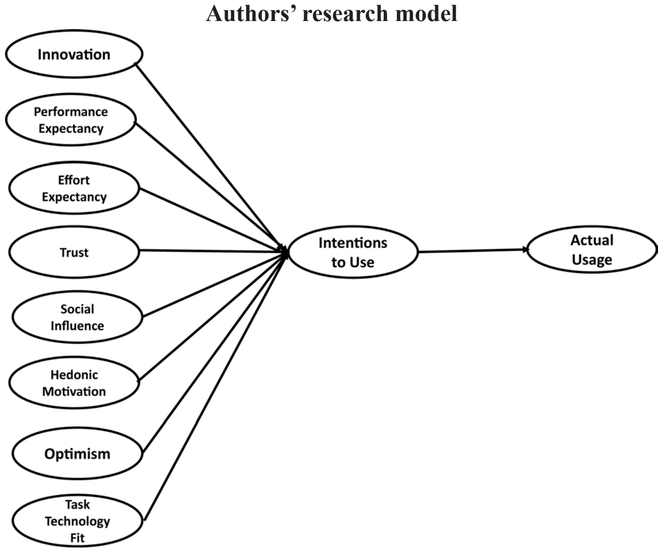

Table 2
Factor loadings of research variables

Item	Factor loading	Chronbach's α	Composite reliability	Average variance extracted
Optimism				
OPT1	0.82	0.881	0.875	0.699
OPT2	0.87			
OPT3	0.82			
Innovativeness				
INVI	0.90	0.934	0.939	0.795
INV2	0.91			
INV3	0.89			
INV4	0.86			
Performance expectancy				
PE1	0.88	0.914	0.914	0.72
PE2	0.81			
PE3	0.88			
PE4	0.84			
Effort expectancy				
EE1	0.85	0.797	0.803	0.517
EE2	0.87			
EE3	0.61			
EE4	0.66			
Trust				
TRU1	0.83	0.908	0.905	0.703
TRU2	0.86			
TRU3	0.87			
TRU4	0.78			
Hedonic motivation				
HM1	0.76	0.857	0.8510.656	
HM2	0.84			
HM3	0.83			
Social influence				
SI1	0.68	0.860	0.813	0.51
SI2	0.77			
SI3	0.72			
SI4	0.72			
Task-technology fit				
TTF1	0.81	0.850	0.842	0.577
TTF2	0.92			
TTF3	0.67			
TTF4	0.61			
Adoption intention				
INTN1	0.79	0.828	0.839	0.763
INTN2	0.88			
INTN3	0.71			

(Continued)

Table 2
(Continued)

Item	Factor loading	Chronbach's α	Composite reliability	Average variance extracted
Actual use				
ACTU1	0.67	0.812	0.844	0.646
ACTU2	0.81			
ACTU3	0.92			

relationship between generative AI adoption intentions and actual use of AI tools.

Assessment of the measurement model: The Cronbach's alpha values exceeding the benchmark of 0.7 indicate construct reliability, and the average factor loadings are above 0.70 for all constructs surpassing the threshold values of 0.5 (Table 2). Discriminant validity was assessed using average variance extracted (AVE), which is above 0.50, establishing discriminant validity. Discriminant validity was also assessed using heterotrait–monotrait ratio analysis (HTMT), and the resultant values were <0.85 for all variables, establishing discriminant validity [37]. Furthermore, the square roots of the constructs were larger than the correlation coefficients, confirming good discriminant validity (Tables 3 and 4).

4.1. Model fit

Confirmatory factor analysis (CFA) was carried out, and the factor loadings were assessed for each variable/item. The 10-factor model "optimism, innovativeness, trust, performance expectancy, effort expectancy, hedonic motivation, social influence, and TTF," the intention to use generative AI tools, and the actual use of generative AI tools fit the data well, as indicated by the following modification indices: CMIN/df = 1.728; CFI, 0.960; NFI, 0.916; IFI, 0.961; TLI, 0.954; SRMR, 0.048; RMSEA, 0.039; and PClose, 1.000, which indicate that all values are within the benchmark ranges [38, 39]. The factor loadings are nonnegative and are >0.5, with average factor loadings for all 10 constructs >0.7, indicating excellent model fit [40, 41]. As the model fit indices are excellent, the structural model was evaluated (Tables 3 and 4).

In the SEM results, the squared multiple correlation coefficient for adoption intention for generative AI tools is 0.12%, and the actual use of generative AI tools is 0.05%, indicating that 12% of the variance is explained by 8 predictor variables, namely, optimism, innovativeness, trust, performance expectancy, effort expectancy, hedonic motivation, social influence, and TTF. Furthermore, adoption intention explains 5% of the variance in the actual use of generative AI tools.

4.2. Common method variance

The common method variance (CMV) may be caused by using self-report questionnaires to collect data from the same individuals [42]. The CMV is a large fraction of the variance explained by a single factor [43]. This study used Harman's single-factor test to assess CMV in the data. All 36 components from the 10 constructs were combined into a single factor after several iterations. The resultant of this factor contributed 23.09% of the overall variance, thus indicating that the study's dataset was not influenced by a common method bias [44].

The CMV arises when using the same method to measure multiple variables in the study (e.g., self-reported questionnaire).

Table 3
Discriminant validity (Fornell and Larcker criterion)

	INNO	PE	Trust	TTF	SI	Optimism	EE	Intention to use	Actual use	Hedonic motivation
INNO	**0.892**									
PE	0.294***	**0.853**								
Trust	0.481***	0.360***	**0.839**							
TTF	0.037	0.004	0.067	**0.760**						
SI	−0.033	−0.031	−0.003	0.346***	**0.722**					
Optimism	0.024	−0.061	0.030	0.163**	0.366***	**0.836**				
EE	0.026	−0.034	0.058	0.442***	0.543***	0.310***	**0.719**			
Intentions to use	−0.011	−0.051	−0.081	0.274***	0.221***	0.196***	0.219***	**0.797**		
Actual use	0.082	−0.001	0.058	0.267***	0.201***	0.174**	0.196***	0.200***	**0.804**	
Hedonic motivation	−0.061	−0.031	0.005	0.237***	0.426***	0.548***	0.350***	0.224***	0.276***	**0.810**

Note: INNO: innovativeness; PE: performance expectancy; EE: effort expectancy; TTF: task–technology fit; SI social influence.

Table 4
Discriminant validity (heterotrait–monotrait ratio analysis)

	INNO	PE	Trust	TTF	SI	Optimism	EE	Intention to use	Actual use	Hedonic motivation
INNO										
PE	0.273									
Trust	0.450	0.335								
TTF	0.027	0.012	0.044							
SI	0.032	0.033	0.005	0.292						
Optimism	0.021	0.052	0.036	0.189	0.308					
EE	0.040	0.002	0.064	0.437	0.466	0.359				
Intentions to use	0.006	0.037	0.056	0.281	0.194	0.189	0.247			
Actual use	0.073	0.010	0.050	0.252	0.183	0.147	0.225	0.206		
Hedonic motivation	0.051	0.034	0.005	0.218	0.356	0.480	0.333	0.208	0.244	

This can lead to inflated or deflated correlations among variables that potentially distort the results, leading to incorrect conclusions regarding the variables. This is because the respondents may answer to questions that they perceive as socially acceptable, which could lead to consistent biases to several questions across the questionnaire. Sometimes the words used in the questions may influence the responses. The Harman's single factor test involves running an exploratory factor analysis on all items in a study to investigate whether a single factor explains a large proportion of the variance, suggesting CMV. It indicates a potential issue with the measurement method rather than the actual constructs being studied. In the present study, this issue is not a concern.

4.3. Testing of hypotheses

This empirical study investigated the impact of optimism, innovativeness, performance expectancy, effort expectancy, trust, hedonic motivation, social influence, and TTF on the adoption intention of generative AI tools and, in turn, the influence of adoption intention on the actual use of generative tools (Table 5).

"H1: performance expectancy has a positive and significant effect on generative AI adoption" was supported ($ß = 0.206$, $t = 5.128$, $p < 0.001$). Performance expectancy is a key element in adopting and using a new technology. Similarly, H2: effort expectancy has a positive and significant effect on generative AI adoption ($ß = 0.303$, $t = 3.675$, $p < 0.001$), and our outcome is inconsistent with the findings of Huy et al. [45], who reported the effects of these two variables to examine their influence on adoption intention and actual use of the generative AI tool ChatGPT. Performance expectancy describes the importance of generative AI and technology, influencing a person to use the latest technology. The independent variable "effort expectancy" is a crucial factor that evaluates the ease of implementing new technologies in tasks.

The third hypothesis H3: hedonic motivation has a positive effect ($ß = 0.106$, $t = 1.496$, $p > 0.05$) on generative AI adoption but has no significant effect on the adoption of generative AI tools. Furthermore, H4: social influence has a positive and significant effect on adoption intentions ($ß = 0.477$, $t = 4.416$, $p < 0.001$). These results are similar to the findings of Ma and Li [46] as well as Ivanov et al. [47], who

Table 5
Results of the direct effect of the hypotheses

Performance	ß	t value	p value	Decision
H1: performance expectancy → generative AI adoption	0.206	5.128	<0.001	Supported
H2: effort expectancy → generative AI adoption	0.303	3.675	<0.001	Supported
H3: hedonic motivation → generative AI adoption	0.106	1.496	>0.05	Not supported
H4: social influence → generative AI adoption	0.477	4.416	<0.004	Supported
H5: TTF → generative AI adoption	0.226	3.548	<0.001	Supported
H6: attitude/intention → generative AI adoption	0.244	4.041	<0.001	Supported
H8: optimism → generative AI adoption	0.357	6.529	<0.001	Supported
H9: innovativeness → generative AI adoption	0.264	4.400	<0.004	Supported

reported that social influence is an important driver of the adoption and use of generative tools in higher educational settings. Social influence is the degree to which users prioritize other beliefs when deciding whether they should utilize the generative AI tools.

Similarly, H5: TTF has a positive and significant effect on adoption intentions for generative AI tools (ß = 0.226, t = 3.548, $p < 0.001$). Vafaei-Zadeh et al. [48] examined the factors influencing AI customer service adoption. With an integrated model of SOR and TTF theory, the adoption of generative AI technology reported that the TTF items trust and curiosity significantly affect the adoption and use of generative AI tools.

Furthermore, H6: attitude/adoption intention toward the usage of generative AI tools and adoption intention positively affecting the actual usage of generative AI tools are statistically significant, and positive results (ß = 0.244, t = 4.041, $p < 0.001$) are supported. Wang and Siau [49] investigated the impact of adoption intentions on the actual use of generative AI tools in the context of the theory of planned behavior in higher education institutes. The authors reported that attitudes and adoption intentions have positive and significant effects on generative AI adoption and actual use. Our results reported similar findings.

H8: optimism affects the adoption intentions of generative AI tools and is statistically significant (ß = 0.357, t = 6.529, $p < 0.001$). H9: innovativeness affects the adoption intentions of generative AI tools and is statistically significant (ß = 0.264, t = 4.400, $p < 0.001$) (Table 5, Figure 3). These results are consistent with the findings of Wang and Siau [49]. Chen [50] and Yang et al. [51] reported the positive

Figure 3
Structural model with relations among the variables

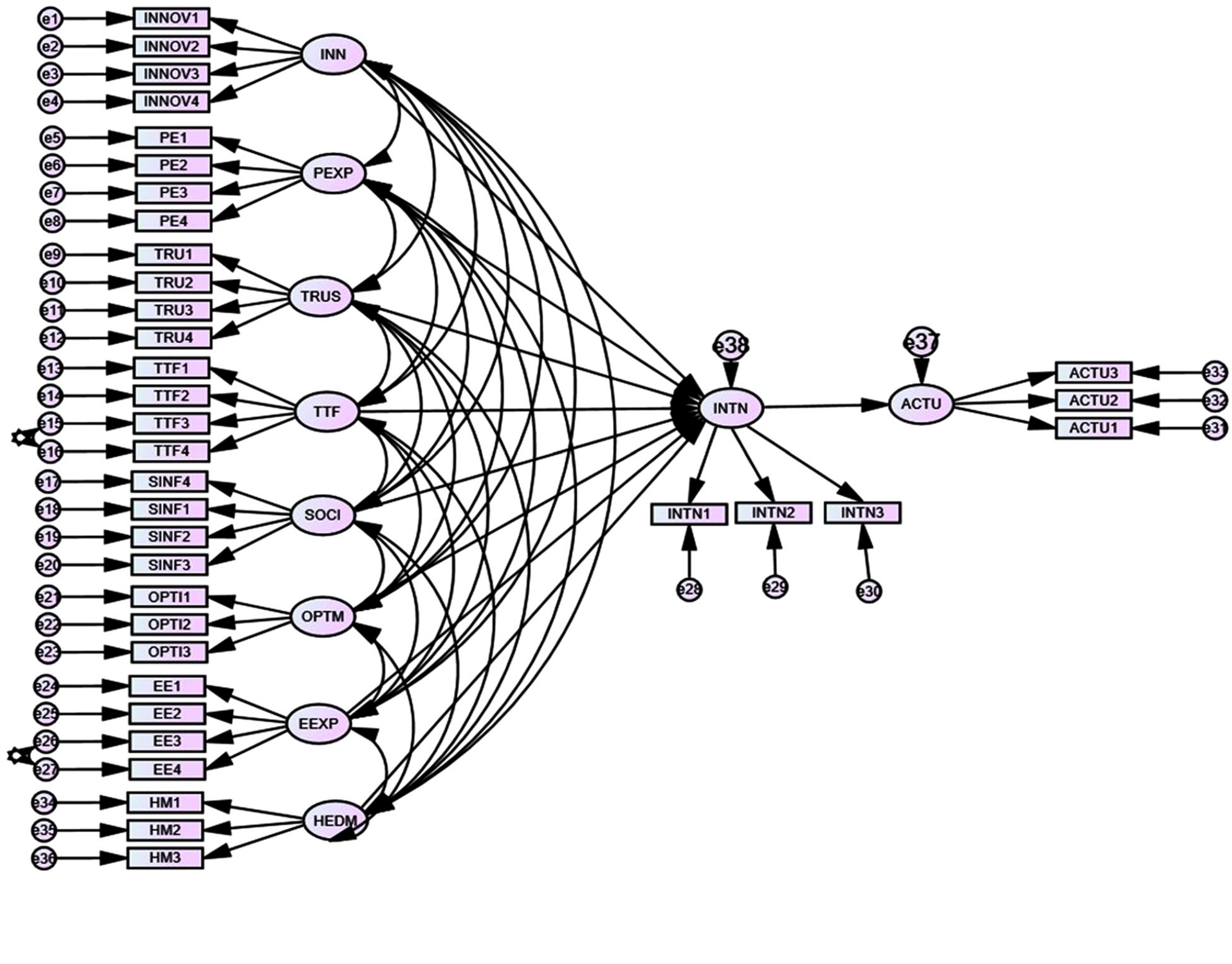

Table 6
Results of the direct effect of the hypotheses

Performance	ß	t value	p value	Decision
Generative AI adoption intentions → trust	0.058	1.511	>0.5	Not supported
Generative AI adoption intentions → actual use	0.266	5.112	***	Supported
Generative AI → trust → actual use	0.236	3.387	***	Supported
	Lower bound	Upper bound	p value	
Indirect effect ß = 0.047	0.024	0.142	<0.005	Full mediation

impact of optimism on the adoption intentions of ChatGPT and other generative AI tools.

4.4. Mediation analysis

The mediator variable is the third variable that affects the relationship between two other variables. The mediator in this study used to go beyond studying a simple relationship between two variables for a fuller picture of the real world. Further, a mediator variable is important in our study because we are dealing with complex correlational or causal relationships between variables. Including these variables can also help you avoid or mitigate several research biases, such as observer bias, survivorship bias, under coverage bias, or omitted variable bias. A mediator is a way in which an independent variable affects a dependent variable. It is part of the causal pathway of an effect, and it tells you how or why an effect takes place. In our study, trust is the mediating variable, which is caused by the independent variable adoption intentions and influences dependent variable actual use.

The mediating effect of trust was tested via a mediation analysis on the nexus between adoption intention toward generative AI and actual use of generative AI. The direct effect between adoption intention and actual use is not statistically significant and positive ($ß = 0.058$, $t = 1.511$, $p > 0.051$), and the indirect effect ($ß = 0.047$, $t = 3.124$, $p < 0.05$) indicates that trust fully mediates the nexus between the adoption intentions for generative AI and the actual use of generative AI (Table 6).

As trust is fully mediating the relationship between adoption intentions and actual use, it fully explains the relationship between the generative AI adoption intentions and actual use. Therefore, managers should foster trust in generative AI tools among employees and promote their use in routine work to enhance employees' performance. Recent studies indicate that trust remains a barrier to consumer adoption of generative AI-enabled products and services.

5. Discussion

The business industry in general and the business sector in particular have paid close attention to the efficacy of generative AI tools. This is due to enhanced performance, quick completion of routine tasks, and increased employee engagement. This empirical study examined the nine factors that influence generative AI tool adoption and actual usage among surveyed IT sector employees in Hyderabad, an Indian Metro. Some studies have focused on the adoption and actual use of generative AI tools but have focused on ChatGPT. We considered other generative AI tools, such as Quillbot, image generation AI tools, Google Gemini, and other AI tools.

This empirical study examined the variables that affect generative AI adoption and, in turn, its effects on actual usage patterns among IT industry employees. The outcome of the study will compliment to the literature on generative AI tools in the context of the IT industry. It measures generative AI adoption using the UTAUT3 scale, TTF, and SOR frameworks. All 10 external variables met the reliability and validity requirements, with 8 out of 10 constructs showing a positive influence on the desire for adoption intentions and actual use. The findings of this investigation offer important new information regarding how generative AI products are actually adopted and used in the IT industry. This study further helps with the use of generative AI tools for the repetitive assignments of employees.

The variables that significantly and favorably influenced the intention to utilize generative AI were performance expectancy, effort expectancy, optimism, innovativeness, trust, social influence, TTF, and the intention toward adoption of generative AI technologies. These findings are in line with those of previous studies [10, 16, 52–54]. The researchers presented how the acceptance and practical application of generative AI tools had a favorable effect on their future use [51]. This study supports all hypotheses, except one: hedonic motivation does not significantly affect the adoption intention of generative AI tools, and the mediator variable fully mediates the relationship between intention and actual use, as reported by Assefa [55] and Yu et al. [56].

IT employees' behavioral intentions are significantly affected by performance expectancy. The outcome is in line with the results presented by Alfalah [57]. Expectancy had a statistically significant and favorable effect on the desire to utilize generative AI tools, which is consistent with earlier studies on mobile devices and online education [16, 35]. Additionally, the outcome showed that PE significantly affects users' intent to use generative AI. This finding is consistent with prior scholarly research that emphasized PE's function in promoting technology adoption [58].

Effort expectancy and generative AI tool usage are significantly correlated, which is consistent with earlier studies that reported that habits are crucial components of technology adoption [59]. The results of past studies on the impact of hedonic motivation on the intention to use and actual usage of educational technology are not supported by the current study [51]. The study revealed no significant correlation between generative AI tool usage and hedonic motivation, but social influence positively influenced users' willingness to use generative AI tools [51]. The outcome emphasizes how crucial learning is in influencing a customer's propensity to utilize generative AI tools. Furthermore, the IT industry is necessary to confirm that users will embrace generative tools when they feel that the benefits outweigh the costs. The results of the present study support those of Yang et al. [51], who reported that social influence is a powerful predictor of employees' intention to use learning-related technologies with respect to the impact of social influence on individuals' intention to actual use. A 2019 study by Dajani and Hegleh provided empirical evidence for the positive association between social influence and actual use.

In predicting the desire to employ generative AI tools, the results demonstrated the importance of perceived TTF. These results are consistent with past research on cloud-based learning tools and e-learning [33]. Furthermore, it was discovered that behavioral intention significantly and directly influences use behavior, suggesting that users' actual usage behavior mirrors their declared goal of using generative AI tools.

6. Conclusions

This empirical study investigated the factors influencing IT employees' adoption intentions of generative AI tools, highlighting their potential for enhancing student engagement and employee performance in higher education. This study targeted IT employees with extensive technology knowledge who frequently utilized generative AI tools for routine tasks and repetitive tasks via convenience sampling. This study incorporated 10 constructs. Eight of the constructs were statistically significant and affected the adoption intentions of generative AI tools. In turn, the adoption intention of generative AI affected the actual use of generative AI tools. The data fit the model well, and all constructs exhibited discriminant and convergent validity. Trust fully mediated the relationship between adoption intentions of generative AI and actual use of generative AI tools. The eight variables of performance expectancy, effort expectancy, optimism, innovativeness, trust, social influence, TTF, and adoption intentions to use generative AI were the key predictors of these three models. The TTF–SOR–UTAUT3 model, when combined with generative AI tools, provides valuable insights for the IT sector and the academic literature. The efficient and timely deployment and adoption of generative AI tools require considering IT employee perceptions because adoption intentions vary among employees.

7. Theoretical and Practical Implications

This empirical study makes a substantial contribution to current theories and research on the adoption and application of generative AI tools for ethical human behavior. This study sheds light on the body of research on generative AI tools and how well liked they are to workers and businesses. By providing technical value in the context of applying generative AI tools, this study broadens the use of the TTF, UTAUT, and SOR model frameworks. Trust has a favorable and significant effect on employee engagement and performance. The established model can be used for student engagement, repetitive assignments, and enhanced social influence in higher education learning setups.

With an emphasis on the use of generative AI tools in educational institutions, this study makes a substantial contribution to the ideas and models already in existence in technology adoption. This study contributes to the knowledge regarding AI chatbots and professional course employees' acceptance of them. By including social influence and TTFs in the context of IT stocks, this study broadens the scope of the UTAUT3 paradigm. The willingness to use generative AI tools is favorably and significantly influenced by both perceived social influence and perceived task completion time. The methodology can be applied to the assessment of many technologies in the fields of education and beyond. The IT industry, HR managers, trainers, and other stakeholders engaged in the development, marketing, and enhancement of generative AI tools can all benefit from the study's useful findings. The conclusions of this study shed light on the variables influencing users' intentions to utilize generative AI tools and provide important insights for increasing its adoption. PE and EE are essential components of the adoption intention of generative AI evaluation, highlighting the necessity of enhancing employees' comprehension of the system. Employees must be given a clear path for improved response accuracy and quicker response times. Helping employees who are unfamiliar with the capabilities of generative AI tools is crucial for ensuring that they can obtain the most out of it. Both educational institutions and individual educators can benefit. Developers can increase the educational value of generative AI by adding customized experiences and optimizing pricing strategies, thereby enhancing its integration into various user contexts.

TTF has a major effect on employees' acceptance of generative AI tools and their adoption and actual use. Prioritizing task effectiveness and improving system intelligence will help developers better grasp student needs and produce accurate results. The inclusion of commonly used tools and technologies with generative AI tools in less tech-savvy pupils may decrease the learning curve in an educational setting. Additionally, this approach enhances usability and accessibility. To maintain employees' critical thinking, problem-solving, and creative skills throughout their work, HR managers must encourage them to use generative AI tools responsibly. This study contributes to the understanding of generative AI tools, which are used in educational settings, and provides observations for policy-makers and administrators to execute these technologies effectively.

Several organizations are experimenting with generative AI to create value on a scale, but a potential challenge may be the people problem. Employees are concerned regarding trusting generative AI tools with personal data, potential misuse, and potential discontinuation of products or services due to concerns regarding information accuracy and social impact. This study indicates that familiarity with the technology aids employees in understanding and embracing it. The increase in generative AI usage suggests a potential decrease in skepticism, with users with more experience showing greater interest and openness. The strategies suggested for organizations to optimize the adoption of generative AI are discussed.

1) Organizations should educate generative AI users on the long-term benefits of these intelligent technologies and their impact on work culture, employee well-being, and sustainable HR practices.
2) Focus on what employees value, i.e., efficiency. Educate employees on the ability to save time and streamline repetitive tasks, which is particularly appealing.
3) Alleviate concerns with transparency: Employees are concerned regarding data privacy, security, and the reliability of generative AI technologies. To foster adoption and trust, employees should be aware of how data are used and should be offered the option to limit data usage or to opt out entirely. Managers can also share information regarding when and how generative AI is incorporated in experiences, providing details through notifications, videos, articles, and other materials.
4) Reassure employees with reliable experiences. With optimists, brands can build confidence in generative AI-based offerings by ensuring that experiences continually improve.
5) Develop trust through human connection: Research suggests that hybrid interaction models, clear communication, personalized experiences, and transparent information regarding generative AI can enhance employee comfort and human-to-human connection.

Furthermore, train employees on the use of generative AI tools. Explain generative AI's fundamental capabilities and applications in the industry. Train employees to apply generative AI tools and techniques to optimize official settings and routine use. Explain ethical considerations, challenges, and best practices in implementing generative AI for routine use. Training programs tailored to the staff that focus on generative AI tool use are essential to build competence and trust. Hands-on sessions with AI dashboards can demystify technology and encourage adoption.

An AI acceptable usage policy (AUP) is a framework for organizations to ethically and responsibly use AI, balancing benefits and risks in the rapidly evolving field. Organizations must establish a policy governing the use of generative AI to prevent data breaches and security compromises, ensuring proper governance over AI-enabled tools. An AI policy should be a document outlining the required and prohibited activities, reflecting the organization's goals, objectives, and culture, and serves as a tool for staff to understand expectations.

The following factors need to be considered before developing an appropriate policy or training programs on the use of generative AI.

Understand generative AI: Familiarize the organization with common generative AI models such as ChatGPT and DALL-E to understand their potential applications, risks, and benefits.

Assess organizational needs: The organization's plan to utilize generative AI for content creation, automation, and data analysis will be crucial in drafting the policy clauses.

Survey the regulatory landscape: Conduct research on legal and regulatory requirements for generative AI in your industry, potentially influencing decisions on technology environment, including the choice between public and private AI platforms.

Conduct risk assessment: Identify potential risks related to generative AI deployment in your organization, including technical issues such as unintended outputs and ethical concerns such as misleading information generation.

Confirm the purpose and scope of the acceptable usage of generative AI: The policy outlines the objective, scope, and boundaries of generative AI, ensuring ethical use, meeting legal standards, and providing user clarity.

Furthermore, check available policies to avoid overlapping. Involve or engage the stakeholders and users and develop more efficient and effective internal and external communication. Establish governance committees to ensure ethical compliance and fairness.

8. Limitations

This study has several limitations: it includes a representative sample of IT sector employees in Hyderabad, a large sample size, and potential inaccuracies due to the self-report questionnaire. These issues can be addressed by future researchers. Future studies should include theoretical frameworks such as TAM, innovation diffusion, service quality, and technology adoption models to comprehend the determinants of generative AI tool adoption. This study utilized convenience sampling to identify generative AI tool users within organizations, laying the groundwork for future research on these relationships across diverse cultural and industry contexts. Researchers are proposing longitudinal studies to assess relationships and gender equality in generative AI, considering moderating variables such as organizational commitment and human resource practices.

The limitations of the study on generative AI use among IT employees include the use of self-report questionnaires and a representative sample issues. Future studies should consider alternative theoretical frameworks, such as the quality of information system services and innovation dispersion, to avoid inaccurate results and the technology adoption model. For more thorough insights, a longitudinal research design is advised because the cross-sectional methodology can miss long-term shifts in employees' views regarding technology use. To increase the study's relevance and consider more factors affecting the adoption of generative AI tools, future research should also consider moderating variables such as demographic profiles, employees' IT proficiency, and technology efficacy. Future research can improve the applicability of generative AI tools and understand the factors driving their adoption by considering these elements.

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Ethical Statement

All subjects provided informed consent before participating in the study. The study was conducted in accordance with the Declaration of Helsinki.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available at https://figshare.com/s/cad95b195de4aa53e43a.

Author Contribution Statement

KDV Prasad: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft. **Shivoham Singh:** Conceptualization, Methodology, Writing – original draft. **Ved Srinivas:** Formal analysis. **Hemant Kothari:** Validation, Resources, Writing – review & editing, Supervision, Project administration. **Ankita Pathak:** Methodology, Investigation, Data curation, Visualization. **Devendra Shrimali:** Investigation, Resources, Writing – review & editing.

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