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AI CHATBOT ADOPTION IN ACADEMIA: TASK FIT, USEFULNESS, AND COLLEGIAL TIES

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ABSTRACT

Aim/Purpose	This mixed-methods study aims to examine factors influencing academicians' intentions to continue using AI-based chatbots by integrating the Task-Technology Fit (TTF) model and social network characteristics.
Background	AI-powered chatbots are gaining popularity across industries, including academia. However, empirical research on academicians' adoption behavior is limited. This study proposes an integrated model incorporating TTF factors and social network characteristics like density, homophily, and connectedness to understand academics' continuance intentions.
Methodology	A qualitative study involving 31 interviews of academics from India examined attitudes and the potential role of social network characteristics like density, homophily, and connectedness in adoption. Results showed positive sentiment towards chatbots and themes on how peer groups accelerate diffusion. In the second phase, a survey of 448 faculty members from prominent Indian universities was conducted to test the proposed research model.
Contribution	The study proposes and validates an integrated model of TTF and social network factors that influence academics' continued usage intentions toward AI chatbots. It highlights the nuanced role of peer networks in shaping adoption.

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Findings	Task and technology characteristics positively affected academics' intentions to continue AI chatbot usage. Among network factors, density showed the strongest effect on TTF and perceived usefulness, while homophily and connectedness had partial effects. The study provides insights into designing appropriate AI tools for the academic context.
Recommendations for Practitioners	AI chatbot designers should focus on aligning features to academics' task needs and preferences. Compatibility with academic work culture is critical. Given peer network influences, training and demonstrations to user groups can enhance adoption. Platforms should have capabilities for collaborative use. Targeted messaging customized to disciplines can resonate better with academic subgroups. Multidisciplinary influencers should be engaged. Concerns like plagiarism risks, privacy, and job impacts should be transparently addressed.
Recommendations for Researchers	More studies are needed across academic subfields to understand nuanced requirements and barriers. Further studies are recommended to investigate differences across disciplines and demographics, relative effects of specific network factors like size, proximity, and frequency of interaction, the role of academic leadership and institutional policies in enabling chatbot adoption, and how AI training biases impact usefulness perceptions and ethical issues.
Impact on Society	Increased productivity in academia through the appropriate and ethical use of AI can enhance quality, access, and equity in education. AI can assist in mundane tasks, freeing academics' time for higher-order objectives like critical thinking development. Responsible AI design and policies considering socio-cultural aspects will benefit sustainable growth. With careful implementation, it can make positive impacts on student engagement, learning support, and research efficiency.
Future Research	Conduct longitudinal studies to examine the long-term impacts of AI chatbot usage in academia. Track usage behaviors over time as familiarity develops. Investigate differences across academic disciplines and roles. Requirements may vary for humanities versus STEM faculty or undergraduate versus graduate students. Assess user trust in AI and how it evolves with repeated usage, and examine trust-building strategies. Develop frameworks to assess pedagogical effectiveness and ethical risks of conversational agents in academic contexts.

Keywords	artificial intelligence, chatbots, network, homophily, TTF

INTRODUCTION

Of the numerous innovations, artificial intelligence has emerged as one of the top technology priorities (Mikalef & Gupta, 2021). It has played a dominant role in dealing with contemporary challenges (Deloitte, 2022). According to Forbes (2023), Artificial General Intelligence (AGI) is a likely successor to Artificial Intelligence (AI), seeking to develop machines that can understand and learn any intellectual task that a human being can. However, due to complexity and the need for more refined data, advanced forms of AI are still in their early stages. Recently, AI has entered almost every field and has seen unprecedented AI software growth. Estimates predict that sales of generative AI will reach $22.6 billion by 2025 (Watts, 2023). It is thus apparent that AI is rapidly transforming the landscape in every industry, and it will continue to be a technological leader over the next few years.

Existing language processing models, trained on large amounts of textual data, have proven successful in research, education, customer service, and content creation. Integrating AI into academia, like any other field, has benefits and concerns. Although AI can revolutionize how we teach, learn, and conduct research in academia, concerns such as the misrecognition of AI-generated texts, privacy issues, and malicious use of AI have also come into the discussion (Dalalah & Dalalah, 2023). Chatbots, for example, have a major impact on various aspects of academia, from teaching and learning to research and administrative tasks. From a research perspective, AI is currently assisting researchers in literature reviews, identifying relevant research studies, and making new findings to advance their fields (Hwang & Chien, 2022).

Recently, Generative Pre-trained Transformers (GPTs) have gained attention as a support tool for conducting and managing research (Burger et al., 2023). A few studies have tried to establish the reliability and validity of generative AI in conducting and processing research outputs (Dwivedi et al., 2023; Tlili et al., 2023). These studies highlight the potential benefits and bottlenecks of using GPTs. Due to the increasing popularity of these platforms, the acceptance of such platforms as ChatGPT is higher than ever before. According to a report published by Pew (Sidoti & Gottfried, 2023), which surveyed teens from the USA, about 19% of teenagers are aware of and have used ChatGPT for academic tasks. The same report states that the percentage of users is higher among older students. Similarly, a qualitative study by Hadi Mogavi et al. (2024) of social media platforms (Twitter, YouTube, and LinkedIn) found noteworthy adoption of ChatGPT in higher education (24.18%), K-12 education (22.09%), and practical skills learning (15.28%).

Attitudes toward technology adoption encompass cognitive processes influenced by positive or negative sentiments toward the technology (Kai-ming Au & Enderwick, 2000). Additionally, strong beliefs regarding the anticipated consequences of technology use play a crucial role in shaping attitudes toward adoption and continuation of use (Karahanna et al., 1999). A substantial body of evidence supports the association between attitude and technology adoption (Rahman, Ming, et al., 2023; Sangeeta & Tandon, 2021; B. Zhang, Ying, et al., 2023). However, limited research exists on the factors that drive the adoption of chatbots among academic professionals (Bojar, 2023). Notably, no study has yet explored the influence of social and peer networks on the adoption of Generative Pre-trained Transformers (GPTs). To address this gap, we propose that the willingness of academics to embrace AI chatbots may be significantly affected by the characteristics of their social networks. Scholars argue that network attributes, such as tie strength and density, play a crucial role in innovating innovative technologies (Cheng, 2017). Previous research demonstrates that social networks substantially influence attitudes toward innovation, subsequently affecting innovation adoption behavior (Talukder & Quazi, 2011). Online social networks are recognized as prominent channels for technology adoption, leveraging effects such as imitation, leadership, lock-in, similarity, recency, and team size (Peng & Mu, 2011). Peer influence further catalyzes network growth when early adopters collaborate to exert influence, though the impact is somewhat diminished within smaller groups (Henkel & Block, 2013).

Exclusively focusing on users' perceptions of technology may not suffice. In line with the Task-Technology Fit (TTF) model, the acceptance of technology by users is more likely when it aligns with the task requirements (Goodhue & Thompson, 1995). The TTF theory elucidates that technology that fulfills users' needs and supports task requirements has a positive impact on performance in the domains of information technology and information systems (Cane & McCarthy, 2009). The TTF model has been extensively employed to examine the adoption of AI in various contexts (e.g., Fan et al., 2020; Lee & Chen, 2022; Pillai & Sivathanu, 2020). However, a review of the literature reveals that the application of the TTF theory in the context of AI adoption in academia is limited (Goodhue & Thompson, 1995; Junglas et al., 2008). Accordingly, despite recognizing technological advancements, we posit that users may choose not to utilize AI technology if they perceive it as incongruent with their tasks or if it fails to enhance work efficiency. Given users' limited understanding and proficiency in utilizing AI chatbots, this knowledge gap can impede the effective adoption of the technology. Therefore, it becomes imperative to empirically examine how AI can align with existing academic and research-related tasks.

The growing utilization of AI-based GPTs among academicians presents an intriguing context for our research. Our study aims to enhance the current body of literature by offering a comprehensive exploration of the combined influence of social network dynamics and task-technology paradigms on user perceptions and adoption intentions within the realm of GPTs. This study is expected to contribute novel insights to the ongoing scholarly discourse concerning the attitudes and perceptions of academics regarding GPTs. To accomplish this, our research consisted of two distinct stages. Initially, we conducted a qualitative inquiry to investigate the general attitudes of academics towards AI-based GPTs. Subsequently, we assessed their opinions regarding the significance of TTF and peer/social networks in relation to the spread, usage, and adoption of GPTs. The second stage of the study involved empirical verification of the proposed conceptual framework.

The subsequent sections of this study are structured as follows. To provide a solid foundation for our research, we commence with a literature review that offers a philosophical justification for our study. Additionally, we present the details of our qualitative inquiry, including the procedures employed and the outcomes obtained, which substantiate our research questions, theoretical model, and formulated hypotheses. Subsequently, we outline the approach, methodologies, and findings of our empirical investigations pertaining to the proposed conceptual framework. Finally, we conclude this article by providing comprehensive insights into our study's theoretical and practical implications.

OVERVIEW OF EXISTING RESEARCH

Several studies have investigated the usage of ChatGPT among academics and students. One study conducted by Jo (2023) examined the factors influencing user behavior of ChatGPT among students and office workers. The study found significant associations between perceived intelligence, knowledge management, and personalization. Another study by Huang et al. (2023) focused on Chinese college students and their use of ChatGPT. The study revealed that these students commonly rely on ChatGPT for information retrieval, coursework, and dissertation writing tasks. Overall, the impact of ChatGPT on learning efficacy was generally positive. In a study conducted by Mohammed et al. (2023), Arab postgraduate students in India reported benefits in academic writing and language competency through the use of ChatGPT. However, some students were not fully utilizing the tool, suggesting there may be room for improvement in its implementation. However, Rahman, Terano, et al. (2023), and Mahama et al. (2023) expressed concerns regarding the use of ChatGPT in academic research and writing. These researchers emphasized potential challenges and called for guidelines to ensure the appropriate use of this technology.

To gain a comprehensive understanding of the impact of AI-based chatbots on academic achievements, it is imperative to investigate the attitudes and preferences of individuals in the academic community when engaging with generative AI systems. Prior studies on the use of chatbots have provided substantial evidence regarding various factors that influence their usage (Dhiman & Jamwal, 2023). Scholars have extensively documented the implementation and ongoing behavior of chatbots in a number of scholarly publications (e.g., Dhiman & Jamwal, 2023; Li et al., 2019; Pillai & Sivathanu, 2020).

Prior models elucidating the diffusion of innovative technologies have predominantly leaned on Rogers' (2002) foundational paradigm, positing that the inherent characteristics of a technology exert a direct influence on its adoption rates. Recent inquiries into the adoption of augmented reality (AR) devices, exemplified by Microsoft HoloLens and Google Glass (Kalantari & Rauschnabel, 2018), have unveiled a nuanced perspective. These investigations underscore multifaceted factors, encompassing considerations of utility, ease of use, and ramifications for self-image shape adoption decisions. Theoretical frameworks rooted in human behavior further contribute to understanding technology adoption, among them the Theory of Planned Behavior (TPB) and the Unified Theory of

Acceptance and Use of Technology (UTAUT). Both these theoretical constructs elucidate factors that play pivotal roles in influencing the adoption of technology, emphasizing the significance of Behavioral Intention (BI) and actual behavior as crucial indicators of acceptance.

In academia, a domain characterized by reliance on knowledge, scholars frequently engage with shared information networks, including Enterprise Social Networks (ESNs) and Social Media Networks (SMNs) such as LinkedIn and Facebook. This interaction extends beyond traditional channels, encompassing word of mouth and direct observation of colleagues and peers. The influence of SMNs on the nature of information dissemination is noteworthy, concurrently reducing interaction costs among users. As the number of adopters within a network grows, the collective benefits of adoption escalate, predominantly driven by the wealth of information contributed by network participants (Bandiera & Rasul, 2006). Therefore, a comprehension of social network properties becomes instrumental in gaining insights into the adoption dynamics of AI chatbots within academic circles.

Based on a thorough review of existing research in the context of chatbot adoption, presented in Table 1, this study outlines how the tasks assigned to academics match the technology to determine the usage intention of AI-based chatbots. It also attempts to increase construct validity by adding social network variables (density, homophily, and connectedness) and examining their role in adoption. It is well known that the role and responsibilities of academics revolve around the activities in higher education institutions, such as teaching, research, question paper setting, answer script evaluation, and student training. The uniqueness of this study lies in the examination of the relationship between Task Technology Fit (TTF) and Social Network Characteristics (SNC) among academicians. The introduction of task-based systems is closely linked to workplace networks, known as social networks.

This study analyzed the characteristics of workplace groups based on three major factors: density, homophily, and connectedness. Previous studies have extensively examined the role of these group characteristics in information flow, knowledge transfer, and feelings of connectedness among academic communities (Ertug et al., 2022; Oddone et al., 2019; Wei et al., 2011). The results of existing studies show significant gaps in the application of AI in this context. This serves as the basis for researchers to develop a model for measuring the adoption of AI-based chatbots by academics.

Table 1. Research involving Chatbots, TTF, and SNC

Authors and year	Sample	Main findings
Ratna et al. (2018)	Hotel front office staff	A high TTF leads to higher use of information systems.
Wan et al. (2020)	University students	TTF influences user satisfaction, which further affects continuance usage intentions.
Kasilingam (2020)	E-commerce users	Trust is one of the most critical factors influencing the intention to use chatbots for mobile shopping.
Lee and Chen (2022)	Mobile banking users	Perceived anthropomorphism enhances users' inclination to adopt mobile banking by increasing TTF and trust levels.
B. Zhang, Zhu, et al. (2023)	Chatbot users	Personalization plays a decisive role in chatbot adoption for tourism-related services.
Dhiman and Jamwal (2023)	Chabot users	TTF has a direct effect on customers' perception of the usefulness of chatbots.
Patil et al. (2022)	Banking professionals	Task characteristics significantly affect TTF. Behavioral intentions to adopt blockchain in banking are influenced by perceived usefulness.

Authors and year	Sample	Main findings
Zhao et al. (2023)	Users of AI-based mobile applications	A higher TTF leads to strong adoption tendencies towards AI-based applications.
Liu et al. (2023)	Prior studies	Instructors' attitudes and technological knowledge play a vital role in the adoption of chatbots in an educational context.
Dinh and Park (2023)	Mobile application-based chatbots service users	Motivation-triggering features in mobile applications influence the adoption of chatbot services.
Network characteristics		
Ertug et al. (2022)	Prior studies	Homophily expedites the flow of information, behavior, products, innovation, practices, and knowledge within groups.
Wei et al. (2011)	Bank employees	Higher network density facilitates the rapid transfer of knowledge.
Widmer et al. (2018)	Secondary data	A high network density brings better support and control to the group.
Rimpelä et al. (2020)	School students	The peer group has a differential impact across behaviors and characteristics.

Research Questions

Based on the discussion above, this study aims to answer the following research questions:

- How does task technology fit the perception and perceived usefulness of AI chatbot platforms among academicians and influence their usage intentions?
- Is there any influence of social network characteristics on perceived task technology fit and perceived usefulness of AI chatbots among academicians?

The present research combined qualitative and quantitative paradigms, adopting a mixed methods approach commonly employed by researchers studying technology adoption and usage (Lim et al., 2022; Liu et al., 2023; Pillai & Sivathanu, 2020; Udeozor et al., 2023). A mixed-method approach delivers high-quality results from a study (Mariani & Baggio, 2020). The reason for adopting this approach is the absence of empirical validation for AI's adoption in academics. The following section outlines the process and outcomes of the qualitative study.

Study 1 - Qualitative Study - Interview Method

A total of 31 structured interviews were systematically conducted to comprehend the perspectives and determinants influencing the behavior of academicians toward the adoption of AI-based chatbots. Each interview, spanning 25 minutes, was administered by three authors, namely VS (11 interviews), AR (13 interviews), and AJ (7 interviews). The interviewers underwent comprehensive training facilitated by a technology expert and a senior faculty member possessing expertise in qualitative research. This training was administered through regular meetings over a four-week period.

To uphold methodological rigor and cultivate a spectrum of perspectives, participants for this study were strategically chosen from a distinguished group of academicians engaged in a national-level workshop focused on the theme of 'higher education policy.' The deliberate selection of participants aimed to ensure diversity by encompassing individuals with various roles within academia and hailing from diverse fields of specialization. An email was communicated to potential participants, elucidating the research objectives, potential outcomes, and the anticipated contribution of the study to the academic discourse. Despite reaching out to 177 individuals, 84 expressed consent, and ultimately, 31 participants were interviewed. It is noteworthy that the constraint posed by budgetary considerations played a pivotal role in limiting the number of conducted interviews. Moreover, Galvin (2015) recommends that a minimum of 20 participants is sufficient for a qualitative study.

Prior to commencing the interview process, participants underwent a reiteration of their role as respondents, and explicit consent was reaffirmed. The interviews were conducted online via Microsoft Teams and Zoom video calls, with the sessions being recorded for reference. Financial constraints dictated a deliberate decision to limit the number of participants, as previously mentioned. To facilitate a more interactive and nuanced exploration of the relevance of the newly added variable, an inductive perspective was adopted by incorporating four open-ended questions focusing on the role of academic work groups in technology adoption. The initial inquiry sought participants' perspectives on the potential utilization of AI-based chatbots in academia. Subsequently, the second question delved into the impact of social networking within workplace groups on the constructive exchange of ideas and thoughts regarding the implementation of AI in academia. The third question aimed to capture insights into the role of interaction among individuals who share similar thoughts and opinions in adopting AI-based chatbots in academia. The fourth question was designed to gauge sentiments concerning the significance of having a larger group of advocates for the use of AI-based chatbots within the workplace.

To ensure the relevance of the added constructs and the development of their respective measures, we conducted a sentiment analysis and extracted pertinent themes as well. We used NVIVO as a tool to analyze academics' sentiments regarding the role of social network characteristics. The results of the sentiment analysis are shown in Figures 1 and 2, indicating academics' positive attitudes toward using AI-based chatbots. The themes extracted from interviews are presented in Table 2. The themes outline the task-technology and network-related paradigms in the context of academic usage of AI chatbots. Hence, it is vital to assess the amalgamated influence of these factors on perceived usefulness and TTF. The insights derived from Study 1 served as the bedrock for the conceptual framework, illustrated later in Figure 3. In Study 2, we endeavored to empirically validate the hypothesized relationships. In the subsequent section, we present the theoretical foundations underpinning the proposed hypotheses.

Figure 1. Academicians' sentiment analysis towards AI-based chatbots

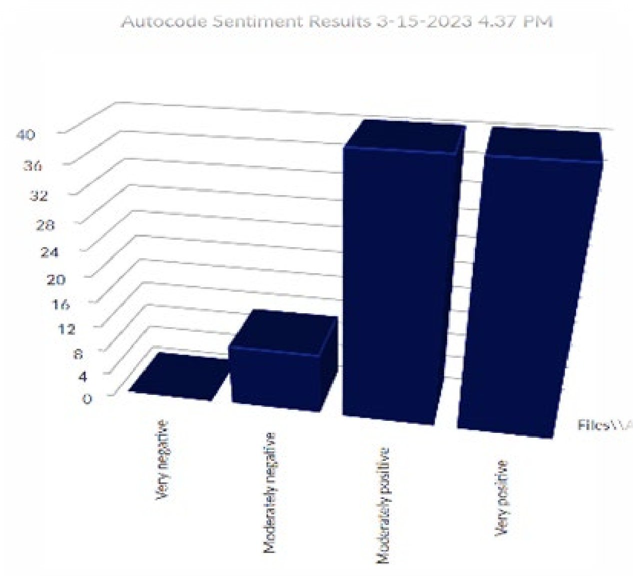

Figure 2. Sentiment analysis bar chart

Table 2. Themes extracted from interviews

Theme	Excerpts
Repetitive tasks	*Chatbots are well-suited for academic activities that involve high volumes of repetitive tasks and standardized processes.*
Task automation	*Chatbots leverage AI to handle high volumes of similar inquiries efficiently.*
Structured tasks	*Structured tasks also make it easier to program the chatbot with comprehensive responses.*
Language capabilities	*Chatbots need to converse fluently in academic terminology.*
System integration	*Important to integrate seamlessly into existing tools like the LMS.*
Data privacy	*Data privacy also has to be robust.*
Personalization	*Personalization is important - chatbots should provide customized guidance using student/faculty profiles and contexts.*
Academic subjects	*The ability to handle academic subject matter is also critical.*
User experience	*The user experience needs to be seamless and intuitive.*
Peer influence	*Connections and information sharing amongst peers play a huge role in the adoption of innovations in higher education.*
Homophily	*Faculty and students with similar interests and backgrounds interact frequently and influence each other.*
Network density	*Dense networks with many connections accelerate diffusion - there are more channels for chatbot information and experiences to be shared.*
Critical mass	*If chatbots find an early foothold in one academic subfield or department, homophily means they will likely spread quickly among peers.*
Reinforcement	*Tight-knit academic communities will reinforce adoption.*
Bridging ties	*Key faculty who link across disciplines due to joint appointments or research can cross-spread innovations like chatbots across the university.*
Shared interests	*The use of chatbots will likely spread quickly amongst peers with shared interests.*
Information diffusion	*Large networks with many connections accelerate diffusion.*
Tight-knit communities	*Tight-knit academic communities will reinforce adoption.*

CONCEPTUAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

TASK TECHNOLOGY FIT MODEL

The Task Technology Fit (TTF) theory, first proposed by Goodhue and Thompson (1995), refers to the extent to which a specific technology aligns with the needs and demands of a particular task or activity. It examines the degree to which a specific technology meets the demands presented by a given task or activity. TTF emphasizes finding an optimal alignment between technology, the user's needs and abilities, and the requirements of the task. Successful utilization of technology hinges on how well it fulfills the user's needs and expectations (Rai & Selnes, 2019). Previous research has employed TTF to evaluate technology effectiveness across diverse contexts, including e-commerce, banking, healthcare, and education (Alyoussef, 2023; Lin et al., 2022; Spies et al., 2020; Vanduhe et al., 2020).

The TTF framework underscores understanding a task's demands and stipulations before selecting a well-suited technology to address those needs (Howard & Rose, 2019). In academic settings, researchers have applied TTF to assess satisfaction and acceptance of MOOCs, social media in higher education, and student digital library use (Al-Rahmi et al., 2022; Alturki & Aldraiweesh, 2023; Alyoussef, 2021; Omotayo & Haliru, 2020). Regarding AI chatbots, task characteristics likely influence TTF. TTF models also encapsulate technology attributes and their impact on task qualities; specifically, technology characteristics encompass functionality, usability, reliability, and other capabilities (Fu et al., 2019). Task, technology, and user characteristics significantly influence TTF, which in turn positively impacts perceived usefulness and ease of use, leading to users' intention to adopt (Daradkeh, 2019; Nhi & Lam, 2020). Therefore, grounded in TTF theory, the authors employed this approach to comprehensively examine AI-based chatbot acceptance in academics. Evaluating AI chatbots' role within the task environment remains necessary. Based on these arguments, the authors propose that:

H1. Task characteristics positively affect academicians' TTF with AI chatbots.

H2. Technology characteristics positively affect academicians' TTF with AI chatbots.

H3. TTF positively affects academicians' perceived usefulness of AI chatbots.

H4. TTF affects academicians' intentions to use AI chatbots.

SOCIAL NETWORK CHARACTERISTICS

Density

Density measures the extent to which members of a network are connected to others. A high-density network has many connections among its members, while a low-density network has relatively few connections (Dasaratha & He, 2021). Density plays an important role in determining the flow of information in a network. A network with multiple members can transfer information effectively because there are direct paths between members. A network with multiple members also allows individuals to collaborate, co-create, and innovate (Valeri & Baggio, 2021)

In addition, dense networks aim to develop social capital through multiple relationships. A common characteristic of networks with multiple members is that they are more likely to know and trust each other and, therefore, more likely to collaborate and share resources within their network (Widmer et al., 2018). Social network density plays a significant role in influencing TTF across various contexts. Dense networks are linked to enhanced task performance and technology efficacy, with the structure of these networks being crucial for optimizing team confidence and performance outcomes.

The interplay between team composition and network structure is also a critical factor in determining the success of a team's performance (Tröster et al., 2014; H.-H. Zhang et al., 2020). Hence, the density of a social network is an important characteristic that can have a significant impact on the adoption of AI in academics. As Skaalsveen et al. (2020) point out, social networks play an important role in the implementation of working methods. Therefore, the researchers assume that the density of social groups plays an important role in ensuring that the technology used is appropriate and effective for the tasks to be performed. It also has an impact on the perceived usefulness of AI chatbots. Based on the theoretical understanding, the study aims to propose the following two hypotheses:

H5a. Social networks' density positively affects academicians' TTF with AI chatbots.

H5b. Social networks' density positively affects academicians' PU with AI chatbots.

Homophily

Homophily refers to the tendency of people to associate with others who are similar to them in certain characteristics. Cultural similarities and differences form the basis for both cohesion and exclusion, as demonstrated by the phenomenon of homophily (Mark, 2003). People tend to form connections with those who are like them in some way rather than with those who are different (Campigotto et al., 2022). Homophily is an important social network characteristic that significantly influences the formation and dynamics of social networks (Smirnov & Thurner, 2016). Research by Ertug et al. (2022) found that homophily accelerates the transmission of information and influences behavior. Studies have also shown that academics are more likely to form associations and bonds with others who are similar to them in terms of their academic background and research interests (Stephens & Cummings, 2021). Therefore, we hypothesize that a close association of individuals in academic workgroups would influence the needs and requirements of the task and, thus, the perceived usefulness of AI chatbots. This leads to the following hypotheses:

H6a. Social networks' homophily positively affects academicians' TTF with AI chatbots.

H6b. Social networks' homophily positively affects academicians' PU with AI chatbots.

Connectedness

Connectedness is an important feature of social networks because it promotes cohesion among group members. Establishing social connections is considered crucial in fostering various facets of psychological wellbeing (Mauss et al., 2011). Connectedness is critical for maintaining collaboration in the workplace (Fapohunda, 2013). Therefore, in the context of formal work groups, it refers to the extent to which individuals in a network are associated with each other. A network with a high degree of connectedness has many direct and indirect connections among its members (Valeri & Baggio, 2021). Connectedness is considered an essential feature of social networks in academia, as it refers to the degree of connection between individuals within a given social system (Rimpelä et al., 2020). In academia, connectedness manifests itself in various ways, including partnerships between faculty members and researchers, co-publishing papers, participating in academic conferences and events, and sharing knowledge and resources across platforms (de Jong et al., 2022). Connectedness in academic social networks involves the establishment of communities of practice where individuals with shared interests or expertise engage in continuous communication and collaboration. These academic communities provide valuable support and resources for individuals pursuing their research goals and can foster a sense of belonging and identity within the academic community (Oddone et al., 2019). Based on theoretical understanding, it is hypothesized that the level of connectedness within academic communities influences the appropriateness of TTF and may play a critical role in determining the perceived usefulness of AI-based chatbots. Therefore, the following hypotheses are tested:

H7a. Social networks' connectedness positively affects academicians' TTF with AI chatbots.

H7b. Social networks' connectedness positively affects academicians' PU with AI chatbots.

PERCEIVED USEFULNESS

Perceived usefulness (PU) refers to the extent to which a user believes that a technology will assist them in performing their job or task more effectively. If users perceive a technology as useful, they are more likely to adopt and use it. Several factors affect the perception of usefulness, such as the user's prior experience with similar technologies, ease of use, and the quality of the technology's performance (Chocarro et al., 2023). It is a subjective evaluation of the usefulness of a technology based on an individual's expectations, attitudes, and experiences (Mohr & Kühl, 2021). PU is relevant in various contexts in technology adoption (Adu-Gyamfi et al., 2022; Astuti, 2023; Singh et al., 2022; Tavitiyaman et al., 2022).

More recently, research revealed the role of PU as an imperative factor in determining chatbot adoption (Dhiman & Jamwal, 2023; Pillai & Sivathanu, 2020). In the context of academic use of AI-based chatbots, potential users are more likely to adopt the chatbots if they believe that it will be useful to them and they see potential benefits in academics. Thus, it makes sense for developers to consider the perceived usefulness of end users in designing new technologies and ensure that the potential users perceive the technology as useful. Based on the theoretical underpinnings, we propose:

H8. Academicians' PU towards AI-based chatbots positively influences their ITU.

Figure 3 presents the conceptual framework.

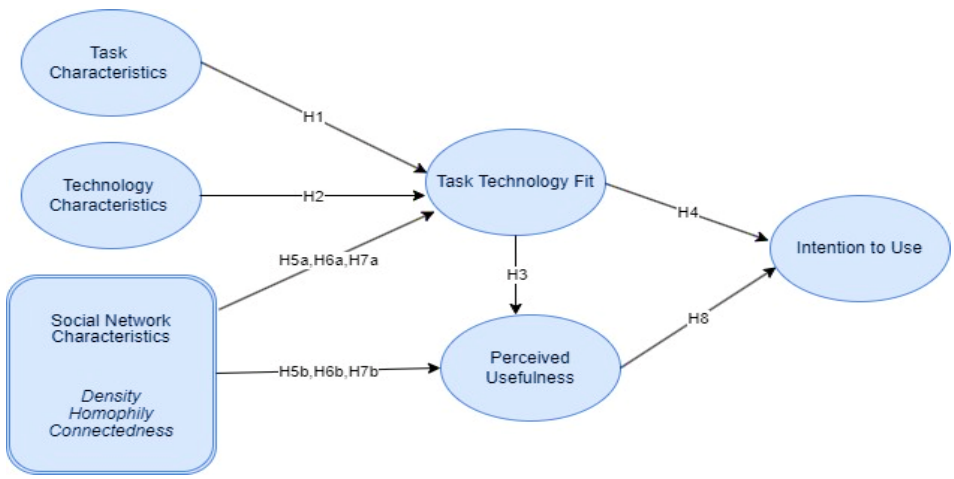

Figure 3. Research framework

STUDY 2 - QUANTITATIVE METHOD - SURVEY

Study 2 used a quantitative approach to empirically validate the Technology Task Fit (TTF) and the Technology Continuance model, as well as to examine social network characteristics. After confirming a positive sentiment score towards the role of social network characteristics in the continued usage of chatbots, this research employed a quantitative method to test additional constructs in conjunction with the variables of TTF and technology continuance theory. Quantitative data analysis was employed as this approach has been extensively used in previous studies related to the adoption of technologies (Dhiman & Jamwal, 2023; Dhir et al., 2021). To assess behavior, this study modified the existing scales to create the research instrument. Current research used validated scales to assess task and technology characteristics and to examine TTF, as supported by previous research (Alyoussef, 2023; Dağhan & Akkoyunlu, 2016; Dishaw & Strong, 1999; Kim & Song, 2022; Rzepka et al., 2022).

SAMPLING

Data for the study was collected from faculty members employed at Indian universities. We used the National Institutional Ranking Framework (NIRF) for the year 2022 as the basis for selecting the universities (National Institutional Ranking Framework, 2022). The NIRF framework is a well-established metric that ranks higher education institutions in India.

Following the suggestions in scholarly studies (Babbie, 2016; Etikan & Babtope, 2019), we used the systematic sampling method. Therefore, our final sample consisted of every 10th university (starting from the 3rd) from the listed universities (population). The sampling process stopped at the 93rd university as NIRF ranks only 100 higher education institutions (HEIs). The study established contact with the teaching faculty members from the sampled university through email. For data collection, we adopted the online survey method to maintain the anonymity of the respondents. Online surveys offer openness, flexibility, a wide scope of research questions, and the ability to reduce bias. Based on the sampling method discussed above, we contacted 712 faculty members. The final number of accurate responses was 448, resulting in an aggregated response rate of 62.9%.

Questionnaire

The first section of the questionnaire was designed to record the demographic details of the respondents. The second section comprised questions that measured various aspects related to TTF, social network characteristics, perceived usefulness, and usage intentions. The measures were adopted from previously validated scales (e.g., Alyoussef, 2023; Dağhan & Akkoyunlu, 2016; Dishaw & Strong, 1999; Kim & Song, 2022; Rzepka et al., 2022).

Reliability and validity measurement

The research utilized Structural Equation Modeling to assess the reliability and validity of latent variables, and the hypothesized relationships were evaluated in the structural model, presented in Table 6. In order to test the existing theory and due to the larger sample size, the researchers employed the Covariance-Based Structural Equation Modeling technique (CB-SEM) as recommended by Hair et al. (2011).

The study used factor analysis with varimax rotation to categorize the constructs and measure the internal consistency of the construct Cronbach's alpha. We established convergent validity by ensuring that the standardized loadings for reflective indicators were above 0.70 and by calculating the AVE values, which were found to be within the permissible range (0.70), confirming the internal consistency of the constructs (Table 3).

Table 3. Item loadings and factor validity

Factors	Items	Λ >0.7	CR >0.7	AVE >0.5
Task characteristics	TS_1: AI chatbots help me in performing complex research and academic tasks.	0.770	0.895	0.683
	TS_2: I must perform a variety of tasks that make use of AI chatbots	0.917		
	TS_3: AI chatbots are useful in routine academic and research tasks.	0.883		
	TS_4: AI chatbots are useful for time-bound tasks, which are very important to me.	0.719		
Technology characteristics	TT_1: AI chatbots can be used anywhere and anytime using online platforms.	0.920	0.924	0.753
	TT_2: AI chatbots provide real-time feedback to my prompts.	0.844		
	TT_3: AI chatbots are secure to use.	0.900		
	TT_4: AI chatbots provide me with a choice to interact using audio, video, and text.	0.802		

Factors	Items	Λ >0.7	CR >0.7	AVE >0.5
Social network characteristics *Density*	DEN_1: More academicians in my networks are using AI Chatbots for academic tasks.	0.796	0.865	0.682
	DEN_2: Academicians who are using AI Chatbots are pushing it among their networks.	0.912		
	DEN_3: The Information about AI Chatbots has spread widely and diffused fast.	0.762		
Homophily	HOM_1: My peers perform similar tasks using AI Chatbots.	0.910	0.897	0.744
	HOM_2: Academic researchers are using AI Chatbots widely.	0.866		
	HOM_3: The performance of my peers has increased while using AI Chatbots.	0.809		
Connectedness	CON_1: Peers in my network support me in performing academic research.	0.759	0.901	0.695
	CON_2: Peers add value to my overall performance in many tasks.	0.811		
	CON_3: Social networks appraise my skills and perception of new technology.	0.901		
	CON_4: I have a high sense of togetherness with my peers.	0.857		
Task technology fit	TTF_1: AI Chatbots match my teaching and research interests.	0.739	0.908	0.712
	TTF_2: My organizational goals and needs can be met by using AI Chatbots.	0.867		
	TTF_3: I would feel more empowered using AI Chatbots.	0.926		
	TTF_4: AI Chatbots are appropriate for and tailored to collaborative academic work.	0.832		
Perceived usefulness	PU_1: AI Chatbots help me to enhance my performance in academics.	0.783	0.893	0.676
	PU_2: I find the AI Chatbots very useful in my day-to-day work.	0.898		
	PU_3: AI Chatbots boost my efficiency in accomplishing the tasks.	0.804		
	PU_4: I appreciate the utility of AI chatbots in my work.	0.799		
Intention to use	ITU_1: I aim to use AI Chatbots in the future.	0.919	0.912	0.723
	ITU_2: I find AI chatbots extremely helpful in my daily tasks.	0.745		
	ITU_3: I predict that I will use AI Chatbots on a regular basis	0.814		
	ITU_4: I would feel more empowered using AI Chatbots.	0.911		

Notes: CR = Composite Reliability, AVE = Average Variance Extracted

Discriminant validity was established by comparing the square root of Average Variance Extracted (AVE) values with inter-construct correlations (Table 4). Additionally, the Variance Inflation Factor (VIF) was assessed to prevent issues related to multicollinearity. Overall, the results indicate that the measurement model utilized in the study is valid and reliable. In order to determine the reliability and validity of constructs, this research utilized the recommendations of scholarly studies (Ab Hamid et al., 2017; Fornell & Larcker, 1981; Hair et al., 2011; Nunnally & Bernstein, 1994; Podsakoff et al., 2012). Researchers conducted a single-factor Harman test to check for common method bias in the research. The measurement model was found to be free of common method bias, as Harman's single factor test returned a satisfactory value of 31.03%, which is below the threshold limit of 50%. The results of the test revealed that 27.11% of the variance was explained by a single factor. This confirms the absence of common method bias in the research, as suggested by Podsakoff et al. (2012).

Table 4. Discriminant validity

	TS	TT	DEN	HOM	CON	TTF	PU	ITU
TS	**0.826**							
TT	0.261	**0.867**						
DEN	0.330	0.233	**0.825**					
HOM	0.107	0.417	0.274	**0.862**				
CON	0.212	0.388	0.311	0.121	**0.833**			
TTF	0.221	0.129	0.210	0.320	0.252	**0.843**		
PU	0.208	0.253	0.198	0.212	0.219	0.107	**0.822**	
ITU	0.417	0.412	0.297	0.175	0.373	0.401	0.124	**0.850**

Note: TS = Task Characteristics; TT = Technology Characteristics; DEN = Density; HOM = Homophily; CON = Connectedness; TTF = Task Technology Fit; PU = Perceived Usefulness; ITU = Intention to Use. Diagonal values (in bold) represent the square root of AVE for each construct.

RESULTS OF PATH ANALYSIS

The present study used AMOS to analyze data and examine the measurement and structural models. The confirmatory factor analysis (CFA) statistics of the measurement model are shown in Table 5, and the results indicate that the measurement model has a good fit, with a $\chi 2/\mathrm{df}$ of 2.06, CFI of 0.912, GFI of 0.909, NFI of 0.918, and RMSEA of 0.068. No item was removed from the list as the overall fit statistics of the measurement model were according to the criteria established by (Fornell & Larcker, 1981). The structural model was then analyzed, and the results showed that it had an excellent model fit, with a $\chi 2/\mathrm{df}$ of 2.02, CFI of 0.934, GFI of 0.926, NFI of 0.933, and RMSEA of 0.042. As can be seen in Table 5, the study found that the measurement and structural models had excellent model fit, and all of the indices met the established criteria according to Bagozzi and Yi (1988) and Malhotra et al. (2017).

Table 5. Model fit statistics

Model	χ^2/df	CFI	GFI	NFI	RMSEA
Standard values (Cangur & Ercan, 2015; Malhotra et al., 2017)	<3	>0.90	>0.90	>0.90	<0.08
Measurement Model	2.06	0.912	0.909	0.918	0.068
Structural model	2.02	0.934	0.926	0.933	0.042

Table 6. Hypotheses test results

Hypotheses	Path	Standardized coefficient (β)	Results
H1	TS →TTF	0.222**	Supported
H2	TT→ TTF	0.191**	Supported
H3	TTF→ PU	0.381***	Supported
H4	TTF→ ITU	0.430***	Supported
H5a	DEN → TTF	0.210**	Supported
H5b	DEN → PU	0.282***	Supported
H6a	HOM→ TTF	0.136**	Supported
H6b	HOM→ PU	0.004	Not Supported
H7a	CON → TTF	0.013	Not Supported
H7b	CON → PU	0.159***	Supported
H8	PU→ ITU	0.322***	Supported

*Note: ***p< 0.01; ** p< 0.05*

The present study utilized the TTF model and TC theory to investigate the usage intentions linked with the adoption of Conversational Chatbots in academics. The factors examined in the study included Task Factors (TS), Technology Factors (TT), Task Technology Fit (TTF), Satisfaction (SAT), Social Network Characteristics including Density (DEN), Homophily (HOM), Connectedness (CON), and Satisfaction (SAT). The study further explored factors of Perceived Usefulness (PU). Analysis revealed that out of eleven hypotheses, all proposed hypotheses were accepted at $p<0.05$.

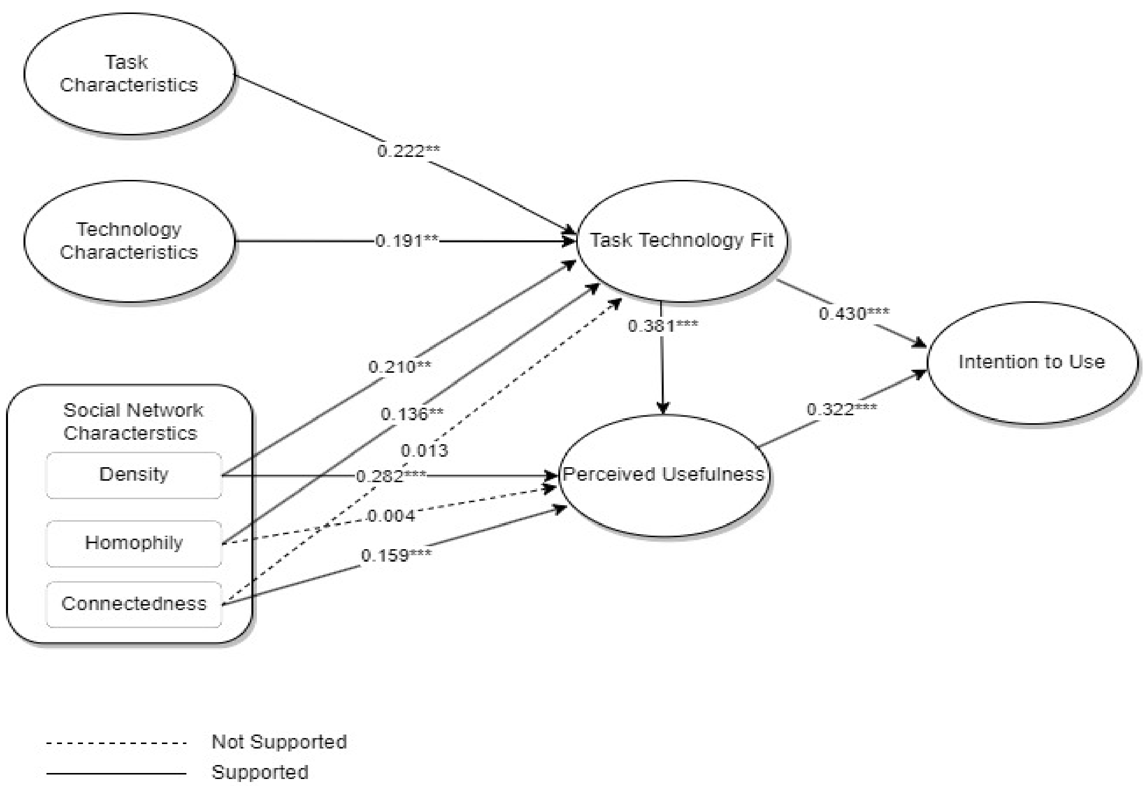

Figure 4. Hypotheses test results

DISCUSSION

In our study, the task characteristics encompass various abstract indicators such as task complexity, variety, routineness, urgency, and task significance. The results indicate that task characteristics, as a construct, have a significant direct effect on TTF. This suggests that higher TTF is promulgated by task characteristics in the context of AI chatbot usage among academicians. The results support the findings of earlier studies, emphasizing that academicians adopt technologies based on their features and alignment with the task environment (Afrilyasanti & Basthomi, 2022; Fu et al., 2019; Ratna et al., 2018). By using AI chatbots, academicians can assist themselves in executing tasks such as developing evaluation schemes, language editing, language corrections, etc., without having to refer to study materials.

The technological characteristics for our study were selected with consideration for the novelty of the technology and its potential application among academics. Measures such as technological accuracy, flexibility, compatibility, processing speed, and ease of access were used. Our results demonstrate that technological characteristics also have a significant influence on TTF. It is well known that ChatGPT, a recent phenomenon in AI-based chatbot systems, provides good answers to queries but also suffers from inaccuracies and is prone to generating false results (Mollick, 2022). This is largely because GPT models lack contextual comprehension abilities, as well as the ability to process common sense and logical reasoning (Lund & Wang, 2023). Another issue with such tools is their compatibility with academic tasks. The prominent underlying reasons are the potential bias within the training data and the potential breach of intellectual property rights.

Additionally, our findings suggest that when academics consider using chatbots, it is important to ensure that their expectations regarding the usefulness of the technology are aligned with other factors that contribute to adoption. This can be achieved through an effective and clear understanding of what the system can or cannot do and effectively communicating it to the users. Furthermore, the study highlights the importance of perceived usefulness in determining the intentions of AI-based chatbots. Therefore, we confirm that academics expect an improved user experience that is user-friendly, intuitive, and meets their needs. These findings corroborate the previous results of scholarly research (Wang et al., 2021; Zhou et al., 2010).

This study incorporated social network characteristics through qualitative validation using sentiment analysis. The analysis revealed interesting results pertaining to the association of social network characteristics. Specifically, the density of social networks (DEN) was found to be significantly associated with TTF. This suggests that group density plays a significant role in the academic task environment, which refers to the physical and social conditions in which academic tasks take place. This includes developing an in-depth understanding of technology through group demonstrations. Furthermore, it also reveals the role played by group members in coordinating, communicating, and motivating the use of technology.

The density of groups appears to influence the perceived usefulness of technology. This is because densely connected groups are likely to have a high degree of interaction and communication among members. These interactions lead to a strong sense of shared purpose and motivation to utilize technology in order to achieve common objectives. Additionally, in a dense group, there is likely to be a higher level of social pressure to conform to the group's norms and values, which may include the use of AI. Therefore, the density of groups can influence the perceived usefulness by affecting the level of interaction and communication among members, as well as the social pressures to adopt AI in academics. Study results corroborate research on the role of groups in adoption and their influence on opinions (Jacox et al., 2022; Sarker et al., 2005).

The positive effect of homophily on TTF implies that a strong preference for conversational AI in academia relies on a shared understanding of the task requirements and the belief that AI is best suited for academic tasks. Interestingly, our study found no link between groups' homophily and perceived usefulness. This leads to the conclusion that academicians find value in adopting conversational AI due to their social group and the challenges they face in their immediate work environment. However, on a personal level, academicians find the adoption of AI in academics to be non-useful. This may be due to the concerns associated with job security, automation, and plagiarism.

Present research further explored the role of group network connectedness in establishing TTF. Surprisingly, our study found no cause-effect relationship between these constructs, inferring that academicians are not inclined towards AI tools just because others are using or professing about them. This may be due to a personal commitment to honesty, integrity, and intellectual superiority. On the other hand, the study found that group connectedness influenced the perceived usefulness of conversational AI. This is likely because adoption is influenced by the nature of the tasks and goals of the group in order to address critical issues (Abrahams, 2010).

Homophily-driven diffusion processes are governed by the distributions of characteristics (Aral et al., 2009), which explains the early contagion effect. This simply explicates the adoption of innovations among early adopters. In the context of AI chatbots' adoption and use, our study highlights that similarity of task characteristics among the academic peers is likely driving the adoption and use (H6a). However, the perceived usefulness of technology ignores the social consequences of using it. However, perceived usefulness may not be affected by shared homophilous characteristics among academic peers, as it disregards the social consequences of technology use. This justifies the rejection of hypothesis (H6b) proposing a significant influence of homophily on the perceived usefulness of AI-based chatbots.

Similarly, our hypothesis that peer network connectedness influences TTF (H7a) does not find any statistical ground for acceptance. Network connectedness signifies the cohesiveness and integration of a network. In cohesive networks, individuals are influential because they are highly connected to one another, therefore influencing the perceived usefulness of members within the network. Previous research shows that the influence of peers is restricted to behavioral changes (both positive and negative) due to the normative expectations of their network members. We argue that the AI chatbot application among academicians is a novel use case. As the use and awareness increase, there may be a substantial influence on how academicians use AI-based chatbots because of peer network influence.

IMPLICATIONS

This study explores how the combination of TTF and group characteristics influences the continued usage of AI-based technologies in academia. The group attributes are represented by density, homophily, and connectedness, which focus on the role of group determinants, including cohesion and sharing of beliefs and values, in shaping intentions. The TTF is based on the TTF model, which assesses the factors based on workplace dynamics. The study contributes to the existing literature by developing an adoption model for conversational AI. The findings indicate that the connectedness of academic groups is significantly associated with the perceived usefulness and TTF, while density and homophily partially affect TTF and PU.

This study sheds light on the extent to which academics' intentions to continue their work are influenced by their work environment. This can help technology development firms understand the impact of the work environment on the adoption of such technologies. This study can also assist in understanding the impact of work culture on the development of futuristic products, aiming to generate more culturally sensitive responses. Furthermore, the study highlights the significance of academic social groups and their priorities and concerns in the adoption of new technology. Different work groups may have varying concerns, which should be considered when designing AI-based products and marketing strategies.

Implications for Practice

AI chatbot developers should ensure alignment with academic tasks and preferences through user-centered design, for example, features like accuracy, language capabilities, personalization, and plagiarism checks. Training programs and peer demonstrations can effectively promote adoption among academic subgroups. Platforms should integrate collaborative features. Targeted promotional messaging tailored to disciplines and roles would better resonate with faculty and student users. Transparent communication about risks like plagiarism, privacy concerns, and potential job impacts can build trust and address uncertainties. Institutions could provide policy support and incentives to drive adoption, for example, credits for integrating chatbots in teaching or research. Customization for individual teaching styles and research areas can improve user experience. Social cues like praise can enhance engagement. Leaders and administrators should encourage experimentation with academic chatbots to uncover use cases. Multidisciplinary influencers can spread adoption. A cost-benefit analysis by institutions would identify financial viability and returns on chatbot investments to support scale-up decisions. Evaluating chatbots' pedagogical effectiveness and ethical implications is vital for formal integration into academic programs.

Theoretical Implications

The study supports TTF theory by showing that alignment between task characteristics and technology characteristics leads to a greater perception of TTF and intention to use AI chatbots among academicians. This validates the core premise of TTF theory in the context of conversational AI adoption. The study highlights the role of social networks and peer influence in technology diffusion. It shows that network density and homophily accelerate adoption by increasing TTF and perceived usefulness. This extends TTF theory by incorporating social dimensions. The study contributes to technology acceptance theories like TAM and UTAUT by empirically testing perceived usefulness as a driver of adoption intentions for AI chatbots. The results confirm the explanatory power of perceived usefulness. The findings related to homophily's lack of impact on perceived usefulness contribute to the diffusion of innovations theory. It shows that while homophily accelerates contagion, personal evaluations of innovations are more complex. The study develops and validates scales to measure adoption drivers of conversational AI systems, contributing new measurement instruments to the field. By focusing specifically on academic chatbot adoption, the study addresses a major gap in existing technology adoption literature, which lacks application domains. The findings provide concrete evidence regarding factors that influence academicians' acceptance of AI systems. This can inform theories related to AI adoption and use across workplace contexts.

Conclusion, Limitations, and Future Directions

This study proposed and empirically tested an integrated model of TTF and social network factors influencing academics' continued usage intentions toward AI-based chatbots. The results showed that task and technology characteristics positively affected academics' perception of TTF with chatbots, validating the core premises of TTF theory. Among the social network variables, density had the strongest effect on TTF and perceived usefulness, indicating its pivotal role in diffusion. Homophily and connectedness exhibited partial effects on TTF and PU. Overall, the study makes significant theoretical and practical contributions. It extends TTF theory by incorporating social dimensions like network density and homophily. It also validates perceived usefulness as a key driver of adoption intentions for conversational AI. The development and validation of scales measuring AI chatbot adoption factors is a methodological contribution. For practice, the findings highlight the need for alignment with academic tasks, transparency about risks, policy incentives by institutions, targeted messaging to disciplines, and engagement of influencers to promote adoption. User experience enhancements like personalization, collaboration features, and plagiarism checks are also suggested.

Like all research, this study has some limitations that provide avenues for further research. First, the data was collected from Indian academics, so extending the investigation across cultures would enhance generalizability. Longitudinal designs tracking usage over time could yield additional insights. Second, comparative studies across disciplines and demographics may uncover differential needs and barriers. Third, exploring the relative impacts of specific network properties like size and frequency of interaction would enrich the understanding of peer effects. In conclusion, this study delivers meaningful contributions regarding academics' adoption of AI systems, guided by robust empirical analysis. The findings and implications provide guidance to theory, practice, and future research on this significant contemporary technology phenomenon.

Overall, the study emphasizes the importance of a comprehensive approach by AI developers, marketers, and policymakers in promoting conversational AI. By understanding the job-specific fit and technology determinants, AI developers can design effective marketing strategies that resonate with academics' values and preferences associated with their daily tasks. Organizations can also provide support through favorable policies that incentivize academics' use of such technologies, as it ultimately enhances effectiveness in the academic environment. Ultimately, understanding the job setting and the role of social networks for academicians can contribute to providing quick access to information, generating ideas, and assisting in the overall academic process. Generative AI can act as a valuable tool for academicians. An understanding of the factors that influence academics' intention to continue using AI-based chatbots is important in promoting the adoption and use of this technology in academia. This can lead to increased efficiency and productivity in academic tasks.

The following suggestions can be used for future research:

- Investigate differences across academic disciplines and roles. Requirements may vary for humanities vs STEM faculty or undergraduate vs graduate students.
- Explore impacts on actual academic performance outcomes like grades, publications, and learning satisfaction through experimental studies.
- Assess user trust in AI and how it evolves with repeated usage, and examine trust-building strategies.
- Study the effects of integrating chatbots in actual classrooms or online teaching and evaluate impacts on student engagement.
- Examine potential biases in training data and algorithms that could negatively affect usefulness for academics.
- Conduct cross-cultural studies on the acceptance of AI in academia across universities in different countries.
- Investigate the impacts of academic leadership, policies, and incentives on adoption rates at an institutional level.
- Explore design aspects like customization, personalization, and social cues that could enhance user experience.
- Develop frameworks to assess pedagogical effectiveness and ethical risks of conversational agents in academic contexts.
- Analyze the economic aspects like cost-benefit tradeoffs and return on investment of implementing academic AI chatbots.
- Study the environmental implications of large-scale adoption in terms of computing needs, resources, and energy impacts.

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