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Examining the Adoption of AI based Banking Chatbots: A Task Technology Fit and Network Externalities Perspective

Eden Samuel Parthiban[a,*], Mohd. Adil[b]

[a] *Research Fellow, Department of Management Studies, NIT Hamirpur, India*
[b] *Associate Professor, NIT Hamirpur, India*

ABSTRACT

The objective of this study is to provide a deeper understanding of the factors that lead to the development and adoption of AI-based chatbots. We analyze the structural relationship between the organizational (externalities), systematic (fit), and the consumer-related (psychological) factors and their role in the adoption of AI-based chatbots. Founded on the theories of task-technology fit and network externalities, we present a conceptual model overlooking common perception-based theories (e.g., Technology Acceptance Model). We collected 380 responses from Indian banking consumers to test the model using the PLS-SEM method. Interestingly, the findings present a positive impact of all factors on consumers' intention to adopt AI-based chatbots. However, the interplays between these factors provide a mixed perspective for literature. Apart from employing a combination of factors that have been used to study technology adoption, our study explores the importance of externalities and their relationship with fit factors, a unique outlook often overlooked by prior research. Moreover, we offer a clear understanding of latent variables such as trust, and the intricacies of their interplays in a novel context. Thereby, the study offers implications for literature and practice, followed by future research directions.

Keywords: AI-based Chatbots, Task-technology Fit, Network Externalities, Usage Intention, Trust, Banking Chatbots

Ⅰ. Introduction

The fourth industrial revolution is fueled by Artificial Intelligence (AI). According to Enholm et al. (2022), AI is developing machines that stimulate intelligence. In other words, AI is intangible much like human intelligence, yet manifestable through systems such as robots (Kot and Leszczyński, 2022; Prentice et al., 2020). Some highlight AI as "*the development of computers able to engage in human-like thought processes such as learning, reasoning, and self-correction*" (Kok et al., 2009, p. 2).

*Corresponding Author. E-mail: leumasnede@gmail.com

At a global scale, the Indian AI market is witnessing a remarkable growth and is emerging as a dynamic sector within the country, largely driven by the ongoing digital revolution. Dogra and Adil (2022) support this notion by highlighting the surging utilization of internet-based services in India, which can be attributed to the extensive internet penetration and the population's increased dependence on the internet following the COVID-19 pandemic. These two factors are also applicable to the AI market, as the consumer usage of majority of AI-based services requires internet access. Moreover, with a combination of technological advancements, government initiatives, and a growing startup ecosystem, AI adoption is expanding across various Indian industries (Anil and Misra, 2022; Jadhav and Mahadeokar, 2019). Being valued at 680.1 million in 2022, and a projected compound annual growth rate (CAGR) of 33.28% from 2023 to 2028, future prospects for the Indian AI market look promising (IMARC group, 2023). Three plausible reasons that fueled AI revolution in India are— its large population, availability of vast data resources, and highly skilled workforce. Furthermore, government initiatives like the National AI Strategy and the promotion of 1900+ AI-based startups through incubators and funding programs are fostering the growth of the Indian AI market (Mitter, 2022; Korreck, 2019).

In this way, AI, or more precisely, embodiments of it like the digital assistants called AI-based chatbots (henceforth, AIC), are revolutionizing the industry through process automation, information exchange, and lead generation, to name a few (Majumder et al., 2021; Murtarelli et al., 2021). In fact, AICs are so well integrated into the online experience that consumers are unable to distinguish between a human and a chatbot (Rafiq et al., 2022). According to Guzman and Pathania (2016) and Sheehan (2018), AICs combine intelligent backend systems with a user interface that facilitates end-user interactions. It is possible to communicate with an AIC through text or voice utilizing unique devices such as Amazon Alexa, computers, and smartphones. In the modern business sphere, AICs play a significant role in almost all stages by cutting costs, aiding sales, and optimizing business hours - ensuring a smooth, fast, and enhanced journey for all stakeholders (Ashfaq et al., 2020; Suhaili et al., 2021; Syvänen and Valentini, 2020). Consequently, the chatbot market will be worth US$ 1.25 billion by 2025, compared to US$ 190.8 million in 2016 (Thormundsson, 2022).

Despite such extensive adoption of AICs, Eliane et al. (2021) stated that further development is needed to perfect AICs to fit businesses and the society through value creation. Furthermore, studies (such as, Zhou et al., 2020; Zhu et al., 2022) highlight that despite being integrated into business models, AICs do not fit the consumer requirements. For instance, when consumers interact with AICs, they still encounter problems such as incorrect responses, which may hinder the adoption of AICs (Nguyen et al., 2021). The findings of previous studies may require further research to gain a deeper understanding of how AICs can fit into consumers' need. Such fitment will aid in consummating and calibrating potential future applications of AIC (e.g., lead conversions, recruitment, advanced healthcare assistance, etc.). Accordingly, literature persistently emphasizes the need to analyze AICs from multiple industries using different theories and models (Adam et al., 2021; Chen et al., 2022; Eren, 2021; Hentzen et al., 2021; Sands et al., 2020; Syvänen and Valentini, 2020). Hence, previous researchers have studied the adoptions of AICs in diverse sectors such as social robotics (Zhou et al., 2020), mental healthcare (Zhu et al., 2022), and tourism (Rafiq et al., 2022), aiming to help industries tailor and perfect their AICs using a varying and diverse category of variables that get adoption-related responses like intention to use and actual use from the consumers.

Given this background, the current study seeks to analyze the adoption of AICs in Indian banking industry for the following reasons: *First*, previous research (for e.g., Rafiq et al., 2022) calls for examining consumers' adoption of financial institutions-based AICs. *Second*, banking is the most commonly adopted context in information systems research, as they are the early adopters of any new technology/system (Adam et al., 2021; Hentzen et al., 2021), placing them at the forefront in the management research (Adil et al., 2020; Sadiq and Adil, 2021; Sadiq et al., 2019). *Third*, according to Szymkowiak et al. (2021), although the number of banking customers experiencing AICs is gradually increasing, their intentions to adopt the technology remain academically underexplored. *Fourth*, understanding the adoption of AICs in banking may help similar Fintech (collective term for technologies and systems in the financial sector) industries further improve their AICs in action (Hentzen et al., 2021).

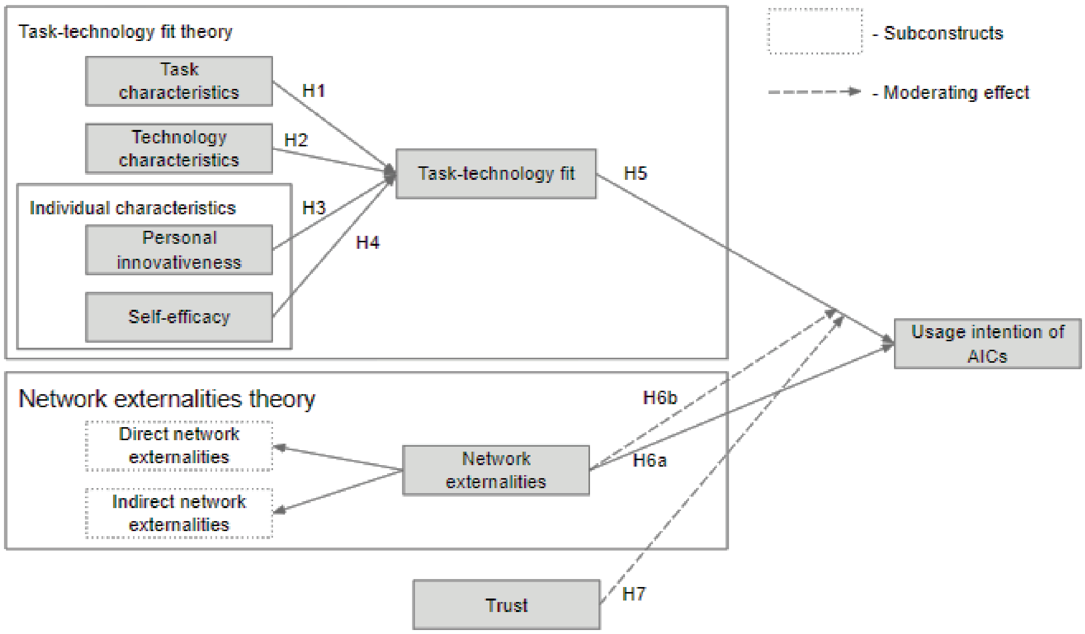
As such, we employ the task-technology fit theory (TTFT) and the network externalities theory (NET) to understand the adoption of AICs. Regarding the TTFT, most of the previous researchers have used theories like the Technology Acceptance Model (TAM) and Unified Theory on Acceptance and Use of Technology (UTAUT) to explain consumer adoption of AICs (Huang et al., 2021; Ling et al., 2021; Pereira et al., 2021). However, unlike TTFT, these theories mainly focus on consumer adoption of technology based on perceptions, and fail to acknowledge the adoption based on its actual performance. Hence, we argue that TTFT is more appropriate for this study as the theory explains, *first*, what determines the fit between the consumer and the system based on actual usage, and *second*, how the fit between the consumer and the system results in the adoption of the system by the consumer.

Regarding the NET, prior literature suggests that an integrated model explains adoption better (Franque et al., 2022). Consequently, factors like the *perceived number of AIC consumers*, and the *available complementary services with AICs* from the NET, were integrated with the model to achieve the objectives for three reasons. *First*, network externalities play a crucial role in developing a technology to increase its adoption (Katz and Shapiro, 1985). *Second*, a number of previous scholars (Gu et al., 2015; Gu and Black, 2020) reported that NET variables interact with TTFT variables. *Third*, a combined model generates a powerful theoretical framework capable of increasing the variance of the dependent variable (Faqih and Jaradat, 2021; Kim et al., 2022). *Fourth*, Cheng (2021) argue that three sets of variables come into play when the adoption of any IS/IT is concerned: organizational (the implementer of the technology), system-related (the technology), and individualistic (the user of the technology).

Accordingly, this study attempts to answer the following research questions:

RQ1: What factors determine the fit between consumers and banking AICs?
RQ2: How does the identified factors affect consumers' usage intention of banking AICs?

As a result, based on the argument above, the study derives variables from two different theories to represent the organization (NET), the user, and the technology (TTFT), and determines the variance of the dependent variable. Qualitative identification and analysis of the variables are further discussed in the sections below. Thus, our study enriches the information systems research by exploring the interaction mecha-



<Figure 1> Conceptual Framework

nisms between the industry, consumer, and the technology through a novel approach. Apart from such theoretical contributions, the study also presents several important implications for banks and marketers by helping them appropriately use human-computer cooperation in service delivery, and deepen their understanding concerning consumers' adoption of AI-based banking chatbots.

Accordingly, the rest of the paper is as follows: first, the *literature review and hypothesis development* sections contain a conception of task-technology fit theory, network externalities theory, and their integration. Next, the *methodology section* includes the study sample demographics and data collection instruments, followed by the data analysis, the measurement model and the structural model discussion. Finally, we have added the *discussion* part, followed by the *limitations and future research* section.

Ⅱ. Literature Review and Hypothesis Development

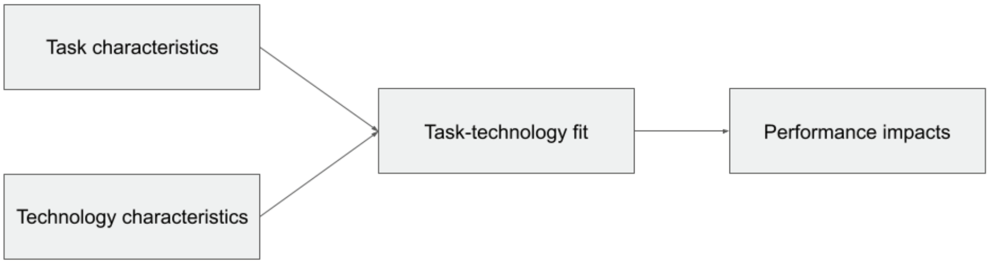
2.1. AI-based Banking Chatbots

AI-based banking chatbots have emerged as a disruptive technology in the banking sector, revolutionizing customer interactions and transforming the way financial institutions deliver services (Adam et al., 2021). This literature review provides an overview of the key findings and trends in the research related to the AI-based banking chatbots. First, the adoption of AI-based chatbots in the banking industry offers numerous benefits. One prominent advantage is the ability to provide incessant customer support, enabling customers to access banking services and obtain assistance at any time. Chatbots can handle a wide range of inquiries, including account balance inquiries, transaction history, and general product information, reducing the workload on human agents and improving efficiency (Majumder et al., 2021; Murtarelli et al., 2021). Studies have also highlighted the potential for improved customer experience through personalized interactions. AI algorithms enable chatbots to understand customer preferences and provide tailored recommendations, thereby enhancing customer satisfaction and loyalty (Shumanov and Johnson, 2021). Furthermore, the use of natural language processing techniques enables chatbots to communicate in a conversational manner, making interactions more intuitive and user-friendly (Sheehan, 2018).

Second, the adoption of AI banking chatbots from a consumer perspective has also garnered considerable attention in recent literature. Researchers have explored the factors influencing consumer adoption of these chatbot services and their impact on the overall banking experience. Studies have indicated that factors such as perceived usefulness, ease of use, trust, and personalization play significant roles in shaping consumer intentions to adopt AI-based banking chatbots (Huang et al., 2021; Ling et al., 2021; Pereira et al., 2021). Consumers value the convenience and efficiency offered by chatbots in providing quick access to information and performing basic banking tasks (Eren, 2021). Accordingly, literature suggests that future research should focus on addressing these concerns and enhancing the personalized and user-friendly aspects of AI banking chatbots to promote wider consumer adoption in the banking industry (Elaine et al., 2021). Overall, AI-based banking chatbots have the potential to reshape customer interactions, streamline banking processes, and drive innovation in the financial services industry.

2.2. Task-technology Fit Theory

The task-technology fit theory (TTFT) states that technology may positively impact individual performance only if utilized and fits the task the technology supports (Goodhue and Thompson, 1995). The definition of TTFT is analogous to the contingency theory of organizations which posits, "*Organizational effectiveness results from fitting characteristics of the organization, such as its structure, to contingencies that reflect the situation of the organization. Contingencies include the environment, organizational size, and organizational strategy. Because the fit of the organizational contingencies lead to high performance, organizations seek to attain fit*" (Donaldson, 2001, pp. 1-2). Despite being continually altered with variations, extensions, and refinements, owing to such a firm foundation in other theories, TTFT consistently asserts its core statement: well-suited task and technology characteristics provide increased technology use and performance benefits. This alignment between the task and technology is called task-technology fit (TTF), which directly affects the performance or indirectly affects the same, through technology use (Goodhue and Thompson, 1995; Zigurs and Buckland, 1998). To measure the level of fit between task and technology, TTF has to be operationalized. The TTF can be operationalized using two approaches: Fit-as-match and fit-as-profile approaches. The fit-as-profile approach - majorly used to study group support systems, measures TTF using the degree to which a technology varies from a preset profile of ideal characteristics. The fit-as-match approach portrays TTF as the fit between the task at hand and the capabilities of the IS system used to carry it out. The fit-as-match approach is most common in survey-based research, and it is gauged directly rather than being synthesized with external constructs (Furneaux, 2012; Howard



<Figure 2> The Task-Technology Fit Model

and Rose, 2019; Zigurs and Buckland, 1998). We adopt FM in the study for the following reasons: First, it simply measures TTF by enabling the respondent to answer whether AICs suit their tasks directly. Second, this simplification has led researchers to prefer the fit-as-match method over others. Third, fit-as-match approach is best for survey-based research evaluating individuals who have already used the technology. Finally, the fit-as-profile method is generally used in experimental studies, and is not applicable to our case (Goodhue and Thompson, 1995; Zigurs and Buckland, 1998). In this regard, the TTF model is visualized as in <Figure 2>.

2.2.1. Task and Technology Characteristics

In the model, *task* refers to the portfolio of actions a consumer has to perform to get outputs (Goodhue and Thompson, 1995). For example, *Quora* consumers get their questions answered (outputs) by posting their questions online (task). Tasks get identified by their characteristics. These characteristics include the hardware, software, and data used to perform tasks (Goodhue and Thompson, 1995). Next, *technology* refers to the system assisting the consumer perform their tasks (Goodhue and Thompson, 1995). If the technology can facilitate or support the consumer's tasks, it will be adopted. The characteristics of the technology are the capabilities of the system in question (Furneaux, 2012). Lu and Yang (2014) argue that a technology should get designed in such a way that it can support the task, so that the degree of fit between the two is increased. Previous research has analyzed the degree of fit between tasks and technologies to in a diverse milieu, including artificial reality in education (Faqih and Jaradat, 2021), Knowledge Management Systems (Lin and Huang, 2008), mobile banking (Oliveira et al., 2014), and mobile cloud healthcare systems (Wang and Lin, 2019). The basic premise of these studies is to determine how much the technologies fit the tasks. Similarly, our primary objective is to understand whether the technology (AICs) fit the tasks (banking operations). As such, we hypothesize the following:

H1: Task characteristics positively influence task-technology fit

H2: Technology characteristics positively influence task-technology fit

2.2.2. Individual Characteristics

Most existing studies test the effect of task characteristics and technology characteristics on TTF while overlooking individual characteristics because TTFT often applies in situations where the technology use is mandatory (Jeyaraj, 2022; Pal and Patra, 2021; Wang and Lin, 2019), like employee adoption of a particular technology in an organization. The individual is the user of the technology. Our case is different, as banking customers hold a choice to utilize chatbots or not: So, we argue that individual characteristics may play a role in AIC adoption, as extant literature emphasizes the role of individual characteristics in technological adoptions and its effect on TTF (Cheng, 2021; Erksine et al., 2019; Pal and Patra, 2021; Park et al., 2015). Furthermore, personal innovativeness and self-efficacy are the most studied individual characteristics in the novel technology adoption context, sometimes together (Chuhan et al., 2019; Coeurderoy et al., 2014; Jokisch et al., 2020; Kim et al., 2022; Makki et al., 2016; Park et al., 2015; Singh et al., 2020).

2.2.2.1. Personal Innovativeness

Defined as the degree to which an individual adopts something earlier than their peers, *personal innovativeness* plays a prominent role in predicting a person's adoption intention of new technology. Some people are more willing to try new things than their peers - meaning they possess a higher risk-taking propensity. Simplistically, people with higher personal innovativeness are prone to try new technologies earlier (Patil et al., 2020; Wu and Lai, 2021). Extant literature, especially in the consumer behavior domain, has extensively used personal innovativeness to predict technological diffusions under the construct label personal innovativeness of information technology (PIIT). The PIIT is a key variable in innovation adoption, and a change receptivity trait determining individual willingness to adopt new technology (Agarwal and Prasad, 1998; Thakur et al., 2016). This trait varies from individual to individual, and the level of PI also differs based on technology (Wu and Lai, 2021). Previously, Park et al. (2015) have linked PI to the TTF construct in the context of TEASER (a digital cookbook) and Kim et al. (2022) have tested the same relationship concerning Buy Online and Pick up in Store. This study links personal innovativeness to TTF to understand whether this individual trait influences the degree of fit between the tasks and technology. Accordingly, we hypothesize that:

H3: Personal innovativeness positively influences the task-technology fit

2.2.2.2. Self-efficacy

Venketesh et al. (2003) state that *self-efficacy* is one's belief regarding the capacity to complete a task (e.g., banking operation) using a technology (e.g., AIC). Jokisch et al. (2020) highlight the importance of exploring domain-specific self-efficacy constructs to unlock domain-focused adoption knowledge. Thus, apart from general-level self-efficacy, researchers study other types like computer self-efficacy, creative self-efficacy, KMS self-efficacy, etc., and their effects on adoption-related constructs (Chen, 2017; Hasse et al., 2018; Lin and Huang, 2008). Studies employing such domain-specific self-efficacy construct based their construct definition on the one given by Bandura et al. (1997): self-efficacy is one's belief in oneself that one can accomplish any job in a specific context. So, in our case, self-efficacy means the self-perceived ability of a person to finish a banking operation using an AIC. Previously, the interplay between self-efficacy and TTF was tested in the context of Spatial Decision Support Systems (Erskine et al., 2019), mobile commerce (Lee et al., 2007), and Knowledge Management Systems (Lin and Huang, 2008). Our research links self-efficacy and TTF to understand whether the trait impacts the degree of fit between the tasks and the technology. Hence, we hypothesize the following:

H4: Self-efficacy influences task-technology fit

2.2.3. Task-technology Fit and Usage Intention of AICs

The *task-technology fit* is the degree to which a technology can help an individual with their task (Goodhue and Thompson, 1995). Although the dependent variable in the original task-technology fit model is *performance impacts* (which denotes the actual work of an individual using an IS/IT) as seen in <Figure 2>, Yoon and Cho (2016) highlight the need to clarify the effect of task-technology fit on technology usage intention. Accordingly, Wang and Lin (2019), and Franque (2022) underline that previous studies employing task-technology fit theory have exclusively used *intent to use/adapt* as the dependent variable, and applied the same in their conceptual models. Howard and Rose (2019) also pointed out that researchers rightfully assume that task-technology fit has the same effect on consumer reaction as it does on performance impacts. Prior research (Franque, 2022; Howard and Rose, 2019; Wang and Lin, 2019; Yoon and Cho, 2016) has replaced the dependent variable of task-technology fit theory for contextual reasons, and most of these studies have replaced the original variable with *usage intention*. Similarly, we replace performance impacts with *usage intention to adopt AICs* as our research aims to assess the consumers' intention to adopt AICs, and not the actual performance. Hence we propose that:

H5: Task-technology fit positively influences the usage intention of AICs

2.3. Network Externalities Theory

The economic concept called *externality* is the basis for the term *network externality* (NE). In theory, an externality occurs when an unrelated third party is affected positively or negatively by an economic transaction in the network. The network is the existing consumers of the product/service/technology in question. The NE concept is based on a simple premise that the number of consumers of a network determines its value - meaning that any future subscriptions rely on this number. Development of new networks, subscription surcharge, homogenizing network actualization elements, inter-network rivals, network extents, and extensions among others depend on this number (Capello, 1995; Choi and Stefanadis, 2022; Katz and Shapiro, 1985). Katz and Shapiro (1995) gave the most standard definition of network externalities stating, "*there are many products for which the utility that a consumer derives from consumption of the good increases with the number of other agents consuming the good. The utility that a given consumer derives from a good depends upon the number of other consumers who are in the same network*" (p. 424).

The above definition spawns two types of network externalities which are direct network externalities (DNE) and indirect network externalities (INE). DNE is the perceived number of consumers in the network. INE is the perceived availability of complementary services available within the network (Katz and Shapiro, 1985; Li et al., 2018). DNE occurs when the perceived value of a network is affected by the number of consumers. The consumers naturally assume that since more people use a particular technology, using it themselves fetches value (Katz and Shapiro, 1985; Zhang et al., 2017). INE happens when consumers believe using a particular technology comes with complementarities. Unlike DNE, which comes from the demand side of the network, INE comes from the supply side. INE is widely applied in IS contexts. It is argued that if consumers of a technology perceive a technology to contain complementary services, they are positively influenced and motivated to adopt the technology as it increases convenience and work efficiency (Dehghani, 2018; Hsu and Lin, 2016). For example, consumers have increasingly adopted payment gateways like Google pay and Apple pay because these applications let them pay almost all of their bills, among other tasks, apart from fund transfers. Similarly, we assume if the consumers believe that using a banking AIC can offer services like payments, account opening, account statement generation, and loan assistance, apart from Q&A sessions, their intent to use AIC will increase. Laboratory experiments by Pontiggia and Virili (2010) proved that DNE and INE can directly influence behavioral intentions related to technology adoptions. Accordingly, Wu et al. (2017) replicated it proving that NE positively influence UI to adopt cloud services, Wang et al. (2016) studied the effect of NE on usage intention of mobile reservation systems, and Lee and Kim (2020) tested the same interplay in the context of internet-only bank adoption. We test the same relationship since we assume that if more people start using AICs, firms will add more features to them, which increases the degree of usage intention and form the hypothesis below.

H6a: Network externalities positively influences the usage intention of AICs

2.4. Integrating the Task-technology Fit Theory and the Network Externalities Theory

Our conceptual framework combines the identified constructs from the TTFT and NET for the following reasons. *First*, the original TTF odel is big, so testing it in one go is challenging (Yen et al., 2010). Thus, research to date empirically tests only parts of the model combined with other theories and models, like the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Innovation Diffusion Theory (IDT) to understand the usage intention and adoption of different technologies (Faqih and Jaradat, 2021; Oliveira et al., 2014; Wang and Lin, 2019; Wu and Chen, 2017; Yen and Chiang, 2021). *Second*, Wu et al. (2007) combined the TTFT, NET and TAM to understand the adoption of end-consumer computing (EUC). Much like Cheng (2021) who point out that psychological, network and fit factors antecede successful IS/IT adoption, Wu et al. (2007) proved that EUC adoption gets influenced by three external variables: individual characteristics (e.g., self-efficacy), organizational characteristics (e.g., network externalities), and information system characteristics (e.g., task-technology fit). *Third*, Gu et al. (2015) and Gu and Black (2020) argue that task-technology fit and network externalities are closely interlinked. They state that network externalities enhance the relationship between task-technology fit and adoption intention. Translated to the case of banking AICs, this statement may implicate that the greater number of consumers will lead to firms adding more features (or complementarities) to the technology – thus increasing the TTF, which then increases the usage intention. This combined network effect seems to moderate the relationship between TTF and adoption. Hence, we propose the following:

H6b: Network externalities moderates the relationship between task-technology fit and usage intention of AICs

2.5. Trust as a Moderator

Mostafa and Kasamani (2021) posit that trust is a vital variable, especially in AI studies, since technologies like AICs primarily mimic human behavior (e.g., natural language conversations). For the reason that, when a consumer detects human-like behavior from a technology, psychological aspects like trust get stimulated resultantly (Ogonowski et al., 2014). Yen and Chiang (2021) define the trust in chatbots as— "*consumers' subjective belief that chatbots possess knowledge and expertise, and goodwill and honesty*" (p. 1179). It is a crucial psychological construct aiding the formation of relationships between parties that eventually lead to long-term mutual exchange of any nature (Oliveira et al., 2014). On one side, the level of that trust depends on the level of task sophistication (or autonomy) a technology could manage (Klumpp, 2018). On the other side, AICs are a relatively new technology - privacy risk, among other concerns, may make the consumer reluctant to adopt them (Eren, 2021; Oliveira et al., 2014). Concurrently, plenty of studies focused on AICs have determined the antecedents of trust, and prove the positive influence of resulting trust on adoption intention and the direct relationship between them (Eren, 2021; Mostafa and Kasamani, 2021; Murtarelli et al., 2021; Pillai and Sivathanu, 2020) - so the link between trust and usage intention is irrefutable. Our framework integrates trust into the model not to test a proven relationship, but to deduce the present stance of consumers on AIC adoption. Wang et al. (2021) imply that the interplay between the task-technology fit and usage intention gets significantly strengthened with trust as a moderator. In other words, a customer must trust a technology to adopt it, despite the technology fitting their needs. Hence, we argue that using trust as a moderator will reveal the present intention of consumers regarding AICs adoption, taking into account the fit between their task and the technology. In view of that, we propose:

H7: Trust moderates the relationship between task-technology fit and usage intention of AICs

Ⅲ. Research Method

We used a survey instrument (refer <Appendix>) to validate the conceptual framework. The questionnaire contained an introduction describing the study objectives and ensuring the anonymity and confidentiality of response handling. Then it included a filter question (e.g., have you used an AI-based banking chatbot before?) to confirm that the sample is familiar with AICs. The rest comprised of scales measured with a seven-point Likert scale (1 = strongly disagree, and 7 = strongly agree) - adapted from previous marketing studies. To collect data, we posted the finalized questionnaire to Google forms.

3.1. Sampling and Data Collection

Concerning the adoption of systems and technologies, prior research (Chen, 2020; Stein, 2013) states the previous generations prefer traditional methods, while Gen Y and Gen Z (population born after 1980) prefer novel approaches. For example, when contemplating a banking-related query, the boomers and Gen X may call or visit the bank, while Gen Y and Z may find answers online/on the banking website. The latter desire faster and convenient services, interact with screens more than humans, and become early adopters of any technology (Alam et al., 2020; Fernandes and Oliveira, 2021; Liu et al., 2020; Magsamen-Conrad and Dillon, 2020; Owusu et al., 2021; Szymkowiak et al., 2021). We limit this study to the Indian youth as more than 87% of the global consumer population will live in Asia, centered in India and China by 2030. India has already surpassed China in terms of population, and by 2030, it will closely follow China to become an economic giant worth more than USD 7.5 trillion (Deva, 2022; Mukhopadhyay, 2023; Ojha and Ingilizian, 2020). Moreover, the Indian consumer population is predominantly youthful (Dychtwald, 2021; Meryl, 2021), and AI businesses presently tailor their technologies to cover the youth (Fernandes and Oliveira, 2021) - making it essential to study them. Another reason to limit this study to India is because the Indian fintech market will serve over 1 billion consumers by 2027, making it a commendable and promising global entity (Report - Statista). Accordingly, to achieve the objectives and precisely check the conceptual framework, we targeted Indian individuals belonging to the generations Y and Z who have used banking chatbots. We used the convenient sampling method to collect data online, following Mostafa and Kasamani (2021), Nasir et al. (2022) and Dogra et al. (2023). Popular social media sites and messaging platforms like Facebook, LinkedIn, Instagram, WhatsApp, Telegram, and Twitter were used to distribute the survey link across the Indian subcontinent. Started in the last week of November 2022, the data collection lasted four weeks.

<Table 1> Respondent Demographics

Variable	Group	Frequency (N = 380)	Percent
Age	0-17	9	2.4
	18-24	215	56.6
	25-34	111	29.2
	35-44	45	11.8
Education	Doctorate	14	3.7
	Post graduate	139	36.5
	Graduate	173	45.5
	High school	18	4.8
	Others	36	9.5
Gender	Male	147	38.7
	Female	223	58.7
	Others	10	2.6
Marital status	Married	220	57.9
	Unmarried	160	42.1
Job description	Government sector	46	12.1
	Private sector	197	51.8
	Self-employed	72	18.9
	Unemployed	65	17.1

Out of the 650 distributed links, we received 414 (response rate of 63.69%) responses. After removing invalid data, we used 380 responses for further analysis. The respondent demographics are presented below.

3.2. Data analysis

We used the Partial Least Squares – Structural Equation Modeling (PLS-SEM) methodology for analysis. SmartPLS version 3 was used for the analysis. The reasons behind selecting the PLS-SEM method are: *First*, PLS-SEM is flexible regarding data requirements, framework complexity, and relationship types. *Second*, the technique can compare two or more groups by specifying a permutation-based analysis of variance approach, thereby retaining family-wise error rates independent of distributional assumptions, and demonstrating a satisfactory statistical accuracy (Fornell and Locker, 1982). *Third*, PLS does not require the data to be normally distributed. Compared to covariance-based (e.g., CB-SEM) models, PLS-SEM is capable of handling smaller sized samples, and accurately yields the overall model fit (Yoo and Alavi, 2001). *Fourth*, PLS-SEM is unequivocally better than traditional methods such as factor analysis, regression, and path analysis as the measurement and structural models are assessed simultaneously in PLS-SEM (Park et al., 2018). To test significance, we use the SmartPLS re-sampling method. We assess path significance with bootstrapping, as the basis for confidence intervals and estimation of factor stability is provided by the bootstrapping estimate.

3.3. Measurement Model

Prior to the analytical phase, we performed tests to detect data outliers and multicollinearity. The data inner VIF values are from 1.228 to 1.900, (< 2.5) and the outer ones are from 1.233 to 3.218, (< 5) (Kock, 2015), showing no data muticollinearity issues. Later, we checked the internal consistency, reliability, convergent and discriminant validity. The construct and discriminant validity tests confirmed the validity of the measurement model. As depicted in <Table 2>, rho_A values show the internal consistency and validity (rho_A > 0.7), confirming the scale reliability

<Table 2> Construct Reliability and Validity

Construct	Items	Factor Loading	rho_A	Composite Reliability	Average Variance Extracted
Task Characteristics (TAC)	TAC1	0.926	0.743	0.825	0.704
	TAC2	0.742			
Technology Characteristics (TEC)	TEC1	0.781	0.859	0.904	0.701
	TEC2	0.883			
	TEC3	0.863			
	TEC4	0.819			
Personal Innovativeness (PI)	PI1	0.896	0.885	0.928	0.811
	PI2	0.895			
	PI3	0.911			
Self-Efficacy (SE)	SE1	0.89	0.826	0.894	0.738
	SE2	0.867			
	SE3	0.818			

<Table 2> Construct Reliability and Validity (Cont.)

Construct	Items	Factor Loading	rho_A	Composite Reliability	Average Variance Extracted
Task-Technology Fit (TTF)	TTF1	0.909	0.907	0.942	0.843
	TTF2	0.924			
	TTF3	0.922			
Network Externalities (NE)	INE1	0.829	0.865	0.902	0.647
	INE2	0.782			
	DNE1	0.786			
	DNE2	0.825			
	DNE3	0.799			
Trust (TR)	TR1	0.739	0.765	0.852	0.659
	TR2	0.813			
	TR3	0.878			
AIC Usage Intention (UI)	UI1	0.877	0.876	0.923	0.8
	UI2	0.909			
	UI3	0.896			

(Dijkstra and Henseler, 2015). The disciminant and convergent validity verified construct validity. The convergent validity was tested for average variance extracted (AVE > 0.5), composite reliability (CR > 0.7), and factor loadings (Hair et al. 2011). Our AVE was above 0.5 (Dijkstra and Henseler, 2015), and the square root of AVE was greater than a construct's correlation with other constructs (observed in <Table 2>), and each item loaded more on the construct it should measure, rather than other constructs (Dijkstra and Henseler, 2015). The Standardized Root Mean Square Residual (SRMR) was 0.056 (< 0.08) indicating that the model is a good fit (Hu and Bentler, 1999).

3.4. Structural Model

The hypothesis results are shown in <Table 4>. We tested the dependent and the independent variable interplay using the path co-efficient and t-statistics at the level of $p < .05$. The R square indicates that 51.6% of the variance is explained by task-technology fit and 73.1% by usage intention of AICs, therefore showing a satisfactory level of explanation. Our results support all the hypotheses except H3, and H6b. The path coefficients in a structural model are predicted using β-statistics. The results are shown in <Table 4>. Regarding moderation hypotheses 6b and 7: The moderation effect of NE is insignificant; however, trust exerts a moderation effect on the TTF-UI relationship ($\beta = -0.082$, $p < .05$). Thus, H7 was supported.

Ⅳ. Discussion

The theoretical framework of the study is based on the Task-technology Fit Theory (TTFT) and the Network Externality Theory (NET). In addition to the variables adopted from these theories, *trust,* and *usage intention of AICs* were also added to the framework. Following are the results and findings obtained by testing the model using the PLS-SEM methodology. *First*, we hypothesized that the *task*

<Table 3> Discriminant Validity

	NE	PI	SE	TAC	TEC	TTF	Trust	UI of AIC
NE	**0.804**							
PI	0.501	**0.901**						
SE	0.615	0.538	**0.859**					
TAC	0.447	0.392	0.468	**0.839**				
TEC	0.733	0.536	0.591	0.451	**0.837**			
TTF	0.676	0.434	0.573	0.494	0.663	**0.918**		
Trust	0.743	0.514	0.605	0.4	0.691	0.61	**0.812**	
UI of AIC	0.741	0.482	0.557	0.427	0.682	0.654	0.816	**0.894**

Note: TAC: task characteristics; TEC; technology characteristics; TTF: task-technology fit; PI: personal innovativeness; SE: self-efficacy; NE: network externalities; UI: usage intention; → moderation

<Table 4> Hypothesis Testing

Hypotheses	Relationships	T Statistics	Path Coefficients (β)	P-Values (<0.05)	Supported
H1	TAC → TTF	3.306	0.189	0.001	Yes
H2	TEC → TTF	7.896	0.447	0	Yes
H3	PI → TTF	0.04	0.002	0.968	No
H4	SE → TTF	3.705	0.22	0	Yes
H5	TTF → UI of AIC	5.24	0.184	0	Yes
H6a	NE → UI of AIC	3.968	0.206	0	Yes
H6b	NE → TTF and UI of AIC	0.01	0	0.992	No
H7	Trust → TTF and UI of AIC	2.108	-0.082	0.035	Yes

Note: TAC: task characteristics; TEC: technology characteristics; TTF: task-technology fit; PI: personal innovativeness; SE: self-efficacy; NE: network externalities; UI: usage intention; → moderation

characteristics and the *technology characteristics* directly impact the *task-technology fit*. These hypotheses reveal whether the technology (AIC) is actually useful for the task (banking operations), as the degree of the *task-technology fit* is determined by the level of alignment between the *task characteristics* and the *technology characteristics* (Goodhue and Thompson, 1995; Zigurs and Buckland, 1998). Our results support the proposed alignment leading to the first finding that the Indian banking AICs fit the consumer requirements, proving H1 and H2. The results resonate with the prior contributions of Pal and Patra (2021), Wang and Lin (2019), and Tam and Oliveira (2016). *Second*, we proposed psychological factors like the *individual characteristics* also play a role in determining the *task-technology fit*. Hence, we have considered two personal traits as *individual characteristics* in our study: *personal innovativeness* and *self-efficacy*. In H3, we hypothesized that *personal innovativeness* influences the degree of *task-technology fit*. However, our results are unsupportive of H3, similar to the work of Kim et al. (2022), leading to the second finding that in the case of Indian banking chatbots, *personal innovativeness* does not determine the degree of *task-technology fit*. Likewise, H4 proposes that *self-efficacy* positively impacts task-technology fit.

Parallel to Hsiao and Chen (2015), and Erksine et al. (2019), our results portray a positive relationship between *self-efficacy* and *task-technology fit*, leading to the acceptance of H4. Therefore, we argue that the consumer's confidence in their ability to complete a task with AICs, directly impacts their perception of the degree of fit between the technology and the task. *Third*, our results also prove that *task-technology fit* positively impacts the *usage intention of AICs*, supporting H5. Therefore, we conclude that the degree of fit between tasks and technology impacts the variance of technology usage intention. In other words, if the bank offers the consumer a technology that fits a task at hand, the consumer will intent to adopt it. This result aligns with Kim et al. (2022), Wang and Lin (2019), and Hsiao (2017).

Fourth, our results state that *network externalities* also affect the *usage intention of AICs*, supporting H6a. Therefore, we posit the intention to adopt AICs gets positively impacted by the perceived number of AICs *(Direct Network Externalities)* consumers and available complimentary features with AICs *(Indirect Network Externalities)*. This result is consistent with Qasim and Abu-Shanab (2016), Chun and Hahn (2007), and Ewe et al. (2015). *Fifth*, H6b hypothesizes that *network externalities* moderate the relationship between *task-technology fit* and *usage intention of AICs*, but our results are unsupportive of it. This result contradicts Gu et al. (2015) but aligns with Gu and Black (2020). Therefore, we argue that the existence of externalities has no effect on the degree of task-technology fit in the case of Indian banking AICs. In other words, the number of other consumers and complementarities may not influence the degree of task-technology fit. *Finally*, H7 proposes that the *trust* in AICs moderates the relationship between *task-technology fit* and *usage intention of AICs*. Although our results support H7, they exhibit that *trust* exerts a negative moderation. We therefore posit that Indian banking AIC consumers exhibit a pattern of distrust towards AICs. This result is normal as consumers are skeptical of any new technology, especially if the tasks performed by the technology are complex and sensitive. This claim is parallel to the findings of Wang et al. (2021), and Kaur and Arora (2020).

Ⅴ. Theoretical Implications

Our study enhances the literature in the following ways. *First*, prior research on the adoption of AI-based chatbots primarily focuses on variables and theories related to their external attributes, like anthropomorphism, humanness, and adaptive-nature (Cheng, 2021). While this perspective is important, a gap exists in the literature where the actual performance of the system has received very little attention (Rzepka et al., 2022; Wang et al., 2021). Our study addresses this gap by considering the task-technology fit theory (TTFT), - a theory that primarily emphases on the performance attributes of a system, rather than the attributes related to its appearance.

Second, another overwhelming attention of the extant AIC adoption literature has been on the consumer perceptions (such as perceived usefulness and perceived ease of use) formed before using of the system (Huang et al., 2021; Ling et al., 2021; Pereira et al., 2021). Our study addresses this gap by considering a performance-related model which tests the adoption intention of a system based on actual usage (Gu and Black, 2020).

Third, while considering the task-technology theory, prior literature often overlooks individual characteristics. Our study, on the other hand, adds individual characteristics to its framework, as we argue that the variable acts as an important boundary condition when the system in question is expendable. Simplistically, the consumer may stick to traditional banking, while avoiding AICs. Yet, our results state that the consumers' individual characteristics, such as the self-efficacy, influence their individual-technology fit, thereby increasing their intention to adopt the system.

Fourth, regarding the integration of theories in adoption literature, we integrated the TTFT and NET for two reasons: a) Franque et al. (2022) suggest that an integrated model explains adoption phenomenon better, and b) the integration enabled our research to deduce the adoption of AICs from three different perspectives, i.e., the organization, the system, and the user. Variables from the TTFT represent the system (fit factors), and the user (individual factors), while the variables from the network externalities theory, represent the organization (network factors) in our study. To the best of our knowledge, prior adoption research has offered this integrated perspective only twice before (Cheng et al., 2021; Wu et al., 2007).

Finally, our results state that despite the negative moderation of trust, TTF exerts a positive impact on usage intention of AICs. This finding adds a decomposed perspective of trust to the chatbot adoption literature by exposing the existence of a negative notion regarding trust among consumers. Therefore, study fulfils a limitation in research by contradicting the positive role usually played by trust in the adoption literature of chatbots.

Ⅵ. Practical Implications

Our research provides the following implications for the industrial stakeholders. *First*, despite the prior existence of alignment between the task and the technology as proved by our study, banks employing AICs should strive to perfect them. For the banks anticipating to implement such systems, the positive effect of task characteristics and technology characteristics on the task-technology fit (TTF) implicates that such banks should identify consumer requirements, and design systems that fit the identified requirements, as employing underdeveloped systems that fail to meet consumer requirements may lead to negative repercussions, such as financial loss and decreasing customer trust in online banking. To aid the perfection of existing systems, and the implantation of new systems, banks may regularly collect data regarding the consumer expectations from AICs to tweak the fit between the tasks and technology.

Second, our results portray that out of the two individual characteristics, only self-efficacy impacts the task-technology fit, while personal innovativeness does not. Therefore, we suggest that bank marketers should portray AICs as a trendy technology with extensive task-handling capabilities to cover consumers with high personal innovativeness. Moreover, such portrayal could add to the existing self-efficacy of the consumers.

Third, the overwhelming positive effect of TTF on the usage intention of AICs implies that banks should employ agents which reassure their expectations behind using such agents. For example, banks should collect data on user expectations, and tailor responses that portray the extensive ability of AICs to meet consumer surmises.

Fourth, our results provide evidence that network externalities also influence the usage intention of AICs. Thus, when employing chatbots, dialogs should be designed so as to highlight the existence of a large consumer base and the features of the technology are demonstrated. While focusing on dialogs that display the fit and network factors, marketers may attempt various techniques to appeal the consumer. For example, the AIC can state the list of tasks it can perform for the consumer, and how other consumers found such tasks useful.

Finally, the impact of task-technology fit on the usage intention of AICs despite lower levels of trust implies that banks should focus on employing strategies to increase the level trust. For example, a chat session may reassure the consumer about the security aspects of the chatbot, and that the information shared with the chatbot will remain confidential.

Ⅶ. Limitations and Future Research

The findings and implications of the study should be deliberated with the following limitations in mind. *First*, the study analyzes only two traits as individual characteristics. Hence, future researchers should integrate other psychological traits like the HEXACO into our model. The present moderators in the framework may also get replaced with the aforementioned traits. *Second*, our study is limited to the Indian banking sector and population, so we suggest replicating the same in other industries and countries using AICs. *Third*, chatbots is an emerging information system, hence future studies could apply the task-technology theory from the firm perspective and understand their adoption in B2B conditions. *Finally*, the fit-as-profile approach for analyzing the task-technology fit could also prove to be a valuable theoretical addition in the future.

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<Appendix> Measurement Scale

Variable	Item Label	Question	Adapted from
Personal innovativeness (PI)	PI1	If I heard about a new technology, I would look for ways to experiment with it.	Erskine et al. (2019); Agarwal and Prasad (1998)
	PI2	Among my peers, I am usually the first to try out new technologies.	
	PI3	I like to experiment with new technologies.	
Self-efficacy (SE)	SE1	I could solve a problem using a chatbot even if there was no one around to tell me what to do.	Erskine et al. (2019); Compeau and Higgins (1995)
	SE2	I could solve a problem using a chatbot if I had never used an application like it before.	
	SE3	I could solve a problem using a chatbot if I had seen someone else using it before trying it myself.	
Task characteristics (TAC)	TAC1	I often need to figure out the problem encountered during e-banking service usage	Lu and Yang (2014)
	TAC2	I often need advice from someone else to make decisions during e-banking service usage	
Technology characteristics (TEC)	TEC1	Banking chatbots provide ubiquitous services	Tam and Oliviera (2016)
	TEC2	Banking chatbots provide real time services	
	TEC3	Banking chatbots provide a quick service	
	TEC4	Banking chatbots provide secure services	
Task-technology fit (TTF)	TTF1	Chatbots fit the task I wanted to do during e-banking service usage	Shin and Jeong (2022)
	TTF2	Chatbots were suitable for the task I wanted to do during e-banking service usage	
	TTF3	Chatbots were appropriate for the task I wanted to do during e-banking service usage	
Direct network externalities (DNE)	DNE1	I think a good number of people use banking chatbots	Lee and Kim (2020)
	DNE2	I think many people are using banking chatbots	
	DNE3	I think there will still be many people adopting banking chatbots	
Indirect network externalities (INE)	INE1	A banking chatbot provides a wide range of services	Hsu and Lin (2016)
	INE2	Using a banking chatbot will allow me to finish various tasks (e.g., bill-payment, payment against product/ service booking, information exchange)	
Trust (TR)	TR1	Banking chatbots seem dependable	Mostafa and Kasamani (2021); Hsu and Lin (2021)
	TR2	Banking chatbots were created to help the client	
	TR3	Banking chatbots seem trustworthy	
Usage intention (UI)	UI1	When required, I will use banking chatbots	Mostafa and Kasamani (2021); Parra-López et al. (2011)
	UI2	I intend to use banking chatbots in the future	
	UI3	I think that more and more people will use banking chatbots	

◆ About the Authors ◆

Eden Samuel Parthiban

Eden Samuel Parthiban, the corresponding author, is a Research Fellow in the Department of Management Studies at NIT Hamirpur, India. He is doing research in the area of consumer behaviour, marketing systems, and technologies. Recognised for academic excellence, he was awarded the Indian University Grants Commission's Junior Research Fellowship in 2020.

Mohd. Adil

Dr. Mohd. Adil works as a Senior Assistant Professor at NIT Hamirpur, India. His present research focuses on services marketing, sustainable marketing, and tourism. He has several publications in journals of repute, such as *International Journal of Hospitality Management, Psychology and Marketing, Journal of Retailing and Consumer Services*, *Journal of Vacation Marketing, Journal of Service Theory and Practice*, *Food Quality and Preferences, Current Issues in Tourism, Business Strategy and the Environment* among others.

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