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UNDERSTANDING ARTIFICIAL INTELLIGENCE ADDICTION IN GEN Z: THE ROLE OF OVERRELIANCE, EMOTIONAL ATTACHMENT, PERCEIVED USEFULNESS AND TRUST

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ABSTRACT

Concerns about excessive usage behaviours, or compulsive behaviour patterns, associated with increased use of Artificial Intelligence (AI) technologies in everyday life are growing. Using Behavioural Addiction Theory, Automation Bias Theory, and Social Response (Media Equation) theory as a basis and then critiquing the underlying assumptions of Technology Acceptance Theory, this study investigates the relationship between reliance (Overreliance), the Perceived Usefulness of an AI system, Emotional Attachment to an AI system and Trust in an AI system to create an "addictive" user experience. A quantitatively based, cross-sectional methodology was utilised in conducting this research, where primary data were collected from 242 actively engaging with AI users were obtained using a structured questionnaire, which is measured using a 5-point Likert scale. Data were analysed using SPSS version 20 and were studied by descriptive statistics, correlation analysis, multiple regression analysis and ANOVA. Results indicate that Overreliance, Emotional Attachment, and Trust are all statistically significant and positively predict AI addiction. However, perceived usefulness does not have a statistically significant direct effect on AI addiction. Overall, the regression model account for approximately 40% of the variance in AI addiction, thereby providing evidence of its strong explanatory power. Statistical analyses of demographics indicate no statistically significant difference across age. However, educational qualification did show statistically selective differences between levels of AI addiction experienced. This research contributes to the theoretical understanding of AI addiction, demonstrating that addiction to AI technologies is largely due to psychological and relational mechanisms, rather than solely being driven by functional utility. The findings emphasize the importance of responsible AI design, user awareness and targeted interventions to mitigate addictive AI usage behavior.

Keywords: Artificial Intelligence, AI Addiction, Emotional Attachment, Generation Z, Perceived Usefulness, Trust in AI

1. Introduction

Generative artificial intelligence (Gen AI) has significantly changed the way we learn, work and use digital technologies. More than ever, AI-powered tools, such as conversational chatbots, are becoming part of our daily life by helping us with searching for information, writing, solving problems and making decisions. With a large population of young people in India, the rapid increase in digital technology use and the increasing number of knowledge-based jobs available, it is important to understand how young people are using Gen AI. One of the most relevant cohort of people, are those born between 1996 and 2015, also known as Generation Z; we can learn about the future of human to AI interaction, by studying this group who are just starting to enter college/university and the workforce. More current studies demonstrate that generative AI has surpassed the experimental stage, or the stages of novelty, from the younger generation, referred to as Generation Z. Instead, young adults now regularly employ AI systems for their educational assignments, their work responsibilities and to meet daily requests for information. The portrayal of Generation Z's use of AI as more emotional or entertaining has been proven false by the evidence collected through research which demonstrates that, for the vast majority of Generation Z, their use of generative AI is functional and based on accomplishing tasks. For example, many Generation Z members are using generative AI in place of conventional search engines, for creating or developing written projects and for increasing their productivity at work. Furthermore, patterns of use for generative AI are very appropriate for Indian youth, who experience significant academic competitiveness, challenging work responsibilities, and heightened pressure to continually keep their skills up to date. Three major concerns define Gen Z's views on generative Artificial Intelligence (AI). The first is an anxiety about the ability of generative AI to provide opportunities for learning through doing and thus building the physical/cognitive skills required to complete tasks. The second is that individuals will stop using critical thinking because there is easy access to information produced by generative AI. The final concern is that AI will reduce the number of opportunities for learning that occur through face-to-face interactions with peers and mentors. This concern is even more important in the context of India's collaborative culture and the importance of teacher/student interactions for skills development. In summary, Gen Z has a complex relationship with generative AI due to utility as well as uneasiness. Increasing use of generative AI in both academic and professional settings decreases productivity while creating concerns about quality of learning, amount of cognitive load required for learning and the way in which individuals will interact socially using generative AI. This duality of utility and uneasiness is critical in understanding Gen Z's relationship to generative AI across India where youth skill development and employability are key areas of focus. As such, this duality should serve as the basis for additional studies involving AI adoption, human capability, work and education into the future. The study undertaken here aims to examine the effect of Overreliance, Perceived Usefulness, Emotional Attachment and Trust on AI Addiction.

2. Literature Review

Due to the explosion of use and availability of generative AI (Gen AI), humans are beginning to express their intellectual, creative and professional abilities in different ways. The key to understanding how the World will work and learn in the future is through the emerging cohorts of Generation Z, who are among the earliest adopters of Gen AI technology. Gen Z users of Gen AI are both numerous and indecisive, indicating a complex relationship between a concern for the future of human ability and the efficiency of technology (Lira et al., 2026). Researchers moved from an early position of treating digital technologies as neutral tools that enhance the productivity and effectiveness of work to a contemporary understanding that AI systems are socio-technical agents that can impact the behaviour, feelings and thoughts of their users (Turkle, 2011). Today's AI systems notably conversational agents and generative tools offer continuous access, customized experiences and human-like interaction which foster increased engagement and dependence by users compared to previous forms of information technology. Preliminary research demonstrating that individuals are often willing to defer to intelligent systems in the interest of enhancing their productivity; for example, research on automation and algorithmic decision-making indicates that deferring to intelligent systems cannot be done while simultaneously maintaining one's critical thinking and self-control. The research on automation bias indicates that users frequently adhere to an algorithm’s recommendations over other contradicting information that they receive, which can produce erroneous decisions (Skitka & colleagues, 1999). As users get more accustomed to receiving positive outcomes from an automated system, the system becomes habitual; thus, a user's ability to be alert and make independent decisions declines over time. Despite algorithms being objectively superior to humans, the manner in which someone uses an algorithm is influenced in complex ways by their psychological response to both algorithmic errors and perceived intelligence; consequently, there are instances of both resistance and overreliance on an algorithm (Dietvorst et al., 2015; Logg et al., 2019). With the growing body of research focused on cognitive reliance on AI, researchers have also examined the emotional and social aspects of AI interaction. According to research conducted using the computers-as-social-actors paradigm, humans apply social rules and emotional responses to interactive technology even when they consciously recognize that the technology is not human (Reeves & Nass, 1996). Although the research base related to how users end up communicating with chatbots is limited, most users report high levels of emotional expression towards AI systems and feel a similar degree of psychological comfort, emotional relief and understanding as they do in human–human interactions (Ho et al., 2018). The ability to emotionally connect with the AI can lead to continued utilization of the technology and an increased attachment to the technology (especially among users experiencing anxiety, loneliness, or a lack of control) (Brailovskaia & Margraf, 2023).

2.1 Overreliance on Artificial Intelligence

Users can have an "overreliance on intelligent systems", which means they rely too heavily on automated/AI-based technology, often in excess of the proper/ideal levels. Automation misuse has been found to occur when people have an excessive reliance on technology that is unreliable or inappropriate; both of which lead to poorer decision-making processes and less monitoring on part of the user (Parasuraman & Riley, 1997). As automation becomes more complex, trust and reliance heuristic are heavily influenced by user understanding of how automation works or their lack thereof (Lee & See, 2004). A large body of empirical research has documented automation bias, meaning that users can be prone to accepting the automated or AI recommendations, even in the presence of consistently opposing evidence. Cognitive laziness and excessive reliance on technology for delegation of responsibility are both contributing factors to this phenomenon (Skitka et al., 1999). Research regarding technology addiction suggests that the compulsion to constantly use technological devices can distort people's cognitive beliefs about them (Griffiths, 2005). Specifically, they often believe that technology usage is an absolute necessity, as well as lack any belief or idea of how much control they over how often they have to use it. AI environments because of their continuous availability and the perception by users that they are engaged in an intelligent conversation (and being helped as such). Thus, within these environments, excessive reliance on such products and processes creates an environment for an individual to develop an AI addiction through continual, habitual and unrealistic dependence on an intelligent system. Thus, in the context of Overreliance on Artificial Intelligence, the following hypothesis is proposed:

H1: Overreliance on Artificial Intelligence has a positive impact on AI Addiction.

2.2 Emotional Attachment

Technological attachments are emotional constructs developed between technology users and systems that provide users with companionship, psychological comfort, or emotional satisfaction. Para-social interaction, a term coined in the 1960s, describes how people create one-way emotional relationships with mediated experiences that simulate inter-personal communication (Horton & Wohl, 2006). AI systems that use conversational cues, adapt to user needs, and have human-like responses intensify this simulation of social intimacy and produce a deeper sense of emotional connection. Research in the media equation theory has demonstrated that people unconsciously utilise social norms and emotional responses towards computers and other digital agents, perceiving them as social entities rather than simply devices (Reeves & Nass, 1996). These socialised responses to digital entities can create an emotional bond or attachment, particularly when systems respond with empathy or adapt to users' emotional states. Theoretical models of addiction support the conclusion that emotional attachments foster emotion-oriented behaviours, whereby individuals develop coping mechanisms (such as using technology) to deal with stress, loneliness, or depressive moods (Griffiths, 2005). A reliance on technology for mood regulation will eventually create a psychological dependence on technology and subsequently produce withdrawal-like symptoms to a reduction in access to technology. Emotionally responsive AI systems may replace or enhance human social interactions and ultimately create a greater degree of dependence. Therefore, emotional attachments to AI systems play a significant role in creating AI addiction through the integration of these systems into users' emotional and psychological regulation systems. Thus, in the context of Emotional Attachment to Artificial Intelligence, the following hypothesis is proposed:

H2: Emotional Attachment to Artificial Intelligence has a positive impact on AI Addiction.

2.3 Perceived Usefulness

The idea of perceived usefulness is that a user believes using that specific technology is going to improve their work performance or work effectiveness. As identified in the body of research around technology acceptance, it is consistently one of the primary influencing variables regarding the acceptance and continued use of technologies (Davis, 1989). After a user has obtained multiple instances of improved work performance through the use of technology, that technology becomes part of their daily routine and they no longer have to consciously evaluate whether or not they need to be using it. Conversely, because many people have developed dependency on technology and use it excessively, the research related to addictions shows that excessive use of technology causes users to have distorted cognitive evaluations. Therefore, users tend to overestimate the advantages of technology and underestimate the disadvantages (Griffiths, 2005). Users of technologies who are addicted to them or are developing an addiction to them will continue to justify their prolonged use of technology based on some functional justification such as benefits related to productivity, convenience or solving problems. Models of acceptance and trust demonstrate that perceived usefulness continues to impact users' intentions to continue using the technology even when there is uncertainty (Pavlou, 2003). As users experience AI systems as increasingly competent, they will be able to rationalize their excessive use of the system as either functional or needed. Thus, in the context of Perceived Usefulness of Artificial Intelligence, the following hypothesis is proposed:

H3: Perceived Usefulness of Artificial Intelligence has a positive impact on AI Addiction.

2.4 Trust

User's willingness, to access or rely on an AI system in uncertain and vulnerable situations is a direct reflection of trust in that AI system. Trust has been shown to be one of the most critical factors in driving a user's decision on whether to rely on an automated system or its outputs (Lee & See, 2004). Additionally, when trust is appropriately calibrated, it positively influences/provides for enhanced performance, while on the other hand, too much trust can lead to either misuse or over-reliance on the system (Parasuraman & Riley, 1997). Research demonstrating automation bias has shown that systems that are trusted can serve as a cognitive shortcut for the user, in turn, causing users to expend less effort checking and monitoring recommended activities or outputs from the automated system (Skitka et al, 1999). Another area of research related to trust has focused on building trust in digital environments and has found that an increase in trust will result in a decreased perceived risk and an increase likelihood of continued interaction/engagement with the digital environment (McKnight et al, 2002). As a user trusts an AI system more, they are more likely to rely on an automated system or use it to assist them in emotional decision-making, reducing the user's own self-evaluative reliance. This phenomenon creates an environment conducive to compulsive use of these types of systems, with trust being a primary reinforcement mechanism of the developing addiction to the use of an AI system. Thus, in the context of Trust in Artificial Intelligence, the following hypothesis is proposed:

H4: Trust in Artificial Intelligence has a positive impact on AI Addiction.

2.5 AI Addiction

The term AI addiction is a type of behavioral addiction that has a range of symptoms which can include salience, loss of control, tolerance, withdrawal, conflict, and relapse (Griffiths, 2005). In contrast to substance addictions, behavioral addictions are typically characterized by compulsive engagement with activities which provide psychological rewards. Due to their interactive, adaptive and emotional responsive qualities, AI systems are particularly good at facilitating this type of compulsive behaviour. Measurement methods of technology/internet addiction emphasise excessive use, dysfunctional functioning, and reliance on technology (Young, 2018). While these characteristics are easily seen in the context of AI use, where compulsive checking, emotional attachment, and difficulty disengaging are common reports from users. Studies have shown that addiction distorts our beliefs about technology and reinforces our understanding of the usefulness, reliability, and emotional comfort of technology (Griffiths, 2005). AI addiction emerges as the result of over-reliance on technology, a strong emotional attachment to technology, a high level of perceived usefulness, and a high trust in technology. Collectively, the four elements synergistically establish excessive use of AI and weaken self-regulation as key factors in creating AI addiction as a product of today's human-AI interaction.

Based on the above literature review, the following model of study was developed:

[Figure 1: Proposed model of study — image not supplied in the source manuscript]

Figure 1. Proposed Model of Study

3. Research Methodology

The systematic process of gathering, evaluating and interpreting data to answer research questions while upholding validity, reliability and ethical standards is known as research methodology. This research takes a quantitative and cross-sectional perspective on the effects of Overreliance, Perceived Usefulness, Emotional Attachment and Trust upon addiction to an AI. Primary data was collected via a structured questionnaire completed by users who actively use AI-based applications. Non-probability sampling, including both convenience and purposive sampling, was used to select respondents who were required to have relevant experience using AI technologies. All constructs were measured using a 5-point Likert scale (1 = “strongly disagree”, 5 = “strongly agree”). The final sample included 242 valid responses, which offered a strong basis for quantitative analysis and hypothesis testing to guarantee trustworthy results. The reliability of the measurement instrument was assessed via Cronbach’s alpha, yielding an overall value of

0.744, demonstrating acceptable internal consistency. Data analysis was performed using SPSS version 20; descriptive statistics and inferential statistics were used to examine the relationships between the variables. The dependent variable in the study is AI addiction, while the independent factors include Overreliance, Perceived Usefulness, Emotional Attachment and Trust. It looks at their combined impact on overuse of AI.

4. Data Analysis & Discussions

Table 1. Demographic Composition of Sample (n = 242)

Demographic	Frequency	Percentage (%)
Gender		
Male	97	40.1
Female	145	59.9
Age		
17–20	195	80.6
21–24	36	14.9
25–28	11	4.5
Educational Qualification		
Undergraduate (UG)	143	59.1
Postgraduate (PG)	99	40.9
Frequency of using AI		
Daily	117	48.3
Often	106	43.8
Rarely	19	7.9
Total	**242**	**100**

Correlation Analysis

Table 2. Correlation Matrix (Pearson)

	OR	EA	PU	TR	AD
OR	1	.401**	.318**	.409**	.527**
EA	.401**	1	.343**	.417**	.428**
PU	.318**	.343**	1	.447**	.077
TR	.409**	.417**	.447**	1	.424**
AD	.527**	.428**	.077	.424**	1

*Source: **. Correlation is significant at the 0.01 level (2-tailed). N = 242. The PU–AD correlation (r = .077) is not significant (p = .233).*

Pearson's correlation analysis was conducted to assess associations among overreliance (OR), emotional attachment (EA), perceived usefulness (PU), trust (TR) and AI addiction (AD). Of the three independent variables; OR ($r = 0.527$, $p < 0.01$), EA ($r = 0.428$, $p < 0.01$) and TR ($r = 0.424$, $p < 0.01$), displayed medium strength positive correlations with AI addiction, while the remaining independent variable PU, had a weak/ negligible correlation with AI addiction ($r = 0.077$, $p > 0.05$). Every independent variable exhibited positive significant correlations with the other independent variables indicating conceptual relatedness without evidence of multicollinearity issues.

Regression Analysis

Table 3. Regression Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.641	.410	.400	3.16291	2.070

Source: Predictors: (Constant), TR, OR, PU, EA. Dependent variable: AD.

According to the model summary, there is a good deal of variance in AI addiction that can be explained with the multiple regression model. The correlation coefficient (R) is equal to 0.641 which is strong indicating that there is a relationship between the independent variables (overreliance, emotional attachment, perceived usefulness and trust) and the dependent variable (AI addiction). The amount of variance accounted for by the independent variables in AI addiction according to the R squared value was 0.410, which means that 41% of the variance in AI addiction can be attributed to the independent variables. Additionally, the adjusted R squared value of 0.400 indicates that there is stability in the model after taking into account the number of predictor variables. There were no indications of autocorrelation found in this data set based upon the Durbin - Watson statistic obtained from the analysis (2.070); thus, all of the regression assumptions were met.

Table 4. ANOVA — Regression Model

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	1650.576	4	412.644	41.248	.000
Residual	2370.949	237	10.004		
Total	4021.525	241			

Source: Dependent variable: AD. Predictors: (Constant), TR, OR, PU, EA.

The significance of the regression model for explaining AI Addiction was confirmed by the ANOVA Results. The Result indicated that the Regression sum of squares (1650.576) plus the residual sum of squares (2370.949) - or total amount of variance accounted for between groups - accounted for a large percentage of the decrease in total variance between the variables being measured. The ANOVA Results demonstrated an F value of 41.248, using degrees of freedom 4 and 237, whose significance level at 0.001 demonstrates that the combined effects of over-reliance, emotional attachment, perceived usefulness, and trust predict AI Addiction in total and how well the model represents the data measured.

ANOVA

One-Way ANOVA of AI Addiction Across Age Groups

Table 5. One-Way ANOVA of AI Addiction Across Age Groups

Source	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	6.569	19	.346	1.289	.192
Within Groups	59.530	222	.268		
Total	66.099	241			

A one-way ANOVA was conducted in order to determine if there was a statistically significant difference between AI addictions for different age groups. The between-groups sum of squares (6.569) and the within-groups sum of squares (59.530) indicates that there was no statistically significant difference between subjects' ai addiction by age group, with an F-value of 1.289 and a significance value of .192 which was larger than the .05 level of significance. Therefore, there was no evidence that age plays a role in influencing the level of ai addition in this sample.

One-Way ANOVA of AI Addiction Across Educational Qualification Levels

Table 6. One-Way ANOVA of AI Addiction Across Educational Qualification Levels

Source	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	8.535	19	.449	1.996	.010
Within Groups	49.965	222	.225		
Total	58.500	241			

The statistic F-tests indicated that there was a significant overall difference (F=1.996; p=.010) between AI addiction across groups providing evidence that educational qualification and AI addiction do differ from each other when analyzed separately by group (i.e., educational qualifications). In order to identify what specific educational/AI addiction relationships exist, a post-hoc test using the Games-Howell method was performed. The results of the post-hoc comparisons identified a small number of significant relationships across individual educational/AI addiction comparisons; however, the majority of comparisons across groups were not statistically significant; most confidence intervals, therefore, included a 0. This suggests that while overall educational qualifications do explain some level of variance in AI addiction; however, the variance that exists among the various levels of educational qualifications was not consistent.

5. Results & Findings

The correlation results show that Overreliance on AI, Emotional Attachment to AI's user experience and Trust in AI are the three major contributing factors of addictive behaviours toward AI. High levels of overdependence are strongly correlated with addictive behaviours toward AI, indicating that users' intellectual dependence on AI systems is an important factor in creating addictive behaviours. The presence of emotional connections to AI is also associated with reinforcing a user's commitment to a certain AI system because emotional connections embed an ongoing relationship to an AI system into the user's emotional & relational experiences. The findings also support the argument that purely functional benefits cannot, on their own, create an addictive behaviour toward AI without also having an emotional or cognitive reliance on the system. This provides partial support for the proposed conceptual model and provides initial empirical evidence to support the proposed hypotheses.

The results from regression analyses indicate that the proposed model is a strong explanation and predictor of AI addiction. In fact, the model explains approximately 40% of the variance in AI addiction, suggesting that cognitive, emotional and relational factors have a significant effect on users who exhibit addictive behaviour when using AI. Additionally, there is a strong R value which reflects that the four independent variables of overdependence, emotional attachment, perceived usefulness and trust have an overall impact on AI addiction that is collectively robust. Statistically significant ANOVA results support that the regression model provides a significant improvement over a null model and establish validation for the conceptual framework as a whole. Durbin-Watson statistic of 2.070 provides evidence of independence of residuals, thereby supporting the accuracy of regression estimates.

The ANOVA findings indicate little difference/variation in level of addictiveness of using Artificial Intelligence (AI) across age categories suggesting relatively even levels of addictiveness across all age groups and no indication that susceptibility to AI addiction is age dependant for respondents in the sample population. In addition, there is no strong evidence that the cognitive, emotional, and relational constructs associated with AI addiction are different based on age meaning that these constructs are somewhat consistent across all age groups. Further, these results suggest that the addictiveness of using AI is primarily influenced by patterns of use and psychological characteristics of addictive behaviour rather than the demographic characteristic of respondents. Thus, age is likely irrelevant for the purpose of understanding AI’s addictiveness in this context as it is unlikely that or worth exploring through differences in this characteristic.

According to the ANOVA findings, it appears AI Addiction (AI addiction) may differ according to degree of education qualifications, suggesting that one's educational background can affect how one interacts with and eventually develops AI dependency. This difference can include variations in both educational experiences and digital literacy as well as complexity of tasks performed at different stages of an individual's education; these differences can all impact the amount of usage/how dependent someone is on an AI-based system. However, additional analyses indicate that these effects are limited to specific degrees and not uniformly present across all degrees and that the degree of educational qualification impacts a person's AI dependency but does not determine it fully (the same may apply to other demographic factors). As such, the results suggest that in addition to the educational qualification factor, there may also be other psychological and behavioural explanations regarding one's AI dependency that may be considered more prominent than simply using demographic reporting factors alone.

6. Study Implications

6.1 Theoretical Implications

The results of this research will have important implications for future research and practice because they extend existing theories into a new area of research (AI addiction). First, results provide strong support for Behavioural Addiction Theory, which posits that addiction is characterised by loss of control, emotional dependence and compulsive behaviour. The findings from our sample demonstrated the significant influence of over-reliance and emotional attachment on the transition from purposeful use of AI technologies to addictive behaviours and therefore validate the application of Behavioural Addiction Theory to AI technologies. Second, this study provides empirical evidence supporting Automation Bias Theory through the demonstration that over-reliance upon AI technologies is a significant predictor of AI addiction. While previous research has primarily examined the influence of automation bias on the accuracy or effectiveness of decision-making, the results of this study provide additional insight into the psychological effects of automation bias by demonstrating habitual exploitation of automated systems and a decrease in self-regulation among individuals who are heavily reliant on intelligent automated systems. Third, the significant effects of emotional attachment and trust on addiction are consistent with Social Response Theory and the Media Equation Theory. Both theories suggest that people interact with intelligent systems in a manner similar to how they would interact with people. The results demonstrate that when intelligent automated systems are responsive to emotions and trustworthy, they develop relationships with users that are similar to relationships between two people, which can lead to increased psychological dependence and vulnerability to addiction for users of intelligent automated systems. Ultimately, the results challenge the assumptions of Technology Acceptance Theory (TAT), which emphasizes the importance of functional benefits as the main determining factor in continued technology use. Although useful technologies can help people adopt them, they do not necessarily sustain an individual's addiction to the technology; rather, the primary driving force behind addictive behaviours towards Artificial Intelligence systems is emotional and/or cognitive dependence. The results illustrate the limitations of traditional acceptance models from a theoretical perspective.

6.2 Practical Implications

The findings of the study can have a significant effect on educators and their students, corporations and their employees, AI developers and policymakers. There are excessive dependencies and emotional attachment that indicate there is a need to promote responsible, thoughtful AI use, especially in academic and other decision-making environments where too much reliance can be harmful to critical thinking. Added trust will be a primary predictor of AI addiction so designers developing AI systems should include features that facilitate human oversight instead of total reliance. Because the degree of perceived usefulness was only a slight predictor of productivity-focused AI adoption, it is important to adopt a balanced risk understanding of the behavioural risks tied to an individual's use of that productivity-focused AI product. Additionally, there were no significant differences in addiction-risk based on age, suggesting the risk of being addicted to AI spans every generation; thus, requiring multiple approaches for improving digital well-being. In conclusion, to improve the use of AI within education; therefore, organizations should include behavioural considerations into the design of AI, education and the policies that govern use.

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ROLE OF PERCEIVED SECURITY, TRUST, AND ATTITUDE ON CONTINUATION INTENTION FOR MOBILE BANKING APPS

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ABSTRACT

Stimulus-Organism-Response model is used to explore the effects of security, trust and attitude to analyse factors influencing users' continuation intention of mobile banking apps. Data was collected through a survey of 204 Gen Y millennials in Gujarat, India. Constructs such as perceived security, trust, attitude, and continuation intention were measured. PLS-SEM, a statistical technique suitable for complex models with small to medium sample sizes, was used. The findings show that perceived security positively impacts perceived trust, which in turn influences users' attitudes towards mobile banking apps. The factors trust and attitude influence security and continuation intention. Enhancing users' perception of security increases trust, fostering a positive attitude and increasing the likelihood of continued use. These findings have implications for mobile banking service providers. Addressing security concerns, building trust, and providing a positive user experience are crucial for user retention. Robust security measures, transparent communication about data protection, and a focus on user experience can contribute to sustaining user engagement and loyalty in the competitive mobile banking landscape. These findings also apply to broader strategies in digital banking, emphasizing the importance of security and trust in user retention.

Keywords: Mobile Banking, Perceived Security, Perceived Trust, User Attitude, Continuation Intention, PLS-SEM, Millennials, SOR theory

JEL Code: G21

1. Introduction

The world is influenced by new technologies every day and the banking sector also has changed drastically which involves mobile banking and internet, where the services are rendered out to the customers wholly through virtual assistance (Shaikh et al., 2015). The lifestyle of citizens of the current decade has changed due to increase in the use of digitalisation through internet, smartphones and online shopping, which as lead to the need of mobile wallets (Joshi & Chawla, 2024) Therefore, the need for mobile banking arises to enable online transactions, bill payments, balance enquiry etc., which can be accessed from anywhere and anytime. This flexibility causes enhanced use of mobile banking apps (Chen, 2012). Post the corona pandemic Indian government has made mandatory to use the mobile wallets for those who have vetted the know-your-customer (KYC) norms, from April 2022 and the QR codes (Quick response) to be interoperable (Wright, 2022). Consequently, the adoption of digital payment systems has also increased. Banking companies incur the high cost for the app development, and hence to cover the cost and sustained the business it is necessary to have loyal and regular users. As acquiring the new customers cost more than the retaining a customer. Despite the increase in the growth of using mobile banking applications, certain factors play a vital role to stick on to the particular mobile applications. The users must feel safe to use a particular mobile application, hence the service providers should make sure that their users have confidence, privacy, security and integrity while using their mobile banking services. As all the data of the users are stored in the smart phones, the users face several issues when their phone is lost or stolen. Any layman can use or access the smartphones using forensic analysis techniques and various other software (Tsobdjou et al., 2024). This brings a big question mark for the users regarding the security, privacy and trust. Online shopping, educational institutions, hospitals, providers of digital wallets, government services and other commercials are the high-profile targets in India. Hence, increase in the use of mobile applications questions the security which leads to fluctuations in user's trust. Therefore, the trust influences the attitude of an individual towards continuation intention on a particular mobile banking application (Joshi & Chawla, 2024). This study focuses on the perceived security (PS), perceived trust (PT), attitude (ATT), and continuation intention(CI) of the mobile application users.

Various studies on technological adoption have been conducted that explored theoretical relationship between security, ATT, trust and intention & the influence of PS (S. Gupta et al., 2023; Mew & Millan, 2021; Trivedi & Yadav, 2020) Certain studies keep trust factor as a mediating factor to examine the intention variable through security and ATT. The gap arises as only trust acts as mediating variable and have direct connection to the outcome variable, whereas other variables are only interlinked (Banerji & Singh, 2021; Trivedi & Yadav, 2020). A study conducted by (Joshi & Chawla, 2024) focuses on PS, ATT, trust and CI regarding mobile wallets. The variables trust, ATT and gender play their roles as mediators and moderators. This paper sheds light on the research gap by focusing on the mobile banking applications by keeping both trust and ATT as a mediating variable. Nitzl (2014), states that most of the research focuses only on the direct relationship and does not give importance to the mediating effects which may give bias results. Hence, mediating role is given a vital role in this paper to analyse the CI.

This research aims to investigates the role of PS, PT, and ATT in influencing CI using SOR framework.

2. Literature review

"Theory of Reasoned Action (TRA)" postulates that "the attribute behaviour is evaluated by intention" (Vallerand, 1992). When an individual trusts and believes, that adopting a technology will bring their expected outcomes, then the ATT of an individual towards the technology would be positive in nature (Sinthiya, 2024). In addition to this intention was explained using "Theory of planned Behaviour(TPB)". "Technology Acceptance Model (TAM)" and "unified theory of acceptance and use of technology (UTAUT)" model was used to explain the technological adoption in previously published literature. In terms of digital payment, Conti et al. (2018) states that there is a risk involved in real time online transaction which affects the trust and belief of the users that influence the ATT of the users which in turn results in the impact of CI. The behaviour of an individual is categorised in three stages as per SOR model. They are environmental stimuli perception (S), cognitive, emotional or mental states of an individual (O) and the response (R). it is stated that external stimuli (S) and cognition (O) of an individual influences the final response of an individual (R) (Molinillo 2022). This study concentrates on relationship between Trust and ATT factors, and therefore SOR model which illustrate the relationship between PS - PT and ATT – CI model is used.

Therefore, by integrating the above-mentioned theories, this study associates the mobile banking application user's behaviour and responses by considering the factor of PS as a stimuli (S) that pushes to final outcome. In the same way, the cognitive and emotional factors refer to the organism (O), where ATT and PT is taken as the factors of emotion and cognition. Finally, the response (R) is driven through the stimuli and organism, that denotes the CI (CI) in this study (Ming et al., 2021). In this research work, ATT and PT are treated as mediating variable between PS and the CI.

2.1 Perceived security (PS)

The confidence of the consumers in adopting new technologies relates to the PS, which brings a strong confidence that the individuals' personal information will not be seen, modified or transferred by illegal persons (Lai, 2017). In brief, security is the assumption of an individual, when there is a reduced risk on financial data (Sarkar, 2020).

2.2 Perceived trust (PT)

Trust may find expression as "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trust, irrespective of the ability to monitor or control that other party"(Suh & Han, 2003). Singh et al. (2020) says that it is an emotional state motivating a person to trust another, which makes the customers to come out of risk and insecurity.

In the new age and the adoption of new technologies, PS includes digital signature, cryptography and certificates that protects the users from losing data, fraudster and hackers which automatically leads to trust (Ranganathan & Ganapathy, 2002;Kim, 2008). Flavián (2006) and Mukherjee & Ryan (2020) have proved that perceived risk and PS are related. An empirical study in mobile commerce revealed that PS and PT are related (Sarkar, 2020). Hence, this study put forth the hypothesis as,

H1: PS significantly influence PT

2.3 Attitude (ATT)

According to Vallerand et al. (1992) ATT may be postulated as "a disposition to respond favourably or unfavourably towards some psychological object." This study considers ATT of an individual towards mobile banking applications adoption as it is determined by the belief and trust perception. Also, it can be stated that ATT is the preference of the individual over the alternatives (Amoroso & Lim, 2017). Generally, customers compare the mobile banking applications with other digital payment modes that is in existence, not only based on the cost but on many other advantages (Garrouch, 2021). Hassan (2016) states that belief determines ATT of acceptance and adoption.

A study revealed that mobile banking users in South Africa, developed knowledge-based trust that involves benevolence, integrity and perceived competence which results in their ATT (Shaikh et al., 2015). Therefore, trust in an important factor for the digital interactions, just like human interactions (D. H. Shin, 2010). Research on Korean internet users, revealed that trust factors influence the consumers ATT and their intention towards online banking Suh and Han, (2003). Similarly, a recent study on mobile application adoption finds that trust impacts ATT positively (Hajiheydaria & Ashkan, 2018). Literature on recent studies shows persistent positive link between trust and ATT (Fan et al., 2020; Mew & Millan, 2021; Moriuchi, 2021). Hence, this paper states,

H2: PT significantly positively influences ATT.

2.4 Continuation Intention (CI)

Continuation intention refers to the stick to the one product and services and continue using it. With regard to financial applications, it implies that the users show positive sign on PS and PT so their ATT towards sustaining on the mobile banking application will be positive (Hassan, 2016). Intention to continue can be taken as a response to perceived value of users as a result of benefits obtained and risk undertaken (Dararuang et al., 2021). At an early-stage CI is used as a dependent variable to study the technological acceptance (Manuel, 2011)

CI and PT are related (Patel et al., 2020; Trivedi & Yadav, 2020). Studies on mobile banking applications, mobile shopping, online banking and e-healthcare records have been done by Cole et al. (2014; Garrouch (2021; K. Gupta & Arora (2019); Mew & Millan (2021) (Marriott & Williams, 2018); (Suh & Han, 2003) (Bashir & Madhavaiah, 2014). PT determines CI of an individual (Manuel, 2011). Other researchers have also found that PT influences the CI (Afshan et al., 2018; Bashir & Madhavaiah, 2014). Hence, this hypothesis is proposed.

H3: PT influences CI.

According to the TPB, ATT and CI have significant relationship (Vallerand et al., 1992). The ATT of Norwegian users on the mobile chat services shows positive influence on intention (Afshan et al., 2018). Previous articles on mobile payments (Ajina et al., 2023), digital shopping (Khalilzadeh, 2017) and technological adoption (Belanche, 2012; Manuel, 2011; Moriuchi, 2021; Y. H. Shin, 2017), have also shown positive influence on ATT and intention. Therefore, this can also be associated with the mobile banking applications, where similar results are expected with ATT and intention.

H4: ATT influences CI

Apart from finding the direct relationship among PS and CI, this study tests the impact of PT and ATT as a mediating variable. Therefore, the study puts forth these hypotheses:

H5: PT mediates between PS and CI

H6: ATT mediates between PS and CI

The influence of serial mediation of ATT and PT on PS and CI is also tested through the following hypothesis:

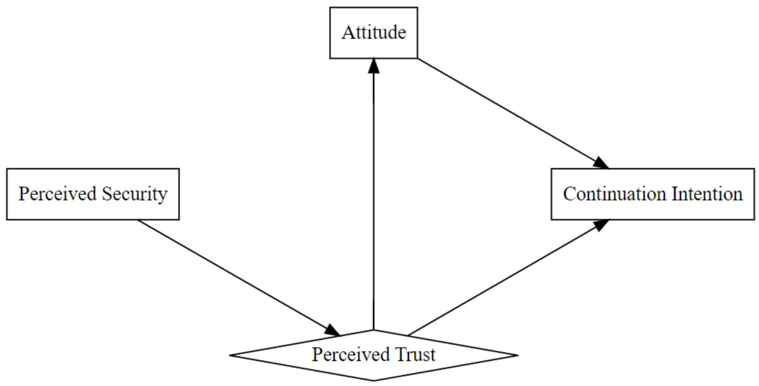
H7: PT and ATT mediate between PS and CI

3. Methodology

3.1 Measures

Variables PS, PT, ATT and CI are taken for the study. The scales were obtained from previous studies. Flavián et al. (2006) provided the scale of PS and was measured using eight item scales. PT was measured using six item scales (Shaw, 2014), (Belanche, 2012). ATT and CI were measured using four item scales each (Davis, 1989) and Venkatesh (2012) respectively. Demographic details such as name, marital status, level of education and digital shopping experience were collected.

Figure 1. Theoretical Framework



Source: Author's creation

3.2 Sample and data collection

A quantitative approach was pursued using "a cross-sectional design". A systematic questionnaire was framed to collect data. The questionnaire was sent to the GEN Y millennials (1986 and 1996) (due to scope of this research work and due to reasons outlined in Van Deventer (2017)) in Gujarat through google form link. The details of the millennials were taken from the alumni records and other purchased database. Out of 1200 questionnaires that were sent via WhatsApp chat, WhatsApp status, text message and emails, 255 questionnaires were received back. After removing the unfilled and inappropriate questionnaire, 204 responses were determined as appropriate. Sample characteristics are tabulated below in table 1.

Table 1. Sample Characteristics (n = 204)

Characteristic	Count	Percentage (%)
Gender		
Female	67	32.84
Male	137	67.16
Education		
Graduation	50	24.51
Post-graduation	139	68.14
Other	24	11.76
Marital status		
Married	114	55.88
Unmarried	75	36.76
Other	6	2.94
Occupation		
Salaried employee	129	63.23
Self-employed / Business	31	15.19
Others	44	21.56

Characteristic	Count	Percentage (%)
Annual Income		
Less than Rs. 5,00,000	89	43.63
Rs 5,00,000 to Rs 10,00,000	106	51.96
More than Rs 10,00,000	18	8.82

Source: SPSS output

4. Data Analysis

PLS-SEM employing Smart PLS 4 software tested the proposed model. PLS-SEM is an efficient technique to determine relationship among the variables within the predictive power, and it can also be used to test small number of respondents. Therefore, this research uses PLS-SEM as the research is conducted using limited number of respondents and to reveal the direct and indirect relation between variables (Hair Jr, 2017).

4.1 Measurement model assessment

Model Reliability and validity was assessed using guidelines proposed by Hair et al. (2019). The outer factor loading check reliability of the indicator. The values in the table 2, satisfy the threshold values (>0.40 and >0.70) stated by Leguina, (2015), which shows good reliability of all constructs. Internal consistency is checked using values of Cronbach's alpha (CA), Composite reliability (CR). The value in the table satisfies the requirement of threshold value >0.7 (Hair, 2019) which shows greater variable internal consistency in the scales. The AVE values are used to determine the convergent validity of the model. The values of AVE in the table satisfies the threshold value (greater than 0.5), specified by Hair (2021).

Table 2. Factor Loadings, CR, CA and AVE

Construct / Indicator	Factor Loading	CR	CA	AVE
Attitude (ATT)		**0.906**	**0.916**	**0.780**
ATT1	0.893			
ATT2	0.905			
ATT3	0.864			
ATT4	0.870			
Continuation Intention (CI)		**0.922**	**0.924**	**0.763**
CI1	0.835			
CI2	0.863			
CI3	0.891			
CI4	0.895			
CI5	0.881			
Perceived Security (PS)		**0.881**	**0.901**	**0.555**
PS1	0.637			
PS2	0.636			
PS3	0.721			
PS4	0.572			

Construct / Indicator	Factor Loading	CR	CA	AVE
PS5	0.797			
PS6	0.893			
PS7	0.812			
PS8	0.831			
Perceived Trust (PT)		**0.933**	**0.937**	**0.749**
PT1	0.906			
PT2	0.798			
PT3	0.843			
PT4	0.902			
PT5	0.890			
PT6	0.850			

Source: Smart PLS-SEM output

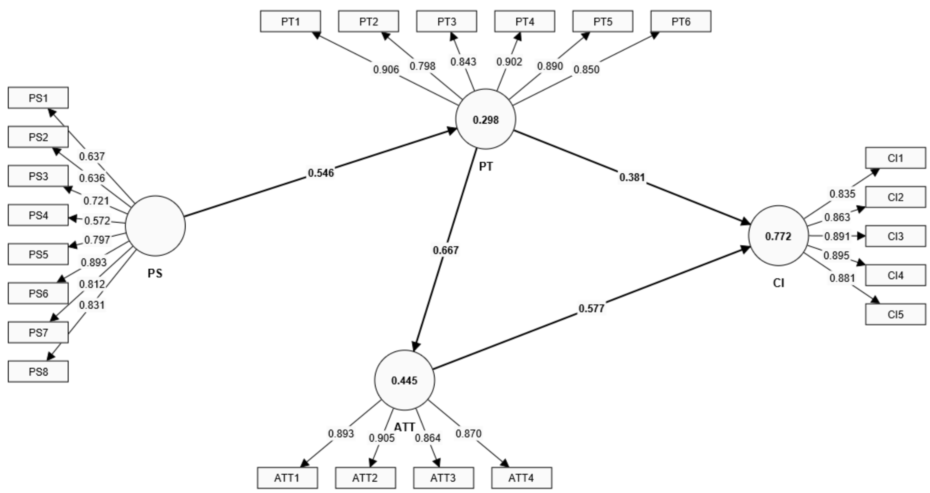


Figure 2. Measurement Model

Source: Author's creation

4.2 Discriminant validity

Model Evaluation needs to be done using convergent and divergent validitation (Hair Jr, 2021). The "heterotrait–monotrait (HTMT) ratio of correlations" (Henseler, 2015) is used to assess the convergent and divergent validity of the model. The threshold value for HTMT ratio is less than 0.9 (Henseler, 2015). The values of the HTMT in the table satisfy the threshold value, hence all the correlations are retained in the model.

Table 3. Discriminant Validity — HTMT Ratios

	ATT	CI	PS	PT
ATT	0.883			
CI	0.831	0.873		
PS	0.600	0.594	0.745	

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	ATT	CI	PS	PT
PT	0.667	0.766	0.546	0.866

SOURCE: Smart PLS-SEM output

4.3 Structural Model Assessment

Bootstrapping technique proposed by Hair and Alamer, (2022), is used to evaluate the model framed. It is utilized to test the significance and to predict path coefficient of the variables. The path outcome of the PLS SEM is given in table 4. The p values are significant as the values are below the threshold limit of 0.50 (Hair Jr, 2021).

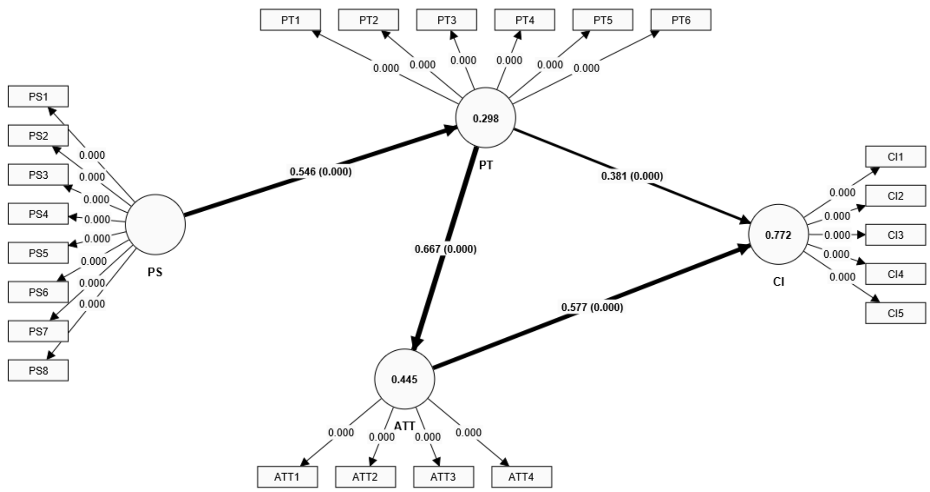

Figure 3. Structural Model

Source: Smart PLS output

Table 4. Path Coefficients

Hypothesis	Path	Path Coefficient (β)	T Statistics	P Values	Supported
H1	PS → PT	0.456	10.065	< 0.001	Yes
H2	PT → ATT	0.667	12.554	< 0.001	Yes
H3	PT → CI	0.381	6.138	< 0.001	Yes
H4	ATT → CI	0.577	8.007	< 0.001	Yes
H5	PS → PT → CI	0.208	4.140	< 0.001	Yes
H6	PT → ATT → CI	0.385	7.403	< 0.001	Yes
H7	PS → PT → ATT → CI	0.210	5.965	< 0.001	Yes

Source: Smart PLS output

The above table shows that H1 (B = 0.456, $p < 0.000$), H2 (B = 0.667, $p < 0.000$), H3 (B = 0.381, $p < 0.000$), H4 (B = 0.577, $p < 0.000$), H5 (B = 0.208, $p < 0.000$), H6 (B = 0.385, $p < 0.000$), H7 (B = 0.210, $p < 0.000$), are accepted as the P value is less than the threshold value of 0.05. It clearly depicts that PS has a strong influence on CI through ATT and PT. It also shows that PT has a strong influence on CI both directly and by mediating ATT, and ATT has a strong influence on CI. PT also has a strong influence on ATT.

The ability of the independent variables to explain the dependent variable is gauged by R^2 values. When evaluating R^2 values, 0.75 is considered "substantial", 0.50 is viewed as "moderate", and 0.25 is deemed "weak". (Henseler et al., 2009). Hence, the effect of independent variable PT on ATT is said to be moderate (0.445), the effect of independent variables PT and ATT on CI is substantial (0.772) and effect of PS on PT is weak (0.298). The effect size of the independent variables is measured using f square values, where the strength of each predictor variable is explained. Shmueli et al. (2019) states the effect size in three categories 0.02(small), 0.15(medium) and 0.35(large). By considering Chin, (1998) effect size ATT, CI, PT has large effect size. Shmueli et al.(2019) suggested blindfolded Stone-Geisser test (Q2 square) to analyze sample predictive power output for the model proposed with a threshold value above 0. The table 5 values of Q2 satisfies the thumb rule, which portrays the robust predictive power of the framework.

Table 5. R^2, Q^2 and f^2 Values

Construct	R^2	Q^2	Relationship	f^2
ATT	0.445	0.616	ATT → CI	0.810
CI	0.772	0.631	PS → PT	0.425
PT	0.298	0.643	PT → ATT	0.803
PS	—	0.441	PT → CI	0.353

Source: Smart PLS-SEM output

In PLS SEM, The "Standardized Root Mean Square Residual" (SRMR <0.08) and "Normalized Fit Index" (NFI = 0.9) are two widely used parameters to test the model fit (Henseler et al., 2016), with values of good fit as given (Sarstedt et al., 2021). The model proposed in current research is said to be well fitted as its SRMR value and NFI values fall within prescribed values.

5. Discussion

Customer perception of continuation use of mobile banking application is explored in this study through security, trust and ATT. The findings indicate that PS plays a crucial role in building trust by creating a sense of reliability. This finding aligns with past research findings (Lai, 2017). The research also explored that PS has an indirect impact on CI by influencing trust and ATT. Creating a secure environment can establish trust in the system or entity. Trust is crucial for users' ATTs towards a system or entity. When users feel secure, it has a positive impact on their perception (Garrouch, 2021). Trust in the system positively influences the ATT towards the continued usage of mobile banking apps. Trust not only influences the ATT, but it also influences the intention to persistently use mobile banking app. Interestingly, trust not only directly impacts the intention to use mobile banking apps but also affects continuation usage through the mediation of ATT. Past studies have shown that PT substantially impacts consumers' willingness to continue using a service (Manuel et al., 2011). By building trust, organizations can enhance users' ATTs towards the system, ultimately leading to a higher likelihood of continued usage. Enhancing trustworthiness can result in users perceiving things more positively. Trust and positive ATTs play a crucial role in decision of users to keep using the system or service, indicating that the service providers must concentrate on building and maintaining trust among the users to provide a positive ATT towards mobile banking applications. It can be achieved by bringing proper security measures, transparency and enhanced customer service which results in customer retention. But it is difficult for the service provider to devel deep into the cognitive and emotional factors of the customers. Therefore, to make it easier and simple user-centric environment can be implemented to increase loyal customers that provides positive experience that leads to retention.

It's important to address security concerns to build trust and influence user intentions. Investing in security measures and building trust among users is crucial. Organizations can create an environment that promotes user engagement and long-term success by prioritizing security, trust, and fostering positive ATT.

5.1 Theoretical and Practical implications

The current research through its findings and model contributed extensively to the theoretical knowledge in the field of CI in mobile banking. This study integrates the ATT and PT to reveal the relationship between PS and CI. The analysis highlighted strong positive connection between PS and CI, mediated by trust and ATT both directly and indirectly. The researchers attempted to find the drivers of CI of the mobile banking application users. The serial mediation analysis enlightens the depth of insights impact of cognitive and emotional factors of the mobile banking application users. By adopting theory of stimuli, organism and response (S-O-R), this study provides more evidence on the proposed variables. This study is successful in identifying the hierarchy of the variables which needs to be addressed step by step for achieving the adoption and continuation of the usage of new technology in context of fintech. By testing the S-O-R model for mobile banking applications, this finding provides an important addition to the existing literature.

It is essential to implement the findings and theories discussed above in practical contexts to enhance user experience and retain customers in mobile banking applications. As the study revealed that trust and ATT play a significant role in user CI, the service providers of banking applications can prioritize establishing and maintaining trust amongst the consumers to inculcate positive ATT towards their mobile banking applications. Implementing enhanced automatic security, transparency and loyal customer service can develop trust that leads to favorable ATT that results in retention of users. As the study emphasis on serial mediation, the significance of interconnection between trust and ATT in influencing user continuation is highlighted. By taking this in mind service providers can design personalized user experiences by focusing on both trust and ATT. The impact of cognitive and emotional factors of the users is paramount in determining the intention of the users. The service providers can tailor the strategies in such a way to keep engaged in the competitive mobile banking landscape. Therefore, all these factors can be put together to create a user-centric environment which leads to positivity in trust, ATT and CI that ultimately drives the mobile banking industry to achieve heights.

6. Conclusion

This study used the Stimulus-Organism-Response paradigm to examine how security, trust, and ATT affect mobile banking app users' CIs. A survey of 204 Gen Y millennials in Gujarat, India was conducted to collect data, and the collected data was analysied using SEM technique in Smart PLS. The results revealed that perceptions of security positively influence trust, which in turn impacts users' ATT towards mobile banking applications. Trust and ATT play important roles in the connection between security and ongoing commitment. Trust and ATT play crucial roles in connecting security and continued intention to use the app. These findings highlight the importance of enhancing users' perception of security to build trust, foster positive ATT, and increase the likelihood of continued usage. This study emphasises the significance of security, trust, and user experience in retaining mobile banking customers. The knowledge gained can help mobile banking service providers implement robust security measures, ensure transparent communication about data protection, and prioritise user experience to foster user engagement and loyalty in the highly competitive mobile banking industry.

6.1 Limitations and future scope

Apart from the insights provided in this study, it's important to acknowledge certain limitations of the study. Firstly, this study is confined to only a particular geographical area with a limited data set. There might be bias in the responses of the respondents in the primary data collection, which might provide unreliable results. Lastly, only mobile banking applications are considered for the study, where the results and the conclusions cannot be implemented for digital applications. Further studies can explore the impact of emerging technologies like artificial intelligence and blockchain on consumer trust, ATT, security and CI. The role of education and awareness programs in developing trust and ATT in mobile banking applications can be explored from the customers side which further provides more practical strategies for the service providers. Additionally trust and ATT towards the mobile banking app is influenced by other variables like, past experience, perceived corporate image, ease of use etc., in future research these variables can be explored.

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