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The Dark Side of AI-Enabled Financial Systems: Evidence from Problematic Use Behaviour

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Abstract

The rapid adoption of smart financial systems has transformed digital behaviours, raising concerns about excessive and problematic usage patterns. The study investigates the transition from adoption through use to problematic use of AI-based financial systems using a comprehensive view including the behavioural, cognitive and psychological dimensions of the user using Behavioural Addiction Theory, Automation Bias Theory, Social Response Theory and Technology Acceptance Model. A quantitatively based cross-sectional research design was used in collecting primary data from 484 active users through a structured questionnaire measured on a 5-point Likert scale. The data were analysed using SPSS version 20, applying Descriptive Statistics, Correlation Analysis, Multiple Regression Analysis and ANOVA. Results show that Usage Dependence, Affective Attachment and Technology Trust positively and significantly influence Problematic Technology Use. However, Perceived Consumer Value does not have a statistically significant direct effect on Problematic Technology Use suggesting that problematic behaviour due to the use of technology is more a result of behavioural and psychological mechanisms than it is a result of rational evaluation of the value of the technology. The regression model accounts for approximately 40% of the variance of the dependent variable indicating a strong amount of explanatory power of the model. ANOVA results indicate no significant differences across age groups, while educational qualification shows statistically significant variation in problematic usage levels. The study concludes that problematic use in AI-enabled financial systems emerges from Usage Dependence, Affective Attachment and Technology Trust, emphasizing the need for responsible system design, user awareness and regulatory attention. The findings underscore the need for responsible AI design, enhanced user awareness and targeted intrusions to prevent problematic usage behaviours.

Keywords: Affective Attachment, AI-Enabled Financial Systems, Problematic Technology Use, Technology Trust, Usage Dependence

1. Introduction

The rapid development of artificial intelligence (AI) has made a huge change in financial services, with AI-powered financial systems providing greater efficiency, tailor-made services, and the ability to make decisions on the spot. They extend from services in digital payments and robo-advisory to automated crediting and fraud detection processes. Therefore, there is an increased reliance on such technologies in performing routine financial functions, which has led to their popularization among various population groups. While existing research has extensively examined the determinants of technology adoption and continuance, relatively limited focus has been directed towards the post-adoption consequences, specifically the emergence of problematic technology use. Problematic use involves overuse, compulsion or maladaptive use of technology and potentially hinders users' behavioural regulation capacities. In the context of AI-enabled financial systems, this raises critical concerns, as over-reliance on automated decision-making tools may reduce users' cognitive engagement and financial awareness. Theoretical perspectives such as the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) have traditionally emphasized rational factors, such as perceived usefulness and ease of use, as key drivers of technology adoption. However, these frameworks offer limited explanations as to why users continue with technology usage even when usage becomes automatic, addictive or excessive. To fill this theoretical gap, this study takes a more holistic interdisciplinary view by incorporating Behavioural Addiction Theory, Automation Bias Theory, and Social Response (Media Equation) Theory. Automation Bias Theory suggests that there is a propensity for individuals to overly rely on and accept the outputs of automated systems without further assessment and verification, especially in a complex decision-making context. This is very likely to occur in AI-enabled financial systems, where there is usage dependence or an over-reliance on automation with the aid of recommendations and processes on the system. Likewise, Social Response Theory assumes that individuals develop social and emotional bonding with a technology, leading to an affective attachment, which, again, results to the reinforcing of repeated usage. In addition, technology trust is a major factor in financial contexts as it not only reduces risk but also helps in establishing repeated use of digital systems. The perceived consumer value remains an important factor in adoption, however, its ability to explain problematic use remains unclear, thus the need for further exploration. Against this backdrop, the present study seeks to examine the transition from adoption to problematic use of AI-enabled financial systems through four determinants of usage dependence, affective attachment, perceived consumer value, and technology trust. By nominating the addiction and behavioural mechanisms instead of rational adoption, this study makes a behavioural and psychographic clarification of digital financial technologies in the long run. The study further addresses an important empirical gap by examining whether problematic usage is based primarily on value or dependence and emotional attachment to technology.

2. Literature Review

The growth of digital technologies and intelligent systems has helped to radically reshape behavioural outcomes and this transformation has resulted in heightened levels of engagements and dependencies, as well as evolving paradigms of technology-use. As digital platforms become a quintessential part of everyday life, understanding the factors prompting excessive and problematic technology use has gained much attention amongst latest research. A key factor in user behaviour is technology that is integrated into daily routine encouraging habitual and automatic use. As individuals interact with digital systems in similar contexts repeatedly, their behaviour becomes less conscious and more automatic. Habit theory stipulates that past behaviour considerably influences future behaviour, particularly when the behavioural sequence requires little cognitive intervention (Ouellette et al., 1998). Such repetitive engagement in digital settings initiates gradual usage dependence, wherein individuals rely heavily on technology for functional and psychological needs. Dependence on technology necessitates low cognitive processing, and users may become ineffective at regulating their behavioural efficacy. Other than habitual use, emotional engagement significantly contributes to technology usage patterns. Modern digital platforms offer tailored, interactive and rewarding experiences that create emotional bonds between users and technology. According to the social-cognitive theory, human behaviour is regulated by cognitive, emotional and environmental factors, with individuals being motivated by rewards and experiences that they perceive (Bandura, 2001). The instant gratification, entertainment and social validation provided by technologies further strengthen the affective attachment to technology, thus promoting prolonged and repeated technology usage. Trust in technology systems is yet another crucial factor that determines users' engagement. Trust eliminates the uncertainty and perceived risks and the basis for relying on the digital platforms for communication, carrying out financial transactions and decision-making. Studies indicate that trust is determined by system quality, reputation and perceived security, which are critical in driving users to interact with digital ecosystems (Mcknight, Choudhury and Kacmar, 2002). As trust in technology increases, users tend to engage with it more unquestioningly, thereby fostering increased reliance. In addition to this, the value perceived from technology also serves as a reinforcing factor for continued usage. Benefits such as convenience, efficiency, personalization and accessibility are some of the perceived values that technology fosters, strengthening further user engagement. This explains the ongoing digital transformation across industries, particularly in banking and finance, where the emphasis is on customer-centric services that maximize value and user experience (Vives, Capobianco and Claessens, 2019). This perceived value is a further pillar on which technology addiction is built. The role of artificial intelligence has changed these dynamics significantly as well. AI technologies such as recommendation engines, predictive analytics and automation have intensified these effects, increasing engagement and dependence on digital infrastructure (Erik, B., & Andrew, 2017). The lack of transparency in many AI systems, however, can pose challenges regarding user comprehension and agency, thereby affecting trust and behavioural results (Rai, 2020). Overall, problematic technology use is a combination of habitual behaviour, emotional attachment, trust and perceived value. Therefore, habitual behaviour, emotional attachment, trust and perceived value require further exploration as core factors of problematic technology use.

2.1 Usage Dependence

Usage dependence refers to the level to which an individual relies on technology to meet functional, social and psychological needs. It is evidenced in the studies that the more interaction with the technology ensues, the more strengthened are the habitual patterns that are eventually culminating to dependence (Van Deursen et al., 2015). Habitual usage based on the frequency of usage and reward expectancy reinforces the habit component of usage and increases technology usage. From a behavioural perspective, usage dependence has high correlation with addiction tendencies. Studies on social networking platforms indicate that usage dependence has a strong addiction-like attribute (Andreassen, 2015). This proves that dependence does not have to be based on what one does or achieves but also on feelings of the system and a psychological exploit to keep the user connected. In organizational and technological contexts, excessive reliance on information and communication technologies (ICTs) has led to increased dependence on users, causing stress and harm to well-being (Ragu-Nathan et al., 2008). This over-reliance is complemented by the benefits one gets from technology and associated emotional benefits. Moreover, technology addiction research emphasizes that dependence can lead to a distorted perception and decision-making capability in the user, thus, creating a bias towards continued use of technology, despite the negative impact (Turel, Serenko and Bontis, 2011). Likewise, unregulated usage refers to the failure of users to control their behaviour concerning digital media, leading to over-dependence (Larose, Lin and Eastin, 2003). Thus, in the context of Usage Dependence, the following hypothesis is proposed:

H_1: Higher levels of Usage dependence on technology have a positive impact on Problematic Technology Use.

2.2 Affective Attachment

Affective attachment refers to the emotional bond that an individual develops with a technology during repeated interactions and emotionally charged experiences with the relevant technology. With the advances in artificial intelligence and interactive technologies, technologies are increasingly designed to mimic the human emotions thus enhancing the emotional attachments. Studies have shown that emotional attachment to non-human entities, including AI and robotic systems, can stimulate social sentiments and trust on a level equal to those experienced in person-to-person relationships (Gillath et al., 2021). The factors that tend to enhance these bonds include empathy, responsiveness and relational factors that exist in the technology. In a digital environment, emotional contagion acts as a further mechanism for strengthening affective attachment. Technologies that are capable of emoting can affect users' affective states and result in a higher level of emotional attachment or engagement (Chuah and Yu, 2021). This process enables internalization of exhibited technology emotions, which results in stronger attachment to technology and enhanced experience. Furthermore, consumer engagement domain identifies emotional engagement as a core dimension that influences users' engagement with digital platforms. Emotional responses to content, interactivity and personalization play a substantial role in nurturing users' connection and sustained engagement with technology (Ma, Ou and Sian Lee, 2022). Emerging research on human–AI relationships suggests that users may develop strong emotional bonds with AI companions, driven by mechanisms such as emotional mirroring and reciprocity. This interaction is enough to cause an illusion of intimacy, leading to attachment and dependency (Chu et al., 2025). However, excessive emotional reliance on technology also tends to blur boundaries and yield negative effects. Also, studies on social networks show that although the communication provided by the computer environment is an additional source of emotional support, it does not always increase the level of well-being and sometimes even lowers the level of emotional support perceived by the individual (Shensa et al., 2016). Thus, in the context of Affective Attachment to Artificial Intelligence, the following hypothesis is proposed:

H_2: Greater Affective Attachment to technology has a positive impact on Problematic Technology Use.

2.3 Perceived Consumer Value

Perceived Consumer Value refers to the overall assessments made by consumers regarding the benefits they get from a given product or technology against the costs incurred. The value is in most cases a trade between what is gained and what is sacrificed in terms of economic, time and effort inputs. This is a subjective evaluation and differs from one individual to another, depending on their expectations and experiences. Perceived value is the overall utility assessment by a consumer resulting from a balance between the perceived quality and perceived sacrifice with value extending price and embracing a wide range of cognitive evaluations (Zeithaml, 1988). Over time, perceived consumer value has been conceptualized as a multidimensional construct. Perceived consumer value latterly got theorized into a multidimensional construct and the dimensions come out to be functional, emotional, social and value for money (Sweeney and Soutar, 2001). The multidimensional nature also stresses that consumers' decisions are not only influenced by the utilitarian aspects but also by the experiential aspects. Technology contexts critically perceive value as a driving force, shaping user behaviour and adoption decisions. Perceived usefulness and value advantage of a technology also influences adoption attitudes and behaviour (Fred D Davis, 1993). In fintech environments, perceived economic benefits such as convenience, efficiency and cost savings act as key drivers of adoption and perceived risks may reduce overall value perception (Appiah and Agblewornu, 2025). Thus, in the context of Perceived Consumer Value of technology, the following hypothesis is proposed:

H_3: Higher Perceived Consumer Value of technology has a positive impact on Problematic Technology Use.

2.4 Technology Trust

Technology trust refers to the extent to which users perceive that a technology system is trustworthy, secure, and capable of fulfilling its intended functions without causing any harm or uncertainty. Trust becomes an important issue in digital environments because of the lack of physical contact and uncertainty in online dealings. Studies show that trust lowers risk perceptions and encourages people to reveal information and conduct transactions (Mcknight, Choudhury and Kacmar, 2002). Thus, trust is conceptualized to include the trusting beliefs, trusting intentions, and institutional trust. In e-commerce contexts, trust is a fundamental aspect of consumer decision-making. This means that for any online transaction to be successful, there is a need for trust, as consumers are unable to trust electronic platforms otherwise (Kim, Ferrin and Rao, 2008). Trust eases uncertainties regarding privacy, security and transaction risks, thus bolstering confidence and the tendency to use such services. Also, trust has a strong correlation with perceived risk and behavioural intentions. On integrating trust with technology acceptance models, the studies indicate that trust holds significant influence on users' behavioural intentions in adopting and using digital systems in an environment of uncertainty (Pavlou, 2003). In the context of mobile and digital banking, initial trust has been found to have a direct bearing on user adoption behaviour, and thus the usage of technology-enabled services. In the context of emerging artificial intelligence, trust becomes even more important because people have to trust autonomous and more complex systems. In fact, trust is shown to be a salient factor in influencing the acceptance and continuous use of AI technological applications and solutions by moulding perceptions and attitudes among users (Choung, David and Ross, 2023). Thus, in the context of Technology Trust, the following hypothesis is proposed:

H_4: Higher levels of Technology Trust have a positive impact on Problematic Technology Use.

2.5 Problematic Technology Use

Problematic Technology Use refers to digital technologies' excessive, compulsive or inappropriate use that causes psychological, social or functional harm. Problematic use, as opposed to normal use, involves loss of control, continued use despite damaging effects and addictive behaviour pattern. Studies theorize it as a behavioural addiction, whose gratification is obtained through the use of technology but its dysfunction in daily life is also a result of this use (Turel et al., 2011). Research highlights that problematic technology use stems from a habitual and compulsive nature. The increased, repeated use of smartphones or digital platforms becomes habit formation at the subconscious level, leading to compulsive addictive tendencies when the user does not intervene to control this pattern (Van Deursen et al., 2015). Immediate rewards like entertainment, social interaction and relief from emotion reinforce such behaviours and detachment becomes difficult. With regards to smartphones, problematic usage encompasses compulsive checking behaviours, dependency and technostress. Not only do users have to compulsively check their phones, but the level of use also depends on dependency and technostress caused by excessive use (Lee et al., 2014). Also, problematic technology use is not limited to individual-level outcomes and may have implications on social and organizational contexts. In the process, it has been linked to work overload, reduced productivity and conflicts between personal and professional life particularly for ubiquitous technologies such as mobile emailing (Turel, Serenko and Bontis, 2011). Overall, problematic technology use constitutes the "dark side" of digital adoption dynamics, wherein overreliance on technological tools and devices subverts user well-being and outcome efficiency to a degree that the phenomenon is a core variable in digital behaviour.

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

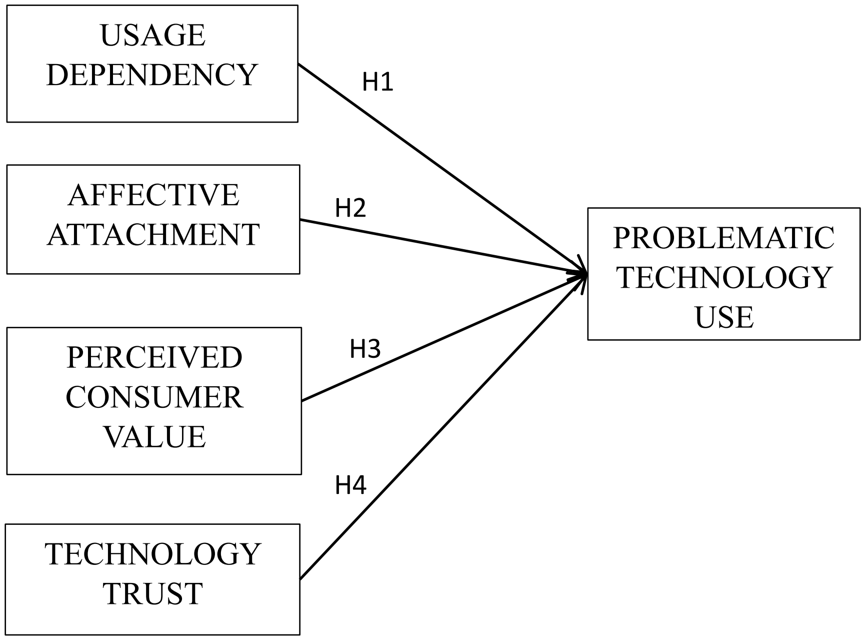

Figure 1 Proposed model of study

3. Research Methodology

Research methodology refers to the systematic process of data collection, analysis and interpretation intended at addressing research objectives with validity, reliability and ethics. The study uses a quantitative and cross-sectional research methodology to determine the impact of Usage Dependence, Affective Attachment, Technology Trust and Perceived Consumer Value on Problematic Technology Use. The primary data for the study was collected using a structured questionnaire administered on individuals who actively use digital technologies such as smartphones, social media platforms and AI-based technologies for financial decision-making. A non-probability-based convenience and purposive sampling technique was used to select respondents with prior and ongoing experience with digital technologies. All constructs in the study were measured using a 5-point Likert scale to maintain uniformity of responses and ease of analysis. Altogether, there were 484 valid responses in the final dataset which is a sufficient amount for conducting the statistical analyses, including hypotheses testing. Cronbach's alpha was used to test the reliability of the scale, which showed that the overall Cronbach's alpha coefficient was 0.744, indicating that the constructs were consistent enough. Data analysis is done using SPSS version 20, employing both descriptive and inferential statistical methods. Descriptive statistics were used to summarize demographic characteristics, while inferential analysis, which included Correlation Analysis, Regression Analysis and ANOVA, was used to analyse relationships between variables. In this study, Problematic Technology Use is a dependent variable, while Usage Dependence, Affective Attachment, Perceived Consumer Value and Technology Trust are independent variables. The research aims to analyse their combined and individual effects on excessive and problematic technology usage behaviour.

4. Data Analysis and Discussions

Table 1 Demographic composition of sample

Demographics	Frequency	Percentage
Gender		
Male	194	40.1
Female	290	59.9
Age		
17-20	160	33.1
21-24	170	35.1
25-28	154	31.8
Educational Qualification		
Undergraduate (UG)	286	59.1
Postgraduate (PG)	198	40.9
Frequency of using Fintech Applications		
Daily	234	48.3
Often	212	43.8
Rarely	38	7.9
Total	484	100

- **Correlation Analysis**

Correlations

		UD	AA	PV	TR	PU
UD	Pearson Correlation	1	.401**	.318**	.409**	.527**
	Sig. (2-tailed)		.000	.000	.000	.000
	N	484	484	484	484	484
AA	Pearson Correlation	.401**	1	.343**	.417**	.428**
	Sig. (2-tailed)	.000		.000	.000	.000
	N	484	484	484	484	484
PV	Pearson Correlation	.318**	.343**	1	.447**	.077
	Sig. (2-tailed)	.000	.000		.000	.233
	N	484	484	484	484	484
TR	Pearson Correlation	.409**	.417**	.447**	1	.424**
	Sig. (2-tailed)	.000	.000	.000		.000
	N	484	484	484	484	484
PU	Pearson Correlation	.527**	.428**	.077	.424**	1
	Sig. (2-tailed)	.000	.000	.233	.000	
	N	484	484	484	484	484

**. Correlation is significant at the 0.01 level (2-tailed).

Pearson Correlation Analysis shows that there is a strong positive relationship between Usage Dependence (UD) and Problematic Technology Use (PU) ($r = .527$, $p < 0$). Affective Attachment (AA) ($r = 0.428$) and Technology Trust (TR) ($r = 0.424$) also appear to have a moderate, significant and positive correlation with Problematic Technology Use (PU). The results show that UD is moderately related to AA (r = 0.401), PV (r = 0.318), and TR (r = 0.409). AA further correlates with PV (r = 0.343) and TR (r = 0.417). However, Perceived Consumer Value (PV) has a weak and insubstantial relationship with PU (r = 0.077, p > 0.05).

- **Regression Analysis**

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.641[a]	.410	.405	3.16291	2.070

a. Predictors: (Constant), UD, AA, PV, TR

b. Dependent Variable: PU

The regression results show a strong relationship between the independent variables and Problematic Use (PU) (R=0.641). The variance in PU is explained by Usage Dependence, Affective Attachment, Perceived Value and Technology Trust at 41%, as shown by the R Square value of 0.410. The model's reliability is confirmed by the Adjusted R Square (0.405) which also means it experienced a minimal reduction. Thus, the standard error of estimate (3.16291) shows that there is an acceptable prediction level. Also, with a Durbin-Watson value of 2.070, there was no autocorrelation, implying that the regression assumptions were met, and the model was statistically sound.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1650.576	4	412.644	41.248	.000[b]
	Residual	2370.949	479	10.004		
	Total	4021.525	483			

a. Dependent Variable: PU

b. Predictors: (Constant), UD, AA, PV, TR

The ANOVA results indicate that the regression model is statistically significant. The F-value of 41.248 associated with a significance level of p = 0.000 (p < 0.05) indicates that the model is an overall good fit for prediction PU (Problematic Use). The regression sum of squares (1650.576) are the measures of variation accounted for by the independent variables, whereas, the residual sum of squares (2370.949) is the measure of unexplained variation. The model has 4 degrees of freedom for regression and 479 for residuals. The significant F-value proves that the independent variables have a collective influence on the dependent variable.

ANOVA

One-Way ANOVA of Problematic Technology Use Across Age Groups

ANOVA

Age

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	13.138	19	.691	1.289	.192

Within Groups	119.060	464	.256		
Total	132.198	483			

One-way ANOVA was conducted to look at differences in Problematic Technology Use across age groups. The sum of squares between groups (13.138) is small compared to the sum within groups (119.060), suggesting that most of the variations lie within age groups. However, the F-value of 1.289 with a significance level of $p = 0.192$ ($p > 0.05$) shows that the differences across age groups are not statistically significant. The degrees of freedom are 19 and 464 for between and within groups, respectively, showing limited explanatory power of age. In total, the analysis shows that age does not play any significant role in problematic technology use.

One-Way ANOVA of Problematic Technology Use Across Educational Qualification Levels

ANOVA

Educational Qualification

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	17.070	19	.898	1.996	.010
Within Groups	99.930	464	.215		
Total	117.000	483			

One-way ANOVA was performed to test for differences in Problematic Technology Use based on the level of educational qualification. Thus, the one-way ANOVA was run to check for differences in Problematic Technology Use across educational qualification levels. However, the F-value of 1.996 with a significance level of $p = 0.010$ ($p<0.05$) indicates that differences across educational groups are significant. The degrees of freedom between the groups were 19 and 464 for within the groups, indicating a significant effect for educational qualification on problematic technology use. Overall, the results confirm that group differences are statistically significant.

5. Findings

1. Correlation results show that higher Usage Dependence on technology is the strongest factor associated with Problematic Technology Use, which means that the more one is dependent, the use increases drastically. Affective Attachment to technology also has a high contribution, where emotional bonding is attached to enhance engagement with technology. Technology Trust also established a positive correlation, indicating that increased trust heightens the likelihood of technology engagement, thereby raising the risk of problematic use. However, Perceived Value does not influence Problematic Technology Use, suggesting that perceived benefits do not explain to addiction. Behavioural and psychological factors such as dependence, attachment and trust are more critical than functional benefits in inducing problematic use.
2. Together, Usage Dependence, Affective Attachment, Technology Trust and Perceived Consumer Value have been confirmed by results to have a significant impact on Problematic Use. The regression results show that Problematic Technology Use is significantly influenced by Usage Dependence, Affective Attachment, Technology Trust and Perceived Consumer Value. The explanatory power ($R^2 = 0.410$) suggests that these factors account for a great portion of Problematic Technology Use. The significant

ANOVA results further validate the model. Overall, behavioural and psychological factors are core in driving excessive usage, although any other relevant variables may be important.

3. The ANOVA results are indicative of the fact that the experience of Problematic Technology Use does not significantly differ from one age bracket to another. This means there is no noticeable variation in excessive or uncontrolled use of technological devices with respect to age. This means that age does play a significant role as a determinant of problematic behaviour when applied in this particular case. Rather, social-psychological and behavioural factors such as dependence, emotional attachment and trust may be more significant. The focus should be on behavioural drivers than on demographic factors.
4. ANOVA results further show that Problematic Technology Use presents a significant difference based on the level/scale of educational qualifications. Education Qualification Differences in Problematic Technology Use. Hence, it is apparent that education partly influences an individual's interaction and regulation with technology use. This shows differences in awareness, digital literacy and usage of technology between Undergraduate and Post Graduate users. Education, unlike age which has an insignificant effect, seems critical in understanding problematic behaviour as a demographic. The information from this study proves that education background is something that should be considered when coming with intervention or ways of dealing with excessive use of technology.

6. Findings & Conclusion

By examining important factors such Usage Dependence, Affective Attachment, Technology Trust and Perceived Consumer Value, the study examined the effects of Problematic Technology Use of AI-enabled financial systems. Perceived Consumer value was insignificant, showing that functional benefits were not enough to warrant excessive use. These constructs were tested against Problematic Technology Use with 41% variance ($R^2 = 0.41$). ANOVA results reveal that age is not significant and there are significant differences for educational qualification. In light of Behavioural Addiction Theory, results indicate that the reward and repletion associated with AI system interaction can cause compulsive usage. Overall, the study suggests psychological and behavioural antecedents as major causative agents of problematic use of AI financial technologies.

7. Theoretical Implications

This research develops theoretical frameworks by merging Behavioural Addiction Theory, Automation Bias Theory, Social Response Theory and the Technology Acceptance Model to explain problematic technology usage. The results verify Behavioural Addiction Theory by showing how dependence and emotional attachment conclude in compulsive behaviour. Technology Trust illustrates Automation Bias Theory, as users excessively depend on AI systems without rigorous assessment. Social Response Theory explains affective attachment, positing that users interact with AI systems as though they were social entities. Moreover, the negligible influence of Perceived Consumer Value challenges conventional beliefs regarding the Technology Acceptance Model, indicating that mere usefulness does not result in detrimental behaviour. This combination of theories provides a broader theoretical framework beyond technology adoption, to explain the detrimental effects of technology use.

8. Practical Implications

The findings have key implications for financial systems that are AI-enabled such as digital banking, robo-advisors, and automated payment platforms. Financial institutions should, therefore, adopt digital well-being features such as usage alerts, spending caps, and decision-support transparency tools, given that usage dependence and emotional attachment fuel problematic use. On the other hand, to mitigate automation bias, design approaches should drive verification and critical thinking over blind reliance on AI recommendations. A higher degree of explainability in AI-driven financial decisions may help users understand risks better and avoid overdependency. On the other hand, they should avoid very persuasive and addictive design features that increase the level of attachment. Financial literacy programs may educate the user on responsible use of AI, including various levels of education. Finally, there is a need for organizations to strike a balance between efficiency and ethical design to avoid overreliance on AI in financial decision-making.

9. Directions for Further Research

This study lays a basis for problematic technology use in AI-enabled financial system but there are many areas for future research. First, future studies can use more variables, including self-regulation, digital literacy, perceived risk and ethical concerns, to improve the model's explained variance. Second, longitudinal research designs can be used to study changes in technology usage behaviour over time to gain more inclusive insights into the evolution of addictive behaviour. Third, future studies can be conducted on moderating variables such as age, gender and cultural differences to understand the implication of demographic and contextual factors in problematic use. Also, comparative studies in a cross-country or system of finance context can provide more generalizability. Specific AI applications, including robo-advisors or algorithmic trading, may also be studied for domain-specific behavioural patterns. Finally, qualitative approaches are helpful in complementing the conclusions of the quantitative methods and providing deeper insights into the perceptions and experiences of users.

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