"Facilitating Conditions and Mobile App Adoption among Retail Stock Traders: The Mediating Role of Behavioural Intentions and Moderating Role of Habit in Rupandehi, Nepal"

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Abstract

This study investigates the relationship between Perceived Risk, Perceived Return, Social Influence, Performance Expectancy, Effort Expectancy, Facilitating Conditions, and Adoption Behaviors among stock market investors. It aims to analyze how these factors individually and collectively influence Adoption Behaviors. Additionally, the research examines the mediating role of Behavioural Intentions and the moderating effect of Habit on the relationships between the independent variables and Adoption Behaviors. Employing a quantitative research design, data were collected from 384 stock market investors in Rupandehi District through a structured questionnaire, using convenience sampling. The data were analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The analysis included evaluation of measurement items, model fit assessment, Importance-Performance Map Analysis (IPMA), and bootstrapping techniques for hypothesis testing. The findings indicate that Perceived Risk, Perceived Return, and Performance Expectancy are significant predictors of Adoption Behaviors. These variables demonstrate strong influence in shaping investors' decisions to adopt stock market-related behaviors. The results underscore the critical role of these factors in driving Adoption Behaviors. Stock market management and policy makers should prioritize these dimensions to foster greater adoption among investors. By tailoring strategies and policies to address Perceived Risk, enhance Perceived Returns, and improve Performance Expectancy, there is substantial potential to boost investor engagement and adoption rates.

Keywords: *Perceived Risk, Perceived Return, Performance Expectancy, Adoption Behaviors and Behavioural Intentions.*

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I. Introduction

The rise of online stock trading has considerably transformed how individual investors operate, especially in developing regions such as Rupandehi District in Nepal. Despite improved access to digital trading platforms, many retail investors face obstacles that complicate their trading experiences. Issues like market fluctuations, a lack of trust in technology, and psychological challenges can negatively impact their investment choices, leading to poorly informed decisions and possible financial drawbacks (Cen, 2021; Hoffmann et al., 2013). In light of these challenges, it is crucial to investigate how facilitating conditions can help promote the use of mobile trading applications and alleviate the negative effects experienced by investors in this rapidly changing market landscape (Shih & Lee, 2017; Ng, 2020). Retail investors, especially millennials, have increasingly engaged in stock market activities, viewing them as viable means for financial growth and diversification (Singh et al., 2021). This trend has been exacerbated by recent global events, such as the COVID-19 pandemic, which has led to fluctuations in employment and income patterns, prompting many individuals to explore the stock market as an alternative source of income (Thapa & Parajuli, 2013).

Just having a stock trading app on your phone isn't a guarantee that you'll actually use it. Things like good internet, easy-to-use apps, and knowing how to use them are really important. If these things are good, people are more likely to not only download the app but also start trading. Mobile applications have become vital tools for retail investors seeking to improve their online trading capabilities. Research indicates that these mobile trading apps empower investors by offering immediate market data, user-friendly interfaces, and streamlined transaction processes (Raut & Das, 2017; Tai & Ku, 2013). Users of these technological solutions often report heightened levels of trading activity, primarily due to the convenience and immediacy afforded by mobile app usage (Fan, 2022; Blakesley & Yallop, 2019). However, despite these advantages, the varying adoption rates and mixed experiences among retail investors signal a need for deeper exploration into the determinants that drive investor engagement with mobile trading platforms (Wang et al., 2006; Potnis et al., 2020). Investors utilizing these technologies report enhanced trading experiences, which are attributed to the convenience and speed of mobile platforms (Tsai et al., 2014). Nonetheless, despite the promising benefits of mobile trading apps, variations in adoption rates and user experiences continue to raise questions about the factors that influence investor behavior.

Lots of studies have looked at why people use technology, including in finance, but we still don't fully understand what's happening in developing countries like Nepal. Many studies focus on richer countries where people are more comfortable with technology and have better internet. While some research has touched on using trading apps, not many have looked closely at how things like good internet and easy-to-use apps, combined with what people want to do and their habits, affect whether they actually trade in these markets. Specifically, we don't know much about how what people intend to do and whether using the app becomes a habit affects the connection between having the right conditions and actually trading in Nepal. Previous studies have addressed elements of technology adoption in financial services, yet there remains a significant gap in understanding how factors such as facilitating conditions, behavioral intentions, and habitual actions collectively shape the adoption behavior of retail investors in online trading contexts (Mirchandani & Gaur, 2019; Potnis et al., 2020). Many existing studies focus on individual constructs instead of investigating their combined impact, resulting in a limited understanding of investor behavior (Usman et al., 2020; Cen, 2021). This research aims to fill this gap by exploring how these various elements interact to influence mobile trading adoption among investors in the Rupandehi District.

The historical context of online trading in Nepal shows a shift from traditional investment methods to digital platforms, influenced by a growing awareness of global investment opportunities. The market has experienced technological advancements that facilitate mobile app usage among retail traders, allowing for greater accessibility and efficiency (Potnis et al., 2020). As a result, understanding the motivations behind this adoption is crucial for enhancing trading experiences for Nepalese investors and aligning mobile application features with user needs. The development of online stock trading in Nepal has coincided with significant progress in mobile technology, enabling investors to access trading markets with ease and speed. However, despite these advancements, there are still many retail investors who inconsistently adopt mobile trading applications, often facing barriers related to perceived risks and social influences that shape their decisions (Nguyen et al., 2020; Grant, 2020). Gaining insights into how these factors converge will provide valuable information for improving the trading experience for retail investors and cultivating confidence in mobile trading solutions within the relatively emerging financial framework of Nepal (Clor-Proell et al., 2020).

This research is important because it can help a lot of different people. For everyday investors, it can provide useful information about what makes mobile trading successful, so they can make smart decisions and feel more confident trading stocks on their phones. By understanding what helps or hinders people, they can figure out if they're ready for mobile trading and where they might need some extra help. For the stock market, this research can help get more people involved and make the market work better. If we know what's stopping people from using trading apps, we can find ways to encourage more people to participate, which is good for the market. This research has important implications for various stakeholders. Retail investors can leverage the findings to deepen their understanding of the elements affecting their trading behaviors and decision-making (Shiva & Singh, 2020). Developers of trading technologies can acquire meaningful feedback regarding user preferences, allowing for enhancements in app functionalities (Phung, 2020). Policymakers can use the research outcomes to create effective regulations that foster digital trading initiatives (Humbani & Wiese, 2019). Moreover, this study intends to establish a foundational framework for future investigations into the changing landscape of mobile trading technologies, contributing to a stronger and more effective online trading environment within the growing financial ecosystem in Nepal (Madhavan et al., 2020).

The research objectives of the study are as follows:

- To examine the relationship between perceived return, perceived risk, performance expectancy, effort expectancy, facilitating conditions, social influence and behavioral intentions
- To analyze the effect of perceived return, perceived risk, performance expectancy, effort expectancy, facilitating conditions, social influence affect behavioral intentions
- To assess the mediating effect of behavioral intentions on the relationship between facilitating conditions and adoption behaviors
- To assess the moderate effect of habits on the relationship between facilitating conditions and adoption behaviors

II. Review of Literature

This section presents a literature review, focusing on the theoretical and empirical aspects relevant to the current research being pursued. The theoretical review examines related theories that support the link between the variables mentioned in the framework. Moreover, the empirical review incorporates the findings of previous research conducted on the same topic.

The following theoretical and empirical reviews support the conceptual framework of the study and form the basis for the development of hypotheses.

Perceived Risk on Behavioral Intentions

Perceived risk is a foundational construct in decision-making theories and is particularly influential in shaping the behavioral intentions of investors in uncertain environments like the stock market. According to Bauer (1960), perceived risk is the subjective anticipation of loss or negative consequences associated with a decision. In investment contexts, this includes the fear of financial loss, emotional distress, or reputational harm. The Theory of Planned Behavior (Ajzen, 1991) offers a key framework, suggesting that behavioral intentions defined as the motivational factors that influence a behavior are shaped by attitude, subjective norms, and perceived behavioral control. Perceived risk diminishes positive attitudes and enhances perceived barriers, thereby weakening investors' intentions to participate in the share market. Furthermore, the Protection Motivation Theory (Rogers, 1983) argues that individuals assess both the threat and their coping ability before engaging in risky behaviors. Investors perceiving higher risks may lack self-efficacy or trust in mitigation strategies, leading to avoidance behavior. In the financial domain, the Technology Acceptance Model (Davis, 1989), when extended to fintech and trading platforms, suggests that perceived risk negatively moderates the relationship between perceived usefulness and behavioral intention to adopt stock market participation tools. Behavioral finance theory also contributes by emphasizing the role of cognitive biases, such as loss aversion and regret aversion (Kahneman & Tversky, 1979), which intensify perceived risks and negatively influence intentions. Thus, theoretically, perceived risk is seen as a deterrent to forming positive behavioral intentions toward stock investment, largely through its impact on attitudes, emotions, and perceived control.

Empirical studies across different markets have validated the significant impact of perceived risk on investors' behavioral intentions. For instance, Nguyen et al. (2019) conducted a study in Vietnam and found that perceived financial and psychological risks had a strong negative impact on individual investors' intentions to invest in the stock market. Similarly, Singh and Bhatia (2021) showed that Indian investors who perceived higher levels of market risk were significantly less likely to form intentions to invest, even if they had prior exposure to the stock market. Their study revealed that even perceived social risks such as judgment from peers in the case of loss also played a role in discouraging investment intentions. In addition, empirical evidence from the fintech sector, such as that by Featherman and Pavlou (2003), confirmed that perceived risk is a key inhibitor of technology-mediated investment behaviors, lowering the intention to use online platforms or invest via digital means. Shrestha (2020), in a Nepalese context, found that perceived risk especially financial and performance risks negatively influenced young adults' behavioral intentions toward entering the stock market. Studies have also shown that demographic factors such as age, income, and financial literacy moderate the relationship between perceived risk and intention. For example, Roszkowski and Grable (2005) found that financially literate individuals perceive less risk and thus have stronger behavioral intentions to invest. These empirical findings align closely with theoretical frameworks, reinforcing that perceived risk significantly undermines the formation of behavioral intention among potential and existing investors in the share market.

H1: There is a significant effect of perceived risk on behavioral intentions

Perceived Return on Behavioral Intentions

Perceived return refers to an investor's subjective evaluation or expectation of the potential profit or gain from investing in the share market. In behavioral finance, perceived return is a critical determinant of investment decision-making and plays a significant role in shaping behavioral intentions. According to the Theory of Reasoned Action and its extension, the Theory of Planned Behavior (Ajzen, 1991), behavioral intention is influenced by attitude, which is shaped by beliefs about the outcomes of a behavior. If investors believe that investing in shares will yield high returns, they are more likely to develop a favorable attitude, thereby increasing their intention to invest. This aligns with Expected Utility Theory**,** which suggests that individuals evaluate the expected benefits and make choices that maximize utility (Von Neumann & Morgenstern, 1944). In investment contexts, a higher perceived return enhances the expected utility of stock market participation. Additionally, the Technology Acceptance Model (TAM**)** and its financial extensions incorporate perceived return as an external variable affecting perceived usefulness, which in turn influences behavioral intention (Davis, 1989). In Behavioral Finance Theory, perceived return is also influenced by cognitive biases such as overconfidence and optimism, which can exaggerate return expectations and enhance behavioral intention toward investing (Barberis & Thaler, 2003). Therefore, from a theoretical perspective, perceived return positively influences behavioral intentions by strengthening investor attitudes, increasing utility expectations, and reinforcing the perceived benefits of share market participation.

Empirical research supports the theoretical claim that perceived return significantly influences the behavioral intentions of share market investors. Numerous studies have found that individuals with higher expectations of returns are more likely to form a strong intention to invest in equities. For example, Nguyen et al. (2019) found that perceived financial return had a significant positive effect on Vietnamese investors' intention to invest in the stock market. Similarly, Singh and Bhatia (2021) observed that perceived return was a major determinant of behavioral intention among Indian investors, even more influential than perceived risk in some cases. Their study also revealed that perceived return had a mediating effect on the relationship between financial knowledge and investment intention. In a study conducted in Nepal, Shrestha (2020) found that among young adults, perceived return played a crucial role in motivating initial investment behavior in the stock market, particularly when paired with moderate financial literacy. In developed markets, Lusardi and Mitchell (2007**)** found that individuals with a better understanding of financial concepts and higher perceived returns were more likely to express strong intentions to invest in stocks.

Moreover, Aren and Aydemir (2014) highlighted that perceived return, along with risk tolerance, significantly predicted individual investment behavior in Turkey. These findings confirm that perceived return functions as a motivational driver that enhances the likelihood of share market participation by influencing an individual's evaluation of the benefits associated with investing. Thus, enhancing perceived return through financial education, transparent market performance, and communication of potential long-term gains can positively influence investors' behavioral intentions.

H2: There is a significant effect of perceived return on behavioral intentions

Social Influence on Behavioral Intentions

Social influence plays a significant role in shaping individual decision-making, particularly in uncertain environments like the stock market. Within the Theory of Planned Behavior (TPB) developed by Ajzen (1991), subjective norms represent the perceived social pressure to perform or not perform a behavior. This concept reflects how social influence, including opinions from friends, family, and financial experts, can affect an investor's behavioral intention to participate in the stock market. If individuals believe that important others (e.g., peers or mentors) approve of or participate in investing, they are more likely to form a favorable intention to do the same. Similarly, Social Learning Theory (Bandura, 1977) asserts that behavior is learned through observation and imitation of others. When investors observe the success of peers or receive encouragement from social networks, their own intentions to invest may increase. Additionally, in the context of behavioral economics, herding behaviour where individuals mimic the actions of others rather than rely on their own information demonstrates how social influence can override rational judgment and shape investment intentions (Bikhchandani, Hirshleifer, & Welch, 1992). In sum, theoretical models across psychology and finance converge on the idea that social influence whether through norms, observational learning, or peer behavior can significantly shape the formation of behavioral intentions toward stock market participation.

Empirical studies have provided strong evidence that social influence significantly impacts the behavioral intentions of share market investors. For example, Nguyen et al. (2019) found that subjective norms had a statistically significant positive effect on the intention to invest among Vietnamese retail investors, especially among those with limited financial knowledge. Similarly, Singh and Bhatia (2021) reported that in India, social influence measured through family advice and peer behavior was a key predictor of equity investment intention, particularly for first-time investors. In a study conducted in Nepal, Shrestha (2020) highlighted those perceived social expectations from peers and family contributed to the growing trend of youth entering the capital market, often without adequate financial analysis. This aligns with Lim et al. (2016) who found that peer recommendations were more influential than financial news in shaping young Malaysian investors' intentions to participate in the stock market. Moreover, studies in behavioral finance show that during times of market volatility, herding behavior increases, and investors tend to rely more on social cues than on fundamental analysis (Chang, Cheng, & Khorana, 2000). Social media has further amplified this effect, with platforms like Reddit, Twitter, and YouTube becoming influential in shaping investment narratives and intentions, especially among younger generations (Yuan et al., 2021). These empirical findings support the theoretical models by affirming that social influence, through both direct interpersonal relationships and broader social channels, plays a pivotal role in shaping behavioral intentions toward share market investment.

H3: There is a significant effect of social influence on behavioral intentions

Performance Expectancy on Behavioral Intentions

Performance expectancy refers to the degree to which an individual believes that using a system, product, or service will help them achieve gains or desired outcomes in this case, financial returns or portfolio growth through share market investment. This concept is most prominently featured in the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003), where performance expectancy is identified as the strongest predictor of behavioral intention. Applied to share market contexts especially digital platforms and investment tools investors are more likely to form an intention to invest if they perceive that participating in the stock market will yield beneficial outcomes such as capital appreciation, dividend income, or financial security. In this light, performance expectancy mirrors constructs like "perceived usefulness" in the Technology Acceptance Model (TAM) (Davis, 1989), and overlaps with expected utility theory (Von Neumann & Morgenstern, 1944), where individuals evaluate choices based on expected returns. Moreover, in behavioral economics, an investor’s expectation of investment performance is shaped by both rational analysis and psychological biases like overconfidence and optimism (Barberis & Thaler, 2003). Thus, from a theoretical standpoint, performance expectancy positively influences behavioral intention by reinforcing beliefs in the instrumental benefits of investing, particularly when those benefits are clear, credible, and attainable.

Empirical evidence strongly supports the assertion that performance expectancy is a key driver of behavioral intentions to invest in the stock market. For example, Venkatesh et al. (2003), in developing the UTAUT model, found performance expectancy to have the most significant effect on intention across multiple domains. Applied to financial contexts, Alalwan et al. (2016) discovered that performance expectancy was the strongest predictor of behavioral intention to use mobile banking, a finding mirrored in investment platforms. Similarly, Singh and Bhatia (2021) reported that among Indian investors, the belief that stock market participation would result in long-term financial gains significantly boosted their intention to invest, especially when returns were perceived as superior to other financial products. In Vietnam, Nguyen et al. (2019) found that performance-related expectations, such as anticipated profit and portfolio growth, positively influenced retail investors' behavioral intentions. Shrestha (2020) also noted a strong correlation between perceived performance benefits and investment intention in the context of Nepal's stock market. The study highlighted that investors with higher expectations of share performance based on past market trends or peer experiences demonstrated a stronger intention to invest. Furthermore, Huang et al. (2011) observed that performance expectancy was a key motivator for users of online investment platforms in Taiwan, particularly among younger, tech-savvy investors. Collectively, these studies indicate that when investors believe their engagement with the share market will produce favorable financial outcomes, they are significantly more likely to intend to invest. Thus, performance expectancy plays a crucial motivational role in shaping behavioral intentions toward stock market participation.

H4: There is a significant effect of performance expectancy on behavioral intentions

Effort Expectancy on Behavioral Intentions

Effort expectancy refers to the degree of ease associated with the use of a system or service, and it plays a crucial role in shaping an individual's intention to engage with that system. In the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003), effort expectancy is identified as one of the core predictors of behavioral intention. When applied to the share market, particularly through digital trading platforms or investment tools, effort expectancy reflects how easily investors believe they can access, understand, and use these platforms to execute trades or monitor investments. If potential investors perceive that investing in the stock market requires minimal effort whether in terms of time, knowledge, or technical ability they are more likely to form positive behavioral intentions to participate. This concept is closely related to perceived ease of use in the Technology Acceptance Model (TAM) by Davis (1989), where easier systems enhance perceived usefulness and intention to adopt. Furthermore, effort expectancy also aligns with Self-Efficacy Theory (Bandura, 1986), which emphasizes that individuals are more likely to intend and act on a behavior when they believe they are capable of performing it easily. Thus, from a theoretical perspective, effort expectancy lowers the cognitive and operational barriers to entry in the stock market, positively influencing the behavioral intention to invest, especially among novice or technology-sensitive users.

Empirical evidence supports the theoretical proposition that effort expectancy significantly influences behavioral intentions to invest in the share market, particularly through digital channels. In the foundational UTAUT study, Venkatesh et al. (2003) found that effort expectancy had a significant impact on behavioral intention, especially during early stages of technology use. In a financial services context, Alalwan et al. (2016) found that ease of use was a key determinant of Jordanian consumers' intention to adopt mobile banking, a concept closely related to online investment platforms. Similarly, Huang et al. (2011) discovered that effort expectancy played a critical role in shaping the intentions of Taiwanese users to continue using online trading systems. In the investment domain, Singh and Bhatia (2021) reported that Indian retail investors were more inclined to invest through stock market apps and portals when they perceived the interfaces to be user-friendly and easy to navigate. Likewise, Nguyen et al. (2019) found that Vietnamese investors' intention to invest in the share market was significantly influenced by their perception of how easy it was to understand and use investment tools. In Nepal, Shrestha (2020) emphasized that first-time investors, especially students and young professionals, were more likely to show investment intentions when they found digital platforms intuitive and required minimal effort. Collectively, these studies confirm that effort expectancy reduces psychological and operational barriers, thereby increasing the likelihood of behavioral intention toward investing in the stock market, particularly in technology-mediated environments.

H5: There is a significant effect of effort expectancy on behavioral intentions

Facilitating Conditions on Behavioral Intentions

Facilitating conditions refer to the degree to which an individual believes that organizational and technical infrastructure exists to support the use of a system or the performance of a behavior. Within the Unified Theory of Acceptance and Use of Technology (UTAUT) framework, Venkatesh et al. (2003) identified facilitating conditions as a key construct that directly influences behavioral intention and actual usage, especially when users perceive that resources (e.g., time, money, internet access, or support) are readily available. In the context of share market investment, facilitating conditions may include access to digital devices, stable internet, user support services, financial advisors, educational content, and regulatory infrastructure. These external enablers reduce the perceived difficulty or cost of engaging with stock market platforms, especially among new or less tech-savvy users. This aligns with Triandis' Theory of Interpersonal Behavior (1977), which posits that facilitating conditions moderate the link between intention and behavior, making the intended behavior more likely if environmental supports are present. Similarly, Self-Efficacy Theory (Bandura, 1986) emphasizes the importance of environmental reinforcement and access to resources in enhancing confidence and forming intentions. The presence of robust infrastructure, technical assistance, and accessible platforms makes the investment process more approachable and less risky, thereby positively shaping behavioral intention. In summary, the theoretical foundation suggests that facilitating conditions are crucial contextual factors that support and strengthen an individual's intention to invest in the stock market.

Empirical studies consistently support the view that facilitating conditions significantly influence behavioral intentions toward share market participation, particularly in digital and emerging market contexts. Venkatesh et al. (2003) originally found that facilitating conditions directly affect usage behavior, especially when behavioral intention is already high. In more recent financial contexts, Alalwan et al. (2016) found that access to support services, stable internet connectivity, and mobile banking literacy positively influenced users' intention to adopt mobile financial services in Jordan. In the realm of stock investing, Huang et al. (2011) found that the availability of technical support and platform accessibility played a critical role in shaping the intention of Taiwanese investors to use online trading platforms. In Nepal, Shrestha (2020) observed that retail investors especially those new to the stock market demonstrated higher investment intention when they had access to educational resources, financial literacy programs, and responsive customer service from brokerage firms. Similarly, Singh and Bhatia (2021) reported that Indian investors showed stronger behavioral intentions to invest in equities when facilitators such as easy access to mobile trading apps, availability of demo accounts, and supportive investment environments were in place. Nguyen et al. (2019) also found that in Vietnam, facilitating conditions such as ease of account opening, low brokerage fees, and support from friends or financial institutions enhanced individuals' willingness to invest. These empirical findings underscore that when investors perceive strong external support and infrastructure, their confidence and intention to invest in the share market increase significantly.

H6: There is a significant effect of facilitating conditions on behavioral intentions

Facilitating Conditions on Adoption Behavior with mediating variable Behavioral Intentions

The relationship between facilitating conditions and adoption behavior is well-established in technology adoption and behavioral models, with behavioral intention frequently theorized as a mediating variable. According to the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003), facilitating conditions defined as the degree to which individuals perceive that an environment exists to support system use primarily influences actual behavior, particularly when behavioral intention is already formed. However, in other models such as the Theory of Planned Behavior (TPB) (Ajzen, 1991), external variables (like facilitating conditions) impact perceived behavioral control, which in turn affects behavioral intentions, eventually leading to the actual behavior. From this perspective, facilitating conditions (e.g., access to technology, time, financial knowledge, or support services) shape an individual's belief about their capability and ease of action, thereby influencing their intention, which subsequently drives adoption behavior. Additionally, Triandis' Theory of Interpersonal Behavior (1977) emphasizes that both facilitating conditions and intentions are necessary precursors to behavior, with intention serving as the immediate antecedent of actual behavior. The model suggests that even when resources and support are present, behavior is unlikely to occur without a strong internal intention. This layered causality supports the mediating role of behavioral intentions in the pathway from facilitating conditions to adoption. Therefore, theoretically, behavioral intention acts as a psychological mechanism through which perceived facilitating conditions translate into concrete investment or adoption behavior, such as actively trading in the stock market.

Empirical research supports the mediating role of behavioral intentions between facilitating conditions and adoption behavior, especially in technology-mediated financial contexts. In their foundational UTAUT study, Venkatesh et al. (2003) observed that facilitating conditions have a direct impact on usage behavior but also indirectly influence it through behavioral intention when users are new or uncertain. Alalwan et al. (2016) found that in the mobile banking sector in Jordan, behavioral intention significantly mediated the relationship between facilitating conditions (like device access and institutional support) and actual usage. In the share market context, Nguyen et al. (2019) studied Vietnamese investors and demonstrated that while facilitating conditions such as brokerage services and online platform availability had a direct effect on stock market adoption, a substantial part of this effect was mediated by behavioral intention suggesting that the perception of external support first shapes motivation before driving behavior. Similarly, Shrestha (2020) in Nepal found that investors who had access to simplified trading platforms, training programs, and responsive customer support were more likely to develop an intention to invest, which in turn predicted actual trading behavior. This mediating pathway was stronger among novice investors, indicating the need for intention as a psychological bridge between infrastructure and action. Singh and Bhatia (2021) further validated this in the Indian context, showing that behavioral intention partially mediated the relationship between facilitating conditions (e.g., mobile app support, market education, peer access) and actual stock market participation. These findings confirm that while facilitating conditions provide necessary external enablers, behavioral intention serves as the motivational driver that activates adoption behavior.

H7: Behavioral intentions mediate the relationship between facilitating conditions and adoption behaviors

Facilitating conditions on Adoption Behaviors with moderating variable Habit

Habit is defined as an automatic response to contextual cues that develops through repeated behavior (Verplanken & Orbell, 2003). In technology adoption and consumer behavior theories, habit is increasingly recognized as a critical factor that influences how facilitating conditions translate into actual behavior. According to the Unified Theory of Acceptance and Use of Technology (UTAUT2), an extension of UTAUT, habit directly affects usage behavior and moderates the influence of facilitating conditions on use (Venkatesh, Thong, & Xu, 2012). When a behavior has become habitual, individuals rely less on external facilitating factors to perform the behavior, as the action requires less conscious effort. Conversely, for non-habitual users, facilitating conditions such as access to resources, technical support, and environmental ease become more crucial to drive adoption behavior. In the context of share market investment, habitual investors those who regularly trade or monitor their portfolios may be less influenced by facilitating conditions since their repeated engagement has made the behavior automatic. In contrast, new or occasional investors might depend heavily on facilitating conditions to overcome barriers to entry. This aligns with Triandis' Theory of Interpersonal Behavior (1977), which acknowledges habit as a determinant that can weaken or strengthen the effect of external conditions on behavior. Hence, theoretically, habit serves as a moderator that can either attenuate or amplify the impact of facilitating conditions on actual adoption behavior, reflecting the user's level of experience and automaticity in investing.

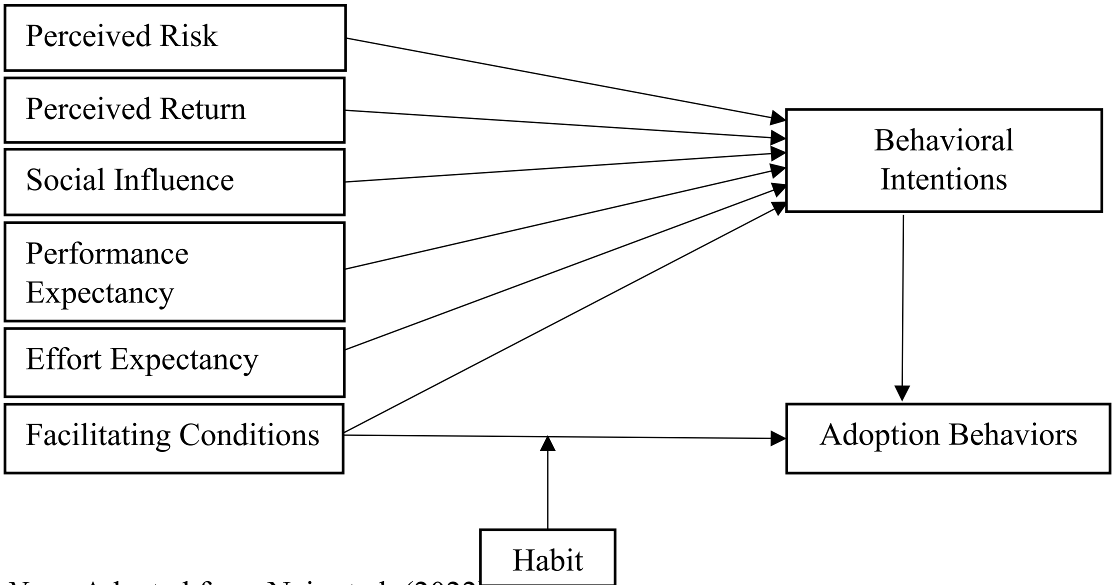
Empirical studies support the moderating role of habit in the relationship between facilitating conditions and adoption behavior, particularly in technology-mediated financial services. For instance, Venkatesh et al. (2012) demonstrated in their UTAUT2 model that habit significantly moderates the effect of facilitating conditions on technology use across various contexts, with habitual users showing less reliance on external support. In mobile banking, Alalwan et al. (2017) found that habit weakened the influence of facilitating conditions on continued usage intentions, suggesting that as users become habitual, the need for external facilitation diminishes. Similarly, in stock market investment, Singh and Bhatia (2021) observed that investors with established trading habits were less affected by factors like platform support or brokerage services, whereas novice investors depended more on such facilitating conditions to engage. In emerging markets like Nepal, Shrestha (2020) noted that habitual investors in the Nepalese stock market exhibited a more autonomous approach to trading, showing minimal sensitivity to facilitating conditions such as customer service or technical training, unlike first-time investors. Further, Nguyen et al. (2019) reported that habit moderated the relationship between facilitating conditions and actual stock market participation among Vietnamese investors, reinforcing the idea that frequent investors rely more on ingrained routines than on environmental supports. These findings suggest that habit, formed through repeated investment behaviors, moderates how facilitating conditions impact adoption, with habit reducing dependency on facilitating resources as investors become more experienced.

H8: Habit moderates the relationship between facilitating conditions and adoption behaviors

Theoretical Framework

The research framework is the structure that illustrates the relationship among various variables. In this context, four variables are employed. Mobile application adoption behaviors for online trading is measured by six indicators Perceived Risk, Perceived Return, Social Influence, Performance Expectancy, Effort Expectancy and Facilitating Conditions as independent variables. Behavioral Intention serves as the mediating variable of Facilitating Conditions and Adoption Behaviors, while Habit is used as the moderating variable of Facilitating conditions and Adoption Behaviors. The research framework of the study is outlined below:

Figure 1 *Theoretical Framework*



Note. Adapted from Nair et al. (2022)

III. Research Methodology

Research Design

A research design is a structured plan that guides data collection and analysis, shaping the study (Cooper & Schindler, 2003). This study adopts Descriptive Research and Casual Research Design to achieve its objectives.

Descriptive Research Design systematically presents characteristics, behaviors, or phenomena without altering variables. It identifies trends, patterns, and relationships within a population (Creswell, 2014). Casual Research Design examines cause-and-effect relationships by comparing groups with existing differences, analyzing the impact of independent variables on dependent variables without direct manipulation (Fraenkel & Wallen, 2009). Likewise, Kerlinger (1986) highlights ex post facto research, where past independent variables are analyzed to assess their effects on dependent variables (Kerlinger, 1986; Pant, 2012, p. 117). Common statistical methods include the Spearman Rank Order Coefficient, Phi Correlation Coefficient, Regression, t-test, Chi-square, and Analysis of Variance (Isaac, 1978; Pant, 2012, p. 118).

By combining descriptive and casual research designs, this study effectively examines variable relationships and their impact (Kerlinger, 1986), ensuring a structured and systematic approach.

Population and sample size

The research area for this study is Rupandehi District. The population consists of individual investors using mobile apps for online trading in emerging financial market of Rupandehi District. However, the total number of retail traders using mobile apps for trading cannot be precisely determined, making the population unknown. To address this, the sample size for an unknown population is calculated using Cochran's formula (Cochran, 1977).

$$n= Z^2 p\,(1 - p)/\,e^2$$

Where, Z = Given Z value based on confidence level (z = 2.576 for 99% level of confidence 1.96 for 95% level of confidence, 1.645 for 90% level of confidence)

- p = Proportion of event of interest for the study (0.5)
- e= margin of error (it depends upon confidence level)

Thus, the calculated sample size of the study n = 384

Sampling Techniques

The sampling method is chosen to select sample respondents from the overall population for data collection. In this context, the Convenience sampling method is specifically retail traders to approach the sample respondents. Given that the study focuses on the mobile app adoption behaviors of retail stock traders in Online Trading in Emerging Financial Markets of Rupandehi District, Nepal, the Convenience sampling technique is deemed appropriate. Convenience Sampling is a non-probability sampling method in which respondents are selected based on their easy accessibility and proximity to the researcher. This method is useful when it is difficult to reach all members of the population due to time, cost, or other constraints. This method is practical and efficient for collecting data quickly from a relevant portion of the population

Nature and Sources of Data Collection

This study primarily relies on quantitative data, which were collected from primary sources. A structured questionnaire was designed to gather first-hand information directly from respondents.

Survey Instrument

A self-structured questionnaire was used as the survey instrument for data collection. It was developed based on operational definitions from previous literature. The questionnaire employs a Seven-point Likert scale (7 = Strongly Agree, 6 = Agree, 5 = Somewhat Agree, 4 = Neutral, 3 = Somewhat Disagree, 2 = Disagree, and 1 = Strongly Disagree) to gather responses from participants.

A set of questions was designed to measure each independent, dependent, moderating and mediating variable, totaling 45 items. To ensure clarity and accuracy, a pilot test was conducted by distributing the questionnaire to a sample of 30 respondents. Out of 450 distributed questionnaires, 384 were fully completed, yielding a response rate of 85.33%**.**

Statistical Tools

The study utilized various statistical tools based on the nature of the data. Descriptive statistics, including mean and standard deviation (SD), were computed to analyze and interpret mobile app adoption behaviors of retail stock traders. Additionally, a reliability test was conducted to assess the consistency of the research instrument. Furthermore, Data were analyzed using statistical tools such as PLS-SEM software, including assessment of measurement items, model fit, Importance-Performance Map Analysis (IPMA), and the bootstrapping technique for hypothesis testing. Correlation analysis was used to measure the relationship between variables, while regression analysis examined the effect of independent variables on the dependent variable.

IV. Results and Analysis

Measurement items Assessment

Table 1 - *Assessment of scale items*

Variables	Items	Outer Loading	VIF	Mean	Standard Deviation
	PR1	0.776	2.009	3.178	1.958
	PR2	0.803	1.967	4.125	1.665
	PR3	0.817	2.115	3.819	1.958
Perceived Risk	PR4	0.737	1.55	4.195	1.782
	PR5	0.73	1.537	4.021	1.936
	PRe1	0.75	1.941	3.62	2.003
	PRe2	0.8	1.998	4.157	1.798
	PRe3	0.809	2.046	4.038	2.018
Perceived Return	PRe4	0.824	1.901	4.268	1.99
	PRe5	0.779	1.752	4.585	1.954

Social Influence	SI1	0.848	2.388	4.328	1.987
	SI2	0.87	2.632	4.516	1.973
	SI3	0.795	2.037	4.303	1.922
	SI4	0.846	2.438	4.641	1.975
	SI5	0.82	2.043	4.735	1.949
Performance Expectancy	PE1	0.876	2.886	4.547	1.992
	PE2	0.85	2.531	4.829	1.867
	PE3	0.854	2.506	4.599	1.881
	PE4	0.852	2.442	4.509	1.804
	PE5	0.805	1.956	4.718	1.947
Effort Expectancy	EE1	0.855	2.469	4.46	2.086
	EE2	0.882	2.848	4.491	1.859
	EE3	0.87	2.719	4.317	1.924
	EE4	0.816	2.291	4.394	1.919
	EE5	0.825	2.29	4.617	2.002
Facilitating Conditions	FC1	0.821	2.096	4.324	1.99
	FC2	0.856	2.391	4.303	1.915
	FC3	0.817	2.173	4.324	1.903
	FC4	0.82	2.097	4.488	1.861
	FC5	0.865	2.467	4.686	1.943
Behavioral Intention	BI1	0.818	2.22	3.798	1.915
	BI2	0.856	2.566	4.091	1.731
	BI3	0.815	2.023	4.331	1.874
	BI4	0.824	2.016	4.209	1.712
	BI5	0.778	1.738	4.206	1.884

Table 1 presents the standardized outer loading and Variance Inflation Factor (VIF) of the scale items employed to measure the variables pertinent to this investigation. In accordance to Sarstedt et al. (2017), the outer loading of an item must exceed 0.708 to signify a substantial contribution of that item in assessing the associated variable. Nonetheless, an outer loading value surpassing 0.70 may also be deemed acceptable, provided that the Average Variance Extracted (AVE) value of the related variable exceeds 0.50. Therefore, all 45 scale items are preserved for subsequent analysis. Furthermore, the VIF values for each item are less than 5, thereby indicating no multicollinearity within the scale items (Sarstedt et al., 2014).

Most of the mean values are on the higher side of the scale representing agreeableness toward each statement for standard deviation values are small indicating less deviation in the responses. Therefore, the data is suitable for further analysis.

Quality Criteria Assessment

Table 2 - *construct Reliability and Validity*

Variables	Alpha	CR (rho_a)	CR (rho_c)	AVE
Perceived Return	0.853	0.864	0.894	0.628
Perceived Risk	0.831	0.831	0.881	0.598
Social Influence	0.893	0.899	0.921	0.699
Performance Expectancy	0.902	0.903	0.927	0.719
Effort Expectancy	0.904	0.915	0.929	0.722
Facilitating Conditions	0.892	0.899	0.921	0.699
Behavioral Intention	0.877	0.878	0.91	0.67
Adoption Behavior	0.832	0.836	0.882	0.599

Table 2 contains the values of Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) to evaluate the convergent validity of the variables employed in this study. The Cronbach's Alpha coefficients for all items exceed the threshold of 0.705, signifying the adequate contribution of each scale item in the assessment of related constructs (Bland & Altman, 1997). Furthermore, the CR values for rho_A and rho_C surpass the minimum criterion of 0.70, denoting a robust measure of internal consistency (Saari et al., 2021; Hair et al., 2022). The AVE values also exceed the pivotal threshold of 0.50, suggesting that each variable accounts for more than 50 percent of the explained variance. This finding confirms the establishment of convergent validity (Hair et al., 2022). Subsequently, the outcomes depicted in the table as mentioned above satisfy all requisite of quality criteria measures.

Discriminant Validity

Table 3 - *Heterotrait-Monotrait (HTMT) ratio matrix*

Variables	Adoption Behavior	Behavioral Intention	Effort Expectancy	Facilitating Conditions	Perceived Return	Perceived Risk	Performance Expectancy	Social Influence
Adoption Behavior								
Behavioral Intention	0.823							

Effort Expectancy	0.535	0.587					
Facilitating Conditions	0.57	0.591	0.857				
Perceived Return	0.657	0.649	0.625	0.664			
Perceived Risk	0.486	0.515	0.49	0.47	0.685		
Performance Expectancy	0.615	0.684	0.814	0.803	0.769	0.453	
Social Influence	0.593	0.63	0.787	0.81	0.739	0.442	0.888

Table 3 contains the HTMT ratio of the correlation matrix, which evaluates the discriminant validity of the latent variables. The values of the HTMT ratio vary from 0.453 to 0.88. The HTMT ratio values need to remain below the critical threshold of 0.85; nevertheless, a range extending up to 0.90 is deemed acceptable, as posited by Henseler et al. (2015). Consequently, the presence of discriminant validity is confirmed among the reflective constructs (Hair & Alamer, 2022).

Table 4 - *Fornell-Larcker Criterion*

Variables	Adoption Behavior	Behavioral Intention	Effort Expectancy	Facilitating Conditions	Perceived Return	Perceived Risk	Performance Expectancy	Social Influence
Adoption Behavior	**0.774**							
Behavioral Intention	0.707	**0.819**						
Effort Expectancy	0.469	0.533	**0.85**					
Facilitating Conditions	0.498	0.53	0.828	**0.836**				
Perceived Return	0.566	0.577	0.57	0.604	**0.793**			
Perceived Risk	0.404	0.443	0.429	0.409	0.573	**0.773**		
Performance Expectancy	0.533	0.612	0.737	0.723	0.694	0.395	**0.848**	

Social Influence	0.516	0.566	0.71	0.725	0.67	0.386	0.798	**0.836**

Table 4 displays the Fornell-Larcker Criterion, an important discriminant validity assessment in a structural equation model (SEM) (Fornell & Larcker, 1981). This criterion is satisfied when the average variance extracted (AVE) for every construct is higher than the squared correlation between that construct and any other construct in the model. The diagonal entries, the square root of AVE of every construct, are to be higher than the off-diagonal values for their corresponding columns and rows. As evident in Table 5, diagonal values of Adoption Behaviors (0.774), Behavioral Intentions (0.819), Effort Expectancy (0.850), Facilitating Conditions (0.836), Perceived Return (0.793), Perceived Risk (0.773), Performance Expectancy (848) and Social Influence (0.836) are all higher than their inter-construct correlations. This means the measurement model's discriminant validity is assured, implying that each construct is unique and taps into a distinct segment of variance (Hair et al., 2010). This ensures that the constructs do not overlap and that the measures are measuring what they should measure.

Model Fit Indices

The SRMR and NFI fit indices evaluate the model's explanatory efficacy. The model's SRMR value is 0.063, below the acceptable threshold of 0.080 (Bollen & Stine, 1992). Consequently, this finding suggests that the model exhibits adequate explanatory capability.

Moreover, the effect sizes of Perceived Risk, Perceived Return, Social Influence, Performance Expectancy, Effort Expectancy, Facilitating Conditions on Behavioral Intensions are quantified as 0.028, 0.020, 0.005, 0.04, 0.002 and 0.001, respectively. This reveals that Perceived Risk, Perceived Return, Social Influence, Performance Expectancy, Effort Expectancy, Facilitating Conditions on Behavioral Intensions have a weak impact on Behavioral Intensions. Furthermore, the effect size of Behavioral Intensions and its influence on Adoption Behaviors is measured at 0.569, indicating a significant and strong effect. Correspondingly, the effect size of Facilitating Conditions on Adoption Behaviors is assessed at 0.044, which also signifies a weak effect (Cohen, 1988).

Finally, the r-square values corresponding to Adoption Behaviors and Behavioral Intentions are 0.521 and 0.447 respectively. This signifies that Adoption Behaviors possess moderate predictive power, whereas Behavioral Intentions demonstrates weak predictive ability (Hair et al., 2013).

Structural Equation Model

Figure 2 - *Path Relationship Diagram*

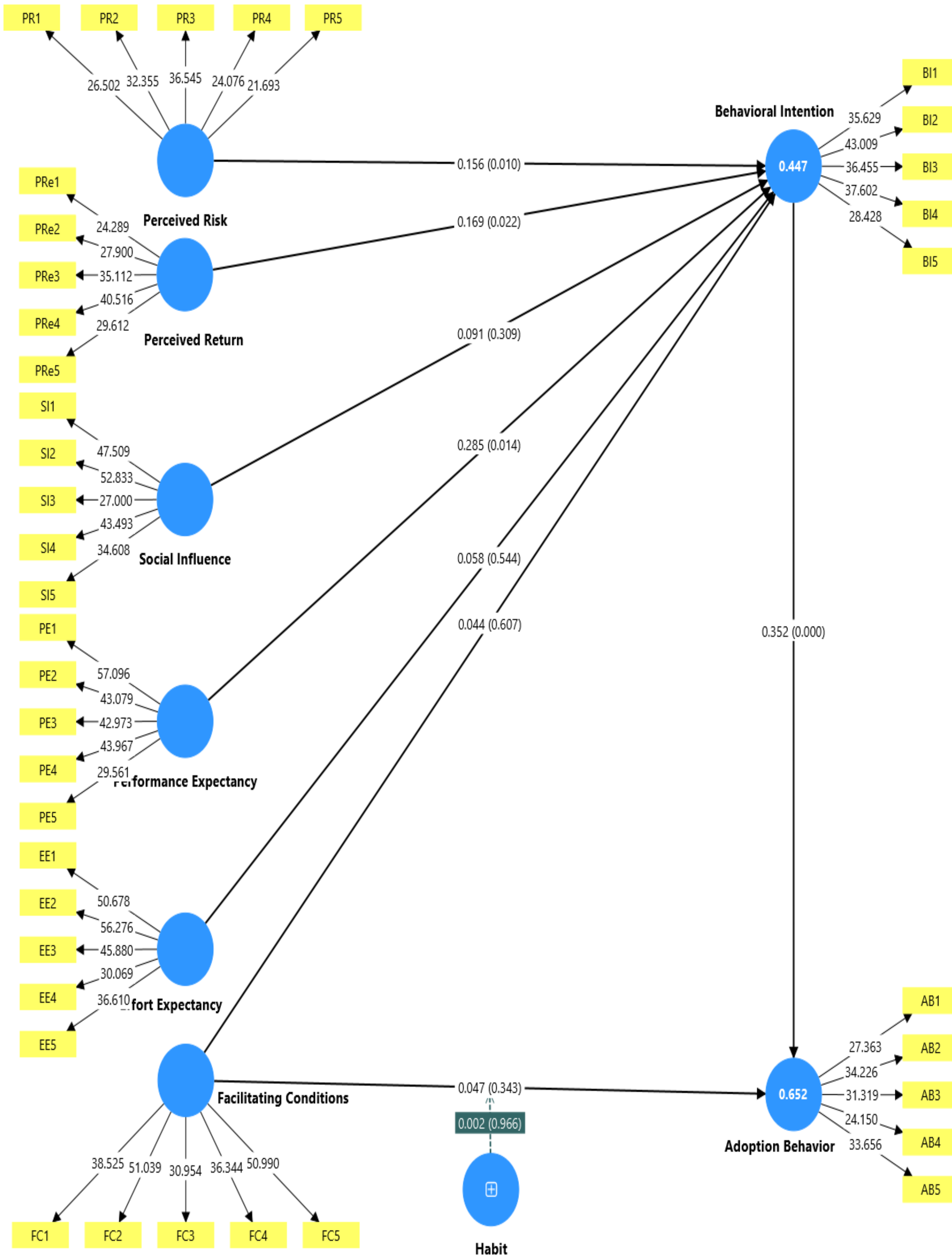


Table 5 - *Hypotheses testing using bootstrapping*

Hypotheses	β	Mean	STDEV	Confidence Interval 2.50%	97.50%	T Stat.	P values	Decision
Perceived Risk -> Behavioral Intention	0.156	0.157	0.06	0.039	0.273	2.579	0.01	Accepted
Perceived Return -> Behavioral Intention	0.169	0.173	0.074	0.029	0.315	2.289	0.022	Accepted
Social Influence -> Behavioral Intention	0.091	0.094	0.09	-0.084	0.268	1.017	0.309	Rejected
Performance Expectancy -> Behavioral Intention	0.285	0.281	0.116	0.055	0.51	2.457	0.014	Accepted
Effort Expectancy -> Behavioral Intention	0.058	0.057	0.096	-0.138	0.243	0.607	0.544	Rejected
Facilitating Conditions -> Behavioral Intention	0.044	0.045	0.086	-0.125	0.211	0.515	0.607	Rejected
Facilitating Conditions -> Adoption Behavior	0.047	0.047	0.05	-0.05	0.146	0.947	0.343	Rejected
Behavioral Intention -> Adoption Behavior	0.352	0.352	0.064	0.229	0.476	5.544	0	Accepted

R-Square = 0.521 [Adoption Behaviors]
R- Square adjusted = 0.517
R-Square = 0.447 [Behavioral Intentions]
R-Square adjusted = 0.435

Figure 2 and Table 5 report the results of a bootstrapping analysis performed with 10,000 subsamples, which examine decisions regarding the proposed hypotheses. Hypotheses H1, H2, H4, and H8 have achieved acceptance at a significance threshold 0.05. However, H3, H5, H6 and H7 are rejected as their p-value is above 0.05. There is a positive and significant impact of Perceived Risk, Perceived Return, Performance Expectancy on Behavioral Intention. However, there is positive and insignificant impact of Social Influence, Effort Expectancy and Facilitating conditions on Behavioral Intention. There is positive and insignificant impact of Facilitating condition on Adoption Behavior but there is positive and significant impact of Behavioral Intention on Adoption Behavior.

The R-square and Adjusted R-square values for two dependent variables: "Adoption Behaviors" and "Behavioral Intention." For "Adoption Behaviors," an R-square of 0.521 indicates that 52.1% of its variance is explained by the model's independent variables, with a very similar adjusted R-square of 0.517. Similarly, for "Behavioral Intention," the model explains 44.7% of its variance (R-square = 0.447), with an adjusted R-square of 0.435. These figures suggest that the models possess a moderate to good explanatory power for both dependent variables, with the model for "Adoption Behaviors" demonstrating slightly stronger explanatory capability. The small difference between R-square and Adjusted R-square for both indicates the relevance of the included predictors and a reasonably good model fit without excessive penalization for predictor count.

Table 6 - *Moderating and mediating Effect*

Hypotheses	β	Mean	STDEV	Confidence Interval 2.50%	97.50%	T Stat.	P values	Decision
H -> Adoption Behavior	0.502	0.502	0.068	0.366	0.631	7.349	0	Accepted
H x Facilitating Conditions -> Adoption Behavior	0.002	0	0.038	-0.075	0.075	0.043	0.966	Rejected
			Mediating Effects					
Facilitating Conditions -> Behavioral Intention -> Adoption Behavior	0.016	0.015	0.031	-0.046	0.076	0.51	0.61	Rejected

Table 6 reports the results of moderating and mediating effects. Habit has a positive and significant direct impact on Adoption Behavior. The moderating effect of Habit is positive and insignificant in the relationship between Facilitating condition and Adoption Behavior. However, there is a positive and insignificant mediating effect of Behavioral Intention in the relationship between Facilitating condition and Adoption Behavior.

Table 7 - *Necessary condition Analysis (NCA)- Bottleneck Values*

	LV scores - Adoption Behavior	LV scores - Behavioral Intention	LV scores - Effort Expectancy	LV scores - Facilitating Conditions	LV scores - Perceived Return	LV scores - Perceived Risk	LV scores - Performance Expectancy	LV scores - Social Influence
0.00%	14%	NN	NN	NN	NN	NN	NN	NN
10.00%	23%	NN	NN	NN	NN	NN	NN	NN
20.00%	31%	23%	NN	NN	NN	20%	NN	20%
30.00%	40%	30%	NN	NN	NN	20%	NN	20%
40.00%	49%	35%	NN	NN	NN	20%	26%	20%
50.00%	57%	37%	NN	NN	NN	20%	26%	20%
60.00%	66%	38%	NN	NN	NN	24%	26%	20%
70.00%	74%	38%	19%	19%	NN	24%	26%	26%
80.00%	83%	38%	34%	50%	24%	28%	29%	29%
90.00%	91%	76%	49%	56%	58%	40%	66%	52%
100.00%	100%	91%	95%	56%	70%	40%	83%	80%

Table no: 7 represents Bottleneck values of latent variables using necessary condition analysis (NCA). To achieve 23% Adoption Behavior no factors are required or necessary. Further, to achieve 31% of Adoption Behavior, 23% of Behavioral 40% of Adoption Behavior, 30% of

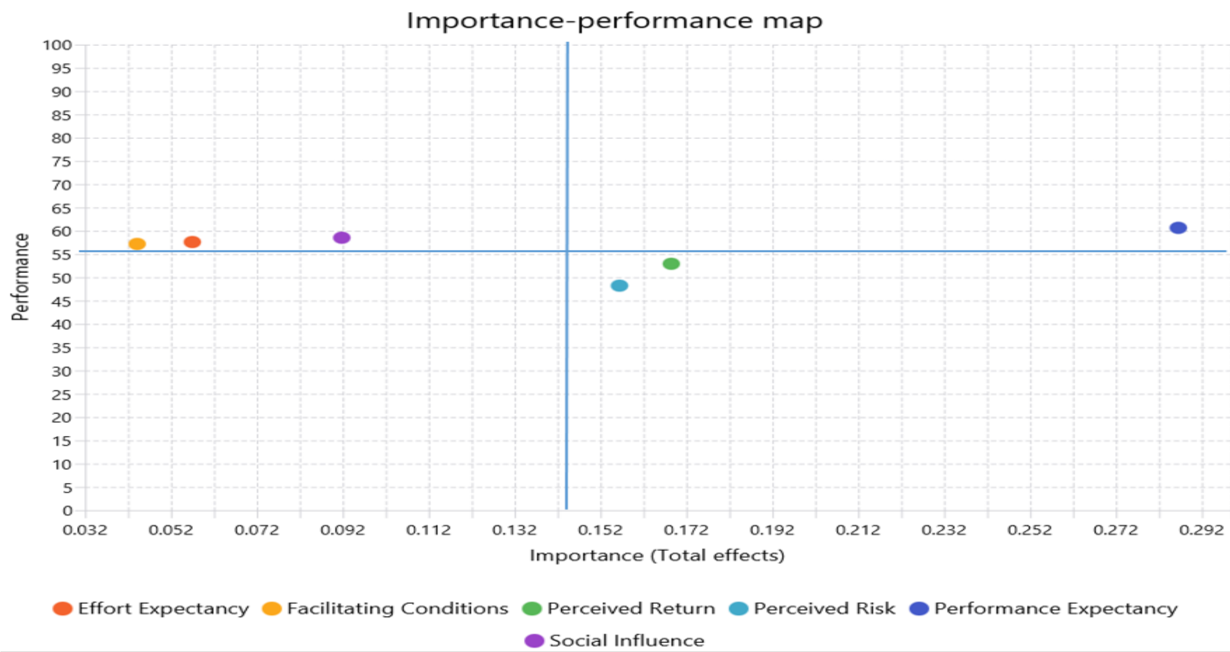
Behavioral intention is required. To achieve 49% of Adoption Behavior, 35% of Behavioral intention,26% of Performance Expectancy is required. To achieve 57% of Adoption Behavior, 37% of Behavioral Intention is required. To achieve 66% of Adoption Behavior, 38% of Behavioral intention and 24% of Perceived Risk is required. To achieve 74% of Adoption Behavior, 19% of Effort Expectancy and Facilitating conditions are required. To achieve 83% of Adoption Behavior, 34% of Effort Expectancy, 50% of facilitating Condition, 24% of Perceived Return, 28% of Perceived Risk And 29% of Performance Expectancy & Social Influence is required. To achieve 91% of Adoption Behavior, 76% of Behavioral Intention, 49% of Effort Expectancy, 56% of facilitating Condition, 58% of Perceived Return, 40% of Perceived Risk, 66% of Performance Expectancy and 52% of Social Influence is required. To achieve 100% of Adoption Behavior, 91% of Behavioral Intention, 95%Effort Expectancy, 56% of facilitating Condition, 70% of Perceived Return, 40% of Perceived Risk, 83% of Performance Expectancy and 80% of Social Influence is required.

Table 8 - *Importance performance map analysis*

	LV performance	Importance
Perceived Risk	48.233	0.157
Perceived Return	52.933	0.169
Social Influence	58.526	0.092
Performance Expectancy	60.647	0.287
Effort Expectancy	57.605	0.057
Facilitating Conditions	57.191	0.044
Mean	55.856	0.134

Table 8 shows the total effects of Perceived Risk, Perceived Return, Social Influence, Performance Expectancy, Effort Expectancy and Facilitating Condition on Behavioral Intention for the unstandardized effects. These effects are the same as the unstandardized weights of ordinary least square regression modelling (Hair et al. 2010). Furthermore, the performance of Behavioral Intention was calculated as 52.308.

Notably, we derived the four quadrants successfully based on the mean values of the constructs' importance and performance value. As per Fig. 3, if we increase 1 unit in Performance Expectancy from 60.647 to 61.647, Behavioral intention increases from 52.308 to 52.595. Similarly, if we increased 1 unit in Facilitating Conditions from 57.191 to 58.191, then credit card use attitude grew to increase from 52.308 to 52.352. Therefore, out of the four determinants of Behavioral intention, the most critical factor was noted to be Performance Expectancy.



V. Discussion

The present study investigated the influence of various factors on mobile app adoption behavior among retail traders in the emerging financial markets of Rupandehi District, Nepal. Drawing upon the UTAUT framework (Venkatesh et al., 2003) and behavioral intention models, the results indicate that Perceived Risk**,** Perceived Return, and Performance Expectancy exhibit a positive and statistically significant influence on Behavioral Intention to adopt mobile trading applications. These findings suggest that when retail traders perceive mobile apps as yielding potential financial gains (Nguyen et al., 2016), offering strong utility (Venkatesh et al., 2003), and manageable levels of risk (Featherman & Pavlou, 2003), they are more likely to develop the intention to use such platforms (Author, 2025).

In contrast, the study found that Social Influence**,** Effort Expectancy, and Facilitating Conditions have positive but statistically insignificant effects on Behavioral Intention. Although prior studies emphasize the role of peer influence, ease of use, and supportive infrastructure in technology adoption (Venkatesh et al., 2003; Zhou, 2011), these factors appear to play a less critical role in this specific context. One possible explanation is that retail traders in emerging markets like Rupandehi may prioritize return and performance considerations over social or institutional support structures when adopting digital financial tools (Author, 2025).

These findings contribute to a more nuanced understanding of mobile app adoption behavior, particularly in financially emerging regions, and suggest the need for policy makers and app developers to focus on enhancing perceived performance and returns while mitigating risk perceptions.

VI. Conclusion and Implications

The study shows factors like how useful investors think mobile trading apps are, how easy they are to use, and whether their friends or peers influence them play a big role in their decision to adopt these apps. Interestingly, the research found that habits and the overall intention to use the apps are the main drivers for actual usage, rather than concerns about risks or the potential to make quick profits. It also highlights that organizations should focus on improving the learning experience and providing better support to help investors use mobile trading tools effectively. Overall, understanding these factors can help financial companies and investors make better decisions and encourage more people to use mobile technology for trading in emerging markets.

The findings suggest that financial firms and advisors should focus on creating user-friendly mobile apps that encourage positive habits among investors. By making these apps easy to understand and use, companies can help investors develop confidence and routine in online trading. Additionally, providing good support and reliable information can motivate more people to adopt these technologies. For investors, developing good habits and trusting the apps can lead to better trading experiences. Overall, improving the usability and support for mobile trading platforms can benefit both investors and service providers in emerging markets.

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