IMPACT OF UTILIZING AI PERSONAL FINANCIAL TOOLS ON FINANCIAL WELL-BEING: INTEGRATION OF UTAUT AND THE EXPECTATION-CONFIRMATION MODEL

Manuscript Info

Manuscript History
Received: xxxxxxxxxxxxxxxx
Final Accepted: xxxxxxxxxxxx
Published: xxxxxxxxxxxxxxxx

Key words:-
AI Personal Financial Tools, Financial Well-Being, Unified Theory of Acceptance and Use of Technology (UTAUT), Expectation-Confirmation Model (ECM)

Abstract

The rapid advancement of Artificial Intelligence (AI) has transformed the financial services landscape, offering innovative personal financial tools that enhance financial decision-making and well-being. For women entrepreneurs managing small and medium-sized enterprises (SMEs), the adoption of AI-powered financial solutions holds significant potential to improve financial inclusion, access to credit, and overall business performance. This study investigates the impact of utilizing AI personal financial tools on the financial well-being of women entrepreneurs, integrating the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Expectation-Confirmation Model (ECM) as the theoretical framework. The research explores key factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions, alongside user expectations, satisfaction, and continuance intentions, to understand adoption behavior. Findings highlight the dual role of motivations and barriers technological, economic, and institutional in shaping adoption decisions. The study emphasizes how AI-driven financial tools empower women entrepreneurs by enhancing savings, investment planning, and risk management, while also addressing policy and regulatory implications for promoting digital financial inclusion. The integration of UTAUT and ECM provides a comprehensive lens to assess both initial adoption and sustained usage, offering valuable insights for policymakers, technology developers, and financial institutions to support women-led SMEs in the digital era.

Introduction:-

Personal finance is one of the industries that has seen revolutionary changes as a result of the exponential growth of artificial intelligence (AI). AI-powered personal finance tools are becoming essential for anyone looking to properly manage their money. These tools provide features like investment planning tracking expenses budgeting and savings optimization and they are powered by advanced machine learning algorithms and data analytics. By offering tailored insights and suggestions they enable users to make well-informed financial decisions thereby empowering them (Shankar 2021). Utilizing technology to improve financial independence and well-being is becoming increasingly popular as evidenced by the adoption of these tools. People who have financial security control over their money and less financial stress are said to be in astate of financial well-being (Netemeyer et al. in 2018. It includes both subjective opinions like financial confidence and satisfaction as well as objective metrics like income and savings. By promoting greater control over spendingimproving financial literacy and facilitating better decision-making research has demonstrated that technological tools canimprove financial well-being (Xiaoand Porto 2017). The ways in which AI personal financial tools impact financial well-being are still poorly understood despite these advantages especially when it comes to the behavioral and psychological aspects that encourage user engagement and continued use. A strong theoretical framework for comprehending technology adoption is offered by the Unified Theory of Acceptance and Use of Technology (UTAUT). Performance expectancy effort expectancy social influence and enabling conditions are identified as important factors that influence the adoption and use of technology (Venkatesh et al. (2003)). Users initial decisions to use AI personal financial tools can be largely explained by these constructs. However post-adoption behaviors and their ensuing consequences like financial well-being are not fully taken into account by UTAUT which mainly concentrates on pre-adoption factors. By providing information on post-adoption behaviors the Expectation-Confirmation Model (ECM) enhances UTAUT in order to overcome this limitation. ECM suggests that initial expectations post-use confirmation or disconfirmation of these expectations and subsequent satisfaction all have an impact on users continued engagement with technology (Bhattacherjee 2001). By combining UTAUT and ECM this study offers a thorough framework that documents the uptake and continued use of AI personal finance tools along with their effects on financial security. This study persuasively argues that expectation confirmation is an essential mediating factor in comprehending the impact of pre-adoption factors like effort and performance expectancies on post-adoption outcomes. Because it gauges how well users expectations and experiences match expectation confirmation is essential for ensuring user satisfaction and long-term use (Bhattacherjee 2001). By looking at this mediating function we can learn more about the dynamic connection between financial performance and technology use. Additionally this study integrates the Expectation Confirmation Model (ECM) with the Unified Theory of Acceptance and Use of Technology (UTAUT) focusing on the crucial mediating role of expectation confirmation greatly strengthening our theoretical framework. Additionally it provides financial technology stakeholders with useful practical insights that highlight ways to improve the design operation and communication of AI-driven personal financial tools which will ultimately improve users financial well-being.

Objectives Of The Study:-

1. To study how women entrepreneurs use AI personal financial tools in managing their SMEs.

2. To find out how these tools affect their financial well-being and business decisions.

3. To identify the main factors that encourage or hinder women entrepreneurs from using AI financial tools.

Review Of Literature:-

UTAUT and Expectation Confirmation

Unified Theory of Acceptance and Use of Technology (UTAUT) is a popular framework for comprehending the adoption and use of technology, developed by Venkatesh and associates. Four major factors are identified by UTAUT (2003) as influencing behavioral intention and usage behavior: facilitating conditions social influence performance expectancy and effort expectancy. These constructs offer a strong basis for examining the elements that influence user adoption in the context of AI-driven personal financial tools. As consumers look for tools that improve financial decision-making and control performance expectancy—a term that describes the perceived advantages of using a technology—becomes increasingly important. Likewise effort expectancy is crucial for user adoption since AI tools need to provide a smooth and simple user experience to promote participation (Venkatesh et al. in 2003). Nevertheless UTAUT has been criticized for its scant attention to post-adoption behaviors and outcomes even though it successfully captures pre-adoption factors (Venkatesh et al. (2012). Researchers have been incorporating complementary frameworks like the Expectation-Confirmation Model (ECM) which focuses on post-adoption dynamics more and more in order to fill this gap. Bhattacherjee (2001) developed ECM which holds that users satisfaction with a technology perceived utility and confirmation or disconfirmation of their initial expectations all affect how long they continue to use it. Given that users frequently form expectations regarding the tools capacity to improve financial well-being and decision-making this model is especially pertinent to AI financial tools. Users report better results and are more likely to stick with the tools when these expectations are met or surpassed. When considering AI-powered personal financial tools the combination of UTAUT and ECM is especially relevant. Research has indicated that the relationship between initial adoption factors and sustained use is mediated by expectation confirmation. For example the UTAUTs performance expectancy and effort expectancy set the stage for users first interactions with AI financial tools. However ECM emphasizes that user satisfaction and sustained use are determined by the extent to which these expectations are validated after adoption (Thong et al. 2006). This implies that expectation confirmation acts as a vital link between the factors that drive adoption and the long-term effects on financial well-being. Though understudied expectation confirmation is becoming more and more important in the field of AI financial tools. Users initially have high expectations because AI tools frequently promise better budgeting investment optimization and personalized financial insights. Positive experiences that validate these expectations increase the likelihood that users will view the tools as valuable which will boost their level of satisfaction and encourage continued use (Shankar 2021). The need for developers to match user expectations with the tools true capabilities is highlighted by the fact that unmet expectations can lead to discontent and discontinuation. Important information about the uptake and long-term use of AI financial tools can be found at the intersection of UTAUT and ECM. UTAUT stresses the significance of initial factors like perceived ease of use and social influence whereas ECM emphasizes how user perceptions change after adoption. By highlighting the significance of controlling user expectations and providing consistent value these frameworks collectively provide a thorough understanding of how AI-driven financial tools can affect financial well-being.

H1: Performance expectancy positively related to expectation confirmation

H2: Effort expectancy positively related to expectation confirmation

H3: Social influence positively related to expectation confirmation

H4: Facilitative condition positively related to expectation confirmation

Expectation Confirmation and Financial Wellbeing

A crucial concept in the Expectation-Confirmation Model (ECM) expectation confirmation is essential to comprehending user satisfaction and sustained technology use. The degree to which users initial expectations of a technology match their actual post-adoption experiences is known as expectation confirmation according to

Bhattacherjee (2001). This alignment is essential for promoting user satisfaction long-term engagement and eventually advantageous results like enhanced financial well-being in the context of AI financial tools. The ability to fulfill financial commitments feel financially secure and make decisions that are consistent with ones values are all components of financial well-being a multifaceted construct (Netemeyer et al. (2018). The adoption and use of technology can be used to understand the connection between financial well-being and expectation confirmation. Users are more likely to see AI financial tools as beneficial and feel satisfied when they believe they meet or surpass their expectation which improves their financial behaviors and results (Shankar 2021). For example AI tools that provide precise budgeting advice tailored financial insights and successful investment strategies help people feel more in control of their finances experience less financial stress and have more confidence—all of which are essential components of financial well-being (Xiao and Porto 2017). Research in the larger field of technology confirms that expectation confirmation plays a crucial part in determining post-adoption outcomes and behaviors. Bhattacherjee (2001) showed that users continual use of technology is significantly predicted by their level of satisfaction which is fueled by expectation confirmation. In the realm of financial technology this contentment results in more frequent and active tool use empowering users to embrace disciplined financial practices and attain superior financial results. Because users have high expectations for AI capabilities research on AI-powered tools has also shown how important it is for user expectations and experiences to interact dynamically (Thong et al. 2006). Users report improved financial well-being through improved resource management and decision-making when these expectations are met. The relationship between pre-adoption elements like perceived ease of use and performance expectancy and post-adoption outcomes like financial well-being is also mediated by expectation confirmation. For instance users post-adoption experiences must match these expectations when they embrace AI financial tools because they promise user-friendly interfaces and actionable insights in order to promote satisfaction and trust (Lee & Kwon 2020). On the other side misaligned expectations may result in decreased usage unfavorable financial effects and discontent. Research on financial well-being that incorporates expectation confirmation offers sophisticated insights into the potential significant effects of AI financial tools. Users who thought AI tools were dependable and insightful for example expressed higher levels of satisfaction and a stronger sense of financial security according to Shankar (2021). This implies that in order to guarantee that tools provide consistent value developers should place a high priority on transparency and effectively manage user expectations. When it comes to AI financial tools expectation confirmation is a crucial factor in determining financial well-being. Because it affects user satisfaction and retention users can use these technologies to enhance their financial results. AI-driven solutions can be made more effective at promoting financial empowerment if developers match initial user expectations with tool performance.

H5: Expectation confirmation positively related to financial well-being

UTAUT and Financial Wellbeing

For studying technology adoption and its effects the Unified Theory of Acceptance and Use of Technology (UTAUT) has become a fundamental framework. Venkatesh and colleagues developed it. Four major constructs are identified by UTAUT (2003) as influencing user adoption and usage behavior: performance expectancy effort expectancy social influence and facilitating conditions. These concepts are crucial to comprehending how people use technology to improve their financial well-being in the context of AI-driven personal financial tools. When adopting AI financial tools user perceptions of financial well-being are closely related to performance expectancy or the conviction that using a technology will yield benefits. Users can optimize their financial resources and lessen financial stress by utilizing these tools features which include automated budgeting investment management and personalized financial insights. Research indicates that tools that are seen as improving financial decision-making and control are more likely to be adopted which eventually improves financial well-being (Shankar 2021). Users expectations of better financial health are in line with AI financial tools capacity to streamline intricate financial tasks which highlights the importance of performance expectancy in this area. For AI financial tools to be used consistently effort expectancy—which is the ease of use of the technology—is essential. Tools with easy-to-use interfaces and low learning curves have a higher chance of drawing in and keeping users. Because it is so simple to use users are more likely to have positive experiences and incorporate the tools into their regular financial management routines. This regular use eventually leads to better financial habits like careful budgeting and wise investment choices which are essential elements of financial well-being (Venkatesh et al. (2003)). One important factor driving the adoption of AI financial tools is social influence or the extent to which people believe that significant others think they should use a technology. Especially when linked to better financial results peer recommendations cultural norms and financial advisor endorsements can boost confidence in these tools (Zhao et al. 2022). The promotion of AI tool adoption and the benefits seen in peers financial well-being frequently serve as a catalyst for wider acceptance improving personal financial results. Access to and use of AI financial tools depend heavily on enabling conditions which are the resources and assistance available for technology use. These include smartphones customer service and dependable internet access all of which work together to guarantee that users can make efficient use of the tools. Users potential financial gains from these technologies may be limited by inadequate enabling conditions which can impede adoption (Venkatesh et al. (2012). Adoption and the impact of these tools on financial well-being can be greatly increased by policies designed to close the gaps in financial literacy and technology. Together the UTAUT constructs shape the adoption and long-term use of AI financial tools which in turn affects financial well-being. Users sustained engagement results in improved financial management and less stress when they adopt tools based on positive expectations (performance and effort expectancy) and are encouraged by their social environment and available resources. Additionally AI tools data-driven insights support well-informed financial decision-making which closely reflects both the objective and subjective aspects of financial well-being (Netemeyer et al. 2018).

H6: Performance expectancy positively related to financial well-being

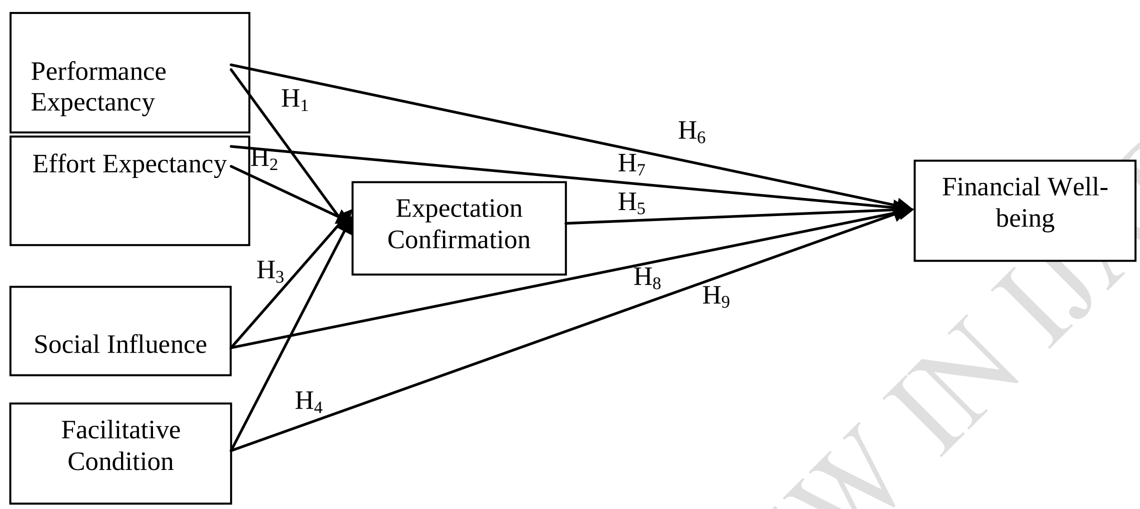
H7: Effort expectancy positively related to financial well-being

H8: Social influence positively related to financial well-being

H9: Facilitative condition positively related to financial well-being

Conceptual model

Figure 1



Source: Rahman et al., (2019), Alnaser et al., 2023, Dzogbenuku et al., (2021)

METHODS

Using a quantitative cross-sectional research design this study investigates the connections among financial well-being expectation confirmation and adoption factors in the context of AI-powered personal financial tools. The studys foundation is an integrated framework that evaluates user behaviors both before and after adoption by fusing the Expectation-Confirmation Model (ECM) with the Unified Theory of Acceptance and Use of Technology (UTAUT). People in Coimbatore a developing urban center with growing fintech adoption among salaried professionals and small business owners who actively use AI personal financial tools make up the target population. Purposive sampling was used to choose 321 responders in order to guarantee the accuracy and relevance of the data. To specifically find and include participants who had firsthand experience with AI financial tools a non-probability sampling technique called purposeful sampling was used. With regard to the study constructs—performance expectancy effort expectancy social influence facilitating conditions expectation confirmation and financial well-being—this method was selected to guarantee that participants could give well-informed answers. It was crucial to give participants hands-on experience with the technology by focusing on post-adoption behavior and user satisfaction. On the other hand random sampling might have led to the inclusion of people who were not familiar with AI financial tools which could have undermined the use of the theoretical models and compromised the validity of the results. The geographic focus was purposefully chosen to be Coimbatore because it offers a pertinent backdrop for investigating the ways in which regional elements like digital literacy infrastructure accessibility and cultural perspectives affect the uptake and long-term application of AI financial tools. A structured questionnaire with validated scales modified to assess the studys constructs was used to gather data. Demographic information expectation confirmation financial well-being and UTAUT constructs (performance expectancy effort expectancy social influence and facilitating conditions) were all covered in the questionnaire. A five-point Likert scale with 1 denoting strongly disagree and 5 denoting strongly agree was used to record the responses. The data analysis process employed Structural Equation Modeling (SEM) to assess both direct and mediating effects and test the proposed relationships. Data cleaning reliability testing and Confirmatory Factor Analysis (CFA) were all part of the preliminary analyses that established construct validity. The study closely followed all ethical rules including those pertaining to institutional approval procedures data confidentiality and informed consent. The purpose of this methodological approach was to validate the integrated UTAUT-ECM framework precisely identify the factors influencing the adoption of AI financial tools and produce useful insights for enhancing user engagement and financial well-being via efficient fintech solutions.

MEASURES

This study utilizes existing survey instruments for UTAUT, ECM and Financial well-being. Based on the study, some of the words and items were modified. This study used a five-point Likert's scale of 5 strongly agree to 1 strongly disagree to measure the variables on latent constructs. The study items are provided in Table 1. The questionnaire covered these constructs and demographic profiles (age, gender, qualification, income).

Table 1

This table shows the construct, statements, factor loading, reliability and source of the statements.

Statements	Factor Loadings	Cronbach alpha	Source
Performance expectancy (PF)			Rahman et al., (2019)
I find AI financial tools useful in my daily life.	.987	.985	
Using AI financial tools increases my chances of achieving things that are important to me.	.962		
Using AI financial tools helps me accomplish things more quickly.	.983		
Using AI financial tools increases my productivity.	.994		
Effort expectancy (EF)			
Learning how to use AI financial tools is easy for me.	.912	.917	
My interaction with AI financial tools is clear and	.904		

understandable.			
I find AI financial tools easy to use.	.923		
It is easy for me to become skillful at using AI financial tools.	.865		
Social influence (SI)			
People who are important to me think that I should use AI financial tools.	.774		
People who influence my behavior think that I should use AI financial tools.	.883	.894	
People whose opinions that I value prefer that I use AI financial tools	.862		
Facilitating condition (FC)			
I have the resources necessary to use AI financial tools.	.975		
I have the knowledge necessary to use AI financial tools.	.971	.972	
AI financial tools is compatible with other technologies I use	.962		
I can get help from others when I have difficulties using AI financial tools.	.931		
Expectation confirmation (EC)			
My experience with AI financial tools is better than my expectation.	.977	.978	Alnaser et al., 2023

The benefits of AI financial tools are better than my expectation	.979		
The AI financial tools had better service level than my expectation.	.945		
My expectations towards AI financial tools are confirmed.	.943		
Financial wellbeing (FW)			
I feel fulfilled with AI financial tools always	.912		
AI financial tools bring me excitement	.961		
Using AI financial tools is economical	.954	.971	Dzogbenuku et al., (2021)
AI financial tools has helped to improve my financial status	.956		
The AI financial tools have been beneficial	.988		
Overall	.969	.991	
Extraction Method: Principal Component Analysis.			

RESULTS

This section presents the outcomes and results of various statistical tests conducted to assess the reliability and validity of the measures, as well as to evaluate the conceptual model. To prove the concepts validity and dependability confirmatory factor analysis or CFA was used. According to Anderson and Gerbing (1988) CFA offers crucial information about whether the scales being used have convergent validity. This entails determining whether the observed variables are correctly loading onto the corresponding latent constructs (Kline 2010). We used the approach suggested by Fornell and Larcker (1981) to prove discriminant validity. We looked at composite reliability and average extracted variance as indicators of construct reliability. A complete structural equation modeling (SEM) approach with AMOS (Version 26) was used to validate the suggested model.

Table 2

CFA model fit indices

Fit indices	**Value**	**Accepted value**	**Result**
Cmin/df	2.346	Less than 3	Supported
GFI	.945	Value greater than .90	Supported
CFI	.903	Value greater than .90	Supported
IFI	.946	Value greater than .90	Supported
RMSEA	.063	Value less than .08	Supported

Since every reported metric meets or exceeds the established thresholds the CFA models fit indices offer compelling proof of its sufficiency and suitability for explaining the observed data. This shows how well the model represents the proposed relationships and how robust it is. The ratio of the degrees of freedom to the chi-square statistic is shown by the Cmin/df (2.346) measure. A satisfactory degree of fit is indicated by a value less than 3 which shows that the model successfully reduces differences between the theoretical model and the observed data. GFI (.945): The Goodness of Fit Index reflects how well the specified model accounts for the variance in the dataset. A value above .90, as observed here, indicates that the model explains the majority of the covariance structure, demonstrating a high-quality fit. CFI (.903): The Comparative Fit Index assesses the model's performance compared to a null model (a model assuming no relationships between variables). With a value exceeding the threshold of .90, the results highlight the strong comparative performance of the proposed model, confirming its adequacy. IFI (.946): Similar to the CFI, the Incremental Fit Index evaluates the model's incremental improvement over a baseline model. The high value of .946 shows that the model achieves excellent improvement, further supporting its strong fit. RMSEA (.063): The Root Mean Square Error of Approximation indicates the degree of approximation error in the model. A value below .08 reflects a close fit, with minimal error, suggesting that the model is parsimonious while still capturing the data's underlying structure effectively. The fit indices collectively validate the CFA model as a robust and reliable framework for the data. With all metrics meeting or exceeding their respective thresholds, the model is well-suited for further analysis and provides confidence in its representation of the constructs under study. This strong fit underlines the model's theoretical and empirical soundness.

Table 2

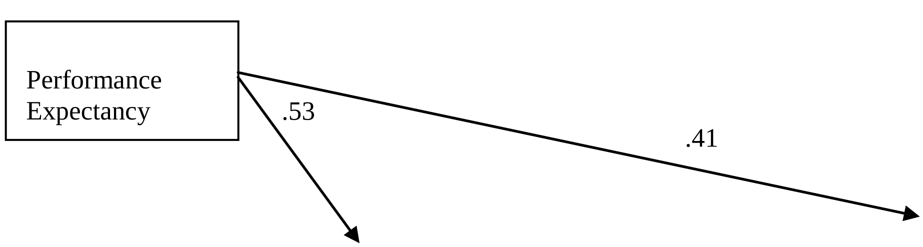
SEM model fit indices

Fit indices	**Value**	**Accepted value**	**Result**

Cmin/df	2.632	Less than 3	Supported
GFI	.924	Value greater than .90	Supported
CFI	.901	Value greater than .90	Supported
IFI	.927	Value greater than .90	Supported
RMSEA	.070	Value less than .08	Supported

An acceptable and reliable fit between the suggested model and the observed data is confirmed by the results of the SEM (Structural Equation Modeling) fit indices. Strong evidence of the models suitability for representing the proposed relationships can be found in the reported indices all of which meet or surpass the established thresholds. The difference between the observed and estimated covariance matrices is within a reasonable range as indicated by the chi-square to degrees of freedom ratio which is below the maximum allowable limit of 3. This demonstrates how well the model fits the data structure. GFI: The Goodness of Fit Index measures the proportion of variance and covariance explained by the model. A value of .924, exceeding the threshold of .90, signifies that the model captures the majority of the data's variability and provides a good representation of the underlying patterns.CFI: The Comparative Fit Index assesses how well the model performs relative to a null model (one assuming no relationships among variables). The CFI value of .901, just above the threshold of .90, confirms that the proposed model is substantially better than the null model, indicating an adequate comparative fit. IFI: The Incremental Fit Index evaluates the model's improvement over a baseline model. The value of .927, which surpasses the accepted standard of .90, suggests that the model exhibits an excellent incremental fit and effectively captures the relationships among variables. The models parsimony and accuracy in approximating the data are gauged by the Root Mean sq. Error of Approximation or RMSEA. A value of . 070 which is below the . 08 threshold shows that the models estimation error is low and that it fits the data closely while still being economical. Together the SEM fit indices confirm the models theoretical soundness and dependability. The outcomes show that the model adequately captures the proposed relationships and fits the observed data guaranteeing its suitability for additional research. These results attest to the structural models stability and suitability for hypothesis testing and extracting valuable information from the data.

Figure 2: **Hypothesis model**



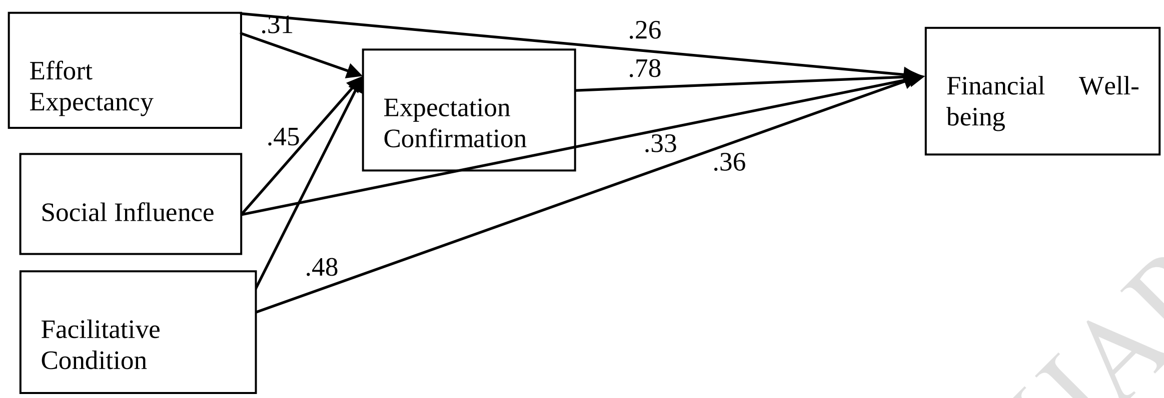


Table 3

This table represents hypothesis and relationships between variables

Hypothesis	Path	Estimates β	C.R	P value	Supported
H_1	PF → EC	.534	1.074	.000	Yes
H_2	EF → EC	.309	1.212	.000	Yes
H_3	SI → EC	.452	1.164	.000	Yes
H_4	FC → EC	.484	1.102	.000	Yes
H_5	EC → FW	.781	0.967	.000	Yes
H_6	PF → FW	.407	1.189	.000	Yes
H_7	EF → FW	.259	1.673	.014	Yes
H_8	SI → FW	.332	1.206	.000	Yes
H_9	FC → FW	.363	1.169	.000	Yes

Note PF-performance expectancy, EF- effort expectancy, SI- social influence, FI- facilitative condition, EC-expectation confirmation. FW- Financial well-being

Table 3 illustrates the hypothesized relationships among key constructs—Performance Expectancy (PF), Effort Expectancy (EF), Social Influence (SI), Facilitating Conditions (FC), Expectation Confirmation (EC), and Financial Well-being (FW). All nine hypotheses (H1–H9) are statistically supported, confirming significant and positive relationships between the variables.

Antecedents and Expectation Confirmation (EC)

Performance Expectancy (H1) exerts a strong and significant influence on Expectation Confirmation (β = .534, p = .000), indicating that users' belief in the usefulness and effectiveness of AI financial tools plays a crucial role in reinforcing their expectations.

Effort Expectancy (H2) also has a positive effect on EC (β = .309, p = .000), suggesting that ease of use contributes to confirmation of expectations, though its impact is comparatively moderate. Social Influence (H3) is significantly related to EC (β = .452, p = .000), highlighting the influence of peers, societal norms, and valued opinions in shaping users' perception of their experience.

Facilitating Conditions (H4) demonstrate a strong positive relationship with EC (β = .484, p = .000), emphasizing the role of access to supportive infrastructure and resources in aligning user expectations with actual experience.

Antecedents and Financial Well-Being (FW)

Performance Expectancy (H6) directly impacts Financial Well-being (β = .407, p = .000), indicating that users' perception of the tool's benefits contributes to their financial satisfaction. Effort Expectancy (H7) shows a significant, albeit moderate, effect on FW (β = .259, p = .014), signifying that ease of use facilitates better financial outcomes, though less powerfully than other factors.

Social Influence (H8) positively affects FW (β = .332, p = .000), reinforcing the role of social support and peer influence in improving users' financial conditions. Facilitating Conditions (H9) also have a positive and significant impact on FW (β = .363, p = .000), suggesting that accessible tools and support systems enhance financial well-being.

Mediating Role of Expectation Confirmation (EC)

Expectation Confirmation significantly influences Financial Well-being (H5) with the strongest observed path coefficient (β = .781, p = .000). This highlights EC as a key mediating variable, demonstrating that when user expectations are met or exceeded, notable improvements in financial outcomes follow.

According to the analysis PF EF SI and FC all have a significant impact on EC and FW with PF and FC having relatively greater effects on EC. Expectation confirmation in turn is a crucial process that transforms adoption motivators into observable financial gains. These results highlight the significance of creating user-friendly systems that live up to expectations in order to support both financial security and psychological well-being.

DISCUSSION

The adoption and long-term use of AI-driven personal financial tools especially when it comes to enhancing financial well-being (FW) are crucially understood through the application of the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Expectation-Confirmation Model (ECM). These models offer a thorough framework for examining the variables that affect both the initial and ongoing adoption of technology emphasizing the dynamic interaction between user experiences and expectations.

UTAUT and Expectation Confirmation

Venkatesh et al. created the UTAUT model. (2003) provides a strong basis for comprehending the elements that influence the adoption of technology. Users initial adoption decisions of AI-driven financial tools are significantly influenced by the four main UTAUT constructs: performance expectancy (PF) effort expectancy (EF) social influence (SI) and facilitating conditions (FC). Because users are likely to adopt AI financial tools based on the perceived benefits they offer such as better financial decision-making and control performance expectancy is especially pertinent in this domain. Similar to this effort expectancy is important for adoption since users look for tools that offer a smooth user-friendly experience (Venkatesh et al. (2003). With a focus on expectations in the decision-making process the UTAUT framework offers insightful information about why users choose to use AI financial tools. Nonetheless the UTAUT model has drawn criticism for its scant attention to behavior after adoption (Venkatesh et al. (2012). To overcome this restriction UTAUT has been progressively combined with Bhattacherjees (2001) Expectation-Confirmation Model (ECM) to capture the dynamics that occur after adoption. ECM asserts that whether or not users initial expectations are met affects their decision to keep using a technology. This model is especially pertinent to comprehending long-term engagement and user satisfaction with AI financial tools. According to Bhattacherjee (2001) users are more likely to stick with a technology if their expectations are met or surpassed. This can lead to benefits like improved financial well-being. This is consistent with Thong et al. s findings. (2006) who propose that a crucial mediator between adoption factors and sustained usage is expectation confirmation. When UTAUT and ECM are combined a thorough understanding of adoption and ongoing use is obtained. UTAUT lays out the framework for initial adoption whereas ECM describes how users satisfaction and experiences after adoption affect their continued use. Studies have demonstrated that users are more likely to view AI tools as beneficial and keep using them which improves financial results when the expectations set by UTAUT are validated by satisfying post-adoption experiences (Shankar 2021).

Expectation Confirmation and Financial Well-being

A key factor in assessing how well AI financial tools improve financial well-being (FW) is expectation confirmation. According to Netemeyer et al. financial well-being is the capacity to fulfill financial commitments experience financial security and make choices that are consistent with ones values. (2018). Users are more likely to express greater levels of satisfaction and financial well-being when their expectations regarding AI tools capacity to enhance their financial decision-making are fulfilled. For instance AI tools that provide accurate budgeting advice and tailored insights give users a sense of control over their money which lowers financial stress and boosts confidence in handling money-related issues (Xiao and Porto 2017). Several studies have shown a connection between financial well-being and expectation confirmation highlighting the fact that users satisfaction with a technology which is influenced by expectation confirmation is a strong predictor of its continued use (Bhattacherjee2001). In the realm of financial technology this contentment results in increased use of AI tools enabling users to partake in more methodical financial activities like investment management and budgeting which directly improve financial results. Since Thong et al. According to (2006) users expectations and experiences must be in line for AI tools because these technologies frequently have high expectations for advanced and customized features. Additionally expectation confirmation mediates the relationship between post-adoption outcomes like financial well-being and pre-adoption factors like performance expectancy and ease of use (effort expectancy). In order to maintain engagement and improve their financial circumstances users must believe that the tool fulfills its promises indicating that initial adoption is only the beginning of the process. A mismatch between expectations and experiences can cause users to become dissatisfied which lowers their willingness to use the tool going forward and has a detrimental effect on their financial results (Lee & Kwon 2020). In order to guarantee that AI financial tools support financial empowerment expectation confirmation plays a crucial role. Users who thought AI tools were smart and trustworthy expressed more satisfaction and a stronger sense of financial security according to Shankars (2021) research. This supports the notion that developers should give careful consideration to controlling user expectations in order to guarantee that their tools consistently provide value.

UTAUT and Financial Well-being

Additionally the UTAUT framework directly advances knowledge of the ways in which AI tools can impact financial well-being. Perceptions of financial well-being in the context of AI financial tools are closely related to performance expectancy which represents users belief that utilizing a technology will yield benefits. AI tools that optimize investments automate budgeting and give users personalized insights can improve users financial decision-making lower financial stress and ultimately improve financial well-being (Shankar 2021). In a similar vein effort expectancy is crucial to maintaining the use of these tools. AI tools that are simple to use and take little learning curve are more likely to be adopted and used consistently which can result in better financial practices like disciplined budgeting and well-informed investment choices (Venkatesh et al. 2003). Financial well-being and adoption are also significantly influenced by social influence. Peer recommendations cultural norms and financial advisor endorsements can all boost confidence in AI financial tools and increase their influence on financial well-being (Zhao et al. 2022). For users to fully utilize AI tools and reap the financial rewards they provide enabling conditions like internet access smartphone use and customer service are essential. Without sufficient enabling circumstances users might find it difficult to embrace or stick with these tools which would reduce their potential financial gains (Venkatesh et al. 2012). The adoption and continued use of AI-driven personal financial tools are explained in this discussion by highlighting the complementary nature of UTAUT and ECM. According to the results social influence performance expectancy effort expectancy and enabling circumstances all have a major impact on financial well-being and expectation confirmation. In the relationship between adoption drivers and financial well-being expectation confirmation is a crucial mediator since it is essential in converting user expectations into favorable financial outcomes. For AI financial tools to improve financial empowerment and well-being developers and legislators should place a high priority on controlling user expectations and making sure that they consistently deliver value.

CONCLUSION

Using the Expectation-Confirmation Model (ECM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) this study offers a thorough analysis of the relationship between user adoption of AI-driven personal financial tools and their effects on financial well-being. According to the findings expectation confirmation plays a crucial role in bridging the gap between pre-adoption factors like social influence performance expectancy effort expectancy and facilitating conditions and post-adoption outcomes especially financial well-being. The study emphasizes the importance of facilitating conditions and performance expectations in influencing user expectations and confirming them following the adoption of AI financial tools. These elements support users long-term engagement and satisfaction which in turn improves their financial well-being by empowering them to make well-informed financial decisions lowering financial stress and boosting their confidence in money management. Further highlighting the significance of these elements in guaranteeing that users initial expectations are fulfilled or surpassed leading to sustained use and better financial results are the positive correlations found between performance expectancy effort expectancy social influence and facilitating conditions with expectation confirmation. Furthermore it was discovered that a powerful mediator between pre-adoption factors and financial well-being was expectation confirmation. When users expectations are met their financial well-being improves leading to better financial outcomes like improved investment planning budgeting and overall financial security. According to this study it is crucial to properly manage user expectations both during the adoption stage and as they continue to use AI-driven financial tools. According to these findings the fintechindustrys developers and stakeholders can increase adoption and long-term satisfaction by putting the user experience first especially through user-friendly interfaces easily accessible resources and open communication. Financial technology companies can promote improvements in financial well-being and guarantee that AI tools live up to their promise of financial empowerment by balancing users expectations with the technologys actual performance.

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