RESEARCH ARTICLE

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

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Manuscript Info	*Abstract*
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The blistering development of the Artificial Intelligence (AI) has altered the financial services environment, providing new personal financial technology, which improves the financial decision-making and well-being. Among women entrepreneurs who operate small and medium-sized enterprises (SMEs), financial inclusion, credit access, and general business performance have a lot of potential in these cases, and the use of AI-based financial solutions can greatly improve them. The paper explores how the use of AI personal financial tools affects the financial status of the women entrepreneurs, merging the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Expectation-Confirmation Model (ECM) as the theory. To understand adoption behavior, the research examines the main aspects of performance expectancy, the expectancy of the effort, social influence, and facilitating conditions, the user expectations, satisfaction, and continuance intentions. The results draw attention to the duality of motivations and barriers technological, economic and institutional in the formation of adoption decisions. The paper highlights the role of AI-based financial solutions in empowering female entrepreneurs to save, plan investment, and manage risks and how policy and regulatory considerations can be used to drive digital financial inclusion. UTAUT plus ECM offer an inclusive perspective to evaluate the preliminary adoption and long-term use, which can be useful to policymakers, technology developers, and financial institutions to enable women-led SMEs to thrive in the digital age.

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Introduction:-

One of the industries experiencing a revolution due to the tremendous increment in the artificial intelligence (AI) is personal finance. Personal finance assistants powered by AI are becoming a necessity to every individual who wants to manage his or her finances appropriately. They have applications such as investment planning that tracks

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expenses and budgeting and savings optimization as well as being powered by highly developed machine learning algorithms and data analytics. They empower users by providing them with an opportunity to make informed financial choices by giving personalized information and recommendations (Shankar 2021). The use of technology in enhancing financial autonomy and well-being is gaining popularity judging by the use of such tools. Those individuals who enjoy financial control over their finances and experience a lesser stress count are reported to be financially well-being (Netemeyer et al. in 2018). It has both subjective opinion such as financial confidence and satisfaction and objective measures such as income and savings. Through the encouragement of more spending control to enhance financial literacy and the ease of decision-making research has shown that technological applications can be used to enhance financial well-being (Xiao and Porto 2017). It is poorly understood how AI personal financial tools can influence financial well-being even in the light of these benefits particularly on the behavioral and psychological elements that can prompt users to engage and keep using it.

The Unified Theory of Acceptance and Use of Technology (UTAUT) may provide a strong theoretical framework to understand the technology adoption. The performance expectancy effort expectancy social influence and enabling conditions are also listed as significant interventions that determine the adoption and use of technology (Venkatesh et al. (2003)). These constructs can be said to be the primary causes of users making initial decisions to utilize AI personal financial tools. However post adoption activities and its consequent effects such as financial well-being are not well considered as far as UTAUT primarily focuses on pre adoption factors. The Expectation-Confirmation Model (ECM) improves UTAUT by offering details of post-adoption behaviors to eliminate this weakness. According to ECM, the first expectations after use confirmation or disconfirmation of these expectations and further satisfaction all affect the further use of technology by users (Bhattacherjee 2001).

This study provides a comprehensive framework through the integration of UTAUT and ECM which records the adoption and the sustained utilization of AI personal finance apps and their impact on financial security. This research paper is effective in convincing the reader that expectation confirmation is another crucial mediating variable in understanding how pre-adoption variables such as effort and performance expectancies affect post-adoption results. Since it measures the similarity between user expectations and experience and expectation confirmation is necessary to make users satisfied and continue to operate over the long run (Bhattacherjee 2001). With the help of such mediating role, one may know more about the dynamic relationship between financial performance and the use of technology. Also this research would include the Expectation Confirmation Model (ECM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) that dwells on the important mediating effect of the expectation confirmation that reinforces our theoretical model significantly. It also offers the financial technology stakeholders a valuable practical insight which points to the need to improve the design functionality and communication of AI-powered personal financial apps which will eventually enhance its 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:
One widely used model of understanding acceptance and use of technology is the Unified Theory of Acceptance and Use of Technology (UTAUT) which was formulated by Venkatesh and others. UTAUT (2003) identifies four key factors as affecting behavioral intention and usage behavior: facilitating conditions social influence performance expectancy and effort expectancy. Those constructs provide a solid foundation when analyzing the factors which are affecting user adoption within the frame of AI-driven personal financial tools. The need to find tools to enhance financial decisions and performance expectancy, which defines the perceived benefits of using a technology, becomes more critical as consumers are in search of it. Expectancy in effort is also a determinant of user acceptance because AI tools must offer an easy and easy user experience to influence involvement (Venkatesh et al. in 2003). However, UTAUT is said to have given minimal consideration to the post adoption behaviors and outcomes despite the success of this tool in capturing the pre-adoption factors (Venkatesh et al. (2012). To address this gap, researchers have increasingly been considering complementary models such as the Expectation-Confirmation Model (ECM) that emphasizes more on the post-adoption dynamics. Bhattacherjee (2001) had formulated ECM in which it

is believed that the users satisfaction with a technology viewed utility and confirmation or disconfirmation of the initial expectations would all influence the length of time they would be using the technology. Since users often develop expectations about the functionality of the tools to enhance financial well-being and decision-making it is particularly relevant to this model in the case of AI financial tools. When expectations are fulfilled or even exceeded, the users will report better results and will have more chances to stay with the tools. With respect to AI-based personal financial applications, the UTAUT/ECM combination is of special importance. Studies have shown the mediation of expectation confirmation between initial adoption factors and sustained use.

To illustrate, the UTAUTs performance expectancy and effort expectancy establish the environment of initial usage of the AI financial tools by the users. ECM notes that the degree to which these expectations are confirmed by the post adoption process, defines the level of user satisfaction and long term use (Thong et al. 2006). It means that expectation confirmation is a crucial mediator between the motivating factors and the long-term impact on financial well-being. Although understudied expectation confirmation is gaining increasing importance in the area of AI financial tools. Users are initially very high-pressured since AI tools often offer more efficient budgeting investments and individual financial recommendations.

These expectations are confirmed by positive experiences that enhance the rate at which the users perceive value in the tools that will raise their mechanism of satisfaction and promote their continued usage (Shankar 2021). The necessity to align the user expectations with the actual possibilities of the tools is stipulated by the fact that the non-fulfillment of the expectations may result in dissatisfaction and abandonment. The crossroad of UTAUT and ECM can provide important information regarding the uptake and long-term use of AI financial tools. UTAUT puts great importance to pre-adoption factors such as ease of use and social influence as compared to ECM, which focuses on the post-adoption perception. Through emphasising the importance of managing user expectations and offering steady value the combination of these frameworks can give an in-depth insight into how AI-based financial tools can influence 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:
One of the most important concepts concerning the Expectancy-Confirmation Model (ECM) expectation confirmation is the key to the understanding of user satisfaction and continued use of technology. Expectation confirmation according to Bhattacherjee (2001) is the extent to which expectations of users towards a technology are the same as their post adoption experience. This is critical in facilitating user satisfaction, long-term engagement and ultimately beneficial outcomes such as improved financial well-being as far as AI financial tools are concerned. Financial well-being is a complex construct that includes the ability to make decisions and choices, which are in alignment with its values; financial security; as well as the financial capacity to honor financial obligations (Netemeyer et al. (2018). The relationship between financial well-being and expectation confirmation can be explained by the adoption and usage of technology.

The end user is also more likely to perceive AI financial products as helpful, and they are satisfied when they feel that they are achieving or even exceeding their expectation enhancing their financial behaviours and outcomes (Shankar 2021). Such is the case of AI-based tools that give individuals accurate budgeting recommendations based on customized financial data and winning investment plans feel more in charge of their money have fewer financial anxieties and feel more assured, which are all vital elements of financial well-being (Xiao and Porto 2017). The larger research in the field of technology has substantiated expected confirmation as having a significant role in influencing post-adoption outcomes and behaviors. As demonstrated by Bhattacherjee (2001), the fact that the user has constant use of the technology can be largely predicted by their satisfaction that is driven by the confirmation of the expectations.

Financial technology In the context of financial technology this satisfaction would lead to increased usage and active utilization of the tools that enable users to adopt a disciplined and financially sound lifestyle and achieve high financial outcomes. Due to the high expectations of users regarding AI capabilities, the research of AI-powered tools has also demonstrated the significant role that the interaction of the user expectations and experience plays dynamically (Thong et al. 2006). When the expectations are met, users report better financial well being by having

better resources management and decision making. Expectation confirmation also mediates the relationships between such pre-adoption factors as perceived ease of use and performance expectancy and post-adoption outcomes as financial well-being. As an example, users after adoption experiences should equal these expectations in picking up AI financial tools as they would promise user friendly interfaces and actionable insights in their pursuit of fostering satisfaction and trust (Lee and Kwon 2020). On the other side a lack of alignment to expectations can lead to a reduction in usage that will have a negative financial impact on it and cause dissatisfaction. The studies in the field of financial well-being, where the confirmation of expectations is involved, provide complex understanding of how much the AI financial tools can influence people.

Users who believed that artificial intelligence resources were reliable and meaningful in case mentioned being more satisfied and felt more financially secure as suggested by Shankar (2021). This means that to ensure that tools have a steady value, they must be high in the priority of transparency that developers adopt and these tools should be well adjusted to the expectations of the users. In the case of the AI financial tools, expectation confirmation is a key criterion in defining financial well-being. Since it influences the user satisfaction and retention, users can employ these technologies to improve their financial outcome. In order to make AI-based solutions more effective in supporting financial empowerment, developers should align the initial user expectations with the performance of tools; this combination of works allows creating a complete picture of how AI-based financial tools may influence financial well-being.H5: Expectation confirmation positively related to financial well-being

UTAUT and Financial Wellbeing:
To examine the technology adoption and its impacts, Unified Theory of Acceptance and Use of Technology (UTAUT) has become a critical theory. It is the creation of Venkatesh and others. UTAUT (2003) identifies four key constructs that have an impact on user adoption and use behavior and they include performance expectancy effort expectancy social influence and facilitating conditions. These ideas are essential to understanding how humans apply technology in order to enhance their economic security within the framework of personal financial services powered by AI. When embracing AI financial technologies the perceptions that individuals have of their financial status are closely connected with performance expectancy or the belief that the use of a technology will result in benefits. These tools features available to users allow them to optimize their financial resources and reduce financial stress through automated budgeting investment management, and custom financial insights. Studies have shown that the tools perceived to enhance financial decision-making and control have a higher probability of adoption that eventually leads to enhancement of financial well-being (Shankar 2021).

The desire of the users to get a better financial health correlates with the ability of the AI financial tools to simplify complex financial operations thus making performance expectancy significant in this field. Ease of use of the technology, referred to as financial tools, is necessary to use AI financial tools on a regular basis. More user-friendly tools that are less difficult to learn are more likely to attract and retain users. It is very easy to use and therefore there are high chances that users will have good experiences and make the tools part of their routine financial management systems. Such frequent utilization finally results to an improved monetary conduct such as budgeting and prudent investment options that are vital components of financial health (Venkatesh et al. (2003)). Social influence or how much an individual thinks that those close to them believe they are supposed to use a technology is one of the reasons behind the use of AI financial tools.

Such confidence in such tools can be increased especially when associated with improved financial outcomes cultural norms and financial advisor endorsements (Zhao et al. 2022). AI tools adoption promotion and the advantages of the peers in financial well-being are often a motivator towards broader adoption enhancing personal financial outcomes. Enabling conditions are the resources and support in using AI financial tools, and access to AI technologies and AI-based services is highly reliant on the enabling conditions. These are smartphones customer service, and reliable internet connectivity among others which individually combine to ensure that customers are able to make optimized use of the tools. The enabling condition that may hinder the adoption of these technologies could limit the financial benefits users may get out of the technology (Venkatesh et al. (2012). The policies that allow bridging the divide between financial literacy and technology can greatly enhance adoption and the effect of those tools on financial well-being.

The UTAUT constructs combined create the adoption and eventual use of AI financial tools that, in turn, influence financial well-being. Maintaining engagement by users leads to the better financial management and reduction of stress in cases of adopting tools with positive expectations (performance and effort expectancy) and being motivated

by the social environment and available resources. Also, the AI tools-based insights are useful in carrying out informed financial decisions that are highly objective and subjective in terms of financial well-being (Netemeyer et al. 2018).

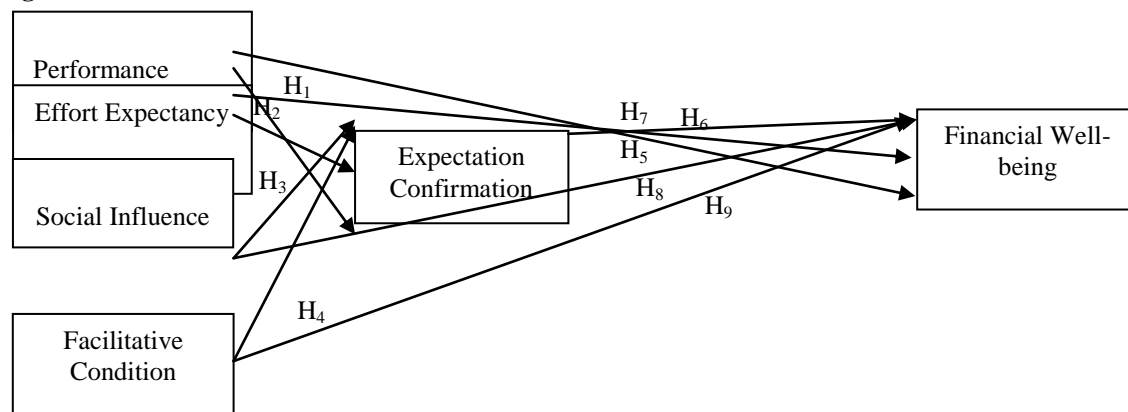**H6:** Performance expectancy positively related to financial well-being
H7: Effort expectancy positively related to financial well-being
H8: Social influence positively related to financial well-being
H9: Facilitative condition positively related to financial well-being

Conceptual model:
Figure 1

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

Methods:-

With a quantitative cross-sectional research design, this study examines the relationships between financial well-being expectation confirmation and adoption variables with regard to AI-based personal financial applications. The basis of the studies is a coherent model that assesses user behaviours prior to and following the adoption through a combination of Expectation-Confirmation Model (ECM) and Unified Theory of Acceptance and Use of Technology (UTAUT). The target population consists of people in Coimbatore, which is a developing urban center that is experiencing the increasing use of fintech among salaried professionals and small business owners that actively use AI personal financial tools. A sample size of 321 responders which was selected using purposive sampling was to ensure that the data is correct and relevant. Purposeful sampling was done as a non-probability sampling method to specifically identify and involve participants that had personal experience using AI financial tools.

This will be in relation to the study constructs performance expectancy effort expectancy social influence facilitating conditions expectation confirmation and financial well-being- this approach was chosen as it would ensure that participants used informed responses. Hands on experience with the technology with emphasis on the post adoption behavior and satisfaction by the participants was essential. Conversely random sampling could have resulted in the incorporation of individuals who were not conversant with AI financial tools that could have invalidated the application of the theoretical models and caused the outcomes to lack validity. The geographic area was strategically selected to be Coimbatore due to the fact that it provides a relevant context in exploring how regional factors such as the availability of digital literacy infrastructure and cultural viewpoints influence the adoption and the use of AI financial instruments in the long term.

Data were collected using a structured questionnaire with validated scales altered to measure the constructs of the study. The questionnaire included the demographic information expectation confirmation financial well-being and the UTAUT constructs (performance expectancy effort expectancy social influence and facilitating conditions). The responses were recorded on a five-point Likert scale where 1 meant strongly disagree and 5 strongly agree. Analysis of data was done using Structural Equation Modeling (SEM) where both the direct and mediating effects were evaluated and the relationships tested. The preliminary tests included Data cleaning reliability, Confirmatory Factor Analysis (CFA), and all of these tests confirmed construct validity. All ethical rules such as the institutional approval procedures, data confidentiality and informed consent were closely adhered to in the study. The methodological strategy was aimed at confirming the combined UTAUT-ECM framework exactly determine the

determinants of the use of AI financial tools and generate valuable knowledge on the improvement of user engagement and financial well-being through effective fintech solutions.

Measures:

The current survey tools are used in the study of UTAUT, ECM and Financial well-being. According to the research, words and items became altered. The variables on the latent constructs were measured using five-point Likers scale of 5 strongly agree to strongly disagree. Table 1 contains the items of the study. These constructs and demographic profiles (age, gender, qualification, income) were included in the questionnaire.

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)			
I find AI financial tools useful in my daily life.	.987		
Using AI financial tools increases my chances of achieving things that are important to me.	.962	.985	
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		
My interaction with AI financial tools is clear and understandable.	.904	.917	
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)			Rahman et al., (2019)
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		
The benefits of AI financial tools are better than my expectation	.979	.978	Alnaser et al., 2023
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		Dzogbenuku et al., (2021)
AI financial tools bring me excitement	.961	.971	
Using AI financial tools is economical	.954		
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 part will outline the findings and the results of different statistical tests performed to determine the reliability and validity of the measures, and also to test the conceptual model. In order to demonstrate the concepts validity and dependability confirmatory factor analysis or CFA was employed. As Anderson and Gerbing (1988) state CFA provides extremely important data concerning the presence of convergent validity of the scales in use. This involves the establishment of whether the observed variables are loading appropriately on the specific latent constructs (Kline 2010). To demonstrate the discriminant validity, we adopted the method recommended by Fornell and Larcker (1981). We have considered composite reliability and average extracted variance as the measures of construct reliability. The proposed model was tested based on a complete structural equation modeling (SEM) utilizing AMOS (Version 26).

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

Because all of the reported measures are below or above the predetermined values the CFA models fit indices provide strong evidence of its adequacy and appropriateness in the explanation of the data at hand. This demonstrates the level of representation of the model to the proposed relationships and strength. The measure of Cmin/df (2.346) displays the ratio of degrees of freedom to the chi-square statistic. A value of less than 3 indicates a satisfactory degree of fit since the model will have managed to minimise the difference between the theoretical model and the observed data. GPI (.945): The Goodness of Fit Index is used to indicate the ability of the given model to explain the variation in the dataset.

The value of above .90 as in this case means that the model accounts for most of the covariance structure which shows that it has a high quality fit. CFI (.903): The Comparative Fit Index is used to measure the performance of a model with respect to the null model (a model that takes the relationships between variables to be zero). Having a value that is greater than the threshold of .90, the results indicate that the proposed model has a high level of comparative performance which proves that it is sufficient. IFI (.946): Like the CFI, Incremental Fit Index is used to determine the incremental fit of a model relative to a base model.

The value of.946 is very high, which demonstrates that the model has high improvement, and this once again justifies its high fit. RMSEA (.063): RMSEA is the Root Mean Square Error of Approximation that shows the level of approximation error in the model. The value of less than .08 indicates a tight fit, and there is not much error, which implies that the model is parsimonious but at the same time, it fits the underlying structure of the data. All the fit indices confirm the CFA model as a solid and sound framework of the data. Having all the metrics within their corresponding thresholds or more, the model would be suitable to continue its analysis and offer any confidence regarding its depiction of the constructs in question. This good fit justifies the theoretical and empirical soundness of the model.
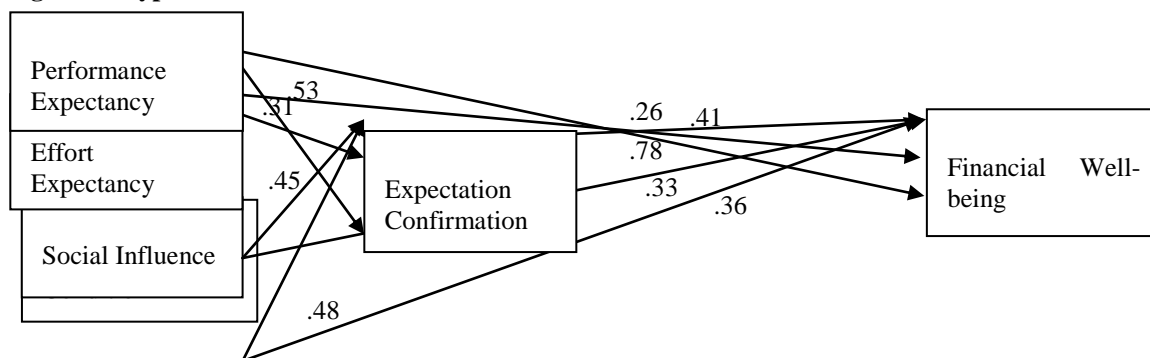
Table 2

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

The results of the SEM (Structural Equation Modeling) fit indices confirm that the results of the SEM provide an acceptable and reliable fit between the proposed model and the observed data. The fact that the models are appropriate in the description of the proposed relationships can be substantiated by the strong reported indices that all exceed or reach the set thresholds. The covariance matrices observed and estimated have a difference that falls within a reasonable range as seen by the chi-square degrees of freedom ratio that is below the maximum allowable value of 3. This shows the level of goodness of fit of the model to the data structure. GPI: The Goodness of Fit Index is a ratio which quantifies the model variance and covariance.

A value above the threshold of.90, which is 0.924, means that the model explains most of the variability of the data and is a good model that represents the underlying patterns.CFI: The Comparative Fit Index evaluates how well the model fits as compared to a null model (which is one that assumes no relationships between the variables). The value of CFI of .901 slightly greater than the value of .90 is enough indication that the model proposed is significantly better than the null model implying a satisfactory comparative fit. IFI: The Incremental Fit Index is used to determine the improvement of the model compared to a basic model. The fact that the model has a value of .927 exceeding the accepted standard of.90 indicates that the model has an excellent incremental fit and is capable of capturing the relationship between variables. Root Mean sq.

Error of Approximation or RMSEA measures the models parsimony and accuracy in approximating the data. A lower figure of . 070 than the . 08 threshold indicates that the error in estimation by the models is minimal and that it fits the data well, and it is also cost-effective. Combined with the SEM fit indices indicate the theoretical soundness and reliability of the models. The results reveal that the model can reasonably describe the intended relationships and within the observed data ensure that the model is effective in future studies. These findings testify to the stability of the structural models and their appropriateness to test the hypothesis and extract valuable information on 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
H₁	PF → EC	.534	1.074	.000	Yes
H₂	EF → EC	.309	1.212	.000	Yes
H₃	SI → EC	.452	1.164	.000	Yes
H₄	FC → EC	.484	1.102	.000	Yes
H₅	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 depicts the postulated causal association among the significant constructs, which are Performance Expectancy (PF), Effort Expectancy (EF), Social Influence (SI), Facilitating Conditions (FC), Expectation Confirmation (EC), and Financial Well-being (FW). The statistical significance of all the nine hypotheses (H1-H9) is established and confirms the existence of significant and positive relations between the variables.

Antecedents and Expectation Confirmation (EC):
The performance Expectancy (H1) also has a high and effective impact on Expectation Confirmation (= +.534, p =.000), which shows that a belief in the usefulness and effectiveness of AI financial tools by the users has a significant influence in confirming their expectations.The positive effect on EC is also manifested by Effort Expectancy (H2) (β =.309, p =.000), which indicates that ease of use helps to confirm the expectations, but this effect is rather moderate.The Social Influence (H3) has a significant relationship with EC (=.452, p =.000), indicating how peers, society, and opinions of people valued affect the perception of users about their experience.Facilitating Conditions (H4) have a positive correlation with EC (0.484, p =.000) because the accessibility of supportive infrastructure and resources can help to synchronize user expectations and actual experience.

Antecedents and Financial Well-Being (FW):
The performance Expectancy (H6) has a direct relationship with Financial Well-being (=.407, p =.000), which means that the perceptions of the users with regard to the benefits of the given tool influence their financial satisfaction.Effort Expectancy (H7) demonstrates a significant (at the same time moderate) impact on FW (=.259, p =.014), which means that the ease of usage contributes to the improvement of financial results, but not as strongly as other aspects.Social Influence (H8) has a positive impact on FW (=.332, p =.000), which supports the contribution of social support and peer influence in enhancing the financial status of the users.FW is also positively and significant influenced by the Facilitating Conditions (H9) (p =.000, 9 =.363), which indicates that available tools and support systems positively increase financial well-being.

Mediating Role of Expectation Confirmation (EC):
Financial Well-being (H5) is another predictor that is affected to a major extent by Expectation Confirmation (0.781 =.000). This makes EC one of the most important mediating variables that show that once user expectations are achieved or surpassed, significant changes in the financial results will occur.

The analysis has shown that PF EF SI and FC all play a big role in EC and FW with PF and FC playing relatively bigger roles in EC. The confirmation of expectation, in its turn, is a key process that would help to convert the motivators of adoption into monetary benefits. The outcomes of this research underscore the importance of developing user-friendly systems that can meet the expectations to ensure a support of the financial and psychological well-being.

Discussion:-
The use and adoption of the AI-based personal financial tools and, in particular, in improving financial well-being (FW) is critically perceived through the implementation of the Unified Theory of Acceptance and Use of Technology (UTAUT) as well as Expectation-Confirmation Model (ECM). The models present an in-depth system of studying the variables influencing both the first and continued adoption of technology highlighting the dynamism of the interaction between user experiences and expectations.

UTAUT and Expectation Confirmation:
The UTAUT model developed by Venkatesh et al. gives a solid foundation to understand the factors that can affect the technology adoption. (2003) The four primary UTAUT constructs (performance expectancy (PF) effort

expectancy (EF) social influence (SI) and facilitating conditions (FC) have a significant impact on the initial adoption decisions of AI-driven financial tools by users. Since users tend to use AI financial tools due to the perceived advantages they have in their use such as improved financial decision-making and control performance expectancy is particularly relevant in this field. Just like this attempt, expectancy of adoption is significant because users are seeking tools that provide them with an easy user-friendly experience (Venkatesh et al. (2003). Having the expectations as the central point of the decision-making process, the UTAUT framework provides an informative piece of information regarding the reason why users opt to use AI financial tools.

However the UTAUT model has been criticized as it gives very little consideration to post adoption behavior (Venkatesh et al. (2012). To resolve this limitation UTAUT has been gradually integrated with Bhattacherjees (2001) Expectation-Confirmation Model (ECM) to define the dynamics that follow adoption. ECM holds that the deliberate response to initial expectation regardless of its fulfilment influences users to continue to use a technology. The given model is particularly relevant to understand the long-term involvement and satisfaction of users with AI financial tools. Bhattacherjee (2001) states that the higher their expectations are met or exceeded, the better the chances are that users will remain with a technology.

This is capable of giving positive gains such as better financial situation. This has been in line with the findings by Thong et al. s. (2006) who postulates that expectation confirmation is a critical mediator between adoption factors and sustained usage. The combination of UTAUT and ECM provides an in-depth insight into the process of adoption and continued usage. UTAUT outlines the model of the first adoption compared to ECM which explains the effects of user satisfaction and post adoption experiences on their subsequent use. It has been established that users tend to believe that AI tools are helpful and continue to use them which enhances financial outcomes when the expectations formed by UTAUT are met by fulfilling post-adoption experiences (Shankar 2021).

Expectation Confirmation and Financial Well-being:
Expectation confirmation is one of the components that are considered when evaluating the effectiveness of AI financial tools in enhancing financial well-being (FW). Netemeyer et al. view financial well-being as the ability to meet financial obligations, have a sense of financial security and take decisions that align with their values. (2018). The higher the expectations of the users with respect to the capacity of AI tools to improve their financial decision-making, the more chances they are likely to express higher levels of satisfaction and financial well-being.

As an example AI technologies offering relevant budgeting recommendations and customized insights give the user a feeling of control over their finances that reduce financial stress and increase their confidence in coping with money-based challenges (Xiao and Porto 2017). A number of studies have also revealed the links between financial status and expectation confirmation that indicate that the level of user satisfaction with a given technology that is mediated by expectation confirmation is a good predictor of the further use of the technology (Bhattacherjee 2001).

Within financial technology, such satisfaction leads to a higher adoption of AI tools that can help users engage in more procedural financial processes such as investment management and budgeting that has a direct effect on financial outcomes. Since Thong et al. As (2006) users expectations and experiences are in line with AI tools since AI tools often pose high expectations of advanced and customized features. Moreover, there exists an intermediation of post-adoption success such as financial well-being, by expectation confirmation and pre-adoption such as performance expectancy and ease of use (effort expectancy).

So that the users can stay engaged and enhance their financial conditions they need to have the belief that the tool does what it promises which means that the first adoption is not the end of the process. The gap in expectations and experiences may lead to dissatisfaction by the users that decreases their intentions to use the tool in the future and negatively influences their financial outcomes (Lee and Kwon 2020).

To ensure that AI financial tools have been used to empower people financially, financial empowerment expectation confirmation is critical. According to the research conducted by Shankars (2021), the most positive results were demonstrated by users who believed that AI tools were intelligent and reliable and felt more content and secure about their financial situation. This helps in endorsing the idea that developers must pay close attention to managing user expectations so as to ensure that their tools will always deliver value.

UTAUT and Financial Well-being:
UTAUT framework is directly moving in the right direction to understand how AI tools can influence financial well-being. The financial well-being perceptions regarding the use of AI financial tools are interconnected with the performance expectancy that signifies user faith that the use of a technology would lead to benefits. AI tools that can optimize investments can streamline the budgeting process and provide users with personalized information will enhance the process of financial decision-making among users, reduce financial stress, and eventually enhance financial well-being (Shankar 2021). Similarly in a similar vein effort expectancy is central to the continued use of these tools. The less complex and less learning curve AI tools have higher chances of being adopted and used regularly which can lead to improved financial practices such as disciplined budgeting and informed investment decisions (Venkatesh et al. 2003). Social influence also plays a major role in financial well-being and adoption.

The confidence in AI financial tools could be enhanced by peer recommendations cultural norms, as well as with the recommendations of financial advisors, and their power to affect financial well-being (Zhao et al. 2022). To have a complete access to AI tools and enjoy the financial gains that the latter offer, such preconditions as the access to the internet and the use of smartphones and customer care are needed. The lack of enabling conditions may make users hard to adopt or even remain with these tools that would decrease their possible financial benefits (Venkatesh et al. 2012). This discussion explains the adoption and further use of AI-based personal financial tools as a result of their complementary nature between UTAUT and ECM. Based on the findings, the social influence performance expectancy effort expectancy significantly affects the financial well-being and expectation confirmation, and the same does the enabling circumstances. The relationship between adoption drivers and financial well-being includes a significant mediator in the form of expectation confirmation as it is a key factor in transforming the expectations of the users to positive financial results. To enhance financial empowerment and financial well-being developers and legislators ought to give a top priority to the management of user expectations and to ensure that they can continually create value.

Conclusion:-
Through the Expectation-Confirmation Model (ECM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), the proposed study provides an in-depth study of the connection between acceptance of AI-driven personal financial tools by the user and their impact on financial well-being. Based on the findings, the expectation confirmation is significant in the reduction of the gap between pre-adoption, such as social influence performance expectancy effort expectancy, and facilitating conditions, and post-adoption outcomes particularly financial well-being. The research highlights this role played by facilitating conditions and performance expectations in shaping user expectations and validating them after the implementation of AI financial tools. These factors reinforce the user long-term interaction and satisfaction that subsequently enhance their financial well-being enabling them to make informed financial choices that reduce financial stress and enhance their trust in money management.

More emphasis on the importance of these factors in ensuring that initial expectations of the user are met or even exceeded to cause continued usage and improved financial outcomes is the positive relationships that exist between expectation confirmation and performance expectancy, effort expectancy social influence, and facilitating conditions. Moreover it was found out that expectation confirmation was a potent mediator between pre-adoption variables and financial well-being. As the expectations of the users are satisfied, they have better financial well-being, which results in improved financial performance such as better investment planning budgeting and the overall financial security.

This research has suggested that it is important to ensure that the user expectations are well managed at the adoption stage and even when they will continue to utilize AI-based financial tools. Based on these conclusions the developers and stakeholders of the fintech industry can make more adoption and long-term satisfaction by prioritizing the user experience particularly by providing user-friendly interfaces that are easy to access and open communication. By redressing the balance between the expectation and the actual performance of the AI tools, financial technology firms can streamline the enhancement of a better financial well-being and ensure that the technology is, as promised, a financial empowerment.

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