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Development of a Digital Financial Awareness Model Using AMOS: A Structural Equation Modeling Approach

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Abstract: The increasing digitalization of financial services has changed how clients interact with financial products, resulting in both advantages and disadvantages. The purpose of this research was to develop and validate a full model of Digital Financial Awareness (DFA) using a structural equation modeling (SEM) approach using AMOS. A questionnaire with a five-point Likert scale was issued to 120 participants, who provided 112 valid responses. Exploratory Factor Analysis (EFA) identified key DFA traits, whereas Confirmatory Factor Analysis (CFA) evaluated and enhanced the model. The findings revealed that awareness of digital products, investor rights, fraud prevention, and ethical usage of financial technology all played important roles in defining DFA. Although the initial models had low fit indices, the adjustments improved model adequacy, demonstrating the multidimensional nature of DFA. This work bridged that gap by creating and verifying a DFA measuring model based on existing literature and tailored to modern usage settings.

Keywords: Digital Financial Awareness, Financial Literacy, Structural Equation Modeling (SEM), Financial Inclusion, Digital Finance.

I. Introduction:

Technology has fundamentally altered the way the financial system functions. The fintech sector was formed by combining money and technology. In terms of financial services, goods, institutions, and markets, the new industry is completely digital. It encompasses digital financial advising, digital insurance, digital payments, digital investments, digital money, and digital financing (Gomber, Koch, & Siering, 2017). Financial clients must have the requisite abilities and awareness to use digital financial services in the current fintech environment and take on more financial responsibility (Morgan et al., 2019). Digital literacy and financial knowledge have been proven to predict risk-averse financial habits such as borrowing, saving, and risk-Digital financial awareness is defined as an individual's acquaintance and grasp of digital financial instruments and services (Koning, 2020). It entails knowing how these technologies work, the advantages they offer, and the possible hazards connected with their use (Gomber et al., 2017). According to Taylor (2019), digital financial awareness is a prerequisite for digital financial literacy, underlining the need of individuals becoming familiar with digital financial services before developing deeper knowledge and competences. DFA therefore requires not just knowledge of accessible digital technologies, but also an understanding of safe practices and the larger digital financial ecosystem (Arora & Barak, 2018).

In 2018, the Organization for Economic Cooperation and Development (OECD) defined various aspects of digital financial literacy, including familiarity with digital financial services and products, knowledge of digital financial dangers, and comprehension of consumer rights and recourse procedures. Each definition requires literacy and skill to be utilized correctly, demonstrating the diversity and relevance of the ideas. Digital financial awareness is the understanding and information required to efficiently manage financial operations in a digital context. This includes knowledge with online banking, mobile payments, digital wallets, and other fintech solutions. Because of the increasing reliance on digital platforms for financial transactions, individuals must be proficient in digital financial awareness. The digitization of financial services has transformed how customers engage with financial goods. However, this transformation necessitates a greater level of digital financial literacy to guarantee that customers can make educated decisions. Digital financial awareness includes the information, abilities, and attitudes required to efficiently manage funds in a digital world. This research seeks to create a complete model that incorporates the components identified from EFA and CFA that influence digital financial awareness using Structural Equation Modelling (SEM) via the popular program AMOS.

The study of digital financial awareness is based on numerous theoretical frameworks. The Technology Acceptance Model (TAM) is an important paradigm for understanding how consumers come to accept and use technology. According to TAM, perceived utility and perceived ease of use are important factors in an individual's decision to accept new technologies (Davis, 1989). In terms of digital financial awareness, this model explains why particular populations are more or less inclined to use digital financial instruments. This study addressed that gap by developing and validating a DFA measurement model grounded in established literature and adapted to contemporary usage contexts. A structured questionnaire using a 5-point Likert scale was designed with guidance from prior multidimensional financial literacy work (e.g., Lyons, Kass-Hanna, & Montoya, 2021) and was administered to respondents selected via stratified random sampling. The research proceeded in four linked stages: (i) identifying latent dimensions of DFA through Exploratory Factor Analysis (EFA); (ii) confirming the factor structure via Confirmatory Factor Analysis (CFA) within a structural equation modeling (SEM) framework; (iii) specifying a theoretically informed model that related DFA dimensions and (iv) evaluating model validity, reliability, and overall fit.

II. Literature Review

Digital financial inclusion has become a strategic priority for the Indian government; hence focus has been made on developing digital infrastructure in India (RBI, 2021). As a result of technological upheavals and the rapid digitization of financial services, a plethora of new and creative Digital Financial Services (DFS) have entered the market. Digital financial services enhance the financial inclusion of financially excluded people by removing obstacles to service (Alliance for Financial Inclusion, DFSWG, and CEMCWG, 2021).

Digital financial literacy is critical for financial inclusion and empowerment, especially in a period of rapidly expanding fintech services (Klapper & Singer, 2015). Individuals who are aware of digital financial services are more likely to use digital payment, savings, and credit solutions, which improves their financial management abilities (Demirguc-Kunt et al., 2018). Furthermore, as digital financial fraud and cyber hazards become more prevalent, understanding of safe procedures such as secure authentication and data privacy is critical for safeguarding personal financial information (Chakrabarti & Chaudhuri, 2020). Individuals without proper understanding may be vulnerable to financial exploitation or exclusion from digital financial services.

Several things contribute to digital financial awareness. Age, education, income, and access to technology all influence an individual's understanding of digital financial services (Ritter, 2018). Younger generations are more digitally savvy due to their experience with technology (Koning, 2020). However, older persons frequently lack both digital skills and awareness of digital financial services, resulting in lower rates of DFA (Arora & Barak, 2018). Socioeconomic status is also a factor, since lower-income persons may lack access to technology and internet connectivity, limiting their understanding and use of digital financial services.

Despite the rising relevance of digital financial literacy, spreading it remains difficult. Chakrabarti and Chaudhuri (2020) see the digital divide as a key hurdle, citing discrepancies in access to technology and internet infrastructure as limiting awareness, particularly in rural and undeveloped areas. Furthermore, fast technology advancements make it difficult for users to keep current on new digital financial products and security measures (Taylor, 2019). Financial education programs that just focus on conventional financial literacy may fail to satisfy these rising demands, demanding new techniques to increase digital financial knowledge (Gomber et al., 2017).

DFL is a multidimensional word that encompasses elements such as access and use of digital financial services, digital literacy, and finance (Lyons and Kass-Hanna, 2021). According to Zait and Bertea (2014), financial literacy consists of a number of components, the most important of which are the ability to acquire and use information, as well as the knowledge itself.

Given the significance of digital financial awareness, a variety of educational interventions have been designed to improve this skill set. These initiatives include official financial education programs in schools, targeted workshops, and online courses for adults. According to research, interactive, immersive learning methodologies are very helpful in increasing digital financial awareness (Mandell & Klein, 2009). Individuals who do not have a thorough grasp of how to use digital financial services successfully may be unable to fully capitalize on the opportunities afforded by these technologies. This digital financial literacy gap has the potential to worsen existing disparities, especially among disadvantaged populations who may already encounter challenges to traditional financial services (Zins & Weill, 2016).

Based on the review of prior literature and the identified research gap, the study seeks to address the following research questions:

- RQ1. What are the key dimensions that constitute Digital Financial Awareness (DFA) among individuals in India?
- RQ2. Can the identified dimensions of Digital Financial Awareness be empirically validated using Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA)?
- RQ3. How well does the proposed Digital Financial Awareness measurement model fit the observed data when tested using Structural Equation Modeling (SEM) through AMOS?
- RQ4. What is the relative contribution of awareness of digital financial products, investor rights, fraud prevention, and ethical usage in shaping overall Digital Financial Awareness?

III. Research Objectives

- To identify factors through EFA (Exploratory Factor Analysis).
- To confirm the factors, generated through EFA, using CFA (Confirmatory Factor Analysis).
- To develop a model.
- To validate the model and its constituents and their

relationship.

IV. Research Methodology

The study adopts a quantitative research design to examine Digital Financial Awareness (DFA). Primary data were collected through a structured questionnaire developed from prior digital and financial literacy literature and measured on a five-point Likert scale. A stratified random sampling method was used to select respondents, and 112 valid responses were retained for analysis.

The data analysis followed a two-stage approach. First, Exploratory Factor Analysis (EFA) was applied to identify the underlying dimensions of DFA. Subsequently, Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were conducted using AMOS to validate the factor structure, assess model fit, and examine relationships among the constructs.

4.1. Questionnaire Design

The questionnaire has been developed by using 5-point Likert scale (1=strongly disagree to 5=strongly agree). The idea was taken from the paper "A Multidimensional Approach to Defining and Measuring Financial Literacy in the Digital Age" (Lyons, A. C., Kass-Hanna, J., & Montoya, A. C. 2021) to prepare this questionnaire. The developed questionnaire's validity and reliability have been checked.

4.2. Sources of data

A survey was conducted using a structured questionnaire to collect data on digital financial awareness among the respondents. The questionnaire was specifically designed to capture multiple dimensions of digital financial awareness. It measured various constructs related to knowledge, usage, and awareness of digital financial services.

4.3. Sampling Procedure

The questionnaire was distributed to 120 respondents whose email addresses were available and who were selected from the population using stratified random sampling. Each respondent was assigned a unique identification code to ensure data accuracy. Out of the total questionnaires distributed, 112 complete and usable responses were received and considered for analysis.

V. Data Analysis and Results

The collected data were analyzed using SPSS and AMOS to examine the underlying structure of digital financial awareness. Exploratory Factor Analysis (EFA) was first applied to identify key latent dimensions, followed by Confirmatory Factor Analysis (CFA) to validate the measurement model. Model fit indices were evaluated to assess reliability, validity, and overall model adequacy.

Table 1- Respondents demographic profile

Individual Characteristics	Frequency	Percentage
Gender	Male 71	63.4%
	Female 41	36.6%
	Total= 112	100%
Family Size	1=3	2.7%
	2 to 4=93	83%
	5 or more=16	14.3%
	Total=112	100%
Income	Below 10000=32	28.6%
	10000 to 30000=15	13.4%
	30001 to 50000=20	17.9%
	50001 to 100000=18	16.1%
	Above 1 lakh=27	24.1%
Education	Below Matric=1	0.9%
	Matric or HS=10	8.9%
	Graduate=43	38.4%
	Post Graduate=45	40.2%
	PhD=11	9.8%
	Any other Professional Qualification=2	1.8%
Occupation	Salaried (private)=50	44.64%
	Government Employee=12	10.7%
	Business=13	11.60%
	Student=26	23.2%
	Retired=1	0.89%

	House Wife=4	3.6%
	Other, having no income=6	5.4%

Table 1 presents the demographic characteristics of the respondents included in the study. The sample was largely male, belonged mainly to nuclear families, and represented diverse income groups. Most respondents were well educated and engaged in salaried employment or studies, indicating a suitable population for examining digital financial awareness.

Table 2- Questionnaire Statements

1.	I know about the function of Demat Account.
2.	I can use my debit card 24 hours a day.
3.	I am aware of RTGS or Real Time Gross Settlement which can be used for fund transfer and the minimum amount is 2 lakh per day.
4.	I am aware of the use of different digital financial services like debit and credit cards, UPI, E-wallet, POS terminals, internet and mobile banking etc.
5.	I am aware of a digital investor's rights and duties.
6.	I am aware of digital loans application and documentation process.
7.	I am aware of digital financial scams and frauds.
8.	I try to access investment related news or updates through trusted mobile apps, official websites, channels.
9.	I keep track of the Sensex and Nifty Index fluctuations and utilize them to make investments.
10.	I am aware of debit cards that come with wireless access used to be placed near POS machine to complete transactions.
11.	I am aware of the fact that banks and other payment systems operators never ask for personal details such as password, PIN, OTP, CVV number.
12.	I know about excessive interest and penalties on instant personal loans which is available through different personal loan apps.
13.	I am aware about existing Digital Financial Services providers like Paytm, Razor Pay, Zest Money, Policy Bazar etc.

5.1. Exploratory Factor Analysis

Establishing measurement validity begins with determining whether the scale is suitable for assessing the intended constructs. It also involves evaluating whether the items accurately represent the underlying characteristics being measured. Valid measurement further requires that the assessment process follows established methodological standards (Mehrens & Lehmann, 1991; Sencan, 2005).

Table 3- KMO and Bartlett's Test of Sampling Adequacy

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.867
Bartlett's Test of Sphericity	Approx. Chi-Square	705.415
	Df	78
	Sig.	0.000

The Kaiser–Meyer–Olkin (KMO) measure assesses the suitability of data for factor analysis by examining shared variance among variables. The obtained KMO value of 0.867 exceeds the recommended threshold of 0.80, indicating good sampling adequacy. Bartlett's Test of Sphericity examines whether the correlation matrix is an identity matrix. The test result was significant ($\chi^2 = 705.415$, $p < 0.001$), leading to rejection of the null hypothesis. These findings confirm that the data are appropriate for factor analysis.

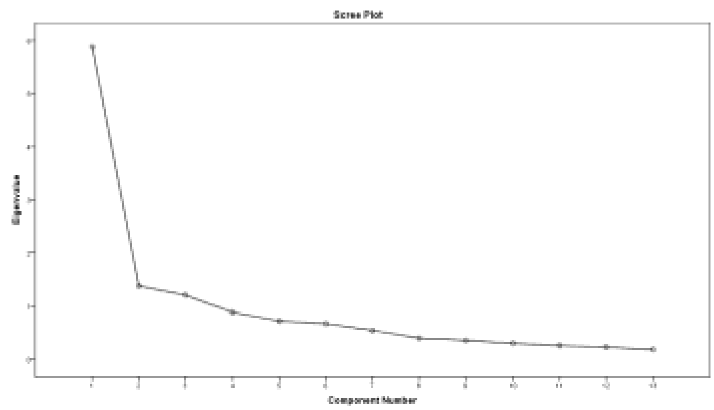

Figure 1: Scree plot (prepared by authors)

A scree plot is a graphical tool used in factor analysis or PCA to display eigenvalues against component numbers. Components with eigenvalues equal to or greater than one is considered significant, and the plot typically forms an elbow-shaped pattern. The factors retained are those on the vertical part of the elbow; in Figure 1, three components meet this criterion and are therefore selected as factors.

Table 4-Rotated Component Matrix[a]

	Component		
	1	2	3
Q1	.842	.212	.137
Q2	.101	.174	.663
Q3	.631	.507	.094
Q4	.265	.789	-.134
Q5	.746	.311	-.245
Q6	.554	.508	-.308
Q7	.169	.496	-.544
Q8	.692	.173	.297
Q9	.868	.044	.014
Q10	.644	.313	-.080
Q11	.207	.758	.168
Q12	.534	.407	.392

Q13	.197	.824	.215

Principal Component Analysis with Varimax rotation (Kaiser normalization) was applied to identify the underlying factor structure. The rotated component matrix indicates that three factors emerged from the 13 items: Factor 1 comprises seven variables with strong loadings, representing a common underlying construct, while Factor 2 consists of six variables measuring a distinct construct. Factor 3 shows a single significant loading, indicating a weaker or isolated dimension compared to the other two factors.

5.2 Confirmatory Factor Analysis through SPSS AMOS:

Structural equation modelling (SEM) is a multivariate statistical technique used to examine multiple relationships among observed and latent variables simultaneously. SPSS AMOS is widely used for SEM as it effectively tests complex theoretical frameworks involving interrelated constructs. In this study, Confirmatory Factor Analysis (CFA) was applied to validate the proposed relationships and assess model fitness, following standard AMOS procedures (Phakiti, 2018; Schreiber et al., 2006).

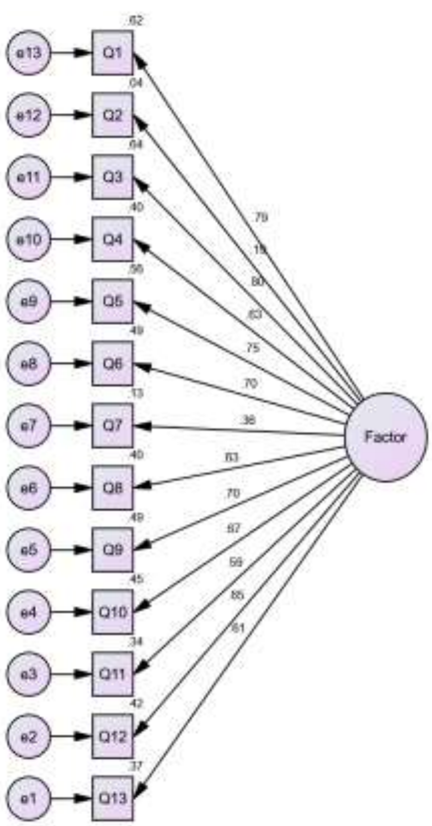

Figure 1- Model 1 (prepared by authors)

Initially, all 13 components were examined to determine whether the data could be represented by a single-factor model. For this purpose, Model 1 was developed and tested as part of the analysis. The structure of this model is illustrated in Diagram 2.

Table 5- Analysis of Model 1 output

Parameter	Required	Result
MODEL CHI-SQUARE- p VALUE	0.05 OR LESS	0.000
CMIN/DF	LESS THAN 5	3.240
GFI	0.95 OR MORE	0.755
AGFI	0.90 OR MORE	0.656
NFI	0.95 OR MORE	0.716
TLI	0.95 OR MORE	0.736
CFI	0.90 OR MORE	0.780
RMSEA	0.08 OR LESS	0.144
SRMR	0.08 OR LESS	0.0873

The model fit indices indicate that the single-factor model does not adequately fit the data. Although the chi-square value is significant and the CMIN/DF (3.240) is within the acceptable limit, most goodness-of-fit indices (GFI, AGFI, NFI, TLI, and CFI) fall well below the recommended thresholds. Additionally, the RMSEA (0.144) and SRMR (0.0873) exceed acceptable limits, suggesting poor overall model fit.

From all the above analysis it is observed that the model 1 does not fit well with the indices. Hence, the modification suggestion as given by AMOS has been utilised in the next to get a better model.

Table 6(a)- Parametric Inference

			Estimate
Q13	<---	Factor	.609
Q12	<---	Factor	.651
Q11	<---	Factor	.587
Q10	<---	Factor	.669
Q9	<---	Factor	.698
Q8	<---	Factor	.631
Q7	<---	Factor	.362

			Estimate
Q6	<---	Factor	.698
Q5	<---	Factor	.747
Q4	<---	Factor	.634
Q3	<---	Factor	.799
Q2	<---	Factor	.189
Q1	<---	Factor	.790

The table presents standardized factor loadings of the observed variables on a single latent factor. Most items (Q1, Q3, Q5, Q6, Q9, and Q10) show strong loadings above 0.60, indicating a good association with the underlying construct. However, Q2 (0.189) and Q7 (0.362) exhibit weak loadings, suggesting they do not adequately represent the factor and may need to be revised or removed.

Table 6(b)- Covariances: (Default model)

			M.I.	Par Change
e10	<-->	e13	7.873	-.147
e8	<-->	e13	4.512	-.135
e8	<-->	e10	5.033	.130
e8	<-->	e9	11.108	.211
e7	<-->	e10	6.075	.135
e7	<-->	e8	8.838	.198
e6	<-->	e13	8.664	.194
e6	<-->	e11	5.133	-.142
e6	<-->	e7	4.097	-.140
e5	<-->	e13	12.521	.235
e5	<-->	e10	10.219	-.194
e5	<-->	e9	4.945	.147
e5	<-->	e6	5.205	.174
e4	<-->	e11	5.382	.131
e3	<-->	e13	6.368	-.140
e3	<-->	e10	7.335	.137
e3	<-->	e5	6.813	-.167
e2	<-->	e10	10.282	-.178
e2	<-->	e9	10.640	-.197
e1	<-->	e10	21.222	.213
e1	<-->	e9	4.050	-.101
e1	<-->	e5	10.902	-.193
e1	<-->	e3	16.722	.199
e1	<-->	e2	5.622	.127

This table shows AMOS Modification Indices (M.I.) suggesting which error terms (e1–e13) could be correlated to improve overall model fit. Higher M.I. values (e.g., e1↔e10 = 21.222, e5↔e13 = 12.521, e8↔e9 = 11.108) indicate the strongest potential improvements if those covariances are added. "Par Change" indicates the expected direction and size of the correlated error if that link is freed (positive or negative).

5.2.2 Analysis of modified model 1 from AMOS output

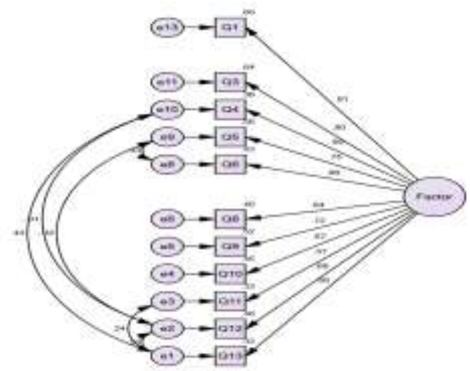

Figure 2 - modified Model 1 (prepared by authors)

The figure illustrates a single-factor Confirmatory Factor Analysis (CFA) model where one latent factor explains the variance in 13 observed items (Q1–Q13). Standardized factor loadings on the arrows indicate the strength of each item's relationship with the latent construct, with most loadings being moderate to strong. Curved arrows between error terms represent correlated measurement errors added based on modification indices to improve model fit.

Table 7- Analysis of Modified Model 1 output

Parameter	Required	Result
MODEL CHI-SQUARE- p VALUE	0.05 OR LESS	0.000
CMIN/DF	LESS THAN 5	2.877
GFI	0.95 OR MORE	0.803
AGFI	0.90 OR MORE	0.710
NFI	0.95 OR MORE	0.791
TLI	0.95 OR MORE	0.813
CFI	0.90 OR MORE	0.850
RMSEA	0.08 OR LESS	0.132
SRMR	0.08 OR LESS	0.11
AVE	0.5 OR MORE	0.48

The revised model shows some improvement, as indicated by an acceptable CMIN/DF value (2.877), suggesting a reasonable relative fit. However, the chi-square remains significant (p = 0.000), which is common in large samples but still indicates model data misfit. Most incremental and absolute fit indices (GFI, AGFI, NFI, TLI, CFI) remain below recommended thresholds, reflecting inadequate overall model fit. Error indices (RMSEA = 0.132 and SRMR = 0.11) exceed acceptable limits, pointing to substantial residuals. Additionally, the AVE value (0.48) falls slightly below 0.50, indicating marginal convergent validity of the construct.

Overall, the Modified Model 1 demonstrates inadequate model fit, as several key fit indices particularly RMSEA and CFI do not meet the recommended thresholds, indicating that the model does not sufficiently capture the underlying data structure. Consequently, Modified Model 1 was rejected for this study, and an alternative model was subsequently developed based on the insights and factor structure suggested by the Exploratory Factor Analysis (EFA).

5.3 Development of Model 2

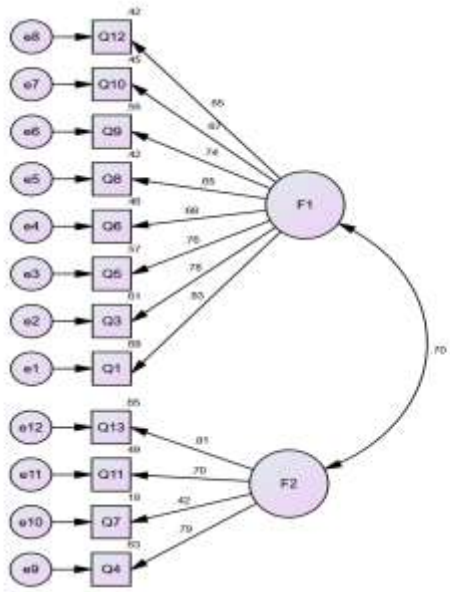

Figure 4- Model 2 (prepared by authors)

This figure represents a two-factor Confirmatory Factor Analysis (CFA) model developed based on the EFA results. The first latent factor (F1) is measured by items Q1, Q3, Q5, Q6, Q8, Q9, Q10, and Q12, all of which show moderate to strong standardized loadings, indicating good representation of the underlying construct. The second latent factor (F2) is measured by items Q4, Q7, Q11, and Q13, with generally acceptable loadings, suggesting a distinct but related dimension. The curved arrow between F1 and F2 (r = 0.70) indicates a strong positive correlation, implying that while the two factors are conceptually distinct, they are closely related.

Table 8. Analysis of Model 2 output

Parameter	Required	Result
MODEL CHI-SQUARE-P VALUE	0.05 OR LESS	0.000
CMIN/DF	LESS THAN 5	2.877
GFI	0.95 OR MORE	0.803
AGFI	0.90 OR MORE	0.710
NFI	0.95 OR MORE	0.791
TLI	0.95 OR MORE	0.813
CFI	0.90 OR MORE	0.850
RMSEA	0.08 OR LESS	0.132
SRMR	0.08 OR LESS	0.10
AVE	0.5 OR MORE	0.52

The fit statistics indicate that the two-factor model shows partial improvement but still does not achieve an acceptable overall fit. While the CMIN/DF value (2.877) is within the recommended limit and AVE (0.52) meets the criterion for convergent validity, most global fit indices (GFI, AGFI, NFI, TLI, and CFI) remain below their respective thresholds. Moreover, the error indices (RMSEA = 0.132 and SRMR = 0.10) exceed acceptable limits, indicating substantial model misfit. Overall, although construct validity has improved, the model fit remains inadequate and suggests the need for further refinement.

Overall, the model demonstrates inadequate fit, with key indices such as RMSEA and CFI falling below recommended thresholds and a significant chi-square indicating model–data misfit. Although the CMIN/DF ratio is acceptable, suggesting reasonable model complexity, substantial refinement is required. Revising the factor structure, re-evaluating poorly performing items, and incorporating missing fit measures (SRMR and AVE) are recommended to improve the model's overall fit.

Table 9- Analysis of Model 3 output

Parameter	Required	Result
MODEL CHI-SQUARE- P VALUE	0.05 OR LESS	0.000
CMIN/DF	LESS THAN 5	1.756
GFI	0.95 OR MORE	0.925
AGFI	0.90 OR MORE	0.860
NFI	0.95 OR MORE	0.917
TLI	0.95 OR MORE	0.942
CFI	0.90 OR MORE	0.962
RMSEA	0.08 OR LESS	0.084
SRMR	0.08 OR LESS	0.0611
AVE	0.5 OR MORE	0.55

The fit indices indicate a substantially improved and acceptable model fit, with CMIN/DF well below 5 and CFI (0.962) and SRMR (0.061) meeting recommended thresholds. Although the chi-square remains significant and RMSEA (0.084) is marginally above the cut-off, overall fit is considered satisfactory given multiple supporting indices. The AVE value (0.55) confirms adequate convergent validity of the construct.

5.4 Development of Model 3

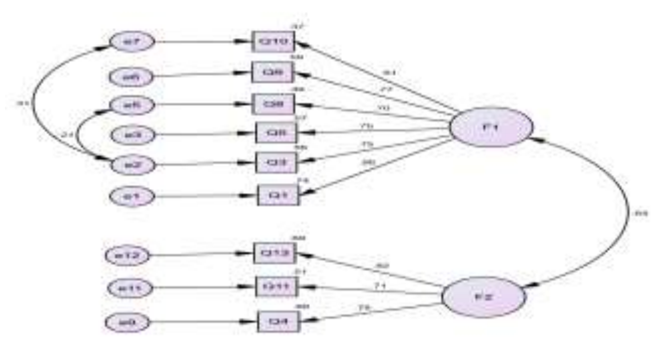

Figure 5- Model 3 (prepared by authors)

This figure presents the final two-factor Confirmatory Factor Analysis (CFA) model with substantially improved model fit. Latent factor F1 is measured by items Q1, Q3, Q5, Q8, Q9, and Q10, all showing moderate to strong standardized loadings, indicating a well-defined construct. Latent factor F2 is measured by Q4, Q11, and Q13, also demonstrating strong loadings, supporting convergent validity. The curved path between F1 and F2 (r = 0.64) indicates a meaningful but not excessive correlation, suggesting that the two constructs are related yet distinct.

5.5 Summary and Recommendations:

Model 3 demonstrates a strong overall fit, with CFI and SRMR indicating particularly good model performance. The CMIN/DF is also favorable, and most other indices are close to recommended thresholds, suggesting a well-specified model. Overall, Model 3 is robust, with only minor scope for further refinement.

VI. Conclusion

This study highlights the growing importance of digital financial awareness (DFA) in an increasingly fintech-driven environment. Using exploratory and confirmatory factor analyses through AMOS, key dimensions of DFA were identified and validated within a structural framework, showing that consumers' engagement with digital finance depends on their understanding of digital products, safe practices, rights and responsibilities, and awareness of fraud and scams. Model refinements improved fit, confirming the multidimensional nature of DFA.

Overall, the findings suggest that digital financial literacy not only promotes financial inclusion and empowerment but also acts as a safeguard against digital financial risks. Enhancing DFA through focused education, supportive regulations, and inclusive digital infrastructure can build consumer trust, encourage responsible usage, and reduce the digital divide, offering valuable guidance for policymakers, educators, and financial service providers.

The study highlights the need to strengthen national financial literacy frameworks by explicitly integrating digital financial awareness (DFA), including knowledge of digital products, consumer rights, ethical use, and fraud prevention. Policymakers and regulators should enhance consumer protection through clearer disclosures, cyber-fraud awareness initiatives, and efficient grievance redressal systems, while also addressing disparities in DFA through targeted interventions for vulnerable groups such as rural users, low-income households, and the elderly. Embedding DFA in formal education and promoting user-centric, transparent, and secure fintech governance can further support responsible digital financial behavior, with the validated DFA model serving as a useful tool for policy design and evaluation.

VII. Limitations and Future Scope

The current research has certain drawbacks. First, the sample size was limited to 112 valid replies from a small geographic area, which may limit the generalizability of the findings. Second, because the data were gathered via a self-reported questionnaire, the results might be influenced by response or social desirability bias.

Future research can extend this study by using a larger and more diverse sample across different regions to improve the generalizability of the Digital Financial Awareness (DFA) model. Additional variables such as trust in digital platforms, behavioral biases, and technology readiness may be incorporated to strengthen the model. Longitudinal and cross-country studies can also be undertaken to examine how DFA evolves over time and across different economic contexts. Moreover, the validated DFA model can be applied to assess the effectiveness of digital financial literacy policies, regulatory interventions, and awareness programs.

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