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Understanding mobile money usage among farmers in the hiran region of somalia: an extended technology acceptance model (TAM) approach

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Abstract
Mobile money (m-money) services have become an essential financial tool in Somalia, particularly for rural communities having restrained access to formal banking infrastructure. This research explores the key factors impacting the adoption as well as use of m-money platforms among Somali farmers, who increasingly rely on services such as Hormuud's EVC Plus and Dahabshiil's e-Dahab for everyday financial transactions. The study also utilized the Technology Acceptance Model (TAM), extended with a context-specific variable digital literacy and Perceived Trust. The survey was conducted on 156 smallholder farmers in the Hiran region using a structured quantitative survey to examine the factors that influence the adoption of m-money. Data analysis was carried out in SPSS in order to extract descriptive statistics and in SmartPLS in a bid to verify the proposed relationships. As a result, the findings indicate that the Perceived Ease of Use, Perceived Usefulness, Digital Literacy, as well as Perceived Trust, have an impressive and strong positive effect in terms of the behavioural intention of the farmers to adhere to the m-money services. Such findings provide valuable insights to service providers and NGOs, as well as policymakers interested in raising digital financial inclusion and access to financial services in rural, underserved areas in Somalia.

Keywords Mobile money, Farmers, Somalia, TAM, Perceived trust, Financial inclusion, Technology adoption

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Introduction

Mobile money (m-money) is an important instrument in fostering financial inclusion among smallholder farmers throughout the globe. It also provided answers to the long-standing problems like the inability to access formal banking, low-interest savings opportunities, and high-priced transactions. In Kenya, m-money has been associated with better rural, farming household welfare and resilience [1, 2]. Likewise, the experimental research in African nations demonstrates that digital finance can play an important role in enhancing access to credit and savings by farmers, which in turn impacts the investment and productivity in the farms [3]. Moreover, the m-money technology is highly significant in the outreach to the populations in the African regions where the conventional banking infrastructure is unreachable [4, 5]. Furthermore, mobile money can benefit the agricultural sector, particularly in countries seeking to explore it [6, 7].

Ghana and Uganda studies have also proved that the use of m-money has increased the input utilization, farm productivity, and market inclusion. As an illustration, more frequent m-money users in Ghana stated that they had increased agricultural output and were able to enter agricultural markets more easily [8, 9]. The use of m-money has been associated with higher off-farm income and better financial management in the household, which confirms its wider contribution to rural development in Uganda [10]. In Tanzania, Mwakifwamba et al. [11] discovered that mobile phones enhance market access and price transparency, which enhances bargaining power and financial inclusion of the farmers due to mobile payments and less reliance on intermediaries. Similarly, the paper looks at how rural Rwanda farmers adopt m-money and integrate it into their lives, which m-money has contributed to their economic growth and social lives [12].

Mobile money has significantly transformed agriculture in developing countries by enhancing farmers' decision-making, improving farming practices, and promoting sustainable agricultural production [13]. For instance, farmers can make use of an efficient mobile money for financial services, agricultural extension, supply chain coordination, and precision agriculture, thereby increasing productivity and contributing to overall agricultural development. This integration allows farmers to conduct informed decision-making, and optimised resource use, driving productivity and sustainability in farming [14, 15]. Through mobile money platforms farmers can facilitate financial transactions among different players in the food system, from farmers to policymakers. This can lead to more efficient and sustainable resource usage, as well as more equitable distribution of food and other agricultural products [16, 17].

The use of mobile money can also transform agriculture, particularly in terms of improving farming practices and promoting sustainable production. In addition to enabling farmers to access money, receive payments efficiently, conduct transactions, and purchase agricultural input, mobile money helps them participate more effectively in markets and manage income flows. In addition, it improves supply chain efficiency, facilitates market linkages, creates new economic opportunities, and enhances consumers' access to agricultural produce [3, 4, 18–22].

M-money services like Hormuud EVC Plus have become important financial instruments in Somalia, where there are no official financial institutions. According to research done recently, these services have greatly enhanced the financial access of the rural population, such as smallholder farmers, by allowing them to conduct transactions more efficiently and safely [23]. In addition, mobile financial services are not only making transactions easier in day-to-day transactions but also acting as agents of the larger developmental objectives. As an example, m-money has enabled farmers to invest in sustainable environmental practices and be better able to overcome financial risks, particularly in weak, post-conflict environments such as Somalia [24]. Moreover, Somali farmers who use mobile money can receive payments from buyers instantly, which improves cash flow and allows them to invest more quickly in farming.

Nevertheless, in spite of these developments, there is a lack of empirical studies that focus on behavioral aspects that affect the adoption of m-money among the Somali farmers in the Hiiran region. The majority of literature is dedicated to financial accessibility at the macro level or business performance; a gap in knowledge on the individual level is the driver of adoption in rural agriculture environments based on digital literacy, trust, and perceived usability. This study aims to address this gap by conducting a more detailed analysis at the farmer level by use of an extended Technology Acceptance Model (TAM). The research also includes the empirical evidence that informs the inclusive financial policy and presents practical recommendations to increase m-money take-up among the underserved farming populations.

Literature review

Mobile money in agriculture

It should be noted that m-money has emerged as an important instrument in increasing the financial inclusion of agriculture, especially where there is a very small banking infrastructure. It allows the smallholder farmers to get access to savings, credit, and payments through mobile channels that enhance productivity and minimize dependence on informal finance [1, 18, 25–29].

Ashoro et al. [30] discovered that mobile money increased agricultural financial inclusion in the state of Delta State in Nigeria by improving productivity and decreasing the use of informal lending, in particular, among remote smallholder farmers with no formal bank access. In like manner, Ampah et al. [31] established that the adoption of the m-money services within the rural Ghanaian setting enhanced the economies of the agricultural households, and the farmers reported that they could obtain credit, use inputs better, and realized significant yield and cost-effectiveness outcomes.

Additional studies emphasize the importance of m-money in supporting the realization of financial empowerment with regard to rural women agripreneurs residing in Nigeria by supporting savings, investment in farm inputs, and access to emergency funds on time [32]. Similarly, Batista and Vicente, [33] established that mobile money enhanced the financial inclusion of households in rural Mozambique by enhancing access to money sent to them, and minimizing income volatility, especially among the cut-off communities that were previously not formally connected to financial services. In a summary, mobile money services support farm operations and boosts financial inclusion, but adoption is hindered by low digital literacy, trust issues, and poor network coverage.

Technology acceptance model

Davis, [34] introduced the TAM, which has since been widely tested and expanded by various scholars [34]. The original TAM framework included five key constructs: perceived usefulness (PU), behavioral intention to use (ITU), attitude, perceived ease of use (PEOU), and actual system usage (AU). Of these, PU and PEOU are regarded as the most important determinants of technology adoption. Over time, numerous studies suggested that the original model could be enhanced by incorporating additional variables to improve its explanatory power [35]. In response to this, [36] developed an extended version of the model, known as TAM2, which integrated social influence factors (such as voluntariness, subjective norm, as well as image) and cognitive instrumental processes (including job relevance as well as result demonstrability), while removing the attitude construct from the model. In this study proposal, the following conceptual research model in Fig. 1.

Perceived usefulness (PU)

PU defines how useful new technology is to a user [37]. Note that the Covid era has ended the status of cash as king. Every person across the globe is rapidly moving towards cards, the internet, and apps to manage their finances. Automatic Teller Machines and m-money are gaining popularity in Africa more than ever. Note that m-money supports the unbanked as well as the banked. As per [38], m-money as a development tool

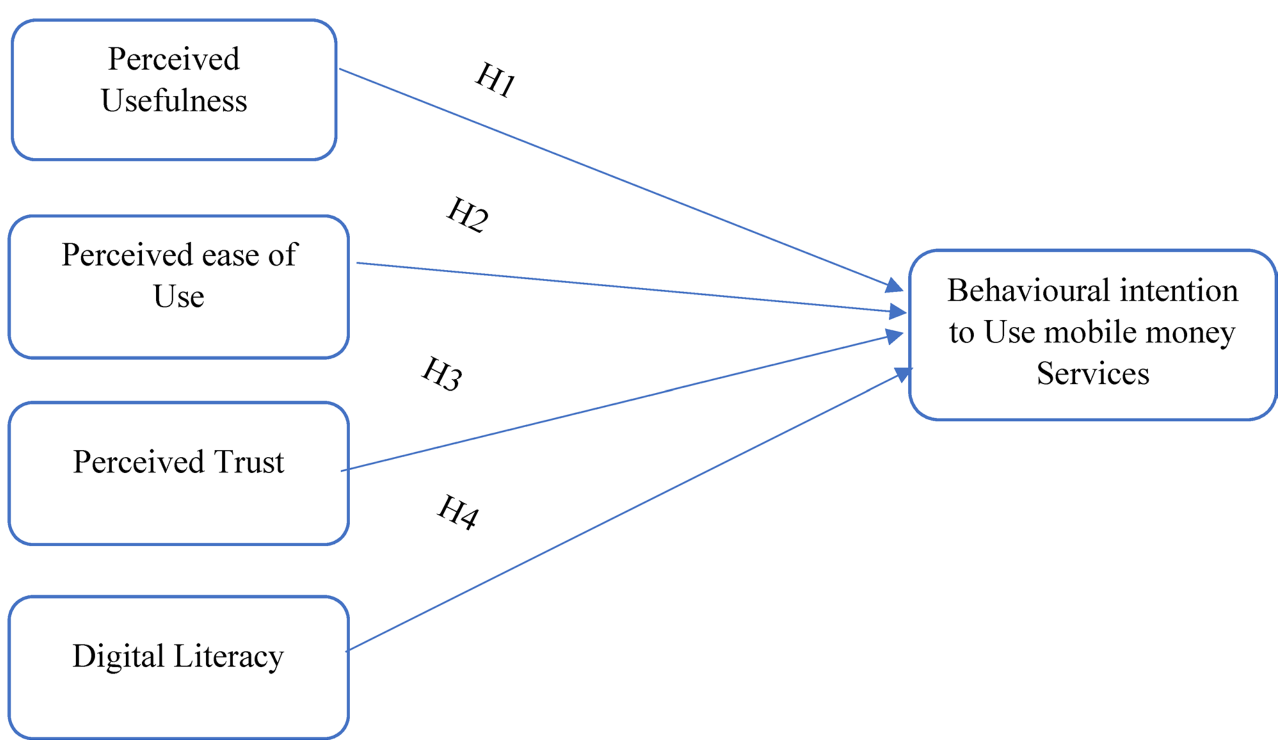

Fig. 1 Proposed research model for the intention to use mobile money services among Somali farmers:

possesses greater probability of simplifying the process of people living in Sub-Saharan Africa accessing money. Hence, [39] carry out a research regarding the impact of m-money on how people utilize financial services concerning sub-Saharan Africa. One of the most important factors was the substantial positive relationship that exists between Financial Technology as well as Financial Inclusion regarding Sub-Sahara Africa Region.(Okello Candiya [40]) examined the social networks effects with regard to the association between m-money as well as financial inclusion locating in sub-Saharan Africa. Other than that, the author opines that the rural Ugandans using m-money have a better connection to financial inclusion since they have both strong and weak social networks. All the past studies have been conducted on the capacity of m-money to increase access to financial inclusions in the emerging markets, especially in Sub-Saharan Africa. Such results are aligned with the TAM, according to which PU is a central role in determining the adoption of technology in diverse settings. A study published in Somalia found a strong correlation between the intention to use ICT services and the PU among agribusiness practitioners. This suggests that PU has a beneficial impact on the utilization of ICT services [41].

H1: Perceived Usefulness (PU) has direct effect on Behavioral Intention (BI) to use MM.

Perceived ease of use (PEOU)

The dual influence of PEOU and BI in mobile money has been widely investigated. in the mobile money context. PEOU describes how easy to use the user determines the technology [37]. AsThompson et al. [42] suggested, the user must feel that using the system does not involve a lot of mechanical procedures, that it does not involve a lot of time out of their normal work, and that it is not complex to understand in terms of adoption and use. Hence, effort expectation indicates the fitness perceptions regarding the consumers against the ease or difficulty of utilizing m-money. In some cases, it is exemplified by the cost-rationality that users feel [43]. Moreover, studies have recognized PEOU as the key determinant in the adoption regarding new technologies [44]. Nyimbiri, [39] assessed the influence of m-money concerning the utilization of financial services by the people in sub-Saharan Africa. One of the most important factors was a substantial positive relationship that exists between Financial Technology as well as Financial Inclusion in the Sub-Sahara Africa Region. This school of thought upholds TAM, originally established by [34], which suggests that PEOU indirectly influences an individual's intention to utilize a technology.Ali and Dhaha, [45] revealed that PU and PEOU possessed statistically substantial as well as positive impact concerning intention to adopt. Accordingly, Abdullahi and Mahmud , [41], noted that PEOU enhances the use of ICTs in agriculture. In their study, they recommend that agribusinesses provide their employees with ICT skills to continually improve their service.

H2: perceived ease of use (PEOU) has direct effect on Behavioral Intention (BI) to use MM.

Perceived trust (PT)

Trust emerges as a critical factor in financial technology adoption.Ali and Dhaha, [45] did a study is to investigate Factors impacting m-money transfer adoption among Somali students. The results indicated that perceived trust had a statistically significant and positive effect on intention to adopt mobile money. In MMT context, trust was found among others to have effect on the behavioral intention to use MMT among Ghana respondents. Tobbin, [46].Kelly and Palaniappan, [47] employed the Technology Acceptance Model (TAM) with 406 mobile money users from Ghana's Savannah and Bono regions. According to the study, perceived risk, perceived cost, social influence, PU, and PEOU possessed repercussions concerning users' attitudes, impacting their final decision to utilize m-money services located in Ghana. Other than that, the social influence possessed a positive impact regarding the users by influencing them to continue as well as adopt utilizing m-money services concerning the study area by way of social networking. The construct of perceived trust however positively influenced the users in making decisions and thus they felt negatively towards m-money services. In addition, [48] investigates how trust as well as risk perceptions concerning m-money users influence the adoption of m-money services in Uganda. They demonstrated that there was no significant impact concerning Trust belief on behavioral intention.

H3: Perceived Trust (PT) has direct effect on Behavioral Intention (BI) to use MM.

Digital literacy

Digital literacy refers to an individual's capability to proficiently use digital devices like smartphones and computers, navigate the internet, and operate various digital tools such as search engines and applications, making it essential in today's digital era [49]. Moreover, digital literacy involves knowledge about online security measures, including protection of personal information, recognizing risks, e.g., viruses and phishing attacks, and using strong and secure passwords. Some of the previous research has pointed to the beneficial aspect of digital and financial literacy as it pertains to digital financial services. For instance, research byKhan et al. [50] employs a Partial Least Squares Structural Equation Modelling (PLS-SEM) approach to examine data from 412 respondents across Lahore, Peshawar, Rawalpindi, and Islamabad. The findings reveal that digital financial literacy enhances the beneficial effects that m-money adoption has on financial inclusion. A study byShehadeh et al. [51] on Digital financial literacy and the use of cashless payments in Jordan also throw light on the fact that digital financial experience, awareness, and skills are among the major drivers of implementing the concept of cashless payments among the target population. Conversely, the digital legal environment and subjective financial literacy are not substantial in using cashless payments. The interaction effect of digital literacy that exists between FinTech's concerning biometrics and m-money as well as digital financial inclusion was found to be positive (Okello Candiya [52]).

H4: Digital literacy has direct effect on Behavioral Intention (BI) to use MM.

Materials and methods

In this research, a non-probability sampling approach, specifically, purposive sampling, was used to examine the participants who fit certain criteria, which were their level of awareness and participation in m-money.

Purposive sampling is a population sampling technique in which a researcher chooses research participants based on their existence in a population of interest, qualities, experiences, or other factors. Purposeful sampling is advantageous because it needs fewer resources and less time than most other study methods. While purposive sampling has advantages such as cost-effectiveness, flexibility, and the capacity to select information-rich situations, it also has certain limitations. First, it is frequently criticized for its lack of generalizability and susceptibility to researcher bias. Second, the study is geographically limited to the Hiran region, which may limit the applicability of its results to other parts of Somalia where access to mobile phones and agricultural practice may differ. The sample size was 156 smallholder farmers, and this size was determined using a filtering question, which ensures accuracy and relevance of the sample. Sarstedt et al. [53]. The sample size is sufficient for the analytical method being used. Specifically, the study used partial least squares structural equation modelling (PLS-SEM), which is appropriate for small sample sizes.

Table 1 Demographic characteristics with regard to the respondents

Variable	Category	Frequency (*n*)	Percentage (%)
Gender	Male	101	64.7%
	Female	55	35.3%
Age group	18–30 years	64	41.0%
	31–40 years	54	34.6%
	41–50 years	26	16.7%
	Above 50 years	12	7.7%
Level of education	No formal education	19	12.2%
	Primary	48	30.8%
	Secondary	55	35.3%
	Tertiary	34	21.8%
Farming experience	Less than 5 years	50	32.1%
	5–10 years	60	38.5%
	More than 10 years	46	29.5%
Mobile money usage	Yes	131	84.0%
	No	25	16.0%
Digital literacy level	Low	37	23.7%
	Moderate	75	48.1%
	High	44	28.2%

According to be identified rules, like the 10-times rule, the sample size should be more than 10 times the largest number of structural paths that can be directed at any model construct. The "10-times rule method" is the most used technique for estimating the minimal sample size in PLS-SEM (J. F. Hair et al. [54], Peng, [55]. These methods vary, but the most popular one requires a sample size more than 10 times the maximum number of inner or outer model linkages pointing at any latent variable [56].

A structured questionnaire was administered in Hiran, especially and beletwein city. Each TAM construct was calculated using a 5-point Likert scale from(Davis, 1989) as well as [57].

The quantitative data that have been collected were subsequently processed through SPSS and PLS-SEM. This method of analysis helped to understand the connection between the researched variables much better. As mentioned in the study by Sarstedt et al. [58], reliability as well as validity regarding the measurement scales were evaluated with the help of confirmatory factor analysis (CFA) whereas the hypotheses were determined with structural equation modelling (SEM). In this way, this study adopted a measuring model based on the CFA to assess data validity as well as reliability (J. F. Hair et al. [59]. It quantified and tested the postulated relationships between the latent constructs utilizing SEM [60].

Data analysis and discussions

Respondents' profile

As depicted in Table 1 the majority of respondents are male (64.7%), while females represent 35.3%, indicating greater male involvement in farming-related digital finance. The age distribution shows that most participants are relatively young, with 41.0% aged 18–30 years and 34.6% aged 31–40 years, suggesting active engagement by the younger working-age population.

In terms of education, 35.3% of respondents have attained secondary education, followed by 30.8% with primary education and 21.8% with tertiary education. Only 12.2% reported having no formal education, highlighting a generally literate population, which may ease the uptake of mobile technologies. Regarding farming experience, most respondents have between 5 and 10 years of experience (38.5%), followed by 32.1% with less than 5 years, indicating a balanced mix of new and moderately experienced farmers.

A significant majority (84.0%) reported using mobile money services, showing a high level of digital financial engagement among Somali farmers. Digital literacy levels are mostly moderate (48.1%), with 28.2% having high literacy and 23.7% low, suggesting that while many are comfortable with digital tools, targeted training could further enhance their digital capabilities.

Assessment of measurement model

To examine the constructs' validity as well as reliability, we conducted the measurement model assessment prior to the structural model assessment. Cronbach's alpha (CA), Factor loadings, and composite reliability (CR) have been determined in this respect. Convergent validity was determined by calculating aVe.

Indicator reliability

Indicator reliability was established through standardized outer loadings, as portrayed in Table 2. All measurement items exceeded the ideal threshold of 0.70 [61], with the exception of DL3 (loading = 0.591), which was retained based on acceptable convergent validity and overall construct reliability. Behavioral Intention (BI) items ranged from 0.798 to 0.837, Digital Literacy (DL) from 0.591 to 0.793, PEOU from 0.77 to 0.858, Perceived Trust (PT) from 0.724 to 0.87, and Perceived Usefulness (PU) from 0.803 to 0.86.

Internal consistency and convergent validity

CA, which is a common measure regarding internal consistency, was utilized to assess reliability [22]. According to Table 3, all the CA values were above the value of 0.6, between 0.707 and 0.889, and therefore, all the constructs have strong reliability. Note that all the CR values achieved falls within the value of 0.823 to 0.918, meeting the above value 0.70 [61, 62]. This ensures the internal reliability consistency of the indicator. AVE also confirms the convergent validity since it examines the communality of the construct [63]. The convergent validity was also determined by the average variance extracted (AVE) regarding each construct, which was greater than 0.50 [64].

Discriminant validity

Discriminant validity was evaluated in the form of the heterotrait-monotrait (HTMT) ratio, which is shown in Table 4. All HTMT values were considerably less than the conservative cutoff of 0.85, indicating high discriminant validity [65]. The greatest correlation was determined between PU and BI (HTMT = 0.864), which, although relatively high, remained within acceptable bounds.

Table 2 Outer loadings (indicator reliability)

	BI	DL	PEOU	PT	PU
BI1	0.837				
BI2	0.836				
BI3	0.836				
BI4	0.798				
DL1		0.764			
DL2		0.784			
DL3		0.591			
DL4		0.718			
DL5		0.793			
PEOU1			0.858		
PEOU2			0.77		
PEOU3			0.78		
PEOU4			0.806		
PT1				0.87	
PT2				0.724	
PT3				0.739	
PU1					0.839
PU2					0.846
PU3					0.86
PU4					0.803
PU5					0.81

Table 3 Construct reliability and convergent validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BI	0.849	0.866	0.897	0.684
DL	0.793	0.837	0.852	0.538
PEOU	0.818	0.83	0.88	0.647
PT	0.707	0.822	0.823	0.61
PU	0.889	0.9	0.918	0.692

Table 4 Discriminant validity (HTMT Criterion)

	BI	DL	PEOU	PT	PU
BI					
DL	0.226				
PEOU	0.684	0.161			
PT	0.162	0.172	0.145		
PU	0.864	0.108	0.753	0.106	

Structural model analysis

Structural model evaluation metrics

Table 5 summarizes the assessment concerning structural model utilizing substantial indicators, for example, Adjusted R-square, R-square (R^2), Q-square (Q^2), F-square (f^2) as well as Variance Inflation Factor (VIF). BI possesses a value of R^2 score of 0.667, implying the independent constructs scored 71.2%, given its variance. On the other hand, the adjusted R^2 of 0.658 proposed the

Table 5 Structural model results for R^2, f^2, Q^2, and VIF

Constructs	*R*-square	*R*-square adjusted	F-square	Q-square	VIF
BI	0.667	0.658		0.509	
DL			0.054		1.017
PEOU			0.027		1.743
PT			0.025		1.007
PU			0.854		1.729

model's robustness, which considers the predictors number. Meanwhile, the F-square (f^2) values demonstrate the relative effect regarding the independent constructs concerning the dependent variable. As shown in Table 5, PU had a large effect (f^2 = 0.854), while DL (f^2 = 0.054), PEOU (f^2 = 0.027), and PT (f^2 = 0.025) exhibited small effects. These findings reinforce the dominant influence of PU on m-money adoption among farmers in the Hiiran region of Somalia. (VIF values are lower than 5, describing that multicollinearity is insignificant issue regarding this model. As shown in Table 4, all VIF values ranged from 1.007 to 1.743, below the recommended threshold of 3.0 [61], indicating no collinearity issues.

Path coefficients and hypothesis testing

Table 6 summarizes the path coefficients, t-statistics, and p-values. Perceived Usefulness (PU) emerged as the most influential predictor of Behavioral Intention (BI) (β = 0.701, t = 10.949, p < 0.001), supporting its central role in TAM-based studies [66]. It implies that once the users find a technology (say, mobile banking or digital tools) useful, they are highly likely to have an intention of using it. Not only is this relationship strong, but it also aligns well with the established theory of technology adoption research. H1 is, therefore, supported, and the result is consistent with [67].

PEOU (β = 0.125, t = 1.680, p = 0.047) and PT (β = 0.091, t = 1.819, p = 0.034) were found to significantly influence BI, though to a lesser extent. This means that when consumers discovered the technology easy to utilise and trust it, they are prone to adopt it. Thus, H2 and

Table 6 Path Coefficients as well as hypothesis testing

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	*P* values	Decision
PU -> BI	0.701	0.695	0.064	10.949	0	supported
PEOU -> BI	0.125	0.127	0.075	1.68	0.047	supported
PT -> BI	0.091	0.092	0.05	1.819	0.034	supported
DL -> BI	0.136	0.142	0.047	2.858	0.002	supported

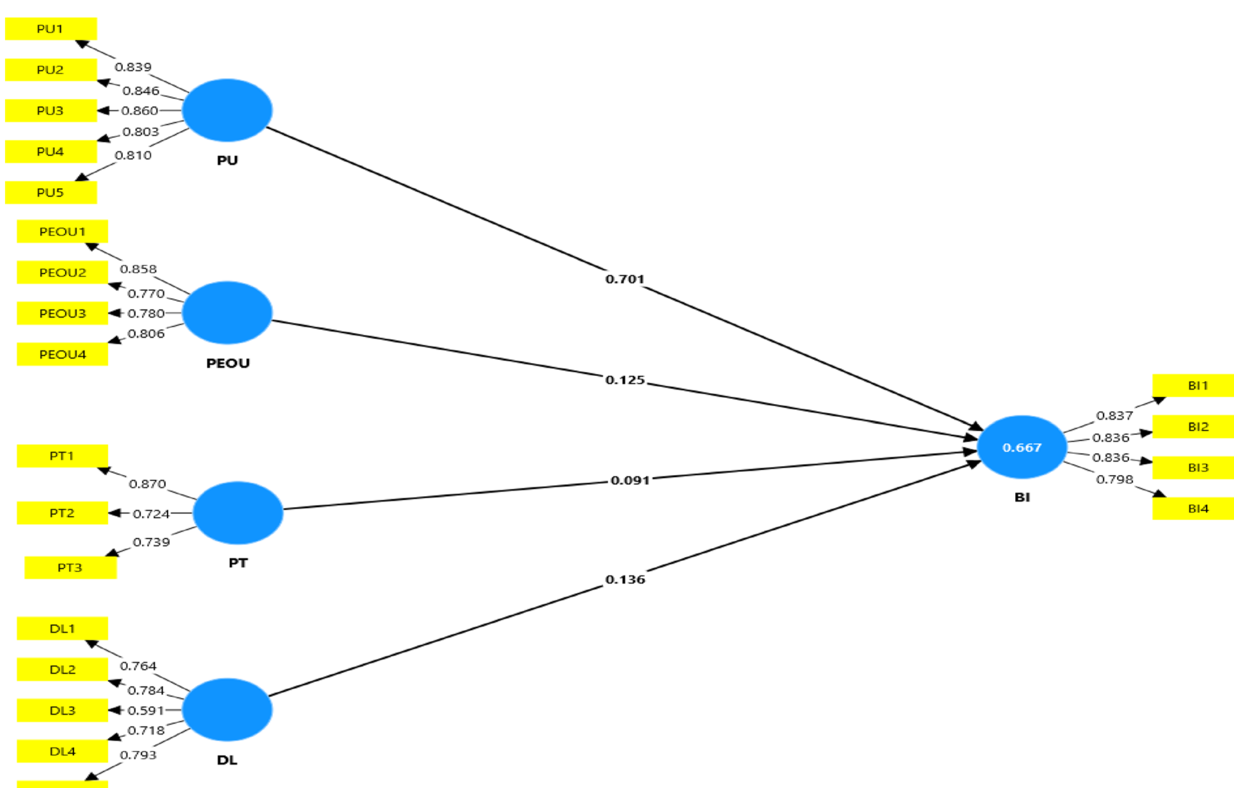

Fig. 2 Structural model

H3 are accepted and the finding is aligned with [68], & Eid, 2011.

Digital Literacy (DL) also showed a significant and positive effect regarding BI (β = 0.136, t = 2.858, p = 0.002), underscoring the importance of digital competency among farmers [69]. Behavioral Intention (BI), meaning that as farmers' digital skills and competencies improve, their intention to adopt and use digital tools (e.g., mobile money or technology platforms) also increases. The more digitally literate the farmers are, the more they are inclined to use and adopt digital financial or agricultural technologies. This observation shows the necessity of capacity-building programs and digital literacy training to encourage greater technology uptake in the farming sector. Thus, H4 is accepted and the finding is aligned with by [70].

Discussion

This study examined the key predictors influencing Somali farmers' behavioral intention (BI) to adopt m-money services, with a particular focus on the Hiran region. Mobile money platforms, particularly Hormuud Telecom's EVC Plus as well as Dahabshiil's e-Dahab, have become essential tools in facilitating secure, cashless transactions in rural Somalia, where formal banking infrastructure is limited or absent. To explore this, an extended TAM was employed, incorporating four constructs: PU, PEOU, Digital Literacy (DL), and Perceived Trust (PT). The model was adapted to the rural Somali context to assess how these factors shape farmers' adoption decisions. As expected, the results demonstrated that all proposed constructs had a significant influence on behavioral intention, confirming the model's relevance in this setting. Below, the findings are discussed in relation to existing literature and contextual realities.

PU developed as the strongest predictor concerning behavioral intention among Somali farmers in Hiran. Farmers who found mobile money services effective for improving transactions, lowering costs, and accessing markets were more inclined to adopt them. Under no formal banking, there are the EVC Plus and e-Dahab that offer critical financial functionality.

This outcome is consistent with previous studies that have shown the key role played by usefulness in facilitating the adoption of digital financial solutions. As an illustration, Amoussouhoui et al. [71] discovered that Nigerian farmers who considered digital extension tools to enhance the productivity of their farms were more likely to use them. Nevertheless, in some cases, other contextual considerations, including task-technology fit and digital confidence, have been observed to surpass PU, as is the case in Uganda, as observed in the study by Aparo et al. [72]. Similarly, Sivakumar and Ismail , [73] presumed that the perceived benefit of trust, as well as community acceptance, is wider and can be more impactful than the perceived utility of individuals. On balance, the results prove that perceived usefulness is a decisive factor that promotes the adoption of mobile money in rural Somalia, where viable results are more important than innovation or aesthetic qualities.

The study also emphasized that PEOU played a major role in the intention of Somali farmers to embrace mobile money in Hiran. Farmers tended to utilize such services as EVC Plus and e-Dahab more frequently because these platforms were user-friendly, particularly in locations with low digital literacy and low access to formal finance.

The outcome can be correlated with other rural settings. In Nigeria, Amoussouhoui et al. [71] found that although perceived usefulness was the strongest predictor, ease of use still significantly supported the adoption of digital advisory tools. Similarly, Rashid et al. [74] Rashid et al. [74] observed in rural India that PEOU played a highly significant role in shaping users' attitudes toward e-wallet adoption, reinforcing its enabling influence in technology uptake.

In East Africa, studies show stronger effects. Murendo et al. [75] highlighted that the simplicity of M-Pesa's interface greatly facilitated mobile money adoption among low-literacy populations in Kenya. Likewise, Aparo et al. [72] found that in Uganda, localized and intuitive system design enhanced mobile platform adoption among smallholder farmers.

However, Sharma et al. [76], in research on FinTech adoption among rural farmers in India, researchers found that PEOU did not significantly influence behavioral intention. Instead, factors, for example, social influence, trust, and facilitating conditions, were more influential. Therefore, while PEOU is a significant enabler in this study, its influence is contingent upon contextual factors such as digital readiness and service accessibility.

This study found that digital literacy significantly influences the BI of Somali farmers in the Hiran region to utilize m-money services. Farmers with stronger digital skills are more capable of understanding and operating platforms like EVC Plus and e-Dahab, increasing their confidence and willingness to integrate these tools into their farming and daily transactions. The same results have been realized in related situations. The digital literacy of rural areas in Mali was also strongly associated with mobile money and resilience of households, according to Diallo [77], with digitally literate farmers being in a more advantageous position to use financial tools to respond to shocks. Similarly, Landmann et al. [78] determined that the more digitally skilled Indian smallholders were, the more they were likely to use smartphones to make agricultural decisions. Moreover, Prodhan et al. [79] noted that in Bangladesh, the digitization literacy limited the uptake of mobile financial services, despite access not being an issue, underpinning that digital literacy is among the main determinants of meaningful use. Therefore, the results confirm that digital literacy is not a supportive capability but rather an essential force behind mobile money adoption, particularly in areas that have a limited formal financial infrastructure.

Perceived trust was a statistically significant predictor of behavioural intention among the Somali farmers in the region of Hiran. This implies that farmers appreciate the security, reliability, and institutional credibility of mobile money solutions like EVC Plus and e-Dahab in making decisions to utilize them, particularly in an environment where formal financial infrastructure is scarce or absent.

This is evidenced in other rural environments. As noted by Malaquias and Silva [80], In Brazil, trust played a central role in furthering the use, as far as mobile banking is concerned, especially in the case of low-literacy users. Likewise, Akinyemi and Mushunje , [5] Also determined that trust influenced risk perception and risk adoption-behavior in rural Sub-Saharan Africa. Nonvide and Alinsato, [81] in Cote d'Ivoire highlighted that mobile money platform users' confidence had been central to mobile money adoption by smallholder farmers, which also supports the latter on confidence in digital financial inclusion.

In contrast to these findings, Khatun et al. [82] reported that perceived trust did not significantly influence mobile banking adoption among rural farming communities in Bangladesh. Their study indicated that factors such as service accessibility and user satisfaction played a more dominant role, suggesting that in mature digital ecosystems, performance and usability may outweigh institutional trust.

Thus, while perceived trust was the least influential construct in the current study, it remains an essential component particularly in fragile, cash-dependent economies like Somalia, where mobile money platforms serve as substitutes for traditional banking.

Conclusion and recommendations

This study examined the factors affecting mobile banking adoption among Somali farmers, focusing on core constructs from the TAM, alongside digital literacy and perceived trust. The results confirm that PU is the most significant predictor of BI, reaffirming its central role in the technology adoption literature. This indicates that farmers would tend to utilise mobile banking platforms when they perceive them to be assisting in improving their financial services and access to services. DL also emerged as a significant determinant, indicating that farmers with higher digital competencies are more inclined to utilize mobile banking tools. This demonstrates the critical role regarding digital skills in bridging the financial inclusion gap in rural Somalia. Furthermore, PEOU and PT had significant but relatively minor effects on BI, indicating that user-friendliness and trust in the system also contribute to adoption, albeit to a lesser extent. In a context like Somalia, in which formal banking infrastructure is limited and mobile money platforms such as Hormuud Telecom's EVC Plus dominate financial transactions, understanding these factors is essential for scaling up adoption and enhancing economic resilience among rural communities.

According to the findings of this research, policymakers, NGOs, and telecom providers are advised to launch targeted awareness campaigns to emphasize the usefulness of mobile banking, particularly in enabling savings, access to credit, and efficient transactions for farmers. Furthermore, Development partners and government agencies should implement community-based digital literacy programs that focus on basic smartphone usage, mobile money applications, and financial management. These programs should be distributed in local languages as well as tailored to low-literacy populations. Finally, Mobile banking platforms should be designed with simplicity in mind, offering intuitive interfaces and voice-guided features in Somali to enhance perceived ease of use, especially for first-time users.

The study provides useful information on how m-money is adopted, but it is limited in the number of methods. First, the cross-sectional design constrains the possibility of tracking the changes in the perception and behavior of farmers with time. Researchers should consider employing longitudinal research designs to assess the impacts of continued exposure to m-money services on patterns of adoption and long-term usage. Secondly, other variables like the quality of mobile networks, the cost of transactions, or cultural values that could also affect the rates of adoption were not taken into account in this study. These factors should be captured in subsequent research models since they would offer a more holistic interpretation concerning the acceptance of m-money. Lastly, while the TAM framework was sufficient, future studies should investigate interaction effects or moderating variables, for instance, age, gender, or education level. This would enhance our understanding of technology acceptance in low-resource agricultural settings.

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Author contributions

Each author authorized the final paper and participated in every stage of the study.

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Data availability

The data supporting the findings of this study are available upon request from the corresponding author.

Declarations

Ethics approval and consent to participate

This research received ethical approval from the Centre for Research and development at SIMAD University.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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