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Acceptance and Uptake of Digital Credit by Owner-Managed Micro, Small, and Medium-sized Enterprises (MSMEs) at La Nkwantanang-Madina Municipality

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Abstract: *Owner-managed micro, small, and medium-sized enterprises (MSMEs) are characterised by substantial financing gaps, which impede their growth prospects and their contribution to employment creation and poverty alleviation. While digital lending offers businesses the opportunity to address the challenge of ever-rising financing constraints in emerging markets, the factors predicting digital credit adoption by MSME owner-managers are understudied. This study examined the determinants of digital credit adoption among owner-managed MSMEs in Ghana using an extended Technology Acceptance Model (E-TAM). This quantitative study obtained data from 336 MSMEs operating at the La Nkwantanang-Madina Municipality and analysed the data using partial least squares structural equation modelling (PLS-SEM). The findings show that perceived usefulness and perceived ease of use significantly and positively influence behavioural intention, while perceived cost has a significant negative effect. Perceived risk, however, does not significantly affect behavioural intention. The model explains 47.9% of the variance in behavioural intention, which in turn explains 41.4% of the variance in actual digital credit uptake. The findings suggest the need to develop MSME-tailored digital credit facilities through special arrangements between governments and service providers, anchored on reduced transaction costs, desirable loan amounts, and user-friendly systems. This study is a groundbreaking attempt that incorporates cost and risk into the TAM for digital credit adoption at the organisational level in an emerging market.*

Introduction

Micro, small, and medium-sized enterprises (MSMEs) are key economic agents that drive the industry, agriculture, and services in economies all over the world. Regarded as the backbone of Ghana's private sector, MSMEs play a major role in economic growth, employment creation, and poverty reduction. Available evidence suggests that they account for about 92% of businesses, employ nearly 60% of the labour force, and contribute close to 70% of the gross domestic product (GDP) of Ghana (Ministry of Trade and Industry [MoTI], 2023; World Bank, 2021). However, it is observed that close to 75% of new businesses in the country fold up before their third year in operation, and those that survive beyond three years hardly reach their tenth year (Awal, 2018). Many of these enterprises fail because of inadequate access to finance, limited technology, high transaction costs, poor management, weak credit quality, and collateral constraints. Among these challenges, inadequate access to credit is reported to be the most significant obstacle to MSME growth in the country (World Bank, 2019a). Yet, increasing access to affordable finance is essential not only for enterprise growth but also for achieving several Sustainable Development Goals (SDGs) (1, 2, 3, 4, 5, 8, 9, and 10). Access to digitally enabled finance can help small firms grow, hire more workers, invest in innovation, stabilise family income for health and education needs, and widen opportunities for women and low-income entrepreneurs.

Small businesses are faced with a huge financing gap because they are in most cases excluded from traditional credit markets (Gyimah, Akande, & Muzindutsi, 2022). Meanwhile, such entities need credit to expand and finance their operations. The emergence of digital credit facilities presents a great opportunity for MSME owner-managers to obtain short-term loans (Ngulale, 2020). While digital credit offers MSMEs stress-free and collateral-free facilities to grow their businesses, only a few owner-managers apply for such loans (World Bank, 2019a). It can be concluded that most MSME owner-managers are in the intentional stage of adoption. Behavioural intention is an essential antecedent of actual behaviour. It is therefore, imperative to determine the facilitating and inhibiting factors that predict behavioural intention towards and actual uptake of digital credit by MSME owner-managers, particularly in an emerging Sub-Saharan African (SSA) market where there is a huge financing gap.

The need for such evidence has become more urgent as many governments promote digital financial services (DFS) to improve financial inclusion. Although a study by the Consultative Group to Assist the Poor ([CGAP], 2023) found that digital credit in East Africa is mostly used for consumption rather than productive investment, MSMEs across SSA are in dire need of affordable credit to expand production and contribute to economic development. Fast forward, the Government of Ghana (GoG) policy documents and reports on DFS outline strategic plans to make digital credit available to low-income earners, using smallholder farmers as pilot beneficiaries(Ministry of Finance and Economic Planning [MoFEP], 2022; World Bank, 2019b). The digital ecosystem of Ghana provides favourable conditions for this transition, with registered mobile money accounts increasing from 32.6 million in 2018 to 55.3 million in 2022, active users rising from 13.1 million to 20.4 million, and transaction values expanding from GHȻ155.8 billion to approximately GHȻ1 trillion over the same period (Bank of Ghana [BoG], 2022). These trends position the emerging market of Ghana to fully embrace and absorb the dividends associated with digital credit. However, the success of these initiatives ultimately depends on whether potential users are willing to adopt and continuously use digital credit facilities.

Knowledge of the potential facilitators and inhibitors of digital credit adoption is greatly insufficient, necessitating the development of a dual-factor model that incorporates both dimensions. Previous studies have highlighted the scarcity of research on digital financial inclusion for small businesses in developing countries (Ahiabenu, 2021; Thathsarani & Jianguo, 2022). Much of the existing literature has concentrated on the broader effects of digitalisation on business performance rather than the determinants of digital credit adoption itself (Frimpong, Agyapong, & Agyapong, 2022; Lambon-Quayefio, Manjeer, & Udry, 2021; Ngulale, 2020). Studies that have examined behavioural intention have focused predominantly on individual users (Kamau, 2021b; Putri, Widagdo, & Setiawan, 2023), with relatively few investigating organisational adoption among MSMEs (Abbott, 2020). Among the various technology acceptance frameworks employed in the extant literature, the Technology Acceptance Model (TAM) is the most widely applied framework in information technology research. Most existing studies that applied TAM found varying directions and different effect sizes of usefulness and ease of use perceptions on behavioural intention for and uptake of digital credit without sufficient recourse to contextual factors. The need to extend the scope of the TAM stems from the observation that its constructs have failed to fully replicate the diversity of the user task environment (Wessels & Drennan, 2010). Given the apparent lack of effectiveness, the present study sought to incorporate risk and cost perceptions into the TAM.

Risk and cost are particularly relevant in the context of digital credit. Owner-managers may hesitate to use digital lending platforms because of concerns about cyber fraud, data security, and financial losses. Studies conducted in Kenya, Malaysia, and Indonesia consistently show that perceived security and risk significantly influence digital lending adoption (Chin, Zakaria, Purhanudin, & Pin, 2021; Ngulale, 2020; Putri et al., 2023). Similarly, borrowing costs, transaction fees, and related charges may discourage adoption. Although studies in Kenya found little difference between the cost of digital loans and conventional credit (Kamau, 2021a, 2021b), governments and development partners across SSA continue to advocate lower transaction costs to enhance digital financial inclusion (Kaffenberger, Totolo, & Soursourian, 2018; MoFEP, 2020; World Bank, 2019b). Yet, empirical evidence on how perceived cost and perceived risk influence digital credit adoption among MSMEs in SSA is scarce. The lack of sufficient information for the development of an appropriate strategy that incorporates contextual factors such as cost and risk can be linked to consumer protection concerns surrounding digital borrowing in SSA (CGAP, 2023).

This study addresses foregoing by examining how perceived usefulness, perceived ease of use, perceived risk, and perceived cost influence behavioural intention and the actual uptake of digital credit among owner-managed MSMEs in Ghana. The findings will support digital lenders in designing user-friendly, affordable, and secure credit products, and assists policymakers in developing regulatory frameworks that strengthen consumer protection and financial inclusion. The study contributes to the growing literature on organisational digital credit adoption by incorporating risk and cost into the TAM. It reports insights for expanding financial access for MSMEs in the context of an emerging market.

The remaining part of the paper is organised into six sections. Section Two presents concepts and subjects relating to MSME development, digital credit, and the theoretical/conceptual frameworks and as well as the hypotheses, underpinning the study. The methodology guiding the selection of the study area, target population and sampling, instrumentation, and data collection and analysis is reported in section Three. The results of the study are presented in section Four. Section Five provides a discussion on the various findings, while section Six presents the conclusions.

Review of Literature

- **Defining Digital Credit**

Digital credit has expanded across emerging markets, particularly in countries such as Kenya, Tanzania, and Ghana, and is commonly delivered through mobile and online platforms that provide short-term loans (Kamau, 2021b; Sharma, Ilavarasan, & Karanasios, 2024). Kamau (2021b, p. 165) defines digital credit as “financial advances accessed through a digital platform available online or by the use of mobile devices”. It is enabled by mobile money systems to offer underserved individuals and MSME owner-managers faster and more accessible financing that was historically denied by conventional banking. The speed and convenience of digital lending in Ghana make digital credit an important source of finance for owner-managed MSMEs seeking timely access to credit.

- **Theoretical Foundation, Empirical Literature, Conceptual Framework, and Hypotheses**

The Technology Acceptance Model (TAM), propounded in 1989 by Fred D. Davis, from the Theory of Reasoned Action (TRA), explains technology adoption through perceived usefulness, perceived ease of use, behavioural intention, and actual usage (Ajzen, 1991; Fishbein & Ajzen, 1975). Figure 1 presents the original TAM. Although TAM has traditionally been applied to individual technology adoption, its application has progressively extended to organisational settings (Kelly & Palaniappan, 2023; Tiwari & Tiwari, 2020). Empirical studies have consistently identified perceptions of usefulness and ease of use as key determinants of FinTech adoption among MSMEs (Gupta, Agarwal, & Nautiyal, 2022; Rahadian & Thamrin, 2023). Furthermore, Nurqamarani, Sogiarto, and Nurlaeli (2021) found these two constructs to be the most commonly applied and influential predictors across TAM-based studies of SME technology adoption. What has not received the necessary attention in the application of the TAM is the identification of predictors of digital credit adoption among MSMEs.

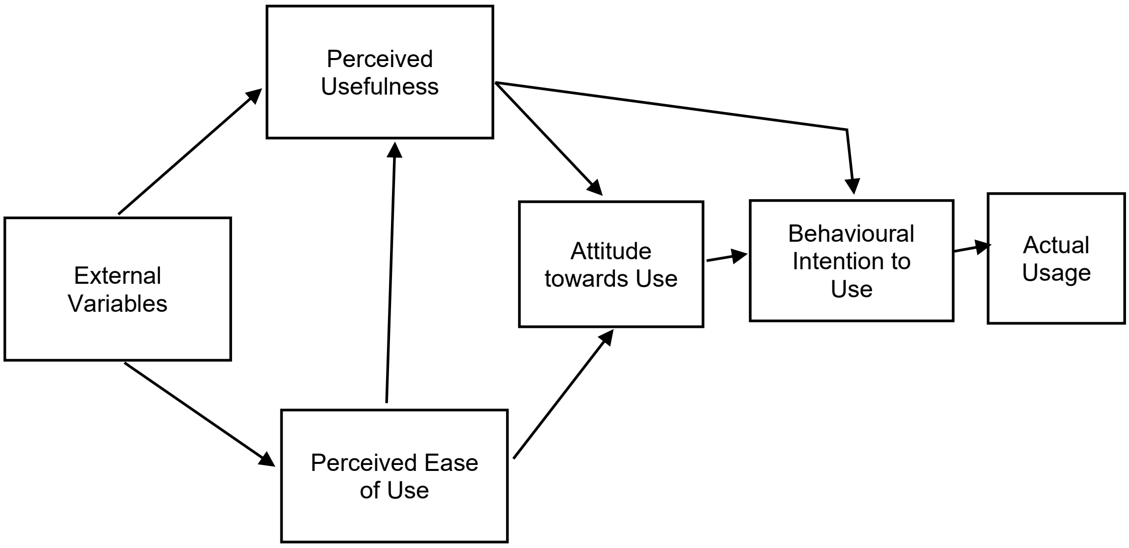

Figure 1: The Technology Acceptance Model

Source: Davis (1989)

The present study adopted the extended Technology Acceptance Model (E-TAM) proposed by Özbek, Günalan, Şahin, and Kaş (2015), incorporating perceived cost and perceived risk (see Figure 2). This extension was considered appropriate because it envelopes contextual factors that predict MSME owner-managers' adoption of digital credit beyond the original TAM constructs. Concerns over cybersecurity, fraud, data privacy, transaction costs, and borrowing charges in Ghana point to the importance of risk and cost in influencing trust and adoption decisions. Several studies have extended the TAM by incorporating risk and cost across various technologies (Kelly & Palaniappan, 2023; Özbek et al., 2015; Sunardi, Suhud, Purwana, & Hamidah, 2021; Tiwari & Tiwari, 2020). However, limited attention has been given to digital credit adoption among MSME owner-managers.

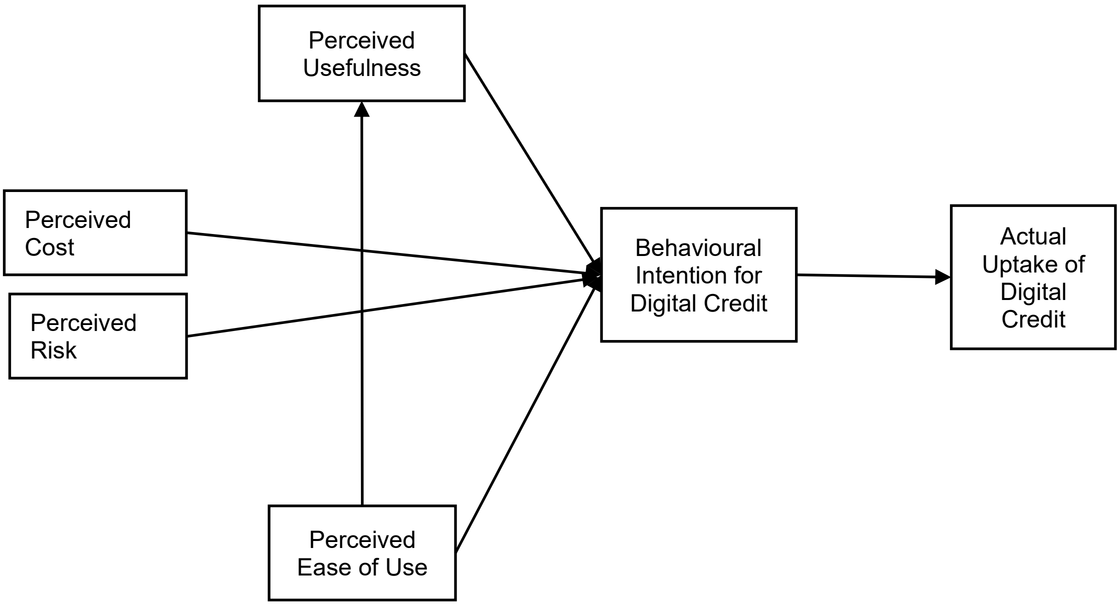

Figure 2: The Conceptual Framework

Source: Modified from Özbek et al. (2015)

Perceived Usefulness and Intention to Take up Digital Credit

Perceived usefulness is “the degree to which a person believes that using a particular system would enhance his or her job performance” (Davis, 1989, p. 320). Empirical studies generally report that perceived usefulness positively influences the adoption of digital lending and P2P financing among SMEs, although inconsistent findings have also been reported (Abbott, 2020; Chin et al., 2021; Putri et al., 2023; Sunardi et al., 2021). Despite this evidence, research on digital credit acceptance and adoption is limited in the Ghanaian MSME context. In this regard, the present study tested the following hypothesis:

H_1: There exists a significant positive relationship between perceived usefulness and behavioural intention to take up digital credit.

Perceived Ease of Use and Intention to Take up Digital Credit

Perceived ease of use can be defined as “the degree to which a person believes that using a particular system would be free of effort” (Davis, 1989, p. 320). The extant literature consistently shows that perceived ease of use positively influences the adoption of digital lending and P2P financing among SMEs by making access to credit faster and less complex (Abbott, 2020; Chin et al., 2021; Ngulale, 2020). The discovery of a substantial influence of ease of use on intention at organisational levels points to the need to formulate the following hypothesis:

H_2: There exists a significant positive relationship between perceived ease of use and behavioural intention to take up digital credit.

Perceived Ease of Use and Perceived Usefulness

Perceived ease of use is expected to enhance perceived usefulness because technologies that require less effort are more likely to be viewed as beneficial (Davis, 1989; Wu & Wang, 2005). In the context of digital credit, MSME owner-managers who find digital lending platforms easy to navigate are more likely to recognise their value for financing and business growth. A study by Putri et al. (2023) confirms a substantial positive nexus between ease of use and usefulness across digital financial services and related technologies. In the face of the foregoing, the present study sought to deal with the following hypothesis:

H_3: There exists a significant positive relationship between perceived ease of use and perceived usefulness.

Perceived Risk and Intention to Take up Digital Credit

Perceived risk, conceptualised in this study as concerns about security and privacy, was incorporated into the TAM to capture factors beyond the original constructs that may influence digital credit adoption (Featherman & Pavlou, 2003; Özbek et al., 2015; Tiwari & Tiwari, 2020). Prospect Theory posits that people are more responsive to potential losses than comparable benefits, making perceived risk an important determinant of behavioural intention (Kahneman & Tversky, 1979). In the context of digital credit, concerns over data privacy, financial security, and system reliability may discourage MSME owner-managers from adopting such services. Empirical evidence indicates that stronger perceptions of security and privacy enhance users' readiness to adopt digital lending and P2P financing (Chin et al., 2021; Ngulale, 2020; Putri et al., 2023). The following hypothesis was therefore, developed:

H_4: There exists a significant negative relationship between perceived risk and behavioural intention to take up digital credit.

Perceived Cost and Intention to Take up Digital Credit

Perceived cost, defined as the financial burden associated with obtaining digital credit, was incorporated into this study because it is expected to influence MSME owner-managers' behavioural intention to adopt digital lending services (Wang & Wang, 2010). Utility Theory suggests that users compare expected benefits with associated costs, which make higher borrowing costs less attractive and reduce adoption intentions (von Neumann & Morgenstern, 1944). Although evidence on digital credit is limited, existing studies generally report a negative relationship between perceived cost and technology adoption (Kamau, 2021a, 2021b; Tiwari & Tiwari, 2020; Wessels & Drennan, 2010). Given the obvious relevance of cost, the present research sought to test the following hypothesis:

H_5: There exists a significant negative relationship between perceived cost and behavioural intention to take up digital credit.

Intention to Take up Digital Credit and Actual Uptake of Digital Credit

Behavioural intention is the immediate precursor of actual technology use in the Technology Acceptance Model, linking users' perceptions to adoption behaviour (Davis, 1989; Davis et al., 1989). Although direct evidence for digital credit is limited, studies on online banking and mobile payments consistently show that behavioural intention positively predicts actual usage (Chaudhari, Linge, Kakde, & Singh, 2023).In light of the confirmed positive and beneficial relationship between intention and actual usage, the present study proposed the following hypothesis:

H_6: There exists a significant positive relationship between behavioural intention to take up digital credit and actual uptake of digital credit.

Research Design and Methods

- **Population, Sampling, and Data Collection**

The target population for this study comprised MSME owner-managers operating at the La Nkwantanang-Madina Municipality in the Greater Accra Region of Ghana. The 2014 Integrated Business Establishment Survey (IBES) recorded 5,832 MSMEs in the municipality, comprising 5,179 micro, 614 small, and 39 medium enterprises (Ghana Statistical Service [GSS], 2016), and was the most reliable source of MSME statistics because the updated report has yet to be published. The minimum sample size was subsequently determined using the margin-of-error approach, which permits the use of an assumed population proportion when the current population size is unknown. It was computed as follows:

$$n = {pqt^2}/{m^2}$$

where:

n: required sample size

t: confidence level at 95% (standardized as 1.96)

p: estimated proportion of the specified category

q: estimated proportion not part of the specified category

m: margin of error at 5% (standardized as 0.05)

The required sample size can be estimated as:

$$n = {0.5(0.5)(1.96)(1.96)}/{0.05(0.05)}$$

$$n = 384\ MSMEs$$

A sample size of 384 MSMEs sufficiently exceeds the minimum sample size of 129 determined using power analysis (G*Power) at an effect size of 0.15 and a 95% significance level. The study, therefore, adopted the 384 sample size established above since, as it was more than twice the size generated by the power analysis. This is a common practice in studies that apply partial least squares structural equation modelling (PLS-SEM) (Cohen, 1988).

Ethical Approval

Ethical clearance approval, referenced ERC-001-2023, was obtained from the Research Ethics Committee of C. K. Tedam University of Technology and Applied Sciences, Navrongo, Ghana, on 2 October 2023. Participating MSME owner-managers were given written informed consent forms to sign before joining the survey. The researchers made use of pseudonyms instead of participants' real names and participation was voluntary.

Study Variables and Measurements

The study adopted previously validated instruments developed in earlier studies (see Table 1). The questionnaire is made of four measures for each of the six variables, giving a total of 24 measurement items**,** in addition to nine demographic characteristics. The constructs were assessed using a scale showing seven-point response categories ranging from 1 to 7, namely “Strongly Disagree” to “Strongly Agree”, respectively.

Table 1: Constructs, Measurement Items, and Authors

Variable	N. of Items	Sources
Perceived Usefulness	4	(Davis, 1989; Davis et al., 1989)
Perceived Ease of Use	4	(Davis, 1989; Davis et al., 1989)
Perceived Risk	4	(Featherman & Pavlou, 2003; Wang & Wang, 2010; Wu & Wang, 2005)
Perceived Cost	4	(Wang & Wang, 2010; Wu & Wang, 2005)
Behavioural Intention	4	(Davis, 1989; Davis et al., 1989)
Actual Usage/Uptake	4	(Davis, 1989; Davis et al., 1989)

The questionnaire was reviewed by two senior academics to establish content validity, after which the revised instrument was pilot-tested with 75 owner-managed MSMEs in the Accra Central Business District, yielding 55 valid responses after removing cases with missing values and outliers. Reliability was evaluated using Cronbach's alpha, and all six constructs exceeded the acceptable threshold of 0.70 (Cronbach, 1951), with values ranging from 0.792 to 0.865 (Table 2).

Table 2: Pilot Survey Outcomes

Construct	Cronbach's Alpha
Perceived Usefulness	0.792
Perceived Ease of Use	0.842
Perceived Risk	0.865
Perceived Cost	0.829
Behavioural Intention for Digital Credit	0.822
Actual Uptake for Digital Credit	0.797

Source: Field Survey (2023)

Data Analysis

The raw data collected were entered into IBM SPSS version 25 and cleaned through editing to improve their quality. The cleaned dataset was analysed via both descriptive (frequencies and percentages) and inferential statistical techniques. Common method bias was assessed using Harman's single-factor test, while the hypothesised relationships were examined using PLS-SEM in SmartPLS version 4. Both measurement and structural models were assessed.

Results and Discussion

The study sought to provide empirical evidence on the determinants of digital credit adoption by distributing 384 copies of the questionnaire to owner-managed MSMEs across the La Nkwantanang-Madina Municipality. Of the 357 questionnaires returned (representing a 92.97% response rate), 21 cases with missing values or outliers were excluded, resulting in 336 valid responses for analysis. These responses formed the basis for the assessment.

Demographic Characteristics

The respondents comprised 336 MSME owner-managers with diverse demographic and business characteristics. The demographic characteristics of the MSME owner-managers are summarised in Table 3. Most participants were male, relatively young, formally educated, and had between 6 and 10 years of business experience, while the majority operated micro-enterprises employing between 1 and 6 workers. These characteristics indicate that the respondents were well positioned to provide informed views on behavioural intention toward and actual uptake of digital credit.

Table 3: Background Information of the Participants (n=336)

Variables		Frequency	Percentage
Gender	Male	189	56.25
	Female	147	43.75
Age	< 30	104	30.95
	31-40	156	46.43
	41-50	64	19.05

	51+	12	3.57
Educational Attainment	Primary/Junior Education	78	23.21
	Secondary/Vocational/Technical Education	203	60.42
	Tertiary Education	55	16.37
Marital Status	Married	186	55.36
	Single	90	26.79
	Divorced	42	12.50
	Widow	18	5.36
Experience	<5	109	32.44
	6—10	202	60.12
	11—15	18	5.36
	15>	7	2.08
Business Type	Sole	246	73.21
	Partnership	19	5.65
	Company	71	21.13
Business Sector	Manufacturing	84	25.00
	Construction	29	8.63
	Service	75	22.32
	Trade	133	39.58
	Agriculture	15	4.46
Employees	>6	246	73.21
	7—30	68	20.24
	31-100	22	6.55
Monthly Sale	< GHȻ100,000	98	29.17
	GHȻ100,001-GHȻ200,000	148	44.05
	GHȻ200,001--GHȻ300,000	43	12.80
	GHȻ300,001--GHȻ400,000	22	6.55
	> GHȻ400,000	25	7.44

Source: Field Survey (2023)

Measurement Model

The measurement model assessment comprises the use of reliability and validity of the study constructs using the PLS-SEM approach. A two-stage PLS algorithm was applied. The estimation includes various reliability, validity, and model fit indices.

Test for Reliability

The outcomes of the reliability tests performed in the second phase of the PLS algorithm are presented in Table 4. The initial PLS algorithm produced four items with less than 0.70 indicator loadings (AUDC1, BIDC1, PR3, and PR4) alongside poor Cronbach Alpha and composite reliability scores (0.480 and 0.530, respectively) for perceived risk. In line with existing practices, the problematic items were deleted and the model re-estimated. Following their removal, the measurement model yielded acceptable indicator loadings, consistent with recommended practice (Cronbach, 1951; Hair, Hult, Ringle, & Sarstedt, 2017). The Cronbach's alpha and composite reliability scores also reached acceptable levels.

Table 4: Tests for Internal Consistency and Indicator Loadings from the Second Phase of the PLS Algorithm

Constructs	Items	Factor Loadings	Cronbach Alpha	Composite Reliability
Actual Uptake	AUDC2	0.795	0.803	0.823
	AUDC3	0.885		
	AUDC4	0.857		
Behavioural Intention	BIDC2	*0.842*	0.702	0.702
	BIDC3	0.775		
	BIDC4	0.755		
Perceived Cost	PC1	0.817	0.839	0.838
	PC2	0.822		
	PC3	*0.867*		
	PC4	0.777		

Perceived Ease of Use	PEOU1	0.794	0.827	0.834
	PEOU2	0.731		
	PEOU3	0.839		
	PEOU4	0.877		
Perceived Risk	PR1	0.846	0.706	0.735
	PR2	0.909		
Perceived Usefulness	PU1	0.787	0.838	0.844
	PU2	0.755		
	PU3	0.856		
	PU4	0.882		

Source: Field Survey (2023)

Test for Validity

Convergent and discriminant validity were established, with all constructs exceeding the acceptable AVE threshold of 0.50 and satisfying the Fornell–Larcker criterion (Fornell & Larcker, 1981), implying adequate convergent validity and discriminant validity among the constructs (Table 5). The Heterotrait–Monotrait (HTMT) ratios were all below the recommended threshold of 0.85 (Table 6), suggesting adequate discriminant validity (Henseler, Ringle, & Sarstedt, 2015). This finding also confirms the absence of discriminant validity concerns.

Table 5: AVE for Convergent Validity and Fornell–Larcker Criterion for Discriminant Validities from the Second Phase of the PLS Algorithm

Constructs & Items	AVE	Fornell–Larcker Criterion					
Actual Uptake	0.717	0.847					
Behavioural Intention	0.627	0.643	0.792				
Perceived Cost	0.675	-0.565	-0.609	0.821			
Perceived Ease of Use	0.659	0.640	0.491	-0.447	0.812		
Perceived Risk	0.770	-0.310	-0.306	0.435	-0.241	0.878	
Perceived Usefulness	0.675	0.490	0.500	-0.408	0.400	-0.202	0.822

Source: Field Survey (2023)

Table 6: Heterotrait–Monotrait Ratio for Discriminant Validity from the Second Phase of the PLS Algorithm

Construct	Actual Uptake	Behavioural Intention	Perceived Cost	Perceived Ease of Use	Perceived Risk
Actual Uptake					
Behavioural Intention	0.839				
Perceived Cost	0.683	0.787			
Perceived Ease of Use	0.790	0.635	0.532		
Perceived Risk	0.407	0.427	0.577	0.307	
Perceived Usefulness	0.597	0.644	0.488	0.475	0.267

Source: Field Survey (2023)

Model Fitness

The goodness of fit of a model is how well the model fits the data under scrutiny (Hair et al., 2017; Henseler & Sarstedt, 2013). Table 7 reports the fit index of standardised root mean square residual (SRMR). It presents an SRMR score of 0.075, below the maximum threshold of 0.08, implying a good fit.

Table 7: Model Fitness

Fit Indices	Criteria	Scores
SRMR	<0.08	0.075

Source: Field Survey (2023)

Collinearity and Common Method Bias

A major requirement for SEM is to test for collinearity (Hair et al., 2011, 2017). The rule of thumb is that a variance inflation factor (VIF) score of 5 or more suggests a high level of collinearity. The VIF scores for the outer model reported in Table 8 were all below 5, which suggests the absence of collinearity issues.

Table 8: Results of Collinearity Test from the Second Phase of the PLS Algorithm (Outer VIF)

Items	Outer VIF
AUDC2	1.587
AUDC3	1.874
AUDC4	1.820
BIDC2	1.711
BIDC3	1.309
BIDC4	1.427
PC1	2.651
PC2	2.037
PC3	2.910
PC4	2.026
PEOU1	1.775
PEOU2	1.640
PEOU3	1.909
PEOU4	2.422
PR1	1.424
PR2	1.424
PU1	1.937
PU2	1.699
PU3	2.028
PU4	2.624

Source: Field Survey (2023)

Common method bias was evaluated using the inner model VIF and Harman's single-factor test. All inner VIF values were below the recommended threshold of 3.3. A single factor explained only 34% of the total variance, which is below the 50% benchmark (Harman, 1967). These results confirm the absence of common method bias in the study.

Table 9: Results of Collinearity Test from the Second Phase of the PLS Algorithm (Inner VIF)

Construct	Inner VIF
Behavioural Intention for Digital Credit	1.000
Perceived Cost	1.559
Perceived Ease of Use	1.348
Perceived Risk	1.238
Perceived Usefulness	1.292

Source: Field Survey (2023)

Table 10: Harman's single factor test for Common Method Bias

Factor	Initial Eigenvalues			Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8.124	33.849	33.849	8.124	33.849	33.849
2	1.973	8.222	42.071			
3	1.738	7.241	49.312			
4	1.636	6.817	56.129			
5	1.165	4.856	60.985			
6	1.051	4.378	65.363			
7	0.863	3.594	68.957			
8	0.816	3.401	72.358			
9	0.803	3.346	75.704			
10	0.746	3.109	78.813			
11	0.708	2.951	81.763			
12	0.609	2.538	84.301			
13	0.599	2.495	86.796			
14	0.529	2.203	88.998			
15	0.451	1.877	90.875			

16	0.377	1.573	92.448	
17	0.359	1.497	93.945	
18	0.309	1.286	95.231	
19	0.268	1.115	96.347	
20	0.249	1.035	97.382	
21	0.202	0.844	98.226	
22	0.156	0.650	98.876	
23	0.144	0.599	99.475	
24	0.126	0.525	100.000	

Source: Field Survey (2023)

Structural Model

The structural model was built using a bootstrapping technique with 5,000 sub-samples (see Figure 3 and Table 11). The various hypotheses in the model were tested using path coefficients, t-statistics, and p-values. The rule of thumb is that a p-value of less than 0.01 or 0.05 indicates a significant association between the underlying variables.

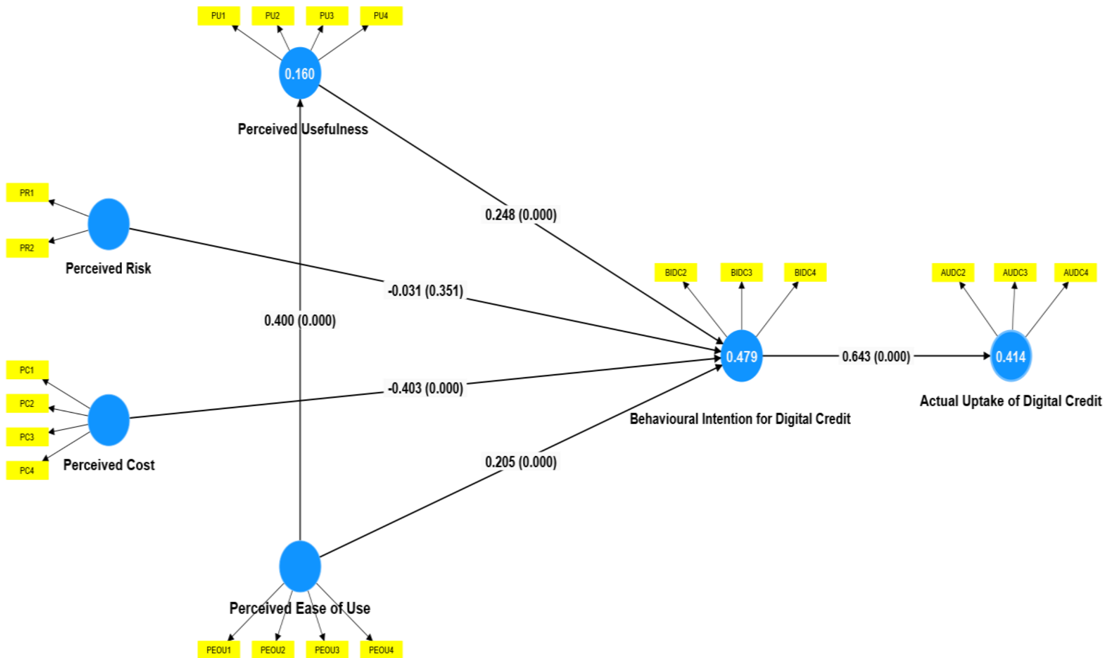

Figure 3: The Structural Model

Source: Field Survey (2023)

Path Coefficients

The structural model depicts a significant direct influence of usefulness on intention to take up digital credit ($\beta = 0.248, p < 0.01$). It supports H_1, which states that there exists a substantial positive association between usefulness perception and behavioural intent to take up digital credit. This implies that the usefulness of the loan in terms of its amount influences owner-managers' intention to adopt digital credit. This finding corroborates several precious discoveries on digital lending in terms of usefulness-intention nexus (Putri et al., 2023; Sunardi et al., 2021, 2022).

The study found a significant positive nexus between ease of use perception and intention to take up digital credit ($\beta = 0.205, p < 0.01$). It supports H_2, which posits that ease of use significantly and positively affects intention to take up digital credit. This finding suggests that, when it comes to intending to take up digital credit, MSME owner-managers place a premium on the ease of navigating the digital credit platform. The identification of a substantial positive association between perceived ease of use and intention to take up digital credit can be traced to the existing findings (Abbott, 2020; Chin et al., 2021; Putri et al., 2023; Sunardi et al., 2022, 2022).

The structural model also depicts a substantial positive influence of ease of use on usefulness ($\beta = 0.400, \mathrm{p} < 0.01$). It supports H_3, which states that there exists a positive and significant association between ease of use perception and usefulness perception. This shows that the ease of taking up digital credit by an MSME owner-manager will eventually translate into its usefulness to the business of the owner. Putri et al. (2023) also reported a similar association.

Table 11: Results of the Structural Model

Hypothesis	Paths	β	t-value	CI	Decision
H_1	PU->BIDC	0.248***	4.644	[0.145 – 0.352]	Supported
H_2	PEOU->BIDC	0.205***	3.663	[0.098 – 0.311]	Supported
H_3	PEOU->PU	0.400***	7.004	[0.281 – 0.505]	Supported
H_4	PR->BIDC	-0.031	0.933	[-0.097 – 0.035]	Not supported
H_5	PC->BIDC	-0.403***	8.051	[-0.506 – -0.310]	Supported
H_6	BIDC->AUDC	0.643***	11.739	[0.527 – 0.739]	Supported

Note: Significance levels: n/s = not significant; ***0.01, **0.05

Source: Field Survey (2023)

The structural system portrays an insignificant inverse influence of perceived risk on behavioural intention to take up digital credit ($\beta = -0.031, \mathrm{p} > 0.05$). The model failed to support H_4, which states that there exists a significant negative association between risk perception and behavioural intention to take up digital credit. However, the study found a strong negative influence of perceived cost on behavioural intention to take up digital credit ($\beta = -0.403, \mathrm{p} < 0.01$). The structural model supports H_5, which states that there exists a substantial negative relationship between cost and intention to take up digital credit. This suggests that the cost of obtaining digital credit has a substantial detrimental effect on owner-managers' behavioural intention to adopt such facilities. The findings further indicate high digital borrowing costs discourage MSME owner-managers from adopting digital credit, thereby reinforcing concerns that both digital lenders and traditional financial institutions charge relatively high lending rates in SSA. For instance, in Kenya, Kamau (2021b) found no substantial difference between digital borrowing costs and the cost of bank credit.

The structural model depicts a substantial positive association between behavioural intention to take up digital credit and actual uptake of digital credit ($\beta = 0.643, \mathrm{p} < 0.01$). It supports H_6, which predicts a strong positive association between the constructs. This finding suggests that the intentions expressed by MSME owner-managers to adopt digital credit facilities are translating into tangible actions.

Variance Explained, Predictive Relevance, and Effect Size

The variance explained and predictive relevance are presented in Table 12. The structural model demonstrated moderate explanatory power, with perceived usefulness, perceived ease of use, perceived risk, and perceived cost jointly explaining 47.9% of the variance in behavioural intention, while behavioural intention explained 41.4% of the variance in actual digital credit uptake. The model also exhibited strong predictive relevance, with Q^2 values of 40.5% for behavioural intention and 39.0% for actual uptake. Table 13 shows that behavioural intention had the strongest effect on actual digital credit uptake ($f^2 = 0.705$), followed by the moderate effects of perceived cost on behavioural intention ($f^2 = 0.200$) and perceived ease of use on perceived usefulness ($f^2 = 0.191$). Perceived ease of use and perceived usefulness exerted small effects on behavioural intention, while perceived risk had a negligible effect ($f^2 = 0.002$).

Table 12: R^2 for Variance Extracted and Q^2 for Predictive Relevance

Construct	R^2	Q^2
Behavioural Intention for Digital Credit	0.479	0.405
Actual Uptake of Digital Credit	0.414	0.390
Perceived Usefulness	0.160	0.143

Source: Field Survey (2023)

Table 13: f^2 for the Model

Paths	f^2	Size
BIDC->AUDC	0.705	Large
PC->BIDC	0.200	Medium
PEOU->BIDC	0.060	Small
PEOU->PU	O.191	Medium
PR->BIDC	0.002	Small
PU->BIDC	0.091	Small

Source: Field Survey (2023)

Conclusions

The study addressed a significant gap in the digital credit literature by extending the TAM to incorporate cost and risk at the organisational level. It is the first of its kind to examine how usefulness, ease of use, cost, and risk perceptions predict the intention of MSME owner-managers to uptake up digital credit in an emerging market. This E-TAM partly addresses the inadequacy of the original constructs in replicating the multiplicity of adopter task settings at the orgainsational level. Future studies could replicate this extended version of the TAM in the assessment of technology adoption and reconsider other concepts or sub-dimensions of perceived risk while retaining the old concepts included in this present study, since they adequately capture the expected outcomes. New direct and indirect paths could be added to extend the proposed model.

A lack of proper understanding of the relevance of cost, usefulness, and ease of use perceptions in the adoption of digital credit by MSME owner-managers could have slowed earlier adoption in many Economic Community of West African States (ECOWAS) countries. The present finding that owner-manager intention to adopt digital credit is significantly impacted by cost, usefulness, and ease of use helps explain why such innovative packages have received poor acceptance during their early stages. However, the MSME owner-managers' awareness of digital credit has not been examined. Future studies could consider assessing digital credit awareness among small businesses. State-sponsored digital literacy programmes should incorporate digital credit awareness initiatives among MSMEs since the major challenge facing these entities centres around accessing finance for their businesses.

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