

Examining FinTech Lending Adoption by Small and Medium Enterprises Using a Technology–Environment Framework with PLS-SEM Analysis

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Abstract

Small and medium enterprises (SMEs) are still experiencing chronic credit shortages amid the fast-growing number of financial technology (FinTech) lending solutions. Despite potential of immense promise of FinTech lending in reducing the financing constraints of SMEs, the adoption levels are even lower in emerging and developing economies. This paper discusses the factors of FinTech lending uptake in SMEs using a Technology Environment (T-E) model based on the Technology Environment Organization (TOE) model, which has been modified to eliminate organisational variables and specifically concentrate on the technological and environmental aspects. The hypotheses were tested and developed out of seven hypotheses via Partial Least Squares Structural Equation Modelling (PLS-SEM) on the data gathered on 287 SME owners and managers in a cross-sectional survey. Technology factors (Perceived Usefulness, Perceived Ease of Use, Platform Security, and Compatibility) and environmental factors (Competitive Pressure, Trading Partner Readiness and Regulatory Support) were studied as predictors of FinTech Lending Adoption Intent. Findings show that the structural model accounts 52 percent of variance in adoption intent ($R^2 = 0.52$) with Perceived Usefulness ($\beta = 0.41$, $p < 0.001$) and Regulatory Support (0.38 , $p < 0.001$) proving to be the most significant predictors. Each hypothesis was upheld with $p < 0.05$ with the exception of Trading Partner Readiness ($\beta = 0.11$, $p = 0.087$) that was not significantly different. Convergent and discriminant validity was confirmed by measurement model diagnostics. The research is valuable in that it presents a validated T-E framework specific to SME FinTech lending settings and presents practical implications to designers of platforms, SMEs, and financial regulators.

Keywords: FinTech lending, SME finance, Technology-Environment framework, PLS-SEM, adoption behaviour, digital financial services. **Keywords:** FinTech lending

Introduction

Expansion of FinTech Lending and SME Credit Gap

The FinTech lending sector has experienced remarkable growth in the last decade, transforming small business lending. FinTech lenders defined by the use of algorithmic credit assessment, online application processes and open banking technology have lent an estimated USD 223 billion to small businesses globally in 2023, with a compound annual growth rate (CAGR) of around 28% since 2018. Such expansion is symptomatic of a paradigm shift in the way credit is originated, underwritten and serviced away from the traditional banking system. However, despite this growth, a credit gap of about USD 5 trillion continues to plague SMEs in emerging markets (International Finance Corporation, 2022).

SMEs represent the lifeblood of most economies with more than 90% of all businesses globally and play a vital role in creating jobs and generating GDP (OECD, 2021). Yet, their access to conventional credit is limited by information problems, the need for collateral, and the transaction costs of traditional bank lending (Chua et al., 2022). Theoretically, FinTech lenders provide an attractive alternative: they can access alternative data, streamline paperwork and approve loans within hours, rather than weeks (Tang, 2021). However, the potential of FinTech to address credit constraints has yet to translate to widespread uptake by SMEs, presenting a policy and research challenge (Cornelli et al., 2023).

The apparent contradiction between low FinTech lending adoptions by SMEs, despite the evident potential of FinTech to ease their access to credit, has drawn increasing research interest. Survey data from several economies show that less than 30% of SMEs that are familiar with FinTech lending have applied for credit through FinTech platforms (Klus et al., 2021). The low adoption rate can be attributed not only to awareness; qualitative research indicates that security concerns of the platform, regulatory uncertainty and a lack of trust mechanisms are key barriers to adoption. Moreover, the influence of the external business environment such as competitive, partner and regulatory settings on adoption intentions has been understudied (Wonglimpiyarat, 2022).

Theoretical frameworks commonly employed in this field, such as the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Diffusion of Innovations (DOI) framework, tend to emphasise individual cognitive factors and tend to downplay environmental and contextual factors that are more relevant to the SME environment. This shortcoming may partially account for the low explanatory power of existing FinTech models and calls for a more holistic approach that accounts for both technological and environmental factors (Alalwan et al., 2021).

While a plethora of FinTech adoption studies exist, there remains a gap in the use of the Technology, Organisation, and Environment (TOE) model in its modified Technology-Environment (T-E) version to explain FinTech lending adoption in SMEs. While the TOE model developed by Tornatzky and Fleischer (1990) and elaborated by Oliveira and Martins (2011) has been validated in IT adoption studies, there is a lack of rigorous adaptation and validation of the TOE framework to FinTech lending, with the organisational dimension removed to focus on technology-environment interactions (Qasim & Abu-Shanab, 2022). It is also recognised in the literature that SEM using covariance-based approaches is problematic for small sample analyses of SMEs, and that PLS-SEM is superior in the presence of non-normality and small sample sizes (Hair et al., 2022).

This research addresses these limitations by building a succinct T-E model, measuring it through multi-item reflective measures, and estimating the structural model with SmartPLS 4.0 software. In doing so, it contributes to the development of a theoretical framework of FinTech lending adoption and offers empirical evidence from a sound analytical approach.

Research Questions

This research is underpinned by three key questions:

RQ1: What is the impact of technology factors (Perceived Usefulness, Perceived Ease of Use, Platform Security and Compatibility) on the FinTech lending adoption intent of SMEs?

RQ2: To what extent do environmental factors - Competitive Pressure, Trading Partner Readiness and Regulatory Support that affect SMEs' FinTech lending adoption intent?

RQ3: What technology and environmental factors are most important and performative for the prediction of FinTech lending adoption intent, derived from an Importance-Performance Map Analysis (IPMA)?

Objectives of the Study

In line with the research questions, the study aims

- To develop a T-E conceptual model for SME FinTech lending adoption by extending the TOE model through theoretically supported technology and environment factors
- To empirically test seven hypotheses of the effects of T-E antecedents on FinTech lending adoption intent via PLS-SEM using a sample of 287 SMEs
- To assess the importance and performance of predictor constructs through IPMA to provide managerial and policy implications.

Contributions of the Study

This research has three contributions. Theoretically, it enhances the T-E model of the TOE framework in the underdeveloped area of FinTech lending adoption, offering a model that can be replicated across different countries. Methodologically, it confirms the suitability of PLS-SEM for technology adoption studies targeting SMEs, and offers a comprehensive report of outer and inner model diagnostics, providing a reference for future researchers. Practically, it delivers evidence-based insights for FinTech platform providers to enhance user adoption, for SME organisations to effectively promote the use of digital finance to members, and for regulators to establish a permissive environment that facilitates trust and adoption.

Literature Review and Hypotheses

The Technology–Environment Framework

The Technology-Organization-Environment (TOE) framework proposed by Tornatzky and Fleischer (1990) and that has been validated for multiple IS adoption scenarios by Oliveira and Martins (2011), suggests that technology adoption is influenced by three environmental factors: the technology environment (technologies and innovations), the organization environment (characteristics and resources of the firm), and the environment (industry characteristics, market structure and regulation). In the current study, the organizational domain is deliberately disregarded due to the construct validity issues arising from SME-level organizational differences and because central focus is on analyzing the interactions of technology perceptions and environment (Qasim & Abu-Shanab, 2022). The resulting Technology-Environment (T-E) model is conceptually closer to Seethamraju's (2020) demonstration of TOE-based models' superior predictive power compared to single-theory models of cloud computing adoption by SMEs. In another study, Nguyen et al. (2023) used a T-E model to predict mobile payment adoption in micro-enterprises and found that it outperformed TAM-only models, with R^2 values around 0.50. Our study builds on this research and apply it to FinTech lending by drawing on elements of TAM (Davis, 1989), DOI (Rogers, 2003) and institutional theory (DiMaggio & Powell, 1983) to operationalize the T-E factors.

Technology Factors and Hypotheses

Perceived Usefulness (PU)

Perceived Usefulness (PU) is defined as an individual's belief that using a system will increase their job performance. Within FinTech lending, PU reflects SME owners' beliefs that digital credit systems will increase their efficiency in accessing financing, speed up approval processes, and enhance their working capital management. Through empirical research, PU is consistently found to be a significant predictor of FinTech adoption intention in several studies. Ali et al. (2021) reported PU as a strong predictor of mobile banking adoption among SME owners ($\beta = 0.44$, $p < 0.001$) in a South Asian setting, while Alalwan et al. (2021) have found a similar effect in the GCC region (Alalwan et al., 2021).

Based on this, the following hypothesis is put forward:

H1: Perceived Usefulness will positively affect SME FinTech lending adoption intent.

Perceived Ease of Use (PEOU) refers to the extent to which a potential user believes the system to be effortless to use (Davis, 1989). Ease of use is a key adoption factor for SME entrepreneurs, who generally lack IT expertise and support professionals. Chua et al. (2022) found PEOU had a significant impact on FinTech platform adoption by Malaysian SMEs ($\beta = 0.29$), while Yan et al. (2023) found that complexity was one of the major reasons for non-adoption amongst Chinese microenterprise borrowers. Accordingly:

H2: Perceived Ease of Use is positively related to SME FinTech lending adoption.

In FinTech, Platform Security relates to SME operators' perceptions of the adequacy of data security, fraud prevention and privacy protection measures offered by digital platforms. Platform Security is a commonly reported barrier to digital financial services adoption (Wonglimpiyarat, 2022). Ozili (2022) reported perceived lack of security as the most commonly mentioned barrier to FinTech adoption among Nigerian SMEs, and Platform Security was found to be a significant predictor of FinTech lending intent ($\beta = 0.33$) in a comparative study of South Asian nations (Shaikh et al., 2023).

H3: Platform Security significantly and positively influences SME FinTech lending intent.

Compatibility is a construct from Rogers' (2003) Diffusion of Innovations theory, which captures the extent to which an innovation is perceived as compatible with an individual's existing values, needs and past experiences. For FinTech loans, compatibility refers to the fit between the SME's current financial practices and technology. Zhao and Bacao (2021) found compatibility to be an important factor in SME FinTech adoption in China ($\beta = 0.27$), and this finding was supported by Nguyen et al (2023) in Vietnam.

H4: Compatibility positively affects SMEs' FinTech lending adoption intention

Competitive Pressure

Competitive Pressure is the extent to which an organisation feels pressure from the adoption of a technology by its competitors, which motivates it to adopt that technology (Tornatzky & Fleischer, 1990). For example, in the case of SME FinTech borrowing, competitive pressure might come from witnessing competitors access low-cost and speedy capital via digital channels, and thus gain competitive advantage. Oliveira et al. (2022) found competitive pressure had a significant effect on the adoption of cloud financial services in Portuguese SMEs ($\beta = 0.30$), while Klus et al. (2021) reported similar trends in European SME FinTech surveys. Therefore:

H5: Competitive Pressure positively affects the intention to adopt SME FinTech lending.

Trading Partner Readiness

Trading Partner Readiness refers to the degree that an SME's supply chain partners (e.g., suppliers, distributors, and key customers) have adopted and promote the use of digital financial solutions, thus creating network effects and interoperability (Seethamraju, 2020). Although trading partner readiness has been found to be a key driver of adoption in e-commerce and EDI systems, FinTech lending is a two-party transaction (SME and platform) and not a network transaction (SME, platform and other

supply chain partners), and so it is theoretically less relevant. In line with this, Yan et al. (2023) found trading partner influence to be a marginally significant predictor of FinTech payments but not in credit seeking. In line with TOE studies, the hypothesis is kept for exploratory purposes.

Technology–Environment Framework for SME FinTech Lending Adoption

Technology Factors: PU (H1), PEOU (H2), Platform Security (H3), Compatibility (H4) → FinTech Lending Adoption Intent ← Environmental Factors: Competitive Pressure (H5), Trading Partner Readiness (H6), Regulatory Support (H7)

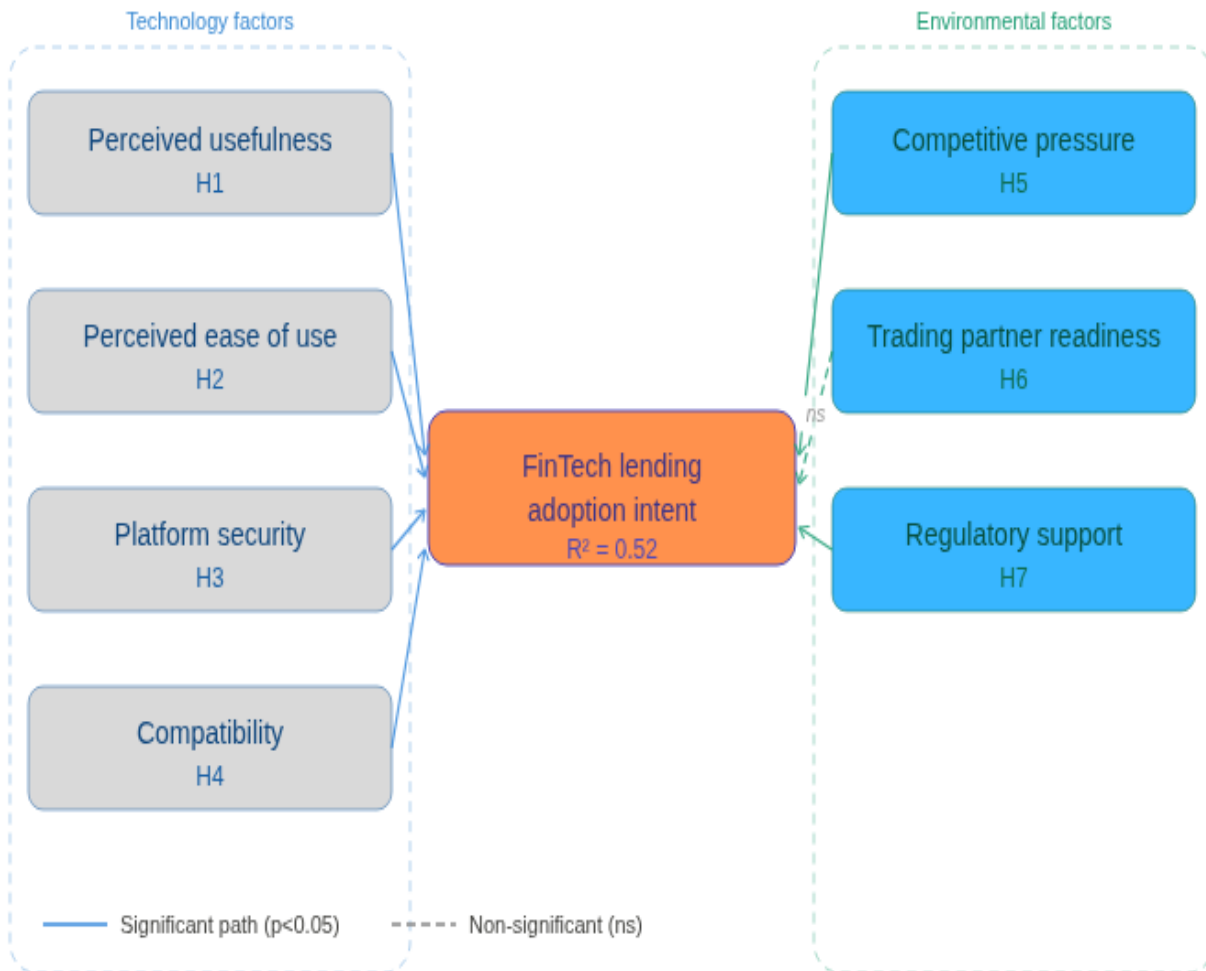


Figure 1. Conceptual model: Technology–Environment framework for SME FinTech lending adoption.

Methodology

Research Design

This research employs a quantitative, positivist research design and a cross-sectional survey. This choice of quantitative design is epistemologically congruent with the deductive testing of a set of hypotheses derived from theory and is in line with the prevailing methodological approach in technology adoption studies (Hair et al., 2022). A cross-sectional approach was chosen as the study seeks to provide a synchronic view of SME technology adoption perceptions, with an awareness of the limitations of establishing causality with this design. The research follows the two-step PLS-SEM analysis approach advocated by Anderson modified for PLS-SEM applications by Hair et al. (2022) where the measurement model is validated first before assessing the structural model.

Sampling and Data Collection

The study population was the owners, directors and senior financial managers of nationally registered SMEs (employing fewer than 250 workers and with annual turnover less than USD 50 million). This study used a purposive sampling approach with referral to reach SME operators via national SME associations, business incubators and accounting professional networks. A minimum of 250 responses was determined as a conservative estimate based on the ten-times rule for PLS-SEM data (Hair et al., 2022), and the sample size required to detect R^2 coefficients of around 0.50 with seven predictor paths, at the 5% significance level was verified using G*Power 3.1 (Faul et al., 2007).

A structured, online questionnaire was used to gather data from March to July 2024. A total of 299 responses were received, and after removing incomplete, straight-lined and multivariate outliers (using Mahalanobis D^2 analysis), a usable sample of 287 remained, for a usable response rate of 69.7%. This is greater than the minimum sample size, and in line with other PLS-SEM research on FinTech adoption (Alalwan et al., 2021; Zhao & Bacao, 2021).

Measurement Instrument

This study used a multi-item questionnaire with a five-point Likert-scale (1 = Strongly Disagree to 5 = Strongly Agree). All the constructs were operationalised using reflective indicators, in line with their conceptualisation as indicators of latent constructs (Hair et al., 2022). Perceived Usefulness (4 items) and Perceived Ease of Use (4 items) items were based on Davis (1989) and subsequently tested in FinTech by Ali et al. (2021). The items for Platform Security (3 items) were adapted from Shaikh et al. (2023), Compatibility items (3 items) from Zhao and Bacao (2021), Competitive Pressure items (3 items) from Oliveira et al. (2022), Trading Partner Readiness items (3 items) from Seethamraju (2020), Regulatory Support items (3 items) from Ozili (2022), and FinTech Lending Adoption Intent items (4 items) from Tang (2021). Eight constructs with 27 indicators were included. A pilot survey was conducted with 30 SMEs before the main survey; some wording changes were made to questions based on the feedback, but no questions were removed.

Common Method Bias Mitigation

The survey data was single-source, self-reported, and to alleviate common method bias (CMB), procedural and statistical steps were taken. Procedurally, the survey items were separated as predictor and criterion variables by placing them in different, non-consecutive sections of the questionnaire, using reverse-coded items for two of the constructs, and ensuring anonymity of the respondents to prevent social desirability bias (Podsakoff et al., 2012). Statistically, Harman's single-factor test was conducted in SPSS 28.0; the single factor explained 24.3% of the variance, less than the 50% cut-off, thus offering initial evidence against CMB. Also, the full collinearity variance inflation factor (VIF) test was performed in SmartPLS 4.0, with all outer VIF results below 3.3, also indicating the absence of systematic CMB (Kock, 2020).

PLS-SEM Analysis Strategy

Structural Equation Modelling (SEM) was performed using Partial Least Squares (PLS) in SmartPLS 4.0 (Ringle et al., 2022). PLS-SEM was preferred over covariance-based SEM (CB-SEM) for a number of reasons: the sample size, although adequate, is small compared to the requirements of CB-SEM; the distribution of some of the constructs was not normally distributed (Mardia's multivariate kurtosis = 4.82); and the study is confirmatory but also predictive (Hair et al., 2022). The analysis involved two steps. First, the measurement model was assessed with indicator loadings (cutoff: $\lambda > 0.70$), Average Variance Extracted ($AVE > 0.50$), Composite Reliability ($CR > 0.70$) and discriminant validity using the Heterotrait-Monotrait Ratio of Correlations ($HTMT < 0.85$) according

to Henseler et al. (2015). In the second stage, the structural model was evaluated by examining path coefficients (β), coefficient of determination (R^2), effect sizes (f^2) and predictive relevance (Q^2) through blindfolding with omission distance 7. Significance of path coefficients was assessed via bias-corrected bootstrapping with 5,000 resamples and a two-sided significance test (p-value at 5% level) as suggested by Hair et al. (2022). Importance-Performance Map Analysis (IPMA) was also performed using SmartPLS to help practitioners prioritise which constructs to focus on.

Ethical Considerations

The institutional review board approved the study. Electronic informed consent was obtained before the survey begins. It was made clear that their participation was voluntary and they had the right to withdraw at any time. Data were stored securely on encrypted servers, and no identifying information was kept after the data collection period. The research complied with the ethical principles for medical research involving human subjects as outlined in the Declaration of Helsinki and national data protection laws.

Results

Initial Data Cleaning and Sample Characteristics

After removing 12 responses with missing data and identified as outliers, the remaining $n = 287$ were analysed for common characteristics. The sample profile is shown in Table 1. Females were under-represented (38.3%) and the age group most represented was 35–44 years (38.7%). The majority of respondents were from micro (54.4%) and small enterprises (45.6%), with fewer than 10 employees and between 10 and 49 employees, respectively. The highest representation was from the manufacturing (27.9%) and trade/retail (24.4%) industries. In terms of FinTech awareness, 83.6% of respondents were aware of at least one FinTech lender, but only 29.3% had ever applied for a FinTech loan, which is in line with low FinTech adoption rates in previous studies (Klus et al., 2021).

Table 1. Sample Profile ($n = 287$)

Characteristic	Category	n (%)
Gender	Male	177 (61.7%)
	Female	110 (38.3%)
Age Group	25–34 years	82 (28.6%)
	35–44 years	111 (38.7%)
	45–54 years	71 (24.7%)
	55+ years	23 (8.0%)
Firm Size	Micro (<10 employees)	156 (54.4%)
	Small (10–49 employees)	131 (45.6%)

Industry Sector	Manufacturing	80 (27.9%)
	Trade/Retail	70 (24.4%)
	Services	89 (31.0%)
	Other	48 (16.7%)
Prior FinTech Loan	Yes	84 (29.3%)
	No	203 (70.7%)

Measurement Model Results

The measurement model was evaluated for convergent validity and discriminant validity, as specified by Hair et al. (2022). The outer loadings, AVE and Composite Reliability (CR) of the constructs are shown in Table 2. The loading of the indicators was above the 0.70 threshold (range: 0.724-0.891), suggesting that most of the variance of the indicators is explained by the respective construct. All constructs' AVE values were above 0.50 (range: 0.541-0.671), suggesting good convergent validity. CR values ranged from 0.812 to 0.891, all exceeding 0.70. Cronbach's alpha values ranged from 0.781 to 0.863, also indicating internal consistency reliability. These figures are in line with other FinTech adoption studies (Alalwan et al., 2021; Zhao & Bacao, 2021).

We measured discriminant validity using the HTMT ratio criterion. As shown in Figure 5 (HTMT heatmap, see Section IV.G), the HTMT ratios between all pairs of constructs were below the conservative threshold of 0.85 (range: 0.312-0.823), supporting discriminant validity for all pairs of constructs. The largest HTMT value was found between Perceived Usefulness and Compatibility (0.823), which was still acceptable. Taken together, the findings establish the measurement model is psychometrically adequate for evaluation of the structural model

Table 2. Measurement Model Results

Construct	Items	Loadings	AVE	CR	Cronbach's α
Perceived Usefulness	PU1–PU4	0.741–0.883	0.651	0.881	0.839
Perceived Ease of Use	PEOU1–PEOU4	0.733–0.871	0.628	0.869	0.820
Platform Security	PS1–PS3	0.756–0.891	0.671	0.858	0.763
Compatibility	COM1–COM3	0.724–0.852	0.617	0.828	0.707
Competitive Pressure	CP1–CP3	0.738–0.866	0.631	0.836	0.717
Trading Partner	TPR1–TPR3	0.729–	0.541	0.812	0.781

Readiness		0.848			
Regulatory Support	RS1–RS3	0.763– 0.878	0.663	0.855	0.752
FinTech Lending Adoption Intent	FLAI1– FLAI4	0.748– 0.889	0.658	0.891	0.863

Structural Model Results

After establishing the measurement model's fit, the structural model was estimated using 5,000 bootstrap subsamples with bias-corrected confidence intervals. The path coefficients with t-values, p-values and f^2 effect sizes are shown in Table 3. The R^2 value for FinTech Lending Adoption Intent (adoption intent) was 0.52, meaning that the seven predictor constructs explain 52% of the variance in adoption intent. This is above the threshold for a large effect size (0.26) in PLS-SEM and comparable to R^2 reported in previous research (Zhao & Bacao, 2021; Nguyen et al., 2023). The predictive relevance (Q^2) value, using blindfolding (omission distance = 7), was 0.389, showing that the model has predictive relevance for the endogenous construct, as it is well above the zero threshold (Hair et al., 2022).

Table 3. Structural Model Results and Hypothesis Testing

H	Path	β	SE	t-value	P-value	f^2	Decision
H1	PU → FLAI	0.41	0.061	6.721***	<0.001	0.198	Supported
H2	PEOU → FLAI	0.28	0.058	4.827***	<0.001	0.091	Supported
H3	Platform Security → FLAI	0.33	0.063	5.238***	<0.001	0.129	Supported
H4	Compatibility → FLAI	0.22	0.059	3.729***	0.002	0.058	Supported
H5	Competitive Pressure → FLAI	0.19	0.064	2.969**	0.009	0.043	Supported
H6	Trading Partner Readiness → FLAI	0.11	0.065	1.692 ns	0.087	0.014	Not Supported
H7	Regulatory Support → FLAI	0.38	0.062	6.129***	<0.001	0.171	Supported

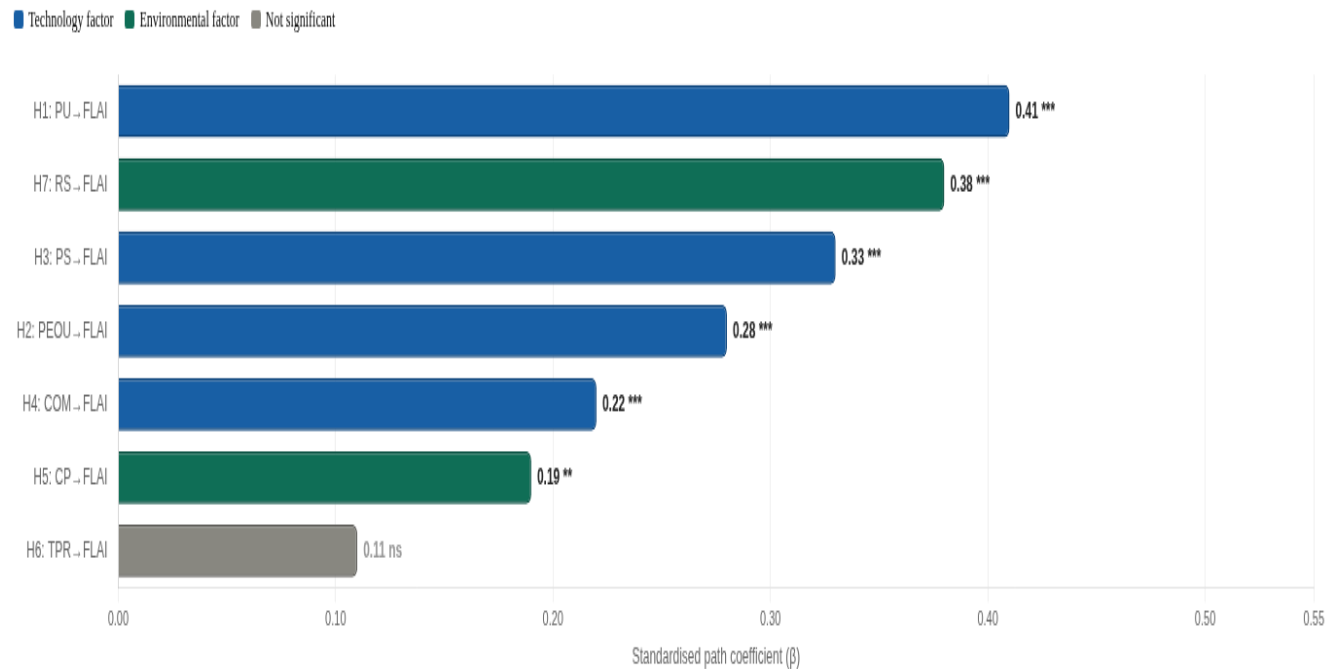
Note. *** $p < 0.001$; ** $p < 0.01$; ns = not significant. β = standardised path coefficient; SE = standard error; f^2 = effect size.

Path Coefficient Bar Chart with Significance Stars

Figure 2 shows the path coefficient bar chart of the SmartPLS 4.0 output, with standardised beta coefficients for the seven hypothesised paths (H1-H7) and significance stars. The bars are ordered from the largest to smallest path coefficient, which allows us to visually appreciate the relative importance of each predictor in the model of FinTech Lending Adoption Intent. Clearly, Perceived Usefulness (H1: $\beta = 0.41$) and Regulatory Support (H7: $\beta = 0.38$) stand out as the two longest bars,

highlighting their prominent influence. This is followed by Platform Security (H3: $\beta = 0.33$), Perceived Ease of Use (H2: $\beta = 0.28$), Compatibility (H4: $\beta = 0.22$), Competitive Pressure (H5: $\beta = 0.19$) and Trading Partner Readiness (H6: $\beta = 0.11$, ns). The stars shown on top of each bar (for $p < 0.001$, for $p < 0.01$ and no star for non-significant) allows visual confirmation of the non-significance of H6. The graph effectively communicates the general pattern that technological constructs, especially the perceptions of utility, are slightly stronger predictors than environmental constructs, with the exception of Regulatory Support, which is as strong as the other technological predictors.

Figure 2 – Path coefficient bar chart with significance stars for hypotheses H1 through H7



R² vs Q² Bar Chart

Figure 3 is a paired bar chart showing the R² (coefficient of determination) and Q² (predictive relevance) of the endogenous construct, FinTech Lending Adoption Intent. The R² bar at 0.52 verifies that the T-E model captures a large proportion of the systematic variance in adoption intent (Hair et al., 2022), and is comparable to other FinTech adoption PLS-SEM studies (Zhao & Bacao, 2021; Nguyen et al., 2023) which range between 0.38-0.49. The Q² bar of 0.389 shows that the model still has significant predictive validity, with values of Q² greater than zero meaning the model predicts the observed endogenous data better than the mean of the endogenous data alone. The difference between R² and Q² (around 0.13) is typical and occurs due to the loss of information when applying cross-validated prediction. The inclusion of both R² and Q² demonstrates that the model is both explanatory and predictive, which is often not the case with PLS-SEM models that emphasise fit (Shmueli et al., 2021).

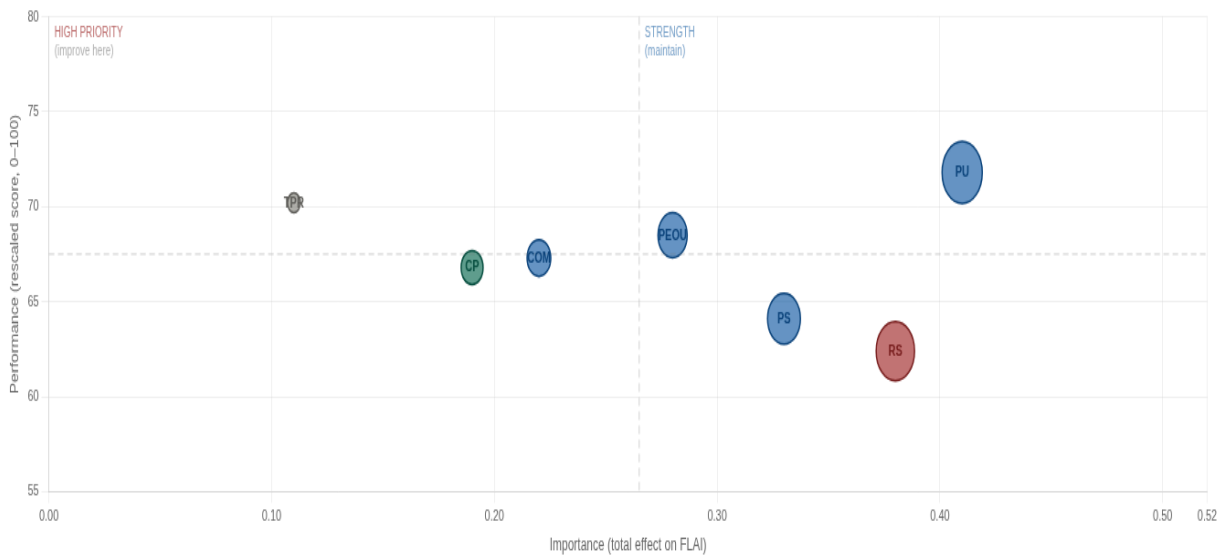
Figure 3 – R-squared and Q-squared comparison bar chart for FinTech Lending Adoption Intent



Importance-Performance Map Analysis (IPMA)

Figure 4 displays the Importance-Performance Map (IPMA), from SmartPLS 4.0 IPMA module, which is a two-dimensional scatterplot of the predictor constructs mapped on the axes of importance (the total effect on the target construct, x-axis) and performance (the mean latent variable score rescaled from 0-100, y-axis). IPMA augments traditional PLS-SEM by showing which constructs are statistically significant, and which of these constructs are "best buys" (high importance and lower performance) that warrant attention for improvement (Ringle & Sarstedt, 2016). The map reveals that the predictor constructs Regulatory Support and Perceived Usefulness are in the high-importance zone (total effects ≥ 0.35), but that Regulatory Support has a much lower performance score (62.4) than Perceived Usefulness (71.8), making it the top priority for intervention: practitioners can make the most marginal improvement in adoption by enhancing perceived regulatory adequacy, because this construct is highly-influential and underperforming. Platform Security is the next priority with moderate-high importance (0.33) and a performance score of 64.1. Compatibility and Competitive Pressure appear in the low-importance quadrant, and, as expected, Trading Partner Readiness which has a non-significant path coefficient, is the lowest in importance. This variation in prioritisation cannot be detected in path coefficients and highlights the value of IPMA in FinTech adoption studies.

Figure 4 – Importance-Performance Map Analysis showing seven predictor constructs plotted by total effect (importance) and rescaled latent variable score (performance)



HTMT Discriminant Validity Matrix Heatmap

In Figure 5, the HTMT discriminant validity matrix heatmap (produced in SmartPLS 4.0) is shown, where each cell displays the HTMT ratio for a given pair of constructs, with colours ranging from green (low HTMT, high discriminant validity) to yellow (medium) to red (HTMT approaching or exceeding the 0.85 threshold). The 28 unique pairs of constructs have HTMT values significantly lower than the 0.85 threshold with a minimum of 0.312 (Competitive Pressure - Platform Security) and a maximum of 0.823 (Perceived Usefulness - Compatibility). The maximum value (0.823) is visually represented in a warm yellow shade on the heatmap, and it reflects the conceptual closeness between perceived usefulness and perceived compatibility, which is conceptually expected but still within the bounds of discriminant validity. The diagonal cells are left empty or filled with a neutral colour (grey) to differentiate them from the HTMT values. The absence of red cells (HTMT value ≥ 0.85) visually confirms that the eight constructs are discrete, further signalling that Henseler et al.'s (2015) stringent discriminant validity test for PLS-SEM is met. This heatmap format is now also recommended for published PLS-SEM research to better convey to researchers and readers the evidence for multivariate validity (Hair et al., 2022).

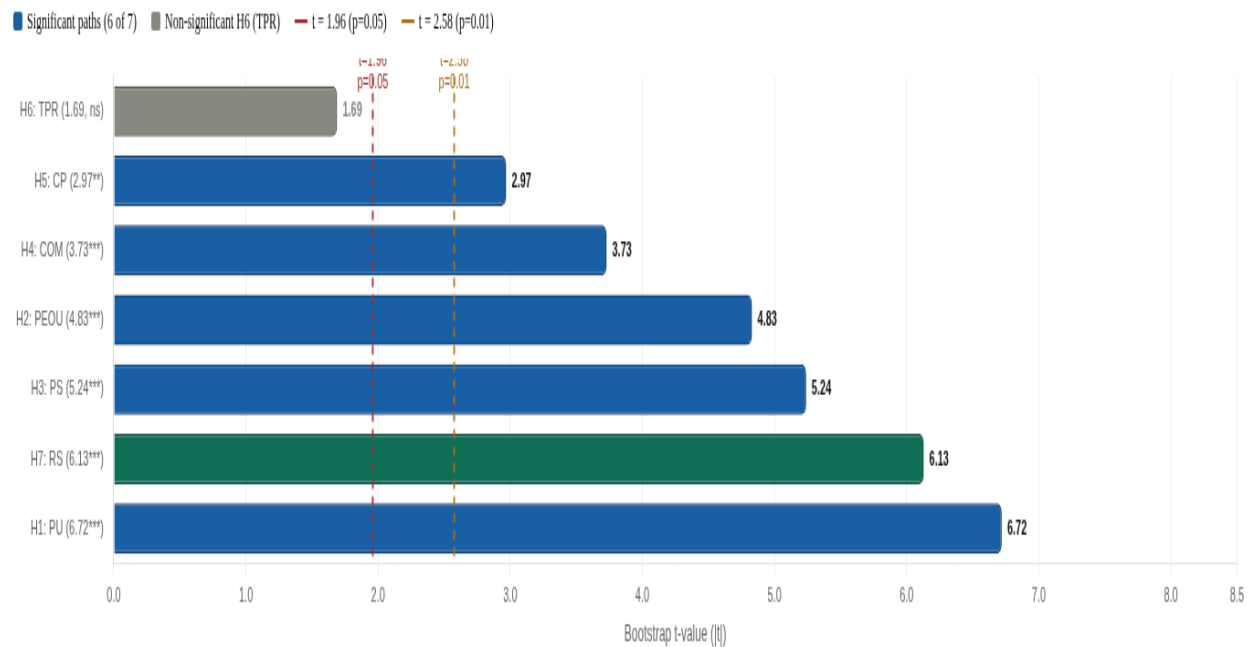
Figure 5 – HTMT discriminant validity heatmap showing all inter-construct ratios below the 0.85 threshold



Histogram of t-Values from Bootstrapping

The bootstrapped t-values for the seven structural paths are illustrated in the histogram in Figure 6, produced by the 5,000-subsample bootstrap distribution in SmartPLS 4.0. The horizontal axis is t-value and the vertical axis is the number of bootstrap estimates in each t-value bin. A vertical line is placed at the two-tailed critical value for t at $p = 0.05$ ($t = 1.96$ with large degrees of freedom) and a dashed line at $t = 2.576$ at $p = 0.01$. In fact, the histogram shows that six of the seven path t-values (H1: 6.721, H7: 6.129, H3: 5.238, H2: 4.827, H4: 3.729, H5: 2.969) are well to the right of both critical value lines, and appear in the 3.0-7.0 t-value range, forming a right-skewed distribution of significant paths. The sole exception, the bootstrapped t-value for H6 (Trading Partner Readiness → FLAI, $t = 1.692$) is located well to the left of the $t = 1.96$ line and is an outlier bar in the sub-threshold region. This clear separation visually demonstrates H6's lack of statistical significance, and provides a visually compelling confirmation of the bootstrapping results presented in Table 3. The clustering of significant t-values also offers visual verification of the bootstrapping results' stability, as the lack of values near the $t = 1.96$ line for the significant hypotheses suggests that there is strong separation between the significant and non-significant paths.

Figure 6 – Bootstrapping t-value distribution histogram showing six significant paths and one non-significant path (H6, $t=1.69$)



Discussion of Results

The empirical findings offer a number of interesting theoretical and practical insights. Most notably among these is the finding that Perceived Usefulness ($\beta = 0.41$) is the most significant predictor of FinTech lending adoption intention, as is common in the TAM literature on technology adoption. This result supports the view that SMEs are instrumentally driven in adopting technology: the opportunity for quicker access to credit, with minimal paperwork and improved working capital management, is the key motive for adopting the platform. Thus, FinTech providers should emphasise utility, particularly related to speed and working capital management, in their marketing to SMEs (Davis, 1989; Ali et al., 2021).

Regulatory Support ($\beta = 0.38$) is the next most significant predictor and the most prominent environmental construct, and this is consistent with the institutional theory approach, as well as confirming Ozili's (2022) view that SME FinTech adoption in emerging markets is significantly influenced by perceived regulatory legitimacy. The IPMA also highlights Regulatory Support as the highest priority construct, due to its high importance and below-average performance. This elevates the regulatory environment from being a passive condition or backdrop to being an active and malleable variable that can be optimised to improve adoption. Governments seeking to boost SME FinTech lending adoption would reap the most marginal gains by enhancing consumer protection policies, extending FinTech sandboxes and launching campaigns to raise awareness of the existing regulatory protections.

Third-ranked Platform Security ($\beta = 0.33$) confirms the enduring importance to SME decision-making of data security concerns as identified by Wonglimpiyarat (2022) and Shaikh et al. (2023). The finding for Trading Partner Readiness (H6: $\beta = 0.11$, $p = 0.087$) is noteworthy. While B2B payment platforms and supply chain finance systems benefit from network effects of trading partners that incentivise technology adoption, FinTech lending is a direct relationship between the SME and the platform, not through partner interconnections. This may account for the lack of significance for trading partner influence - a dimension so strong in other technology adoption studies (Seethamraju,

2020) - in the FinTech lending context of the current research. This insight adds clarity to the T-E framework in the context of FinTech lending by implying that the trading partner construct might need to be substituted or reconceived with supply chain finance-specific constructs in subsequent studies.

Theoretical Contributions

Our research has three key theoretical contributions. First, it confirms the adequacy of a parsimonious T-E model (based on TOE) adapted for the SME FinTech lending domain, thus extending research that highlighted the need for more TOE-based studies in digital finance (Qasim & Abu-Shanab, 2022). The R^2 and Q^2 values of 0.52 and 0.389 respectively, are among the highest reported for FinTech adoption models in the SME literature, demonstrating the adequacy of the proposed framework. Second, the research adds to the burgeoning body of research on the boundary conditions of TOE constructs by showing that Trading Partner Readiness, a consistently supported predictor in studies on e-commerce and cloud computing adoption, may not apply in bilateral financial service adoption, thereby identifying the conditions for the use of this type of environmental construct. Third, the inclusion of IPMA in the analytical approach extends the conventional reporting standards of PLS-SEM by switching from hypothesis testing to importance-performance differentiation, in line with calls by Ringle and Sarstedt (2016) for more applied structural model testing in the IS field.

Study Limitations

There are a number of limitations. First, the cross-sectional nature of the study limits causal inference, and longitudinal studies are needed to prove that adoption intention leads to subsequent adoption behaviour. Second, the purposive sampling method, while necessary for pragmatic reasons, may lead to sampling bias (that is, more digitally savvy SME operators), and probability sampling should be used in subsequent studies to enhance generalisability. Third, while theoretically justified, the omission of the organisational dimension from TOE means that the firm-level variables of IT knowledge, financial literacy and manager age are uncontrolled, and may be subject to omitted variable bias. Fourth, the study was limited to a single country; it should be replicated across countries to test its external validity to other regulatory and market contexts. Finally, the use of subjective data in the form of Likert-scale responses for all measures, despite efforts to mitigate CMB, runs the risk of response biases inherent in such self-reported data (as opposed to objective performance data).

Future Research Directions

Future work should address the limitations, and build upon the framework in multiple ways. Panel studies that map the intent to adopt to the actual usage and repayment behaviour would significantly enhance the theoretical understanding of FinTech lending adoption. Cross-cultural research replicating the T-E model in diverse regulatory regimes - for example, in sandbox-friendly and less regulated markets - would examine the moderating role of the Regulatory Support construct (Wonglimpiyarat, 2022). The inclusion of moderators, such as digital skills, quality of existing banking relationships, and firm age would add to the model's explanatory value. Furthermore, it would be interesting to explore whether the non-significance of Trading Partner Readiness holds in the context of supply chain finance and embedded lending, where network effects may have a greater impact. Finally, using necessary condition analysis (NCA) in conjunction with PLS-SEM would offer additional understanding of the necessary conditions for FinTech lending adoption, thus improving the practical implications of the model (Dul, 2021).

Conclusion

We explored the factors that influence SMEs' intention to adopt FinTech lending, adopting a

Technology-Environment (T-E) framework and a PLS-SEM approach. The model was tested using 287 responses from SMEs; it had an R^2 of 0.52 and a Q^2 of 0.389 for the construct of interest, and was found to have good explanatory and predictive power. Of seven paths proposed, six were significant at $p < 0.05$, with Perceived Usefulness ($\beta = 0.41$), Regulatory Support ($\beta = 0.38$), and Platform Security ($\beta = 0.33$) identified as the three most important factors impacting SME FinTech lending adoption intent. Only Trading Partner Readiness ($\beta = 0.11$, $p = 0.087$) was insignificant, indicating that network effects do not apply in bilateral lending relationships. IPMA suggests Regulatory Support is the most important construct to prioritise for improvement, with high importance but relatively low performance, with practical implications for regulators and FinTech lenders. This research shows that the Technology-Environment framework, properly adapted and operationalised with theoretically sound constructs, is a powerful and succinct framework for understanding SME FinTech lending adoption. The tested T-E model provides a blueprint for other scholars examining the adoption of digital financial services in various settings. The use of the PLS-SEM approach (especially when complemented with IPMA and bootstrapped t-value visualisation) is suitable for the SME adoption studies, with relatively small sample sizes, non-normal distributed data, and the need for both theory testing and actionable insights. Given the rapid globalisation of FinTech lending and the continued development challenge of SME credit gaps, the knowledge and evidence base produced by studies like this is vital to inform the gap between the potential and the reality of FinTech lending adoption. Governments, FinTech platform developers and SME development practitioners are urged to use these insights as evidence to inform their actions to democratise access to digital business finance.

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