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Sustained FinTech Adoption in Malaysian Food and Beverage SMEs: Antecedents and Business Performance

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ABSTRACT

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Financial technology (FinTech) supports payment, transaction-recording, settlement, and operational activities among Malaysian food and beverage (F&B) small and medium-sized enterprises (SMEs). Research has concentrated on initial adoption, so little is known about what sustains FinTech use at firm level, or how continued use relates to performance in this transaction-intensive sector. This study examines the antecedents and outcomes of sustained FinTech adoption among Malaysian F&B SMEs. A cross-sectional survey of 250 management-level respondents was analysed using partial least squares structural equation modelling. Perceived ease of use ($\beta = 0.182$) and economic benefit ($\beta = 0.296$) were positively associated with sustained FinTech adoption, whereas privacy and security was not; the social impact path was borderline and was treated conservatively as unsupported. Sustained adoption was positively associated with operational performance ($\beta = 0.565$) and with financial performance ($\beta = 0.246$), and operational performance was in turn positively associated with financial performance ($\beta = 0.460$). The indirect association through operational performance was also significant ($\beta = 0.260$), indicating complementary partial mediation. FinTech therefore appears to carry greater business value when its continued use is embedded in routine transaction handling. Managers, providers, financial institutions, and policymakers should look beyond initial adoption by strengthening usability, visible economic benefits, and post-adoption support. The cross-sectional design does not support causal interpretation.

1. Introduction

Financial technology (FinTech) is now part of routine work for many small and medium-sized enterprises (SMEs), especially in payment handling and financial record keeping. Beyond receiving money, firms use these tools to record transactions, follow financial activity, and support day-to-day decisions. Sanga and Aziakpono [1] link digital financial technologies with lower transaction frictions

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and broader SME access to financial services. In food and beverage (F&B) firms, this may involve e-wallets, quick response (QR) payments, point-of-sale systems, online banking, digital financing, delivery-platform settlements, digital receipts, and electronic financial records. These tools matter most where ordering, billing, collection, settlement, and reporting recur throughout the day.

The issue also matters at the scale of the Malaysian F&B sector. In 2022, Malaysia had 136,453 F&B establishments that generated RM99.0 billion in gross output and RM43.8 billion in value added, while employing more than 1.07 million people [2]. SMEs are similarly important to the wider economy. In 2025, micro, small, and medium enterprises contributed RM689.8 billion in value added, or 39.7% of gross domestic product (GDP), and employed 8.09 million people, representing 48.7% of total employment [3]. The size of both the sector and the SME economy makes the way Malaysian F&B firms use digital technology worthy of closer examination.

Malaysia has also seen a sharp expansion in digital payments. Bank Negara Malaysia recorded 18.4 billion e-payment transactions in 2025, 25% more than a year earlier, while retail e-payment transactions totalled RM831 billion [4]. DuitNow QR transaction volume alone doubled to 3 billion, supported by almost 3 million registered acceptance points at year-end [4]. For F&B SMEs, these payment channels are increasingly part of everyday business activities. They can reduce the need for cash handling, speed up payment processing, improve transaction records, and make payment information easier to connect with other business records.

Yet adopting a FinTech service initially does not guarantee that a firm will keep using it. Sharma *et al.*, [5] observe that research on FinTech in small businesses has concentrated heavily on adoption, leaving longer-term use and value creation comparatively underexplored. In the SME setting examined by Krah *et al.*, [6], perceived ease of use was positively related to attitudes toward FinTech, although no significant direct relationship with adoption was found. Jafri *et al.*, [7] likewise emphasise trust and security as important issues in digital financial services, while Kilani *et al.*, [8] extend the discussion to consumers' post-adoption e-wallet behaviour. Closer to the present setting, Abdul-Halim *et al.*, [9] examined e-wallet continuance among Malaysian users and reported that continuance intention was associated with satisfaction, attitude, price benefit, and habit, but not with perceived usefulness or trust; perceived ease of use entered only indirectly, through perceived usefulness and attitude. That study, like most post-adoption work in this area, takes the individual user rather than the firm as its unit of analysis. In practice, an F&B SME can accept digital payments yet still rely on manual reconciliation, fragmented sales records, informal financial monitoring, and disconnected operating processes. Evidence on what supports sustained organisational FinTech use in F&B SMEs therefore remains comparatively limited.

Continued FinTech use may also matter for business performance. Najib *et al.*, [10] linked FinTech adoption with innovation and business sustainability among small food businesses. Evidence on SME performance is beginning to show similar patterns for digitalisation. Kurniasari *et al.*, [11] associate routine digital use with longer-term SME performance, whereas González Morales and Caverio Rubio [12] identify possible profitability benefits from digital sales tools in restaurants. Malaysian evidence is available but still narrow. Lee and Ling [13], surveying 150 F&B and retail SMEs in Kuching, Sarawak, found that respondents generally viewed e-wallet use as beneficial to business performance. Their descriptive, e-wallet-focused study did not examine whether use remained embedded over time or whether operational and financial performance followed separate paths. That distinction matters because continued FinTech use may affect transaction speed, billing accuracy, workflow coordination, and service efficiency in different ways. Better digital records may also support cash-flow monitoring and financial control. These operational improvements may, in turn, be linked to financial outcomes.

Three unresolved issues motivate this study. First, post-adoption research on digital financial services has been conducted mainly at the level of the individual user, as in Abdul-Halim *et al.*, [9], so comparatively little is known about why a firm keeps FinTech embedded in its routines once practical experience has accumulated. Second, studies that connect digital technology use to SME performance, among them Kurniasari *et al.*, [11] on Indonesian traditional-market SMEs and Lutfi *et al.*, [14] on digital accounting system usage in Jordan, generally treat performance as a single outcome; the separate operational and financial routes, and the indirect route running from continued use through operational performance to financial performance, have received far less attention. Third, the regional SME evidence is weighted towards the drivers of initial adoption, as in Nugraha *et al.*, [15], rather than towards sustained organisational use within a specific transaction-intensive sector such as Malaysian F&B. Addressing these issues advances FinTech research from the adoption decision toward sustained organisational use and its performance consequences, while also informing managers, FinTech providers, financial institutions, and policymakers seeking to strengthen the business value of continued use. The study therefore pursues three objectives: to determine how perceived ease of use, economic benefit, privacy and security, and social impact relate to sustained FinTech adoption among Malaysian F&B SMEs; to evaluate the direct links from sustained adoption to operational and financial performance together with the relationship between operational and financial performance; and to examine whether operational performance carries an indirect effect from sustained adoption to financial performance.

2. Literature Review and Hypotheses Development

2.1 Theoretical Foundation

The theoretical basis combines the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Information Systems Success Model (ISSM) to account for both the drivers and consequences of sustained FinTech adoption. Within this framework, TAM is used for perceived usefulness and perceived ease of use. Davis [16] links perceived ease of use to the effort expected when operating a system. At firm level, a system that staff can learn and handle without excessive effort is easier to carry into recurring work, whereas a difficult system is less likely to become routine.

UTAUT adds two further considerations to this account: performance expectancy and social influence. Venkatesh *et al.*, [17] treat performance expectancy as the benefits expected from a technology and social influence as the effect that important people or groups have on its use. In this study, Economic Benefit reflects the expected financial and business value of FinTech. Social Impact refers to the influence of customers, competitors, suppliers, platforms, payment providers, and the wider move toward digitalisation. Privacy and Security is included because FinTech use also depends on concerns about system quality, trust, and risk.

ISSM is used to explain how continued system use may be related to business outcomes. DeLone and McLean [18] argue that information-system use can create net benefits when the system supports organisational needs. Jeyaraj [19] also shows that system use is relevant to organisational performance. In this study, TAM and UTAUT are therefore used mainly to explain the factors associated with Sustained FinTech Adoption, while ISSM helps explain its relationship with Operational Performance and Financial Performance. One further choice requires comment. Expectation-confirmation theory is the usual basis for studying continued use, and Bhattacharjee [20] shows that confirmation and satisfaction account well for individual continuance intention. Those constructs describe a person's evaluation of a system, however, and the unit of analysis here is the firm. Sustained use is accordingly treated as an organisational condition with usability and realised

economic value as antecedents, and satisfaction is left out of the model. Abdul-Halim *et al.*, [9] take the individual-level route for Malaysian e-wallet users, which makes their findings a useful comparison for the firm-level model tested here.

2.2 Hypothesis Development

2.2.1 Sustained FinTech Adoption (SFA)

Sustained FinTech adoption refers to the continued and routinised use of FinTech following initial implementation. In Malaysian F&B SMEs, it involves the recurring use of digital payments, e-wallets, point-of-sale systems, online banking, platform settlements, and digital financial records in operational and financial activities. Initial adoption may involve experimentation or limited use, whereas sustained adoption indicates that FinTech has become embedded in normal business practices.

Bhattacharjee [20] distinguishes post-adoption continuance from initial acceptance. Building on that distinction, this study focuses on actual organisational use and asks whether FinTech remains integrated into recurring business routines after implementation. Melville *et al.*, [21] contend that information technology produces value through its combination with organisational processes, and Sharma *et al.*, [5] call for small-business FinTech research to extend beyond adoption toward longer-term use and value creation. This distinction matters in F&B SMEs because payment activities are intertwined with ordering, billing, settlement, transaction recording, and financial monitoring. Gomber *et al.*, [22] further describe FinTech as a force reshaping payment and financial-service processes. Sustained adoption therefore creates the post-adoption context needed to investigate both the factors supporting continued use and the performance outcomes associated with it.

2.2.2 Perceived Ease of Use (PEOU) and Sustained FinTech Adoption (SFA)

Perceived ease of use captures how straightforward a technology is to understand and operate. TAM suggests that lower effort requirements make acceptance and use more likely [16]. In a post-adoption setting, this belief remains relevant because a system is more likely to be used repeatedly when it can be incorporated into daily work without adding avoidable complexity.

Ease of use matters more in F&B SMEs because employees may have very different levels of digital experience. Payment interfaces that are easy to navigate, automatic transaction records, and reports that can be accessed quickly reduce the effort required to use FinTech during routine work. Krah *et al.*, [6] found that perceived ease of use was positively related to SME attitudes toward FinTech, although its direct relationship with adoption was not significant. The OECD [23] likewise notes that limited digital capability and scarce resources remain practical constraints for many SMEs. Under these conditions, FinTech that can be learned with little additional effort is more likely to survive beyond initial adoption and stay in everyday use.

H1: Perceived ease of use is positively associated with sustained FinTech adoption among Malaysian F&B SMEs.

2.2.3 Economic Benefit (EB) and Sustained FinTech Adoption (SFA)

Economic Benefit describes the financial and business gains that managers can recognise from continuing to use FinTech. The construct is related to perceived usefulness and performance expectancy, but its scope is intentionally more concrete. It focuses on benefits visible in routine operations, including clearer transaction records, less reconciliation work, better visibility of working

capital, lower cash leakage, and stronger financial documentation. For this reason, Economic Benefit is treated as a factor that can encourage continued FinTech use rather than as another indicator of Financial Performance.

High transaction volumes make manual control difficult for many F&B SMEs. Cash discrepancies, incomplete revenue records, slow reconciliation, and poor visibility of daily inflows can become recurring problems. Digital payment and transaction-recording systems address part of this problem by leaving a traceable electronic record that managers can return to when checking transactions. Sanga and Aziakpono [1] link FinTech to lower transaction costs and less information asymmetry for SMEs, while Gomber *et al.*, [22] describe efficiency improvements in payment and financial-service processes. Kurniasari *et al.*, [11] further associate financial and technological factors with digital adoption and longer-term SME performance. When FinTech delivers clear and recurring economic value, SMEs have stronger reasons to retain and integrate it into their activities.

H2: Economic benefit is positively associated with sustained FinTech adoption among Malaysian F&B SMEs.

2.2.4 Privacy and Security (PS) and Sustained FinTech Adoption (SFA)

Privacy and security concern the protection, reliability, and integrity of information and transactions processed through FinTech systems; F&B SMEs use these systems to manage customer payments, settlement information, sales records, and other sensitive business data. Continued use may therefore depend on whether managers believe that the technology can protect information from misuse, unauthorised access, fraud, and system failure.

DeLone and McLean [18] identify system quality as an important condition of information-system use and outcomes. Privacy and security are also closely related to trust and perceived risk. Featherman and Pavlou [24] show that financial, privacy, and performance risks can discourage electronic-service use, while Pavlou [25] explains that trust reduces uncertainty in technology-enabled transactions. Jafri *et al.*, [7] identify trust and security as recurring concerns in FinTech adoption. Chawla and Joshi [26] report that trust and security influence mobile-wallet adoption, while Kilani *et al.*, [8] show that trust remains relevant to post-adoption e-wallet behaviour. Although these studies are not specific to Malaysian F&B SMEs, they provide related evidence that confidence in privacy and security can support continued use of digital financial services.

H3: Privacy and security are positively associated with sustained FinTech adoption among Malaysian F&B SMEs.

2.2.5 Social Impact (SI) and Sustained FinTech Adoption (SFA)

Social Impact refers to the influence of external social and market actors on an SME's continued use of FinTech. It is grounded in the social-influence logic of UTAUT, which proposes that technology-use decisions can be shaped by the expectations of important others [17]. In the F&B context, these actors may include customers, competitors, suppliers, delivery platforms, payment providers, and industry networks.

External actors can shape whether an SME keeps digital-payment capabilities in place. Customer preferences may encourage continued acceptance of digital payments, suppliers and delivery platforms can create compatibility or settlement requirements, and competitor uptake may add pressure to maintain comparable capabilities. Najib *et al.*, [10] report that social influence was associated with FinTech adoption among small food businesses. Sharma *et al.*, [5] stress contextual and market influences in small-business FinTech research, while Nugraha *et al.*, [15] identify social

and external factors among the drivers of SME FinTech adoption in Indonesia. The OECD [23] adds that SME digitalisation can be reinforced by competitive pressures. This evidence suggests that pressure from customers, competitors, and other market actors may encourage SMEs to continue using FinTech after adoption.

H4: Social impact is positively associated with sustained FinTech adoption among Malaysian F&B SMEs.

2.2.6 Sustained FinTech Adoption (SFA) and Financial Performance (FP)

Financial Performance in this study refers to managers' views of changes in revenue, profitability, cash-flow management, financial-record accuracy, and financial losses. ISSM suggests that continued system use can create benefits when the system supports the needs of the organisation [18].

One way sustained FinTech use may affect Financial Performance is through better access to timely transaction information. Electronic capture in payment and point-of-sale systems reduces dependence on manual records and gives managers a more current basis for tracing inflows, reconciling sales, and reviewing revenue and expenses. Sanga and Aziakpono [1] connect FinTech with improved information flows and lower financing frictions for SMEs, while González Morales and Cavero Rubio [12] report possible profitability gains from digital sales tools in restaurants. On this basis, continued FinTech use is expected to strengthen financial management and, over time, financial performance.

H5: Sustained FinTech adoption is positively associated with financial performance among Malaysian F&B SMEs.

2.2.7 Sustained FinTech Adoption (SFA) and Operational Performance (OP)

Operational Performance concerns how effectively a firm carries out routine activities. In an F&B SME, this can be reflected in transaction speed, billing accuracy, workflow coordination, service efficiency, and customer waiting time. ISSM holds that organisational benefits depend on whether system use supports the work the organisation actually performs [18]. Jeyaraj [19] similarly relates information-system use to organisational outcomes.

The operational effect of FinTech is most visible when it replaces repeated manual steps or brings previously separate tasks into the same workflow. QR payments, e-wallets, digital receipts, and point-of-sale systems can shorten payment handling and reduce billing mistakes. Once these tools are used routinely, they can also make ordering, billing, settlement, and sales reporting easier to coordinate. Najib *et al.*, [10] associate FinTech adoption with innovation and business sustainability in small food businesses, and the OECD [23] identifies digitalisation as a contributor to SME productivity and operating capability. Taken together, these arguments support a positive relationship between sustained FinTech use and day-to-day operational performance in F&B SMEs.

H6: Sustained FinTech adoption is positively associated with operational performance among Malaysian F&B SMEs.

2.2.8 Operational Performance (OP) and Financial Performance (FP)

Operational Performance and Financial Performance are kept as separate outcomes in the model, although stronger operations can still feed into financial results. Hudson *et al.*, [27] argue that SME performance assessment should cover both process and financial dimensions. For an F&B firm, quicker order and payment processing can increase service capacity, accurate billing can reduce

disputes and revenue leakage, and smoother workflows can lower avoidable labour or administrative costs.

The same sequence appears in the IT business-value literature, which links financial returns to changes in business processes. Melville *et al.*, [21] connect IT value with the use of technology in organisational processes, while Schweikl and Obermaier [28] emphasise complementarity between digital resources and business capabilities. Less waste, greater service capacity, and better information for decisions can therefore provide an operational route to stronger financial performance.

H7: Operational performance is positively associated with financial performance among Malaysian F&B SMEs.

2.2.9 Mediating Role of Operational Performance (OP)

The benefits of sustained FinTech use may become visible in routine operations before they appear in financial results. Repeated use changes the way payments, billing, settlements, transaction records, and financial monitoring are carried out. If these activities become faster, more accurate, or easier to coordinate, the immediate improvement should be operational; financial gains may follow later, as inefficiency falls, service capacity expands, and the firm uses its resources more effectively.

This idea is consistent with the IT business-value perspective. Melville *et al.*, [21] argue that technology creates value through its use in organisational processes and together with other business resources. Schweikl and Obermaier [28] similarly synthesise evidence that IT business value depends on complementarities with organisational processes and other non-IT resources. Based on this reasoning, this study tests whether Operational Performance forms part of the pathway between Sustained FinTech Adoption and Financial Performance.

H8: Operational performance mediates the association between sustained FinTech adoption and financial performance among Malaysian F&B SMEs.

2.3 Conceptual Framework of the Study

Figure 1 presents the model tested in this study. Perceived Ease of Use, Economic Benefit, Privacy and Security, and Social Impact are examined as antecedents of Sustained FinTech Adoption. Sustained FinTech Adoption is linked to Operational Performance and Financial Performance. Operational Performance is also linked to Financial Performance. H1–H7 test the direct paths, while H8 tests the indirect SFA → OP → FP path.

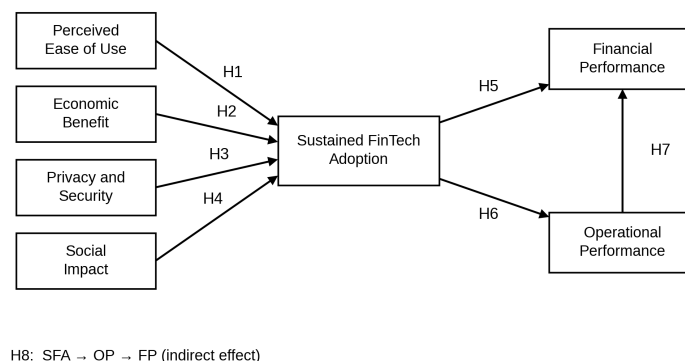


Fig. 1. Conceptual framework

3. Research Methodology

3.1 Research Design

A quantitative cross-sectional survey design was adopted to investigate the antecedents of sustained FinTech adoption and its performance implications in Malaysian food and beverage (F&B) SMEs. Analysis was conducted at the SME level, with a management-level representative acting as the key informant. Eligible informants were owners, managers, supervisors, or other personnel involved in payment, financial, or operational decisions. All assessments of FinTech use and performance were made with reference to the firm rather than the respondent's personal use of technology.

Seven reflective constructs were specified in the model: perceived ease of use, economic benefit, privacy and security, social impact, sustained FinTech adoption, operational performance, and financial performance. Partial least squares structural equation modelling (PLS-SEM) was chosen to estimate this prediction-oriented model, which contains multiple latent-variable relationships and a specific indirect effect. Measurement- and structural-model analyses were performed in SmartPLS 4 [29].

3.2 Population, Sample and Data Collection

The population of interest was Malaysian SMEs in the F&B service sector. Under the Malaysian SME definition for services and other sectors, firms qualified when annual sales turnover did not exceed RM20 million or when they employed no more than 75 full-time employees [30].

Purposive sampling was applied because participation required both organisational decision knowledge and experience with FinTech after adoption. Three eligibility requirements were then applied. The business had to qualify as a Malaysian F&B SME, the respondent had to hold a management-level position or participate in relevant business decisions, and the firm needed at least six months of FinTech use. Eligible forms of use included digital payments, online banking, digital financing, online accounting platforms, point-of-sale systems, and platform settlements. The six-month requirement was used to ensure that respondents had sufficient post-adoption experience to evaluate continued use rather than a recent trial or early implementation.

Data collection lasted eight weeks and was conducted through Google Forms. Survey invitations were shared through WhatsApp, email, business networks, and direct contact with firms that appeared to satisfy the eligibility criteria. Participation was voluntary, and respondents were informed that the survey was being conducted for academic research. No personally identifiable business information was collected. Anonymity and neutral wording were also used to reduce possible evaluation concerns [31].

Before analysis, responses were screened for eligibility, missing data, straight-lining, and unusually short completion times. The survey was distributed through several open channels rather than to a fixed list of firms, so the total number of firms reached could not be established and a conventional response rate could not be calculated. After screening, 250 complete and eligible responses were retained for analysis, and no missing-data treatment was required. Sample size was also checked using G*Power 3.1.9.7. With an effect size of 0.15, alpha of 0.05, statistical power of 0.80, and four predictors of Sustained FinTech Adoption, the minimum required sample was 85 [32]. The final sample of 250 therefore exceeded this requirement.

3.3 Questionnaire Design and Measurement

The questionnaire was divided into two sections. Section A included three screening questions to confirm that the firm was a Malaysian F&B SME, that the respondent held a management or decision-making role, and that the firm had used FinTech for at least six months. Section B contained the measures for the seven constructs. All items used a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. Each construct was measured with five items, giving a total of 35 measurement items.

Where suitable measures were available, the items were adapted from previous empirical studies. To align respondent judgements with the SME as the unit of analysis, organisational wording such as “our firm” and “the business” was used throughout the relevant items [33]. Table 1 reports the main measurement focus and principal theoretical sources for each construct rather than the origin of individual items; the complete list of measurement items is provided in Appendix B.

Table 1

Construct operationalisation and sources

Construct	Items	Measurement focus	Theoretical sources
Perceived Ease of Use	5	Ease of learning, operation, clarity, effort, and integration	Davis [16]; Krah <i>et al.</i> , [6]
Economic Benefit	5	Transaction transparency, reconciliation effort, working-capital visibility, cash leakage, and financial documentation	Davis [16]; Venkatesh <i>et al.</i> , [17]; Sanga and Aziakpono [1]
Privacy and Security	5	Data protection, transaction security, settlement reliability, privacy, and unauthorised transactions	DeLone and McLean [18]; Featherman and Pavlou [24]; Jafri <i>et al.</i> , [7]
Social Impact	5	Influence of customers, competitors, suppliers, platforms, providers, and digitalisation initiatives	Venkatesh <i>et al.</i> , [17]; Kilani <i>et al.</i> , [8]; Sharma <i>et al.</i> , [5]
Sustained FinTech Adoption	5	Continued use, routine use, consistent use, process integration, and normal business use	Bhattacharjee [20]; DeLone and McLean [18]
Operational Performance	5	Transaction speed, billing accuracy, workflow coordination, service efficiency, and waiting time	DeLone and McLean [18]; Jeyaraj [19]; Najib <i>et al.</i> , [10]
Financial Performance	5	Revenue, profitability, cash-flow management, record accuracy, and financial-loss reduction	DeLone and McLean [18]; Melville <i>et al.</i> , [21]; González Morales and Caverio Rubio [12]

Note: Each construct was measured with five reflective indicators

Prior to the main data collection, five experts assessed the questionnaire for content validity, wording clarity, and contextual suitability [34]. The instrument was then pilot-tested with 35 members of the target population to identify ambiguous wording and practical response problems [35]. Only minor wording refinements were required, and these did not alter the theoretical structure or coverage of the constructs. All 35 pilot responses were excluded from the final sample of 250.

3.4 Data Analysis

SmartPLS 4 estimation used the path-weighting scheme with standardised data, a 3,000-iteration maximum, and a 1.0E-7 stopping criterion. The analytical sequence covered the measurement model, common method bias diagnostics, the structural model, mediation, and out-of-sample prediction.

Assessment of the reflective measurement model considered indicator loadings together with Cronbach’s alpha, rho_A, composite reliability (rho_C), and average variance extracted (AVE). A

loading near or above 0.708 was treated as preferable. Loadings between 0.40 and 0.708 were reviewed rather than deleted by rule. An indicator was removed only when doing so improved reliability or convergent validity without narrowing the construct's intended content. Reliability values of 0.70 or above and AVE of 0.50 or above were used as the general benchmarks [29]. Loading significance and 95% bias-corrected and accelerated (BCa) confidence intervals were then obtained from the Complete Bootstrapping procedure described below.

The heterotrait-monotrait ratio (HTMT) was the main check on discriminant validity. Point estimates were read against the 0.85 and 0.90 reference values [36], but the 95% BCa confidence intervals were also examined, especially whether any interval reached 1.00. Upper bounds above 0.85 or 0.90 were noted as cases requiring caution rather than being ignored. The Fornell–Larcker criterion [37] was used as a secondary check. OP and FP were relatively close empirically, so an alternative model was also estimated in which their ten indicators formed a single Performance construct. Measurement quality, R^2 , and cross-validated predictive ability test (CVPAT) loss from this alternative were compared with those from the two-construct specification.

Common method bias was addressed procedurally and examined statistically because all seven constructs were measured in the same questionnaire. The survey was anonymous, the items were phrased neutrally and referred to the firm, and no personally identifiable business information was collected [31]. For the statistical checks, Harman's single-factor test was run on all 35 indicators and full-collinearity variance inflation factors (VIFs) were calculated for the seven latent constructs using 3.3 as the reference value [38]. Harman's test is included only as a diagnostic; Podsakoff *et al.*, [31] caution that it is not sensitive enough to establish the absence of method bias. Because no marker variable was collected, method variance cannot be isolated from substantive covariance in this design. These two checks are therefore presented as descriptive diagnostics rather than as conclusive evidence that method bias is absent.

Structural-model evaluation covered collinearity, path coefficients and their uncertainty, explained variance, and effect sizes. Accordingly, the analysis reported inner VIFs, standardised path coefficients, t-values, p-values, 95% BCa confidence intervals, R^2 , adjusted R^2 , and f^2 . Inner VIFs were evaluated following Hair *et al.*, [29]. For R^2 , values of approximately 0.25, 0.50, and 0.75 were used as reference points for weak, moderate, and substantial explanatory power. Effect sizes followed Cohen's [39] conventions, with f^2 values of 0.02, 0.15, and 0.35 interpreted as small, medium, and large; values below 0.02 were treated as negligible [29]. Complete Bootstrapping used 10,000 subsamples, two-tailed tests, BCa confidence intervals, and $\alpha = 0.05$. This procedure supplied t-values, p-values, and 95% BCa confidence intervals for evaluating the H1–H7 direct relationships and the H8 specific indirect effect. The same bootstrap procedure supplied inference for outer loadings and HTMT intervals.

For mediation, significance of the SFA $\rightarrow$ OP $\rightarrow$ FP indirect effect was established when its 95% BCa confidence interval did not contain zero. Interpretation of mediation type also incorporated the direct SFA $\rightarrow$ FP relationship, following the classification of Zhao *et al.*, [40] as applied to PLS-SEM by Nitzl *et al.*, [41].

Predictive assessment used PLSpredict with 10 folds and 10 repetitions. Indicator-level Q^2 predict values were first inspected for predictive relevance against the indicator-average benchmark. Prediction errors from PLS-SEM, expressed as root mean square error (RMSE) and mean absolute error (MAE), were then compared with errors from the corresponding linear-model benchmark [42]. RMSE was prioritised when error distributions were not severely asymmetric; otherwise, MAE was considered. CVPAT provided an additional inferential comparison of average prediction loss against the indicator-average and linear-model benchmarks [43,44].

4. Results and Analysis

4.1 Data Screening and Sample Eligibility

A total of 270 responses were initially available for screening. Thirteen responses were excluded because the firms did not meet the SME eligibility criterion. Among the remaining responses, one was excluded because the respondent did not hold a managerial-level role or participate in relevant organisational decision-making, while a further four responses were removed because the firms did not meet the FinTech-related eligibility criterion. Once these eligibility criteria had been applied, 252 responses were left for data-quality screening. Each case was checked for completeness and response quality. No missing values were found, so no imputation was needed. Two cases showed complete straight-lining, with one response category repeated across every measurement item; both were removed before analysis. After all eligibility and data-quality checks, 250 usable responses remained for analysis. This sample size also remained well above the a priori G*Power minimum requirement of 85 and was retained for all subsequent analyses.

4.2 Descriptive Statistics

Construct-level responses were generally high, with means ranging from 4.212 to 4.593 on the five-point scale. Operational Performance ($M = 4.378$, $SD = 0.424$) and Financial Performance ($M = 4.443$, $SD = 0.432$) were concentrated toward the upper end of the scale. Across the ten OP and FP indicators, 93.2% to 96.8% of respondents selected response categories 4 or 5. This concentration is worth keeping in mind when interpreting the relatively strong association between the two performance constructs. Table 2 reports the construct-level descriptive statistics and the OP/FP item-level response distributions.

Table 2

Descriptive statistics and response distributions

Variable	Mean	SD	1 (%)	2 (%)	3 (%)	4 (%)	5 (%)
Panel A. Construct-level descriptive statistics							
PEOU	4.593	0.462	0.2	1.2	4.2	28.2	66.3
EB	4.350	0.539	0.6	1.4	6.0	46.2	45.8
PS	4.319	0.623	0.8	4.2	4.8	42.8	47.4
SI	4.212	0.593	2.9	4.4	4.6	44.8	43.3
SFA	4.487	0.436	0.1	0.5	2.8	43.9	52.7
OP	4.378	0.424	0.2	0.9	3.4	52.1	43.4
FP	4.443	0.432	0.0	0.7	4.1	45.4	49.8
Panel B. OP and FP item-level response distributions							
OP1	4.332	0.638	0.4	1.2	3.2	55.2	40.0
OP2	4.380	0.611	0.0	0.8	4.4	50.8	44.0
OP3	4.380	0.611	0.0	1.2	3.2	52.0	43.6
OP4	4.336	0.607	0.4	0.4	3.6	56.4	39.2
OP5	4.460	0.595	0.0	0.8	2.8	46.0	50.4
FP1	4.428	0.578	0.0	0.4	3.2	49.6	46.8
FP2	4.472	0.596	0.0	0.4	4.0	43.6	52.0
Table 2 (Continued)							
FP3	4.452	0.633	0.0	0.8	5.2	42.0	52.0
FP4	4.500	0.589	0.0	0.8	2.4	42.8	54.0

FP5	4.364	0.646	0.0	1.2	5.6	48.8	44.4
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Note: N = 250. Construct means and standard deviations are based on respondent-level averages across the five indicators of each construct. For Panel A, percentages represent the pooled response distribution across the five indicators of each construct. Panel B reports the item-level response distribution for OP and FP. Percentages may not sum to exactly 100 because of rounding.

4.3 Measurement Model Assessment

4.3.1 Initial measurement model and indicator retention

The initial measurement model contained 35 reflective indicators across seven constructs. Outer loadings ranged from 0.616 to 0.794, with several indicators falling below the preferred 0.708 level. Social Impact and Operational Performance required closer examination because their AVE values were 0.455 and 0.480, respectively, both below the conventional 0.50 benchmark [29].

For Social Impact, SI3 had the lowest loading within the construct (0.616), and a sensitivity re-estimation was therefore conducted after removing this indicator. Although the deletion increased SI's AVE from 0.455 to 0.510, Cronbach's alpha and rho_A declined from 0.699 and 0.704 to 0.681 and 0.682, respectively, while rho_C remained unchanged at 0.806. Removing SI3 therefore improved convergent validity but weakened part of the reliability evidence.

A similar sensitivity check was conducted for Operational Performance by removing OP2, which had the lowest loading within that construct (0.659). Its removal increased OP's AVE from 0.480 to 0.526, but Cronbach's alpha declined from 0.728 to 0.699 and rho_A from 0.730 to 0.698, while rho_C decreased slightly from 0.821 to 0.816. Thus, as with SI, deleting the weakest OP indicator improved AVE but did not produce a consistent gain in overall measurement quality.

AVE was not considered on its own when deciding whether to retain the measures. Hair et al., [29] allow some judgement when AVE falls slightly below 0.50, provided that composite reliability remains satisfactory and the construct still has adequate shared variance. That situation applied to OP and SI, with composite reliability of 0.821 and 0.806, respectively. Similar decisions can be found outside the FinTech literature. Paul *et al.*, [45], for example, retained domains with AVE of 0.45–0.46 after reviewing the items because composite reliability remained between 0.70 and 0.77. Gültekin and Duru [46] also retained a construct with AVE of 0.45 where reliability was high, loadings were significant, and earlier evidence supported the scale. These cases are not presented as substitutes for the 0.50 guideline. Rather, they show why a small AVE shortfall should be considered together with reliability and content coverage. In the present data, removing SI3 or OP2 improved AVE but weakened other reliability indicators. Because the gain in AVE came with that trade-off, and because the items had already passed content review, all five indicators were retained for SI and OP. The measurement model therefore remained at 35 indicators.

4.3.2 Reliability and convergent validity results

For the 35-item model, Cronbach's alpha ranged from 0.699 to 0.826, rho_A from 0.704 to 0.831, and rho_C from 0.806 to 0.877 (Table 3). Bootstrapping confirmed that all outer loadings were statistically different from zero ($t = 9.104$ – 24.714 , all $p < 0.001$), and none of the 95% BCa confidence intervals included zero. Figure 2, presented in Section 4.5, shows the loadings, with the complete bootstrap results reported in Appendix A. Five constructs met the usual AVE benchmark of 0.50. Operational Performance (AVE = 0.480) and Social Impact (AVE = 0.455) fell below it, although their composite reliability values remained 0.821 and 0.806. Convergent validity was therefore clear for

five constructs and less convincing for OP and SI, so findings that involve those two constructs are read more cautiously.

Table 3
Construct reliability and convergent validity

Construct	Outer-loading range	Cronbach's alpha	rho_A	rho_C	AVE
PEOU	0.674–0.755	0.763	0.767	0.840	0.512
EB	0.732–0.790	0.817	0.822	0.872	0.576
PS	0.734–0.794	0.826	0.831	0.877	0.589
SI	0.616–0.763	0.699	0.704	0.806	0.455
SFA	0.727–0.770	0.800	0.800	0.862	0.555
OP	0.659–0.758	0.728	0.730	0.821	0.480
FP	0.636–0.778	0.754	0.757	0.836	0.506

Note: PEOU = Perceived Ease of Use; EB = Economic Benefit; PS = Privacy and Security; SI = Social Impact; SFA = Sustained FinTech Adoption; OP = Operational Performance; FP = Financial Performance.

4.3.3 Discriminant validity

Inference was based on the HTMT confidence intervals rather than on point estimates alone [36]. All 21 HTMT point estimates were below 0.85, ranging from 0.460 to 0.801 (Table 4), and none of the 95% bias-corrected confidence intervals included 1.00 (Appendix A). The interval evidence was nevertheless less decisive for a few pairs. The upper limit exceeded 0.90 for OP–FP (HTMT = 0.801; upper limit = 0.918), and exceeded 0.85 for SI–EB (0.884), SI–OP (0.863), and SI–PS (0.876). These pairs were therefore read with some caution rather than treated as failures of discriminant validity.

Supplementary evidence from the Fornell–Larcker criterion was also favourable because, for every construct, the square root of AVE was greater than its correlations with the other constructs [37]. The full Fornell–Larcker matrix is reported in Appendix A.

Because H7 and H8 depend on OP and FP being treated as separate constructs, the pair was examined further. In the retained model, their correlation was 0.599, below the square roots of AVE for OP (0.693) and FP (0.711), and the OP–FP HTMT estimate was 0.801 with a 95% BCa interval of [0.661, 0.918]. The rival specification did not support collapsing the two dimensions into a single factor. When the ten OP and FP indicators were combined under one Performance construct, AVE dropped to 0.392 and all ten loadings were below 0.708, ranging from 0.573 to 0.690, although rho_C remained acceptable at 0.865. For reference, the combined Performance construct produced $R^2 = 0.361$. Because this dependent variable is not defined in the same way as OP or FP in the main model, the figure is treated only as a descriptive comparison. The CVPAT comparison likewise showed no improvement in predictive performance. The overall average loss differences were –0.054 against the indicator-average benchmark and –0.011 against the linear-model benchmark, the same as the two-construct model at the reported precision. These results support retaining OP and FP as separate constructs. The relatively high upper HTMT limit still calls for some caution when interpreting H7 and the indirect effect.

Table 4
Discriminant validity: HTMT matrix

Construct	PEOU	EB	PS	SI	SFA	OP	FP
PEOU							
EB	0.610						
PS	0.460	0.583					
SI	0.478	0.720	0.738				
SFA	0.526	0.649	0.502	0.611			
OP	0.649	0.756	0.607	0.724	0.733		
FP	0.605	0.608	0.522	0.615	0.647	0.801	

Note: HTMT = heterotrait–monotrait ratio. All point estimates were below 0.85, and no 95% BCa confidence interval included 1.00 [36].

4.4 Common Method Bias

Using all 35 indicators, Harman’s single-factor analysis yielded a Kaiser–Meyer–Olkin value of 0.880 and a significant Bartlett test ($\chi^2 = 3,831.789$, $df = 595$, $p < 0.001$). The first unrotated component accounted for 29.301% of total variance, which was lower than the conventional 50% reference level [31]. Full collinearity VIFs were between 1.503 and 2.193 and therefore also remained below the 3.3 criterion [38]. Neither diagnostic can establish that common method bias is absent. The single-informant design leaves the association between sustained use and self-reported performance open to method variance, and the results that follow should be read with that constraint in mind.

4.5 Structural Model Assessment

Figure 2 presents the final 35-indicator PLS-SEM model, including outer loadings, standardised path coefficients, and the R^2 values of the endogenous constructs. The structural model is then assessed in terms of explanatory power, collinearity and effect sizes, and the significance of the proposed direct and indirect relationships.

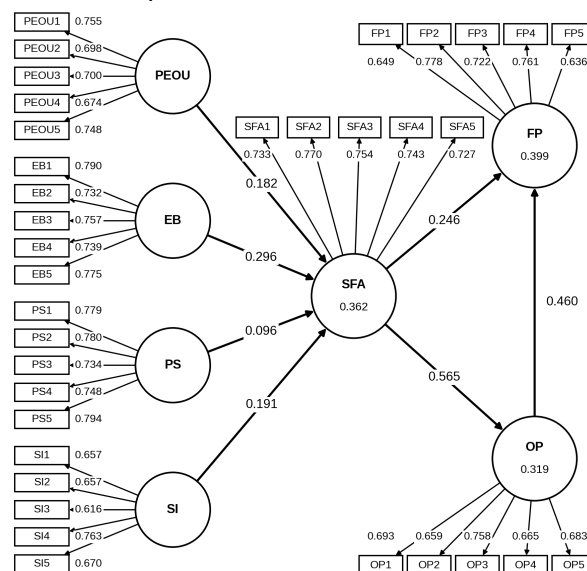


Fig. 2. Final PLS-SEM Model

4.5.1 Explanatory power

Table 5 shows that Perceived Ease of Use, Economic Benefit, Privacy and Security, and Social Impact jointly accounted for 36.2% of the variance in Sustained FinTech Adoption. Sustained FinTech Adoption explained 31.9% of Operational Performance, and together with Operational Performance it explained 39.9% of Financial Performance. Using the 0.25, 0.50, and 0.75 reference points commonly applied in PLS-SEM [29], the three endogenous constructs show weak-to-moderate explanatory power.

Table 5
Explanatory power of the structural model

Endogenous construct	R ²	Adjusted R ²
Sustained FinTech Adoption	0.362	0.352
Operational Performance	0.319	0.316
Financial Performance	0.399	0.395

4.5.2 Structural collinearity and effect sizes

As shown in Table 6, inner VIF values ranged from 1.000 to 1.722, comfortably below common PLS-SEM collinearity cut-offs [29]. The f^2 results show small effects of Economic Benefit (0.080), Perceived Ease of Use (0.039), and Social Impact (0.034) on Sustained FinTech Adoption, while Privacy and Security was negligible (0.009). Sustained FinTech Adoption had a large effect on Operational Performance ($f^2 = 0.468$) and a small effect on Financial Performance ($f^2 = 0.069$). Operational Performance, in turn, had a medium effect on Financial Performance ($f^2 = 0.240$) [29].

Table 6
Structural collinearity and effect sizes

Structural path	Inner VIF	f^2
PEOU → SFA	1.341	0.039
EB → SFA	1.722	0.080
PS → SFA	1.606	0.009
SI → SFA	1.673	0.034
SFA → FP	1.468	0.069
SFA → OP	1.000	0.468
OP → FP	1.468	0.240

Note: VIF = variance inflation factor. f^2 values of approximately 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively; values below 0.02 indicate negligible effects [29]

4.5.3 Structural relationships and hypothesis testing

Inference for H1–H8 was based on Complete Bootstrapping with 10,000 subsamples, two-tailed tests, and 95% BCa confidence intervals (Table 7). Economic Benefit was positively associated with Sustained FinTech Adoption ($\beta = 0.296$, $p < 0.001$, 95% BCa CI [0.140, 0.473]), as was Perceived Ease of Use ($\beta = 0.182$, $p = 0.033$, 95% BCa CI [0.019, 0.352]); H1 and H2 were therefore supported. Privacy and Security was not significant ($\beta = 0.096$, $p = 0.249$, 95% BCa CI [−0.070, 0.257]), so H3 was not supported. Social Impact produced a positive coefficient and a p-value below 0.05 ($\beta = 0.191$, $p = 0.031$), but its 95% BCa confidence interval narrowly included zero [−0.003, 0.346]. The two inferential indicators therefore led to slightly different conclusions at the 5% level. Where the p-value

criterion and the confidence interval diverge, established PLS-SEM guidance is to give precedence to the bootstrap confidence interval, because it does not assume a symmetric sampling distribution and is the more conservative basis for inference [29]. A recent empirical study by Alam [47] applies the same rule, treating a positive but interval-spanning path as unsupported. H4 was therefore conservatively treated as not supported, although the result is considered borderline rather than evidence of no association. Sustained FinTech Adoption was positively related to Financial Performance ($\beta = 0.246$, $p = 0.001$) and Operational Performance ($\beta = 0.565$, $p < 0.001$), while Operational Performance was positively related to Financial Performance ($\beta = 0.460$, $p < 0.001$), supporting H5–H7. H8 was also supported: the SFA $\rightarrow$ OP $\rightarrow$ FP indirect effect was positive and significant ($\beta = 0.260$, 95% BCa CI [0.165, 0.359]). Since the direct SFA $\rightarrow$ FP effect and the indirect effect were both positive and significant, the pattern is consistent with complementary partial mediation [40,41].

Table 7
Hypothesis testing results

Hypothesis	Relationship	β	STDEV	t	p	95% BCa CI	Decision
H1	PEOU $\rightarrow$ SFA	0.182	0.086	2.127	0.033	[0.019, 0.352]	Supported
H2	EB $\rightarrow$ SFA	0.296	0.085	3.501	<0.001	[0.140, 0.473]	Supported
H3	PS $\rightarrow$ SFA	0.096	0.083	1.153	0.249	[-0.070, 0.257]	Not supported
H4	SI $\rightarrow$ SFA	0.191	0.089	2.163	0.031	[-0.003, 0.346]	Not supported
H5	SFA $\rightarrow$ FP	0.246	0.077	3.192	0.001	[0.093, 0.395]	Supported
H6	SFA $\rightarrow$ OP	0.565	0.054	10.395	<0.001	[0.441, 0.659]	Supported
H7	OP $\rightarrow$ FP	0.460	0.070	6.615	<0.001	[0.314, 0.586]	Supported
H8	SFA $\rightarrow$ OP $\rightarrow$ FP	0.260	0.050	5.186	<0.001	[0.165, 0.359]	Supported

Note: H1–H7 report direct effects; H8 reports the specific indirect effect. β = standardised coefficient; STDEV = bootstrap standard deviation; BCa CI = bias-corrected and accelerated confidence interval

4.6 Predictive Assessment

4.6.1 PLSpredict results

PLSpredict used 10 folds and 10 repetitions (Table 8). Prediction-error skewness ranged from -0.944 to -0.140 and did not indicate severe asymmetry, so RMSE was used as the main error measure [42]. Q^2 predict was positive for all 15 endogenous indicators, ranging from 0.086 to 0.236. Relative to the linear-model benchmark, PLS-SEM produced a smaller RMSE for 12 of the 15 indicators: four of five SFA indicators, three of five OP indicators, and all five FP indicators. The remaining three indicators (SFA2, OP1, and OP5) had slightly larger PLS-SEM RMSE values. Overall, the pattern supports out-of-sample predictive relevance, while leaving room for the formal CVPAT comparison below [42].

Table 8
PLS predict summary

Endogenous construct	Q ² predict range	Q ² predict > 0	PLS RMSE < LM RMSE
Sustained FinTech Adoption	0.101–0.195	5/5	4/5
Operational Performance	0.094–0.236	5/5	3/5
Financial Performance	0.086–0.172	5/5	5/5
Overall	0.086–0.236	15/15	12/15

Note: LM = linear-model benchmark. All Q²predict values were positive [42]

4.6.2 Cross-validated predictive ability test

CVPAT provided the inferential predictive comparison [43]. Against the indicator-average benchmark, PLS-SEM showed significantly smaller prediction losses for SFA ($p = 0.011$), OP, FP, and the overall model (all $p < 0.001$; Table 9). The same result held at the manifest-variable level for 14 of the 15 endogenous indicators. SFA3 was the only exception: its PLS loss was lower than the indicator-average benchmark (average loss difference = -0.035), but the difference was not statistically significant ($p = 0.176$). Against the linear-model benchmark, PLS-SEM produced lower loss values for SFA, OP, FP, and the overall model, but none of these differences was statistically significant ($p = 0.132$ – 0.723). Thus, the model demonstrated predictive relevance beyond the naive indicator-average benchmark but did not show a statistically significant incremental advantage over the linear model. The indicator-level results did not change that interpretation. Relative to the linear-model benchmark, none of the manifest-variable loss differences reached significance ($p = 0.070$ – 0.886). Appendix A gives the complete manifest-variable CVPAT output.

Table 9
CVPAT latent-variable results

Benchmark	Construct	PLS loss	Benchmark loss	Average loss difference	t	p
Indicator average	SFA	0.289	0.343	–0.055	2.578	0.011
	OP	0.318	0.377	–0.060	5.951	<0.001
	FP	0.326	0.373	–0.047	5.108	<0.001
	Overall	0.311	0.364	–0.054	4.785	<0.001
Linear model	SFA	0.289	0.297	–0.009	1.078	0.282
	OP	0.318	0.322	–0.004	0.354	0.723
	FP	0.326	0.347	–0.021	1.511	0.132
	Overall	0.311	0.322	–0.011	1.466	0.144

Note: A negative average loss difference indicates that PLS-SEM produced a lower prediction loss than the benchmark [43]

5. Discussion and Conclusion

This study examined the factors associated with Sustained FinTech Adoption among Malaysian food and beverage (F&B) SMEs and considered how continued use relates to operational and financial outcomes. Perceived Ease of Use and Economic Benefit were both positively associated with sustained adoption. Privacy and Security was not significant, while the result for Social Impact was less clear-cut. Although its p -value fell below 0.05, the corresponding 95% BCa confidence interval

narrowly crossed zero, and H4 was therefore treated conservatively as not supported. Sustained FinTech Adoption was positively related to both Operational Performance and Financial Performance, and Operational Performance was also positively related to Financial Performance. The indirect SFA → OP → FP relationship was significant. Since the direct and indirect effects were both positive and significant, the results are consistent with complementary partial mediation [40,41]. Viewed together, these results indicate that continued FinTech use is associated with financial outcomes both directly and through the operational changes that accompany sustained use.

The post-adoption focus is one of the main contributions of this study. Registering for or initially trying a digital financial service does not tell us whether it will become part of normal business practice. In this sample, where firms had at least six months of FinTech experience, continued use was related to both ease of use and perceived economic value. The PEOU result suggests that day-to-day manageability still matters after adoption, when staff are dealing with the system in real operating conditions rather than forming expectations about it. Abdul-Halim *et al.*, [9] also found perceived ease of use to be relevant to e-wallet continuance among Malaysian users, although its influence was indirect, running through perceived usefulness and attitude rather than directly to continuance intention; perceived usefulness and trust were not significant predictors of continuance intention in their model. Krah *et al.*, [6] likewise found no significant direct PEOU effect on FinTech adoption among Ghanaian SMEs, with the effect operating through perceived usefulness and intention. The direct path reported here may therefore reflect the stage and unit of use being studied. Once a technology is already in place, effort is experienced rather than anticipated. Economic Benefit was the strongest supported antecedent in the present model. Continued use was more common where managers associated FinTech with clearer transaction records, better financial visibility, and more efficient financial processes.

Privacy and Security and Social Impact are harder to interpret. Neither path received clear support, but this does not mean that security or external pressure becomes irrelevant after adoption. Security may already function as a minimum condition among firms that continue using FinTech, leaving little variation for it to explain. External pressure may matter more at the adoption stage than once the technology is already in place. The measurement results also indicate some construct overlap. Social Impact was relatively close to Economic Benefit (HTMT = 0.720, upper limit = 0.884) and Operational Performance (HTMT = 0.724, upper limit = 0.863), and the corresponding inner VIFs were 1.673 and 1.722. Some of the variance attributed to these antecedents may therefore be shared. Because the present analysis cannot distinguish this statistical explanation from a substantive one, the unsupported paths should be interpreted cautiously.

Operational Performance was the most direct connection between sustained use and business outcomes in the model. The strongest structural coefficient linked Sustained FinTech Adoption with Operational Performance, a result that is consistent with how FinTech is used in practice for payments, transaction recording, billing, account settlement, and service delivery. Changes in speed, accuracy, and coordination are likely to be visible in these operating activities before they are reflected in financial results. The significant SFA → OP → FP effect follows this pattern. Lutfi *et al.*, [14] report related evidence for digital accounting systems in Jordan, and Kurniasari *et al.*, [11] do so for digital adoption among Indonesian traditional-market SMEs, although neither separates operational and financial performance in the same way as the present study. Evidence from the region is not entirely consistent. Putri *et al.*, [48], for example, found no significant association between e-financial transformation and SME performance among m-wallet adopters in Surakarta. This difference suggests that initial adoption may be too broad a measure of business value; continued integration with routine work may be more important. The direct SFA → FP path also remained significant, indicating that Operational Performance explains only part of the association

with Financial Performance. The findings therefore extend the ISSM perspective to post-adoption FinTech while showing that operational improvement is one, but not the only, route to financial value.

The predictive results were more restrained. Relative to the indicator-average benchmark, PLS-SEM produced better results, which suggests that the model carries useful predictive information. Its advantage did not extend to the linear-model comparison, because the difference in prediction loss was not statistically significant. The model is therefore more defensible as an explanation of the observed relationships among antecedents, sustained use, and performance than as evidence that PLS-SEM predicts better than the linear alternative.

For managers, what matters is whether FinTech is woven into routine work, not simply whether the firm accepts it. A business may receive digital payments yet gain little if those transactions remain disconnected from operating and financial processes. Signs of integration include quicker reconciliation, easier transaction tracing, dependable billing and records, and information that staff use in day-to-day decisions. Short task-based training, clear responsibility for checking digital transactions, and tighter links between payment records and accounting processes can make continued use easier and help operational gains persist.

FinTech providers and financial institutions face a similar challenge after adoption. Ease of use remains important, but firms also need to see a business return from continuing with the service. For smaller firms, that points to interfaces that are easy to understand, reliable transaction records, reporting functions that are readily accessible, and compatibility with existing work practices. The non-significant Privacy and Security path should not be read as a reason to relax security. Among established users, security may simply be treated as a minimum requirement rather than a factor that explains differences in continuance. Providers may therefore communicate value more effectively through specific business outcomes, such as less manual reconciliation, clearer cash-flow information, or fewer recording errors, than through broad messages about digitalisation.

The policy implication is that adoption numbers do not tell the whole story. SME digitalisation programmes often count how many firms take up a technology, but that measure says little about what happens afterwards. A firm can register for a FinTech service, or even start using it, without making it part of routine operations. Public agencies, financial institutions, industry associations, and technology providers could therefore place greater emphasis on post-adoption support. Assistance with interpreting digital transaction data, linking payment systems to accounting processes, and using FinTech information for cash-management decisions may be particularly useful. Evaluation of such programmes could also consider continuity of use, integration with routine processes, and perceived operational benefits alongside the number of adopters.

Several limitations should be recognised. First, the study used a cross-sectional design, so the observed relationships describe associations at one point in time rather than causal sequences. It is possible, for example, that firms with stronger existing performance are better able to keep FinTech embedded in their routines. Longitudinal or time-lagged research would be better suited to examining this issue, as would an explicit endogeneity assessment such as the Gaussian copula approach. Second, the discriminant validity evidence for Operational Performance and Financial Performance was not unequivocal. Their HTMT upper confidence limit reached 0.918, and responses on both constructs were concentrated in the top two scale categories, so the strong observed association may partly reflect a ceiling effect. The rival single-factor specification did not support collapsing the two dimensions, so OP and FP were kept separate. Even so, interpretation of H7 and the H8 indirect effect depends on those constructs capturing genuinely distinct aspects of performance. A further limitation is that each firm was represented by one management-level respondent, with both operational and financial performance measured through self-report.

Although the procedural and statistical diagnostics did not indicate serious common method bias, the use of one source and subjective assessments can still add measurement error. Future studies could address this more directly by pairing survey responses with a second informant or with objective records, for example accounting data, point-of-sale records, transaction histories, or platform-use data. The purposive sample also limits generalisability because it covers only Malaysian F&B SMEs. No subgroup tests were conducted for firm size, firm age, ownership, managerial experience, intensity of FinTech use, or digital capability. These differences should be examined in later work, both within F&B and in other industries and national settings.

The overall pattern is that FinTech value depends more on what firms do after adoption than on the adoption decision itself. Perceived Ease of Use and Economic Benefit were the only antecedents with supported relationships to Sustained FinTech Adoption. Continued use was associated with both Operational Performance and Financial Performance, and part of the financial relationship operated through Operational Performance. The findings are therefore consistent with a setting in which FinTech becomes more useful when employees can handle it without excessive effort, managers can recognise concrete benefits, and the technology is absorbed into ordinary operating and financial work. For managers and policymakers, initial adoption is better treated as the first stage of digitalisation rather than the final outcome.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. No author has held, within the three years preceding submission, any consultancy, employment, or financial interest with a FinTech provider, financial institution, or industry body relevant to this study.

Ethics and Informed Consent

Participation was voluntary, the academic purpose of the study was disclosed on the first page of the questionnaire, respondents could withdraw at any point before submission, and no personally identifiable information about individuals or firms was collected. Informed consent was obtained through an acknowledgement item that respondents completed before beginning the questionnaire.

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Appendix A. Supplementary Model Assessment Results

Table A.1

HTMT point estimates and 95% BCa confidence intervals

Construct pair	HTMT	2.5%	97.5%
FP–EB	0.608	0.449	0.759
OP–EB	0.756	0.663	0.835
OP–FP	0.801	0.661	0.918
PEOU–EB	0.610	0.458	0.730
PEOU–FP	0.605	0.455	0.735
PEOU–OP	0.649	0.490	0.782
PS–EB	0.583	0.426	0.731
PS–FP	0.522	0.387	0.652
PS–OP	0.607	0.457	0.742
PS–PEOU	0.460	0.313	0.621
SFA–EB	0.649	0.498	0.785
SFA–FP	0.647	0.487	0.778
SFA–OP	0.733	0.603	0.834
SFA–PEOU	0.526	0.335	0.685
SFA–PS	0.502	0.317	0.675
SI–EB	0.720	0.523	0.884
SI–FP	0.615	0.480	0.754
SI–OP	0.724	0.592	0.863
SI–PEOU	0.478	0.302	0.632
SI–PS	0.738	0.570	0.876
SI–SFA	0.611	0.373	0.801

Note: HTMT = heterotrait–monotrait ratio. No confidence interval included 1.00.

Table A.2

Fornell–Larcker Criterion

Construct	PEOU	EB	PS	SI	SFA	OP	FP
PEOU	0.716						
EB	0.481	0.759					
PS	0.366	0.489	0.767				
SI	0.314	0.536	0.558	0.675			
SFA	0.420	0.533	0.414	0.461	0.745		
OP	0.491	0.585	0.474	0.522	0.565	0.693	
FP	0.449	0.474	0.411	0.440	0.505	0.599	0.711

Note: Diagonal entries in bold are the square roots of AVE; off-diagonal entries are latent-variable correlations. Each diagonal value exceeded the correlations in its row and column [37]

Table A.3

Bootstrap outer loadings

Indicator	O	M	STDEV	t	p
EB1	0.790	0.788	0.032	24.714	<0.001
EB2	0.732	0.727	0.046	15.786	<0.001
EB3	0.757	0.752	0.045	16.857	<0.001
EB4	0.739	0.737	0.043	17.009	<0.001
EB5	0.775	0.773	0.034	22.555	<0.001
FP1	0.649	0.647	0.054	12.109	<0.001
FP2	0.778	0.776	0.033	23.459	<0.001
FP3	0.722	0.721	0.046	15.548	<0.001
FP4	0.761	0.761	0.038	20.181	<0.001
FP5	0.636	0.635	0.056	11.354	<0.001
OP1	0.693	0.694	0.038	18.140	<0.001
OP2	0.659	0.661	0.041	16.063	<0.001
OP3	0.758	0.755	0.038	19.844	<0.001
OP4	0.665	0.663	0.047	14.022	<0.001
OP5	0.683	0.680	0.047	14.444	<0.001
PEOU1	0.755	0.753	0.057	13.241	<0.001
PEOU2	0.698	0.697	0.064	10.939	<0.001
PEOU3	0.700	0.693	0.063	11.156	<0.001
PEOU4	0.674	0.669	0.074	9.104	<0.001
PEOU5	0.748	0.743	0.068	11.036	<0.001
PS1	0.779	0.776	0.038	20.620	<0.001
PS2	0.780	0.777	0.043	18.051	<0.001
PS3	0.734	0.731	0.049	15.016	<0.001
PS4	0.748	0.744	0.060	12.388	<0.001
PS5	0.794	0.792	0.037	21.583	<0.001
SFA1	0.733	0.732	0.047	15.514	<0.001
SFA2	0.770	0.769	0.032	24.147	<0.001
SFA3	0.754	0.752	0.033	22.844	<0.001
SFA4	0.743	0.741	0.039	18.977	<0.001
SFA5	0.727	0.723	0.041	17.881	<0.001
SI1	0.657	0.649	0.069	9.573	<0.001
SI2	0.657	0.651	0.066	9.901	<0.001
SI3	0.616	0.618	0.061	10.100	<0.001
SI4	0.763	0.759	0.045	17.020	<0.001
SI5	0.670	0.662	0.067	9.977	<0.001

Note: O = original sample; M = bootstrap sample mean; STDEV = bootstrap standard deviation. All outer loadings were statistically significant at $p < 0.001$.

Table A.4

Manifest-Variable CVPAT Results

Panel A. PLS-SEM vs. indicator-average benchmark (IA)

Indicator	PLS loss	IA loss	Average loss difference	t	p
SFA1	0.283	0.351	-0.068	2.743	0.007
SFA2	0.302	0.365	-0.063	2.319	0.021
SFA3	0.314	0.349	-0.035	1.357	0.176
SFA4	0.287	0.352	-0.065	2.278	0.024
SFA5	0.257	0.299	-0.042	1.978	0.049
OP1	0.312	0.409	-0.097	5.039	<0.001
OP2	0.318	0.375	-0.057	4.536	<0.001

Indicator	PLS loss	IA loss	Average loss difference	t	p
OP3	0.318	0.376	-0.058	3.511	0.001
OP4	0.317	0.370	-0.053	2.800	0.006
OP5	0.322	0.356	-0.033	2.436	0.016
FP1	0.308	0.337	-0.029	2.913	0.004
FP2	0.319	0.357	-0.038	2.930	0.004
FP3	0.344	0.403	-0.058	4.596	<0.001
FP4	0.289	0.349	-0.060	4.666	<0.001
FP5	0.370	0.418	-0.049	4.077	<0.001

Panel B. PLS-SEM vs. linear-model benchmark (LM)

Indicator	PLS loss	LM loss	Average loss difference	t	p
SFA1	0.283	0.310	-0.027	1.435	0.153
SFA2	0.302	0.295	0.007	0.383	0.702
SFA3	0.314	0.322	-0.008	0.426	0.671
SFA4	0.287	0.302	-0.015	0.813	0.417
SFA5	0.257	0.259	-0.002	0.144	0.886
OP1	0.312	0.272	0.040	1.818	0.070
OP2	0.318	0.344	-0.026	0.875	0.382
OP3	0.318	0.326	-0.008	0.470	0.639
OP4	0.317	0.347	-0.030	1.704	0.090
OP5	0.322	0.319	0.003	0.158	0.874
FP1	0.308	0.329	-0.022	1.410	0.160
FP2	0.319	0.329	-0.009	0.533	0.594
FP3	0.344	0.370	-0.026	1.188	0.236
FP4	0.289	0.298	-0.008	0.435	0.664
FP5	0.370	0.411	-0.041	1.240	0.216

Note: IA = indicator-average benchmark; LM = linear-model benchmark. A negative average loss difference indicates lower prediction loss for PLS-SEM than for the benchmark. SmartPLS values displayed as p = 0.000 are reported as p < 0.001