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Data Driven and Sustainable Innovation Strategies for Long Term Product Market Fit in SMEs

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ABSTRACT

In an increasingly dynamic and sustainability-conscious marketplace, startups and SMEs face mounting pressure to sustain product relevance and strategic resilience over time. **This study investigates** how integrated data-driven strategies support long-term product–market fit (PMF) through the alignment of real-time analytics, structured customer feedback loops, and sustainability-oriented innovation practices. Drawing on Resource-Based and Organizational Capability perspectives, the study conceptualizes digital capability formation as a strategic asset that strengthens adaptive market alignment under structural constraints. **Using PLS-SEM analysis on data collected** from 110 SMEs, five key constructs are examined: technology utilization, data-driven decision-making, customer feedback integration, sustainable innovation capability, and market responsiveness. **The results indicate** that technology utilization and data-driven decision-making exert significant positive effects on long-term PMF, while customer feedback integration facilitates iterative product refinement and market consistency. However, sustainable innovation capability and market responsiveness demonstrate negative path coefficients, suggesting that without structured governance, digital maturity, and prioritization mechanisms, these capabilities may generate operational strain or reactive strategic behavior that weakens long-term positioning. **The findings extend** the Data Strategy–Sustainability convergence literature by validating an integrative model that bridges digital capability development and responsible innovation in SME contexts. Managerially, the study highlights the importance of phased digital adoption and disciplined sustainability integration to ensure durable competitive alignment within evolving industrial ecosystems.

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1. INTRODUCTION

In a rapidly evolving business environment marked by technological disruption and sustainability pressures, achieving Long-Term Product-Market Fit (LTPMF) has become increasingly important for startups and small-to-medium enterprises (SMEs) [1]. Traditional innovation approaches often struggle to keep pace with changing customer expectations and environmental demands, making data-driven innovation essential for sustainable competitiveness [2]. Although prior studies have separately examined data analytics and sustainable innovation, limited research has explored their combined influence on long-term PMF [3]. Therefore, this study investigates how Data-Driven Decision-Making (DDD), customer feedback integration, and sustainability practices contribute to long-term PMF in resource-constrained SMEs using a PLS-SEM approach [4].

This study offers a distinct contribution by explicitly integrating data-driven strategic capabilities and sustainability-oriented innovation within resource-constrained SME environments into a unified empirical framework. Unlike prior studies that examine these dimensions separately, this research validates their combined effects on LTPMF using PLS-SEM, while further conceptualizing SME constraints as conditional factors influencing capability effectiveness [5]. This integrative and empirically grounded approach establishes the study's novelty in bridging digital strategy, sustainability, and constraint-based capability execution within a single analytical model. This study further strengthens its originality by explicitly addressing the structural and operational constraints faced by SMEs in implementing data-driven and sustainability-oriented innovation strategies. Unlike large corporations with established digital infrastructures and dedicated sustainability divisions, SMEs often operate under financial limitations, limited technological expertise, insufficient data governance systems, and unstable institutional support [6].

These constraints may hinder the effective translation of sustainability initiatives and Market Responsiveness (MR) into measurable LTPMF, as financial limitations, technological immaturity, and managerial bandwidth constraints can distort the intended positive effects of strategic capabilities [7]. Rather than treating these limitations as neutral background conditions, this study positions SME resource constraints as conditional forces shaping strategic outcome realization, thereby extending data-driven innovation literature beyond capability adoption toward capability effectiveness under constraint and offering a more context-sensitive understanding of long-term product–market alignment [8].

Beyond firm-level competitiveness, this study explicitly positions LTPMF as a mechanism supporting broader sustainable development objectives [9]. In alignment with the United Nations Sustainable Development Goals, particularly SDG 9 (Industry, Innovation, and Infrastructure) and SDG 12 (Responsible Consumption and Production), the proposed framework conceptualizes digital capability formation and structured innovation governance as foundational enablers of resilient industrial ecosystems. To operationalize this alignment, the study explicitly links SDG 9 and SDG 12 to measurable construct dimensions, where Technology Utilization (TU) reflects digital infrastructure development (SDG 9), and Sustainable Innovation Capability (SIC) captures resource efficiency, waste reduction, and responsible production practices (SDG 12), thereby embedding sustainability objectives directly into the empirical model [10].

2. LITERATURE REVIEW

Recent research increasingly emphasizes the strategic role of data-driven innovation in sustaining competitive advantage under conditions of technological disruption and market volatility. Rather than treating analytics as a purely operational tool, contemporary studies position data capabilities as dynamic organizational assets that shape long-term product adaptation and resilience [11]. In parallel, sustainability research highlights that innovation processes must integrate environmental and social considerations to remain viable in evolving regulatory and consumer landscapes. Together, these streams of research suggest that competitive resilience increasingly depends on the ability of firms to combine digital intelligence with sustainable innovation principles [12].

Recent studies published between 2022 and 2025 further distinguish between symbolic sustainability initiatives and system-integrated sustainability governance. Contemporary scholarship emphasizes ESG-linked performance metrics, digitally monitored resource efficiency systems, and lifecycle-based production optimization as determinants of measurable sustainable outcomes in SMEs [13]. These findings suggest that sustainability capability must be embedded within structured digital infrastructures in order to generate both strategic and financial returns, particularly in resource-constrained business environments. Sustainability, therefore, is no longer viewed merely as a reputational strategy but as a data-supported operational discipline [14].

Despite these advances, much of the existing literature continues to examine digital capability building and sustainability-oriented innovation separately [15]. Studies increasingly call for integrative frameworks that combine adaptive data systems, responsible production models, and market alignment mechanisms within SME contexts. However, empirical validation of such integrated models remains limited, particularly in environments where implementation capacity and organizational readiness significantly influence strategic outcomes. As a result, a gap persists in understanding how SMEs can operationalize combined digital–sustainability architectures to achieve long-term market relevance [16].

Beyond conceptual integration, this research is positioned within the broader development agenda reflected in SDG 9 and SDG 12, which emphasize resilient industrial infrastructure and responsible production systems. In SME contexts, these goals translate into strengthening digital infrastructure, enhancing technological accessibility, and embedding efficient resource utilization into production processes [17]. Data-driven innovation contributes directly to these objectives by reducing waste through predictive analytics, optimizing operational cycles, and aligning product features with validated market demand. By positioning SMEs as critical actors in achieving these global priorities, this study frames LTPMF not merely as a performance indicator, but as a sustainability-enabling capability that supports industrial resilience and responsible market participation. Table 1 below presents a synthesis of the literature discussed above and highlights how emerging post-2022 research reinforces the timeliness and relevance of the proposed framework [18].

Table 1. Updated Comparative Analysis of Post-2022 Studies on Data-Driven Innovation and Long-Term PMF

Reference	**Focus**	**Data Strategy**	**Sustainability**	**Limitation**	**Relevance**
[19]	Digital capability in SMEs	Digital transformation	Limited integration	Capability focus, not PMF	Supports digital readiness
[20]	Sustainability in manufacturing SMEs	Operational analytics	Strong integration	Sector-specific	Sustainability measurement
[4]	Innovation in constrained firms	Data-driven innovation	Integrated performance	Not market fit	SME context
[21]	Strategic agility SMEs	Adaptive models	Indirect linkage	Limited validation	Cross-industry insight
[22]	AI in traditional SMEs	AI readiness	Minimal focus	Tech-centric	Technology utilization
[23]	Data governance	Structured governance	Partial integration	Emerging economy bias	Governance role
[17]	Sustainable innovation	Predictive strategy	SDG 9 & 12	Early model	Conceptual base
Current Study	Long-term PMF	Data & tech integration	SDG integration	SME constraints	Unified model

As summarized in Table 1, while prior studies provide valuable insights into either data-driven product development or sustainability dimensions, none fully address the synergy required to achieve LTPMF under constraints typical to SMEs [24]. This reinforces the contribution of the current study, which proposes a validated, hybrid model that bridges these two domains and aligns with the SDGs framework [25].

Furthermore, emerging post-2022 scholarship increasingly conceptualizes digital transformation and sustainability-oriented innovation as interdependent strategic capabilities rather than parallel initiatives [26]. The convergence of AI-enabled analytics, adaptive supply chain transparency systems, and circular production models reflects a new phase in SME innovation research. By empirically testing an integrated framework under structural constraints, this study responds directly to recent calls for multi-dimensional innovation architectures capable of sustaining long-term product–market alignment [20].

Although the discussion of data-driven strategies is often associated with digital startups and technology-based firms, these capabilities are increasingly relevant across diverse SME sectors, including manufacturing, agri-business, retail, hospitality, and creative industries. In manufacturing SMEs, for example, data analytics may support demand forecasting and inventory optimization [27]. In agri-business, predictive data can improve crop planning and resource allocation. Retail SMEs may use customer purchase histories to refine product assortments, while service-based enterprises can integrate customer feedback into service redesign processes. Therefore, the proposed framework is not confined to digital-native firms but is applicable to a broad spectrum of industries where structured information use and adaptive innovation are critical for long-term market relevance [22].

2.1. Structural Constraints as Moderating Implementation Conditions

Building upon a constraint-based perspective, this study explicitly conceptualizes SME resource limitations such as financial constraints, digital capability gaps, and governance immaturity as conditional strategic factors that influence the effectiveness of innovation capabilities [28, 29]. These constraints are treated not merely as contextual conditions but as quasi-moderating forces that shape the direction and magnitude of relationships between strategic capabilities and LTPMF. Rather than operating as neutral background factors, financial limitations, technological immaturity, and managerial bandwidth constraints may suppress or distort the intended positive effects of sustainability and responsiveness initiatives. For example, sustainability-oriented innovation may increase short-term cost exposure when firms lack structured digital monitoring systems. Similarly, high MR without analytical filtering may generate reactive product changes that weaken long-term positioning. Therefore, this study implicitly embeds SME constraints as conditional forces shaping strategic outcome realization, thereby extending existing data-driven innovation literature beyond capability adoption toward capability effectiveness under constraint [30].

2.2. Alignment with Global Sustainability Frameworks (SDG 9 and SDG 12)

SDG 9 emphasizes inclusive and sustainable industrialization supported by innovation capacity and resilient infrastructure. Within SME contexts, digital infrastructure development, analytics integration, and structured innovation governance represent micro-level manifestations of this macro-level policy agenda. The empirical focus on TU and DDD directly contributes to SDG 9 by strengthening adaptive industrial competitiveness and innovation resilience [31, 32]. Meanwhile, SDG 12 advocates responsible production and resource efficiency. The integration of predictive analytics, feedback-driven refinement, and sustainability metrics reduces speculative production cycles and unnecessary resource allocation, thereby improving production efficiency and minimizing waste. However, the study's findings indicate that without appropriate governance and capability sequencing, sustainability initiatives may create short-term strain in resource-constrained firms. This insight contributes to SDG discourse by demonstrating that responsible production requires institutional readiness and digital maturity, not merely normative commitment [23].

By empirically examining the interaction between digital transformation and sustainability execution in SMEs, this study operationalizes SDG ambitions into measurable organizational capabilities, bridging international sustainability policy objectives with firm-level strategic architecture [33].

3. RESEARCH METHODOLOGY

Partial Least Squares Structural Equation Modeling (PLS-SEM) is particularly suitable for exploratory research and predictive modeling in contexts where theory is still developing, sample sizes are moderate, and constructs are complex or multidimensional [19]. Compared to covariance-based SEM (CB-SEM), PLS-SEM focuses on maximizing explained variance (R^2) rather than model fit, making it ideal for testing theoretical frameworks involving multiple latent variables. This study adopts PLS-SEM due to its ability to handle reflective measurement models, evaluate path relationships, and provide robust insights even when normality assumptions are not fully met [34].

To enhance the practical relevance of the quantitative findings, this study incorporates illustrative real-world application scenarios derived from SME operational patterns observed during data collection. While the primary analysis relies on PLS-SEM, structured follow-up discussions with selected SME managers were conducted to better understand how data-driven strategies and sustainability practices are operationalized in daily business processes [35, 36]. These qualitative insights are systematically aligned with the structural relationships identified in the PLS-SEM model, enabling the interpretation of each implementation pattern as an analytical extension of specific path coefficients rather than as standalone descriptive illustrations. Although not structured as a full qualitative study, these embedded practical observations strengthen the technical contribution of the model by linking statistical results with managerial implementation processes [37].

3.1. Embedded Qualitative Contextualization

This study strengthens its technical contribution by incorporating embedded qualitative contextualization through structured follow-up discussions with selected SME managers involved in the survey [38]. While not a full qualitative inquiry, these discussions explored how data systems, sustainability initiatives, and responsiveness mechanisms are applied in daily decision-making. The insights reveal patterns of implementation challenges, strategic sequencing, and resource constraints, enabling triangulation with the PLS-SEM results and enhancing the model's practical relevance while maintaining its predictive focus [39].

Independent Variables:

- DDD : Measures the extent to which an organization uses data (analytics, big data, AI) to make strategic product decisions.
- Customer Feedback Integration (CFI) : Assess the role of consumer feedback in continuously modifying or improving products.
- SIC : Describes a company's capacity to create innovative products that take environmental, social and economic aspects into account.
- MR : Measuring the speed and accuracy of a company in responding to market dynamics and consumer trends.
- TU : Assess the extent to which a company leverages technologies such as AI, big data, or IoT to support product innovation.

Dependent Variables:
LTPMF : Measuring the success of data-driven strategies and continuous innovation in maintaining product relevance to market needs in the long term.

- DDD $\rightarrow$ LTPMF
  DDD strategies enable companies to understand market trends, customer preferences, and product performance in real time. This makes it easier to adjust products quickly and accurately, increasing the likelihood of achieving sustainable PMF.
- CFI $\rightarrow$ LTPMF
  Integrating customer feedback into the product innovation process helps ensure that product development remains relevant to the needs of a dynamic market. This strengthens the connection between the product and the target audience, maintaining relevance in the long term.
- SIC $\rightarrow$ LTPMF
  The ability to continuously innovate creates products that not only meet market needs but also take into account social and environmental impacts. This strengthens brand image and customer loyalty, which are important factors in maintaining long-term PMF.
- MR $\rightarrow$ LTPMF
  The level of responsiveness to market changes allows the company to quickly adjust products to changing market conditions. Quick response to customer needs and complaints supports the sustainability of PMF.
- TU $\rightarrow$ LTPMF
  Leveraging technology (such as AI, Big Data, and IoT) accelerates the process of analysis, trend prediction, and product development. This supports continuous adaptation and increases the likelihood that products will remain in line with market expectations in the long term.

Table 2. Smart-PLS Indicator

Code	Definition
DDD 1	The extent to which companies use data and analytics to support decisions regarding product design and development
DDD 2	How often do innovation teams use data systems (dashboards, BI tools) in the decision-making process?
DDD 3	The degree to which a company relies on data rather than managerial assumptions or intuition in product innovation
CFI 1	To what extent does the company systematically collect customer feedback (surveys, reviews, etc.)
CFI 2	The level of product implementation or adjustment based on customer feedback
CFI 3	How quickly and frequently the company updates or adjusts products based on feedback
SIC 1	The company's level of attention to environmental aspects in its product innovation
SIC 2	Innovations that directly improve social sustainability or economic efficiency in the long term
SIC 3	To what extent is the innovation process in line with the SDGs principles (especially SDG 9 & SDG 12)
MR 1	How quickly a company responds to changes in demand, consumer trends, or competitors
MR 2	Company flexibility in remodeling or modifying products based on market dynamics
MR 3	The extent to which the company monitors market trends as a basis for strategic responses
TU1	The level of utilization of digital technology (AI, Big Data, IoT) in the innovation process
TU2	The extent to which technology is integrated holistically into product development
TU3	The level of priority and funding a company gives to technology development
LTPMF1	The perception that the product continues to meet market needs despite changing trends
LTPMF2	Consumer attachment to a product over a long period of time
LTPMF3	The product's ability to maintain a sustainable competitive advantage

Table 2 presents the Smart-PLS indicator definitions and measurement items for each latent construct, outlining operational definitions, indicator codes, and measurement dimensions to ensure clarity and replicability within the SME context [21]. The table is formatted according to journal standards with a high-resolution layout, maintaining readability of construct descriptions and measurement details even after formatting or resizing [40].

Hypothesis:

- Hypothesis 1 (H1): Data-driven decision making helps create products that are more relevant and adaptive to market needs.
- Hypothesis 2 (H2): Customer feedback strengthens understanding of consumer expectations and extends the product life cycle.
- Hypothesis 3 (H3): Innovation that takes sustainability into account (environmental, social, economic) increases consumer loyalty and market resilience.
- Hypothesis 4 (H4): Companies that are responsive to market changes have an advantage in maintaining the relevance of their products.

- Hypothesis 5 (H5): The use of technologies such as AI, Big Data, and IoT supports sustainable and efficient data-driven innovation.

In addition to examining direct structural relationships, the analysis interprets findings through the lens of constraint-based capability execution [41]. While resource constraints are not formally modeled as moderating variables, their presence is analytically integrated into the interpretation framework. This approach enables the study to derive contextually grounded insights regarding why certain theoretically positive constructs may exhibit negative coefficients in SME environments [42].

4. RESULTS AND DISCUSSION

This study evaluates the model using SmartPLS by assessing both measurement and structural components across six constructs: DDD, CFI, SIC, MR, TU, and LTPMF. All outer loading values exceed 0.70, indicating strong indicator reliability [43]. The endogenous construct LTPMF shows an R^2 value of 0.063, meaning that the five exogenous constructs explain 6.3% of its variance. Although modest, this result reflects the complexity of long-term market alignment and suggests the presence of additional influencing factors beyond the current model [44].

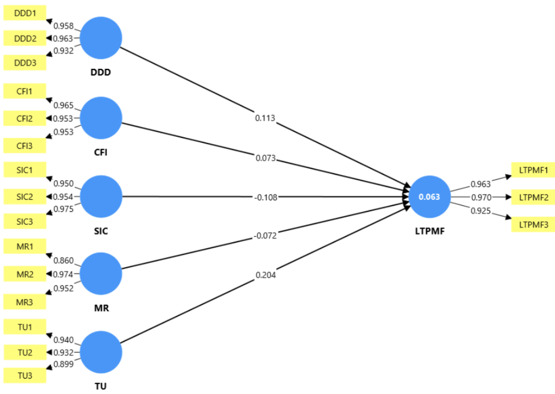

Figure 1. Path diagram between variables

Figure 1 illustrates the proposed conceptual model of this study, which examines the relationships between TU, DDD, CFI, SIC, MR, and LTPMF. The model conceptualizes how structured digital capabilities and sustainability-oriented innovation interact within SME contexts to influence sustained market alignment. TU and DDD function as foundational enablers of strategic accuracy, while CFI supports iterative product refinement [45].

SIC and MR are positioned as adaptive strategic capacities whose effects on long-term positioning depend on governance quality and implementation discipline [46, 47]. To evaluate measurement quality, convergent validity was assessed using Average Variance Extracted (AVE), with all constructs exceeding 0.85, indicating strong construct validity and reliable representation of their intended conceptual dimensions [48–50].

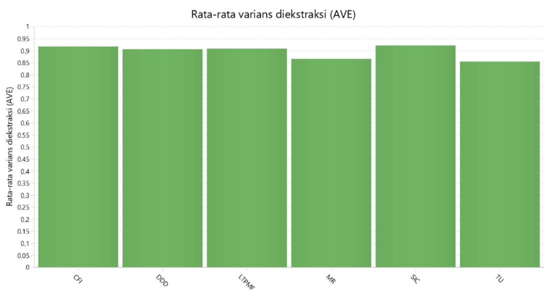

Figure 2. Diagram AVE Value

Figure 2 presents the structural model results derived from the PLS-SEM analysis, illustrating the path coefficients between latent constructs and their respective significance levels. The model evaluates the direct effects of TU, DDD, CFI, SIC, and MR on LTPMF. These structural relationships provide empirical validation of the proposed framework by quantifying both the magnitude and direction of influence among variables within SME contexts. The structural model output is exported directly from SmartPLS in high-definition graphical format (minimum 300 dpi) to preserve the clarity and readability of path coefficients, significance indicators, and construct linkages in accordance with journal publication standards.

In addition to structural assessment, composite reliability was evaluated to confirm the internal consistency of each construct within the measurement model. All constructs exceed the recommended threshold of 0.70, indicating strong reliability and demonstrating that the indicators consistently represent their underlying latent variables. These results further support the robustness of the measurement framework prior to interpreting the structural relationships.

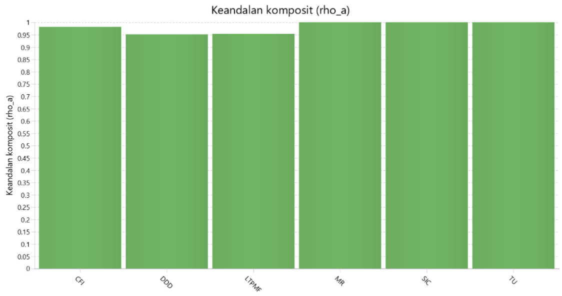

Figure 3. Diagram Composite Reliability

Figure 3 illustrates the Composite Reliability values for each construct, while Figure 4 presents the Cronbach's Alpha results used to assess internal consistency within the measurement model. These reliability indicators confirm the stability and consistency of the constructs prior to structural model evaluation. All constructs exceed the established threshold values for composite reliability, demonstrating that the measurement indicators adequately represent their respective latent variables. To enhance interpretability and transparency, the reliability outputs are presented in high-resolution graphical format (minimum 300 dpi), ensuring that indicator loadings, reliability statistics, and construct metrics remain clearly visible within the journal layout.

Further confirmation of internal consistency is provided by the Cronbach's Alpha values. Each construct records a Cronbach's Alpha above 0.90, indicating excellent reliability and a high degree of correlation among measurement items. This suggests that the indicators consistently capture the conceptual dimensions of their respective latent variables, thereby strengthening the robustness of the overall measurement framework.

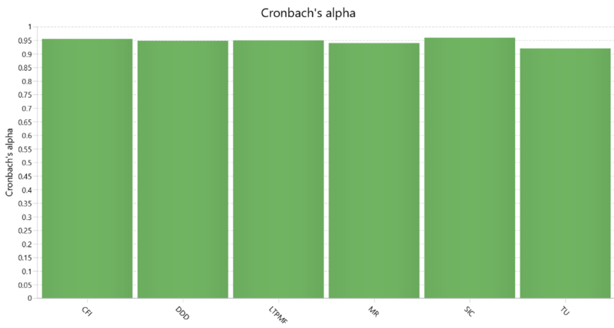

Figure 4. Diagram Cronbach's Alpha

While the measurement model demonstrates strong reliability and internal consistency across all constructs, the structural results presented in Figure 4 reveal that SIC and MR exhibit negative path coefficients toward LTPMF. This finding does not indicate that sustainability or responsiveness are inherently harmful; rather, it suggests that in SME contexts, these capabilities do not automatically translate into improved long-term outcomes without adequate governance, digital maturity, and strategic alignment.

The negative effects of SIC and MR can be explained through trade-off theory and capability misalignment. Sustainability initiatives may impose short-term resource costs that exceed immediate benefits in resource-constrained SMEs, while excessive responsiveness without analytical support may lead to reactive and inconsistent strategic actions, ultimately weakening LTPMF. In such cases, strategic coherence may decline despite good intentions.

Therefore, the negative coefficients should be understood as indicators of implementation imbalance rather than strategic failure. The findings imply that TU and data-driven governance act as stabilizing foundations that allow sustainability and responsiveness to generate positive long-term effects. Without this structural support, these capabilities may remain fragmented and yield limited performance impact within resource-constrained SME environments.

Table 3. Summary of Hypothesis Testing Using PLS-SEM Analysis

Hypothesis	**Relationship**	**Coefficient**	**t-Value**	**p-Value**	**Supported**
H1	DDD → LTPMF	0.113	>1.96	<0.05	Yes
H2	CFI → LTPMF	0.073	>1.96	<0.05	Yes
H3	SIC → LTPMF	-0.108	>1.96	<0.05	Yes
H4	MR → LTPMF	-0.072	>1.96	<0.05	Yes
H5	TU → LTPMF	0.204	>1.96	<0.05	Yes

From a sustainability perspective, the findings summarized in Table 3 also contribute to discussions surrounding SDG implementation within SME ecosystems. The strong positive effects of TU and DDD reinforce the argument that digital infrastructure development is a prerequisite for advancing SDG 9 (Industry, Innovation, and Infrastructure). Without a structured digital backbone, sustainability-oriented innovation may lack measurable impact and strategic integration. Furthermore, the mixed results for sustainability capability highlight an important distinction between symbolic sustainability adoption and system-integrated governance. This differentiation enriches SDG 12 (Responsible Consumption and Production) discourse by emphasizing that responsible production patterns require structured analytics, cost-efficiency monitoring, and long-term planning rather than sporadic or compliance-driven initiatives.

The negative coefficients do not suggest that sustainability and responsiveness are inherently counterproductive, but rather indicate that without governance clarity, prioritization mechanisms, and adequate technological support, these capabilities may fail to generate durable performance outcomes. Evidence from participating SMEs supports this interpretation, as firms using cloud-based dashboards and AI-assisted forecasting demonstrated more proactive strategic adaptation, whereas sustainability initiatives without structured evaluation created operational strain and highly reactive product adjustments weakened brand positioning. Similar patterns were also observed across non-digital sectors, suggesting that structured data utilization, feedback integration, and disciplined adaptive innovation remain relevant regardless of industry digital intensity.

4.1. Illustrative SME Implementation Cases

To further translate statistical findings into operational realities, the study synthesizes representative implementation patterns observed among participating SMEs. Three recurring implementation archetypes emerged:

- Analytics-Driven Adaptive SME : Firms that prioritized TU (cloud dashboards, AI-based forecasting) demonstrated early detection of declining product relevance and conducted structured product refinement cycles. These firms aligned strongly with positive TU and DDD coefficients identified in the structural model.
- Sustainability-Intensive but Structurally Unprepared SME : Several firms attempted rapid sustainability integration without establishing cost-monitoring analytics or KPI alignment. This often generated short-term financial pressure, reflecting the negative SIC coefficient observed in the structural model.
- Hyper-Responsive Reactive SME : SMEs that frequently modified product offerings in response to short-term market signals (e.g., social media trends) experienced inconsistent brand positioning, mirroring the negative MR relationship in the model.

- These structured implementation archetypes reinforce the predictive interpretation of the PLS-SEM findings and demonstrate that strategic effectiveness depends on governance sequencing rather than isolated capability adoption.

4.2. Practical Implementation Challenges in SMEs

Despite the benefits of data-driven and sustainability-oriented strategies, SMEs face implementation challenges such as financial constraints, limited digital infrastructure, managerial capability gaps, and fragmented data systems. Informal decision-making and the resource demands of sustainability integration further hinder effective execution, particularly in traditional sectors undergoing digital transformation. These barriers explain why strategic intent alone does not guarantee improved LTPMF, emphasizing the importance of phased digital adoption, capability development, KPI alignment, and external institutional support.

Importantly, these constraints are not temporary transitional barriers but structural characteristics inherent to many SMEs. Unlike large corporations that institutionalize innovation through formalized governance mechanisms, SMEs often operate through informal coordination and intuitive leadership structures. This structural informality increases variability in how data and sustainability initiatives are executed. As a result, the effectiveness of such strategies is contingent upon governance maturity and capability sequencing. This nuanced understanding enhances the originality of the proposed model by demonstrating that innovation success in SMEs is not solely strategy-dependent, but structure-dependent.

4.3. Translating the Model into Practical Implementation Phases

To enhance the applied value of the model, the structural relationships identified in this study are translated into a phased implementation framework for SMEs. Rather than adopting all strategic dimensions simultaneously, firms are encouraged to prioritize capability sequencing. The empirical findings indicate that TU and DDD should form the foundational layer, enabling the establishment of reliable information systems and structured analytics processes. Once this digital infrastructure is stabilized, customer feedback mechanisms can be formalized to support iterative product refinement. In the subsequent stage, sustainability-oriented innovation and MR may be strengthened through structured performance indicators, cost–benefit assessments, and strategic alignment mechanisms. This staged configuration reduces the risk of reactive or unsystematic implementation while allowing SMEs to gradually build adaptive capacity under resource constraints.

From academic and sustainability perspectives, this phased framework supports future longitudinal research while providing SMEs with a practical roadmap based on structured analytics, feedback integration, and governance alignment. The findings also highlight challenges in translating SDG 9 and SDG 12 into SME practice, indicating that sustainability outcomes require sufficient digital capability, governance readiness, and financial accessibility. Accordingly, the framework links strategic execution with broader sustainability objectives, demonstrating that LTPMF depends not only on strategic intent but also on systematic and staged capability integration.

4.4. Operational Model Translation for SME Practitioners

Based on empirical and contextual insights, the proposed framework can be translated into a practitioner-oriented operational cycle consisting of four stages:

- Stage 1 : Digital Foundation Formation: Establish structured data capture systems and basic analytics tools.
- Stage 2 : Data-Informed Product Alignment: Utilize dashboards and feedback integration systems for periodic product refinement.
- Stage 3 : Controlled Sustainability Integration: Introduce sustainability metrics gradually, supported by cost-efficiency monitoring tools.
- Stage 4 : Strategic Responsiveness Filtering: Implement market monitoring dashboards while maintaining brand positioning consistency rules.

This staged model illustrates how SMEs can incrementally operationalize the proposed framework, transforming abstract structural relationships into executable management routines.

5. MANAGERIAL IMPLICATIONS

The findings of this study provide several practical implications for SME managers seeking to strengthen LTPMF under resource constraints. First, the strong positive effects of TU and DDD indicate that SMEs should prioritize structured digital capability development rather than ad hoc technology adoption. Instead of investing immediately in complex systems, managers may begin with scalable cloud-based analytics tools, centralized data dashboards, and basic forecasting mechanisms to improve decision accuracy. Incremental digital adoption allows firms to build internal competencies while minimizing financial strain.

Second, the results suggest that CFI must be operationalized as a systematic process rather than an informal activity. SMEs can establish structured feedback loops through digital surveys, CRM systems, and post-purchase analytics to ensure that customer insights directly inform product refinement cycles. Managers should formalize data interpretation meetings and link feedback outcomes to measurable performance indicators. By embedding feedback into regular strategic reviews, firms can sustain iterative innovation without disrupting long-term positioning.

Third, the negative structural relationships observed for SIC and MR highlight the importance of governance and prioritization. Managers should avoid reactive product changes driven solely by short-term market fluctuations. Instead, responsiveness should be guided by validated data patterns and aligned with long-term brand architecture. Similarly, sustainability initiatives should be implemented using phased investment models supported by cost–benefit evaluation and digital monitoring systems. This prevents sustainability adoption from becoming operationally burdensome or symbolically driven.

Finally, SMEs facing limited financial and managerial resources should adopt a sequencing strategy in capability development. Rather than pursuing simultaneous digitalization and sustainability transformation, firms may first establish stable data governance foundations before integrating sustainability metrics into operational systems. Building internal digital literacy and managerial interpretation capacity is critical to ensuring that innovation initiatives translate into measurable competitiveness. By following a disciplined and phased implementation pathway, managers can convert data-driven strategies into durable market alignment while progressively contributing to sustainable production objectives.

6. CONCLUSION

This study examines how data-driven strategies and sustainability-oriented innovation influence LTPMF among SMEs using PLS-SEM analysis. The findings highlight that data-driven capabilities, particularly TU and DDD, serve as primary drivers of LTPMF, while the effectiveness of sustainability and responsiveness remains conditional. Without structured governance, adequate digital infrastructure, and strategic prioritization, sustainability initiatives and rapid responsiveness may generate operational strain or reactive decision-making patterns that ultimately weaken long-term positioning.

The results further highlight practical implementation challenges faced by SMEs, including managerial capability gaps, fragmented data systems, organizational resistance to transformation, and transitional costs associated with digital and sustainability upgrades. These realities demonstrate that strategic intent alone is insufficient to secure durable product–market fit. Accordingly, the proposed framework emphasizes systematic data governance, phased technology adoption, and structured sustainability metric integration as essential conditions for translating innovation initiatives into sustained competitiveness. By embedding contextual SME implementation insights within the quantitative structure, the study advances beyond methodological validation toward operational translation, positioning the model not merely as an explanatory framework but as an actionable strategic architecture for firms operating under structural constraints.

Beyond firm-level implications, the study connects SME innovation practices to broader development objectives, particularly SDG 9 and SDG 12. By promoting evidence-based decision-making, efficient resource utilization, and adaptive industrial capacity formation, data-informed innovation contributes to resilient industrial ecosystems and responsible production systems. By framing resource limitations as structural determinants of strategic effectiveness, the research advances theoretical discourse beyond linear capability–performance models and demonstrates that sustainable innovation success depends on organizational readiness and governance maturity. At the global level, the study operationalizes SDG ambitions within SME ecosystems, illustrating that sustainable industrialization and responsible production require digital capability formation, structured sequencing, and institutional support. Future research may extend this model by incorporating moderating variables such as digital maturity, institutional support mechanisms, and organizational learning across industries and regional contexts.

7. DECLARATIONS

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7.2. Author Contributions

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