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Sustainable Omnichannel Operations and Sustainable Performance: The Roles of Digital Innovation and Analytics Capabilities

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ABSTRACT

Purpose – This study examines the relationships between Sustainable Omnichannel Operations (SOO), Digital Innovation Capability (DIC), Business Data Analytics Capability (BDAC), and Sustainable Performance (SP) among Indonesian SMEs, with BDAC examined as a proposed intervening capability.
Design/methodology/approach – A quantitative explanatory survey was conducted with 331 SME owners, managers, and owner-managers from SMEs that used both online and offline sales channels. Data were analyzed using PLS-SEM with a disjoint two-stage approach for higher-order formative/composite constructs and a first-order formative/composite specification for DIC.
Findings/Results – In the primary model, SOO was positively associated with BDAC ($\beta = 0.644$, $p < 0.001$) and SP ($\beta = 0.910$, $p < 0.001$). However, a sensitivity analysis using a narrower SOO specification yielded an SOO–SP coefficient of approximately 0.287, indicating that the estimated magnitude depends on operationalization. DIC was positively associated with BDAC ($\beta = 0.308$, $p < 0.001$), but not with SP ($\beta = -0.019$, $p = 0.575$). BDAC was not significantly associated with SP ($\beta = 0.045$, $p = 0.490$). The indirect effects of SOO and DIC on SP through BDAC were also not statistically supported.
Originality/Value – The findings show that SOO is directly associated with sustainable performance, while the proposed indirect pathways through BDAC were not supported in the final model.

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1. Introduction

Digital transformation has reshaped how small and medium enterprises (SMEs) operate, interact with customers, and create value. Digital technology is increasingly used not only to replace manual activities but also to reshape business processes, customer relationships, product development, decision-making, and business models. Verhoef et al. (2021) argue that digital transformation involves broader changes in organizational strategy, structure, business models, and value creation, while Ciampi et al. (2022) emphasize that technology adoption needs to be accompanied by organizational capabilities that enable firms to adapt to changing environments. This issue is particularly relevant for SMEs because their limited financial, technological, and human resources mean that digital investment does not necessarily translate into business value. The use of marketplaces, social media, digital payments, and business applications may expand market access, but these technologies alone do not necessarily produce long-term sustainable business performance. Therefore, Sustainable Performance is considered more broadly by incorporating economic, environmental, and social dimensions of business sustainability. Previous studies have also highlighted the relationship between digitalization, innovation, and sustainability in SMEs (Melo et al., 2023; Avelar et al., 2024).

One organizational capability that is particularly relevant in this transformation is Sustainable Omnichannel Operations (SOO). SOO refers to the organizational capability to integrate and coordinate online and offline channels, improve operational efficiency, and reduce resource waste. In SMEs, omnichannel integration can support better coordination across sales and service channels, more efficient operations, and more sustainable resource utilization (Neslin et al., 2022; Gao & Huang, 2021; Sousa et al., 2021). However, the sustainability benefits of omnichannel operations depend not only on the availability of multiple channels but also on how effectively these channels are integrated and managed as part of overall business operations. Recent studies indicate that omnichannel practices can contribute to sustainability through improved supply chain efficiency, reduced operational duplication, and better resource allocation (Vhatkar et al., 2024; Khan et al., 2024).

Digital Innovation Capability (DIC) represents another relevant organizational capability in the context of digital transformation. DIC refers to the capability of SMEs to generate, develop, implement, and continuously improve digital innovations in products, services, processes, and business models. Digital innovation can enable SMEs to adapt to technological changes, develop new value propositions, and redesign business processes. However, digital innovation does not necessarily translate directly into Sustainable Performance because its outcomes may depend on how digital capabilities are integrated with organizational processes and decision-making. Another capability that may influence how digital resources are transformed into organizational value is Business Data Analytics Capability (BDAC). BDAC refers to the capability to acquire, integrate, analyze, and utilize business data from different sources to support decision-making and organizational performance. BDAC can help SMEs convert data into actionable information and support operational and strategic activities (Gupta & George, 2016; Akter et al., 2016; Wamba et al., 2017). Thus, the value of digitalization depends not merely on the availability of technologies but also on how effectively organizations integrate operations, process information, and use that information in decision-making.

Despite these developments, an important gap remains. Research on omnichannel operations has predominantly focused on customer experience, channel integration, and marketing

outcomes, while its role as an operational capability for sustainability has received comparatively less attention. At the same time, studies on digital innovation and BDAC have often examined these capabilities separately rather than explaining how they relate to Sustainable Performance within an integrated framework. Consequently, how digital operational integration and digital innovation relate to sustainable outcomes remains insufficiently explained. This gap is particularly relevant in Indonesian SMEs, where digital adoption is expanding but organizational capabilities for integrating channels, managing data, and using analytical information may differ substantially across businesses.

The present study addresses this gap by bringing Sustainable Omnichannel Operations, Digital Innovation Capability, Business Data Analytics Capability, and Sustainable Performance into a single analytical framework. BDAC is positioned as a proposed intervening capability, allowing the study to examine whether the benefits associated with digital operations and digital innovation are related to the organization's ability to convert business data into information that can support decision-making and performance. The framework is grounded in the complementary perspectives of the Resource-Based View, Dynamic Capability Theory, and Information Processing Theory. RBV views SOO, DIC, and BDAC as organizational capabilities that may create value when effectively developed and managed (Barney, 1991). Dynamic Capability Theory explains how SMEs adapt resources and processes through digital innovation, while Information Processing Theory explains why increasing digital complexity requires greater organizational capacity to process information (Galbraith, 1973).

The empirical results provide a more nuanced understanding of these relationships. SOO was positively and significantly associated with Sustainable Performance, whereas DIC was not significantly associated with Sustainable Performance. Both SOO and DIC were positively and significantly associated with BDAC, but BDAC was not significantly associated with Sustainable Performance. Consequently, the indirect effects of SOO and DIC on Sustainable Performance through BDAC were not statistically significant. These findings indicate that BDAC is relevant as an organizational capability for managing and utilizing information generated by digital activities, but its role in linking digital capabilities to Sustainable Performance is not empirically supported in the present model. Because the study uses cross-sectional survey data, these relationships are interpreted as statistical associations rather than evidence of temporal or causal mechanisms.

Accordingly, this study aims to examine the relationships of Sustainable Omnichannel Operations and Digital Innovation Capability with Sustainable Performance and to examine the proposed intervening role of Business Data Analytics Capability among Indonesian SMEs. The study contributes to the literature in two ways. First, it extends the omnichannel literature by examining channel integration from an operational sustainability perspective rather than focusing primarily on customer experience. Second, it examines the proposed role of BDAC as an intervening capability in the relationships between digital capabilities and Sustainable Performance. The empirical analysis is based on survey data from 331 SME owners, managers, and owner-managers in Indonesia who use both online and offline sales channels and are directly involved in digital and operational activities.

2. Literature Review and Hypothesis Development

2.1 Resource-Based View

The Resource-Based View (RBV) explains that firms may create competitive advantage by developing and managing valuable organizational resources and capabilities (Barney, 1991). In this study, SOO, DIC, and Business Data Analytics Capability are treated as organizational capabilities that may help SMEs respond to changes in their business environment. SOO coordinates online and offline activities, DIC supports digital innovation, and BDAC captures routines for turning business data into information for decision-making. Gupta and George (2016) conceptualize big data analytics capability through combinations of tangible, human, and intangible resources. Their framework provides a broad capability perspective, but it is not identical to the nine business-data items used in the present study. We therefore use it as conceptual background rather than claiming that our indicators reproduce their validated scale.

2.2 Dynamic Capability Theory

Dynamic Capability Theory explains how firms integrate, develop, and reconfigure resources and capabilities to respond to changing environmental conditions (Teece et al., 1997). This perspective is relevant to DIC because digital innovation requires SMEs to continuously adapt products, services, processes, and business models. It is also relevant to SOO because coordinating online and offline channels requires adjustments in operational processes and information flows. Therefore, DIC and SOO can be viewed as capabilities through which SMEs adapt their resources and operations to changing digital and market conditions.

2.3 Information Processing Theory

Information Processing Theory (IPT) argues that environmental complexity increases organizations' requirements to acquire, process, and use information (Galbraith, 1973). This perspective is relevant to SMEs using both online and offline sales channels. SOO may generate information from transactions, customers, inventory, orders, payments, and distribution, while DIC may expand information sources through digital activities. Business Data Analytics Capability represents organizational routines for collecting, integrating, analyzing, and applying such information. IPT therefore provides a theoretical basis for examining the relationships of SOO and DIC with BDAC, without assuming that the data necessarily meet technical definitions of big data.

2.4 Sustainable Omnichannel Operations and Sustainable Performance

Sustainable Omnichannel Operations refers to the ability of SMEs to coordinate online and offline activities within an integrated operational system while improving efficiency and responsible resource utilization. Integration of sales, inventory, customer information, ordering, payment, and delivery can reduce operational duplication and improve resource utilization. Previous studies associate omnichannel integration with operational and supply-chain efficiency and sustainability outcomes (Sousa et al., 2021; Vhatkar et al., 2024; Khan et al., 2024). Therefore, stronger SOO is expected to be associated with higher Sustainable Performance.

Although Sustainable Omnichannel Operations (SOO) and Sustainable Performance (SP) represent conceptually different constructs, some aspects of their operational content may be closely related. SOO focuses on the coordination of online and offline business activities, including operational efficiency and resource utilization, whereas SP represents the economic, environmental, and social outcomes of business activities. Because operational efficiency and resource utilization may also contribute to sustainability outcomes, potential

conceptual proximity between the constructs should be considered when interpreting their empirical relationship.

H1: Sustainable Omnichannel Operations has a positive effect on Sustainable Performance.

2.5 Digital Innovation Capability and Sustainable Performance

Digital Innovation Capability represents the ability of SMEs to develop and implement digital innovations in products, services, processes, and business models. Such capability can support adaptation to technological and market changes and may improve the efficiency of business activities. Previous studies associate digitalization and innovation capability with SME development and sustainability (Ciampi et al., 2022; Hassan et al., 2024; Avelar et al., 2024). Therefore, stronger DIC is expected to be associated with higher Sustainable Performance.

H2: Digital Innovation Capability has a positive effect on Sustainable Performance.

2.6 Sustainable Omnichannel Operations and Business Data Analytics Capability

Integrated online and offline operations generate business information from transactions, customers, inventory, payments, marketing, and distribution. Information Processing Theory suggests that organizations need sufficient capacity to acquire, process, and use information as information requirements increase (Galbraith, 1973). Business Data Analytics Capability (BDAC), as operationalized in this study, represents organizational practices used to collect, integrate, analyze, and apply business data. SMEs with more coordinated omnichannel operations may therefore have stronger routines for handling and using business information. This argument concerns general business-data analytics practices; it does not assume that all sampled SMEs use advanced big-data infrastructure.

H3: Sustainable Omnichannel Operations is positively associated with Business Data Analytics Capability.

2.7 Digital Innovation Capability and Business Data Analytics Capability

Digital innovation can create additional business information through digital products, services, customer interactions, marketing activities, and redesigned business processes. As these activities expand, SMEs may need stronger routines for organizing, analyzing, and using the resulting information. The resource-based view treats these routines, together with relevant human and organizational resources, as capabilities that may support the use of data in business decisions (Barney, 1991; Gupta & George, 2016). In this study, BDAC refers to general business-data analytics practices rather than a verified capability to process data with the volume, velocity, variety, or technical complexity associated with advanced big-data systems.

H4: Digital Innovation Capability is positively associated with Business Data Analytics Capability.

2.8 Business Data Analytics Capability and Sustainable Performance

Business Data Analytics Capability captures how SMEs collect, integrate, analyze, and use business data to inform operational and strategic decisions. Such practices may support resource allocation, operational efficiency, customer service, and responses to business conditions. Prior research on analytics capabilities provides a broad theoretical rationale for examining links between organizational data-related resources and performance (Gupta & George, 2016; Wamba et al., 2017). However, the present instrument does not directly measure advanced big-data infrastructure or the technical characteristics of big data. Accordingly, the hypothesis is framed in terms of business-data analytics capability.

H5: Business Data Analytics Capability is positively associated with Sustainable Performance.

2.9 Business Data Analytics Capability as a Proposed Intervening Capability

The proposed intervening role of Business Data Analytics Capability is based on the view that digital capabilities may be associated with organizational outcomes when business data are converted into useful information for decision-making. SOO generates information through coordinated operational activities, while DIC may expand information sources through digital innovation. BDAC may therefore represent a set of organizational routines for processing and using business information. Because the present study uses cross-sectional data, the proposed intervening relationships are examined as statistical indirect associations rather than evidence of a temporal causal mechanism.

2.10 Business Data Analytics Capability as a Mediating Mechanism

Sustainable Omnichannel Operations (SOO) can generate information from multiple business channels, including customer interactions, sales transactions, inventory movements, and service activities. However, the availability of such information does not automatically translate into improved Sustainable Performance (SP). SMEs need the capability to collect, integrate, analyze, and utilize business data to convert information generated by omnichannel operations into actionable insights. From the Information Processing Theory perspective, Business Data Analytics Capability (BDAC) represents an organizational capability that supports the processing and interpretation of business information for operational and strategic decision-making. Through this capability, SMEs may identify operational inefficiencies, respond to customer needs, allocate resources more effectively, and support decisions related to economic, environmental, and social performance. Therefore, BDAC may serve as an intervening mechanism through which SOO contributes to SP. Accordingly, the following hypothesis is proposed:

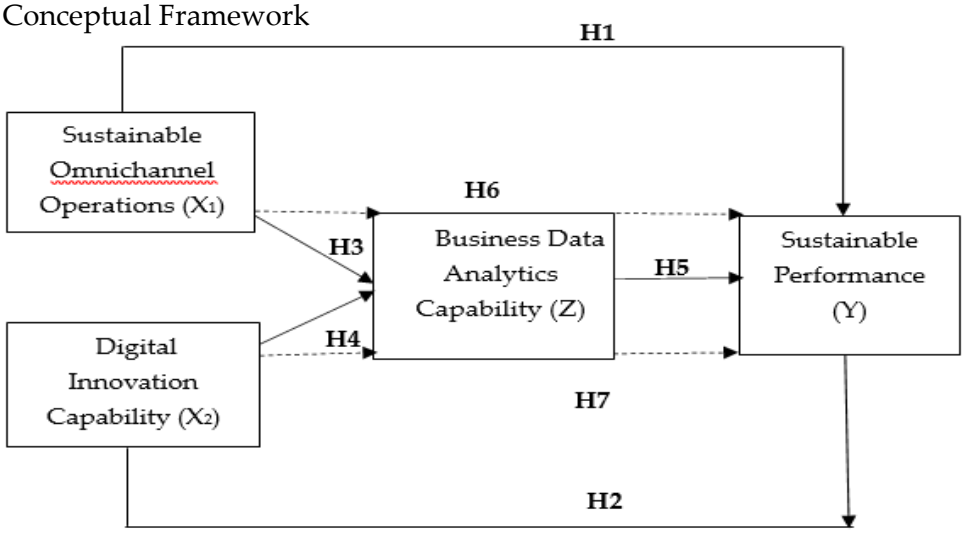
H6: Business Data Analytics Capability mediates the relationship between Sustainable Omnichannel Operations and Sustainable Performance.

2.11 Business Data Analytics Capability as a Mediating Mechanism between Digital Innovation Capability and Sustainable Performance

Digital Innovation Capability (DIC) enables SMEs to develop and implement digital solutions in their products, services, business processes, and business models. These innovations can generate new business information and opportunities to improve performance. Nevertheless, the contribution of digital innovation to Sustainable Performance (SP) may depend on whether SMEs can effectively interpret and use the information associated with their digital activities. Business Data Analytics Capability (BDAC) can support this process by enabling SMEs to organize, analyze, and utilize business data in operational and strategic decisions. Consistent with Information Processing Theory, digital innovation may increase the availability of information, while BDAC helps SMEs process that information and translate it into decisions that support economic, environmental, and social objectives. Accordingly, BDAC may act as an intervening mechanism through which DIC contributes to SP. The following hypothesis is therefore proposed:

H7: Business Data Analytics Capability mediates the relationship between Digital Innovation Capability and Sustainable Performance.

Figure 1. Conceptual Framework



3. Methodology

3.1 Research Design

This study employed a quantitative explanatory research design using survey data to examine the relationships among Sustainable Omnichannel Operations (SOO), Digital Innovation Capability (DIC), Business Data Analytics Capability (BDAC), and Sustainable Performance (SP) among Indonesian SMEs. The study focused on SMEs that actively used both online and offline sales channels and on respondents who had direct knowledge of their business operations, digital activities, and organizational performance. Data were collected in February 2026.

The empirical model was estimated using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS. The analysis treated SOO, DIC, BDAC, and SP as composite/formative constructs rather than assuming that all indicators were interchangeable reflective manifestations of a single underlying trait. The multidimensional constructs were specified through lower-order components and estimated using a disjoint two-stage approach. In Stage 1, conceptually distinct lower-order components were estimated from the relevant indicators. In Stage 2, these component scores were used to construct the higher-order composite representations of SOO, BDAC, and SP, while DIC was specified as a first-order formative construct.

For conceptual precision, the construct previously labelled Big Data Analytics Capability is referred to in this revision as Business Data Analytics Capability (BDAC). The nine questionnaire items assess data collection, integration, routine analysis of transaction/customer data, use of analytical results in decisions, employee capability, management support, timely business information, and performance evaluation. These items do not directly assess data volume, velocity, variety, or advanced big-data technologies. The four component labels—Data Acquisition and Integration (DAI), Analytics and Data Use (ADU), Organizational Analytics Support (OAS), and Information and Performance Use (IPU)—are study-specific groupings of the questionnaire items, not dimensions claimed to have been reproduced verbatim from Wamba et al. (2017) or Falahat et al. (2023). The construct is estimated using the same composite/formative specification and the same data as in the prior model.

The structural model examined the direct relationships of SOO and DIC with BDAC and SP, as well as the relationship between BDAC and SP. The hypothesized indirect effects of SOO and DIC on SP through BDAC were tested using bootstrapping. Predictive relevance was additionally assessed using PLSpredict. Because the study used cross-sectional, self-reported survey data collected from the same respondents, the statistical mediation results were interpreted as evidence concerning indirect associations rather than as proof of a temporal or causal mediation mechanism.

3.2 Population and Sampling

The population of the study consisted of SMEs actively operating in Indonesia. A purposive sampling approach was used because the study required respondents with specific characteristics relevant to the research model. Three inclusion criteria were applied: (1) the SME was actively operating in Indonesia; (2) the SME used at least one online sales channel and one offline sales channel in its business activities; and (3) the respondent had direct knowledge of the business operations, digital activities, and overall business condition, such as an owner, owner-manager, or manager. A total of 331 valid responses met these criteria and were included in the analysis. Data were collected in February 2026.

The use of both online and offline sales channels was defined as an eligibility characteristic rather than as evidence of a uniform level of omnichannel capability. The extent to which these channels were coordinated and integrated was measured through the Sustainable Omnichannel Operations (SOO) construct. This distinction was maintained to avoid assuming that all sampled SMEs had the same degree of omnichannel integration.

Because the study used purposive rather than probability-based sampling, the sample was not intended to provide statistically representative estimates for all Indonesian SMEs. The findings should therefore be interpreted as empirical evidence from purposively sampled SMEs that use both online and offline sales channels. The observed sector and business-age variation provides contextual diversity within the sample, but it does not eliminate the limitations associated with non-probability sampling.

3.3 Characteristics of the Sample

Table 1 summarizes respondent roles, business sectors, business age, employment size, sales channels, and duration of digital channel adoption for the 331 sampled SMEs.

Table 1. Characteristics of the Sampled SMEs and Respondents

Category	Subcategory	Frequenc	Percentage
Role in the Business	Owner	133	40.1%
	Manager	24	7.3%
	Owner–Manager	174	52.6%
Type of Business	Culinary	195	58.9%
	Fashion and Accessories	50	15.1%
	Retail	30	9.1%
	Services	31	9.4%
	Handicrafts	15	4.5%
	Other	10	3.0%
Business Age	< 1 year	23	6.9%
	1–3 years	122	36.9%
	4–6 years	120	36.3%
	> 6 years	66	19.9%

Number of Employees	< 5 employees	208	62.8%
	5–10 employees	95	28.7%
	11–20 employees	18	5.4%
	> 20 employees	10	3.0%
Sales Channels Used	Physical Stores	301	90.7%
	Marketplaces (e.g., Shopee, Tokopedia)	205	61.9%
	Social Media (e.g., Instagram, WhatsApp, TikTok)	235	71.0%
	Own Website or Application	53	16.0%
Duration of Digital Channel Adoption	< 1 year	34	10.3%
	1 – 3 years	164	49.5%
	4 – 6 years	106	32.0%
	> 6 years	27	8.2%
Total Respondents		331	100%

Note: Sales channel categories are multiple-response items; therefore, percentages do not sum to 100%.

3.4 Measurement of Constructs

The measurement architecture was specified according to the conceptual dimensionality of each construct. Sustainable Omnichannel Operations (SOO), Business Data Analytics Capability (BDAC), and Sustainable Performance (SP) were specified as higher-order formative/composite constructs and assessed using a disjoint two-stage approach. In Stage 1, the relevant lower-order components were estimated from their assigned indicators. In Stage 2, the component scores were used as formative/composite indicators of the corresponding higher-order constructs. DIC was specified directly as a first-order formative/composite construct. This specification reflects the view that the components contribute distinct content to the broader composite rather than acting as interchangeable reflective manifestations.

For SOO, the higher-order construct comprised Omnichannel Integration (OI), Operational Efficiency (OE), and Sustainable Resource Utilization (SRU). BDAC comprised Data Acquisition and Integration (DAI), Analytics and Data Use (ADU), Organizational Analytics Support (OAS), and Information and Performance Use (IPU). SP comprised the Economic, Environmental, and Social dimensions. These components were retained to represent the multidimensional content of each construct.

Table 2. Operational Definitions and Measurement of Constructs

Construct	Operational Definition	Measurement Components / Indicators	Measurement Specification	Main References
Sustainable Omnichannel Operations (SOO)	The capability of SMEs to integrate online and offline business activities into a coordinated operational system that improves customer service,	Omnichannel Integration (OI): SOO1-SOO5; Operational Efficiency (OE): SOO6; Sustainable Resource Utilization (SRU): SOO7	Higher-order formative/composite; OI, OE, and SRU → SOO	Khan et al. (2024)

Construct	Operational Definition	Measurement Components / Indicators	Measurement Specification	Main References
	operational efficiency, and sustainable resource utilization.			
Digital Innovation Capability (DIC)	The organizational capability of SMEs to utilize digital technologies, knowledge, and resources to generate, develop, implement, and continuously improve innovative products, services, business processes, and business models in response to changing customer needs and market conditions.	DIC1: digital idea generation; DIC2: digital technology utilization; DIC3: digital product/service innovation; DIC4: digital process innovation; DIC5: digital business model innovation; DIC6: digital innovation implementation; DIC7: continuous digital innovation	First-order formative/composite; DIC1–DIC7 → DIC	Kroh et al. (2024); Ciampi et al. (2022); Hassan et al. (2024)
Business Data Analytics Capability (BDAC)	The organizational routines of SMEs for collecting, integrating, analyzing, interpreting, and using business data to support operational and strategic decisions and performance evaluation. This operationalization does not directly measure advanced big-data infrastructure or data volume, velocity, variety, or	Data Acquisition and Integration (DAI): BDAC1–BDAC2; Analytics and Data Use (ADU): BDAC3–BDAC5; Organizational Analytics Support (OAS): BDAC6–BDAC7; Information and Performance Use (IPU): BDAC8–BDAC9	Higher-order formative/composite; DAI, ADU, OAS, and IPU → BDAC	Gupta & George (2016); Wamba et al. (2017); Falahat et al. (2023), as conceptual background ; item groupings are study-specific.

Construct	Operational Definition	Measurement Components / Indicators	Measurement Specification	Main References
	complexity.			
Sustainable Performance (SP)	The extent to which SMEs achieve economic, environmental, and social objectives simultaneously to maintain long-term business sustainability.	Economic: SP1-SP3; Environmental: SP4-SP6; Social: SP7	Higher-order formative/composite; Economic, Environmental, and Social → SP	Giang & Dung (2025); Khan et al. (2024)

3.5 Data Analysis

The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS. The analysis followed the final formative/composite specification of the research model and was conducted using a disjoint two-stage approach for the higher-order constructs.

In Stage 1, the lower-order components of Sustainable Omnichannel Operations (SOO), Business Data Analytics Capability (BDAC), and Sustainable Performance (SP) were estimated from their respective indicators. The resulting lower-order component scores were then used as indicators of the corresponding higher-order constructs in Stage 2. Digital Innovation Capability (DIC) was specified directly as a first-order formative/composite construct using its seven indicators.

In Stage 2, the formative/composite specifications were assessed by examining indicator or component weights, their statistical significance, indicator loadings, and variance inflation factors (VIF). Indicators or components were retained based on a combination of statistical evidence and conceptual relevance. In particular, a nonsignificant formative weight was not treated as an automatic basis for deletion when the indicator contributed conceptually distinct content to the construct and showed acceptable collinearity and loading evidence.

The model was estimated in SmartPLS 3. Significance testing used 5,000 bootstrap subsamples. The SmartPLS export provided percentile and bias-corrected and accelerated (BCa) confidence intervals; percentile 95% confidence intervals are reported in the sensitivity-analysis table to maintain consistency across the compared specifications. The available export identifies the major software version as SmartPLS 3 but does not establish the exact point release.

The structural model was subsequently evaluated by examining the path coefficients, bootstrapping-based t-statistics, p-values, and confidence intervals. The coefficients of determination (R^2) were used to assess the explained variance of the endogenous constructs. Inner VIF values were examined to assess collinearity among the structural predictors.

The indirect effects of SOO and DIC on SP through BDAC were assessed using bootstrapping. Because the data were collected cross-sectionally from the same respondents, the indirect effects were interpreted as statistical mediation or indirect associations rather than evidence of a temporally established causal mechanism.

Predictive relevance was additionally assessed using PLSpredict. The assessment considered Q^2_predict values and the comparison of prediction errors between the PLS-SEM model and the linear benchmark model. The interpretation therefore distinguished predictive relevance from predictive superiority over the benchmark model.

3.6 Common-Method Bias Assessment

Because this study used cross-sectional, self-reported questionnaire data collected from the same key informants, common-method bias (CMB) was considered a potential methodological concern. To help reduce potential response bias, respondents were assured that their answers would be kept confidential and were informed that there were no right or wrong answers. The questionnaire items were arranged with the intention of encouraging respondents to provide answers reflecting their actual business conditions and experiences.

As a statistical diagnostic, Harman's single-factor test was conducted using an unrotated principal component analysis of the 30 questionnaire items. The first component accounted for 39.36% of the total variance, below the conventional 50% screening threshold. However, this result does not establish that CMB is absent.

An additional full-collinearity assessment was conducted using the final latent variable scores exported from the primary Model A SmartPLS results. Each construct score was regressed on the other three construct scores, and the corresponding VIF was calculated as $1/(1 - R^2)$. The resulting VIF values were 4.897 for Business Data Analytics Capability (BDAC), 2.537 for Digital Innovation Capability (DIC), 10.785 for Sustainable Omnichannel Operations (SOO), and 8.070 for Sustainable Performance (SP). This supplementary calculation was performed using the exported construct scores rather than reported as native SmartPLS full-collinearity output.

Using the commonly applied 3.3 screening threshold, the VIF values for BDAC, SOO, and SP warrant concern, whereas the value for DIC is below the threshold. These findings do not establish that CMB is present, because high VIF values may also reflect substantive relationships and conceptual proximity among constructs. Nevertheless, CMB cannot be ruled out, and the estimated structural relationships should be interpreted with appropriate caution.

3.7 Research Ethics and Informed Consent

The study received approval from the Research Ethics Committee of Universitas Budi Darma. Before respondents completed the questionnaire, the Google Form presented a consent statement explaining that they agreed to provide information by completing the survey. Respondents indicated their agreement through the form before proceeding to the questionnaire. Participation was voluntary, and responses were treated confidentially. Because the questionnaire collected identifying details, including respondent and business names, the data should not be described as anonymous.

4. Results and Discussion

4.1 Measurement Model Assessment

The measurement model was assessed according to the final formative/composite specification of the research model. Sustainable Omnichannel Operations (SOO), Business Data Analytics Capability (BDAC), and Sustainable Performance (SP) were specified as higher-order formative/composite constructs, while Digital Innovation Capability (DIC) was specified as a first-order formative/composite construct. The higher-order constructs were

estimated using a disjoint two-stage approach. In Stage 1, the lower-order components were specified and estimated from their respective indicators. In Stage 2, the resulting lower-order component scores were used as formative/composite indicators of the corresponding higher-order constructs. This procedure was used to represent the multidimensional nature of SOO, BDAC, and SP without assuming that all indicators were interchangeable reflective manifestations of a single underlying construct.

4.1.1 Stage 1: Lower-Order Component Assessment

In Stage 1, the indicators were organized into conceptually distinct lower-order components according to the measurement structure defined for each construct. For SOO, five indicators (SOO1–SOO5) represented Omnichannel Integration (OI), while SOO6 represented Operational Efficiency (OE) and SOO7 represented Sustainable Resource Utilization (SRU). For BDAC, BDAC1–BDAC2 represented Data Acquisition and Integration (DAI), BDAC3–BDAC5 represented Analytics and Data Use (ADU), BDAC6–BDAC7 represented Organizational Analytics Support (OAS), and BDAC8–BDAC9 represented Information and Performance Use (IPU). For SP, SP1–SP3 represented the Economic dimension, SP4–SP6 represented the Environmental dimension, and SP7 represented the Social dimension. The operational definitions and indicator groupings follow the measurement structure established for the study.

The purpose of Stage 1 was to obtain empirically estimated scores for these lower-order components before constructing the corresponding higher-order composites. The lower-order components were therefore treated as building blocks of the broader SOO, BDAC, and SP constructs rather than as separate structural predictors in the final research model. Because the final analysis adopted a disjoint two-stage approach, the Stage 1 component scores were subsequently transferred to Stage 2 for the estimation of the higher-order formative/composite constructs.

Table 3. Stage 1 Lower-Order Component Specification

Higher-Order Construct	Lower-Order Component	Indicators
SOO	Omnichannel Integration (OI)	SOO1–SOO5
SOO	Operational Efficiency (OE)	SOO6
SOO	Sustainable Resource Utilization (SRU)	SOO7
BDAC	Data Acquisition and Integration (DAI)	BDAC1–BDAC2
BDAC	Analytics and Data Use (ADU)	BDAC3–BDAC5
BDAC	Organizational Analytics Support (OAS)	BDAC6–BDAC7
BDAC	Information and Performance Use (IPU)	BDAC8–BDAC9
SP	Economic	SP1–SP3
SP	Environmental	SP4–SP6
SP	Social	SP7

Note: DIC was not included in the Stage 1 higher-order specification because it was modeled directly as a first-order formative/composite construct.

4.1.2 Stage 2: Higher-Order Formative/Composite Assessment

In Stage 2, the lower-order component scores obtained from Stage 1 were used as formative/composite indicators of the corresponding higher-order constructs. The assessment focused on component weights, indicator loadings, and collinearity. Component retention was determined by considering both statistical evidence and the conceptual contribution of each component to the broader construct. Therefore, a nonsignificant

formative weight was not treated as an automatic basis for removing a component when the loading was statistically significant and the component represented conceptually distinct content.

For SOO, the three lower-order components-OI, OE, and SRU-were retained in the final model. OE had a weight of 0.098 ($p = 0.007$) and a loading of 0.598 ($p < 0.001$). OI had a weight of 0.172 ($p = 0.002$) and a loading of 0.777 ($p < 0.001$). SRU had the largest weight, 0.820 ($p < 0.001$), with a loading of 0.985 ($p < 0.001$). These results indicate that all three components contributed to the composite representation of SOO, with SRU showing the largest relative contribution in the final model. Component-level VIFs calculated from the final Stage 2 component scores ($N = 331$) were 1.569 for OE, 2.552 for OI, and 2.181 for SRU.

For BDAC, the four lower-order components-DAI, ADU, OAS, and IPU-were retained. DAI had a weight of 0.663 ($p < 0.001$) and a loading of 0.962 ($p < 0.001$). ADU had a weight of 0.132 ($p = 0.010$) and a loading of 0.776 ($p < 0.001$). OAS had a weight of 0.163 ($p = 0.001$) and a loading of 0.770 ($p < 0.001$), while IPU had a weight of 0.167 ($p = 0.005$) and a loading of 0.806 ($p < 0.001$). The results support the representation of BDAC as a multidimensional composite in which the four components jointly contribute to the higher-order construct. The corresponding component VIFs were 2.463 for DAI, 2.822 for ADU, 2.110 for OAS, and 2.853 for IPU.

For SP, the Economic, Environmental, and Social dimensions were retained. The Economic component had a weight of 0.085 ($p = 0.019$) and a loading of 0.529 ($p < 0.001$). The Environmental component had a weight of 0.077 ($p = 0.066$) and a loading of 0.700 ($p < 0.001$). Although the Environmental weight was not statistically significant, the component was retained because its loading was statistically significant and it represents a conceptually distinct dimension of sustainable performance. The Social component had the largest contribution, with a weight of 0.907 ($p < 0.001$) and a loading of 0.994 ($p < 0.001$). Component VIFs were 1.387 for Economic, 1.866 for Environmental, and 1.757 for Social.

Table 4. Stage 2 Higher-Order Formative/Composite Assessment

Higher-Order Construct	Component	Weight	p-value	Loading	Loading p-value	Component VIF
SOO	OE	0.098	0.007	0.598	<0.001	1.569
	OI	0.172	0.002	0.777	<0.001	2.552
	SRU	0.820	<0.001	0.985	<0.001	2.181
BDAC	DAI	0.663	<0.001	0.962	<0.001	2.463
	ADU	0.132	0.010	0.776	<0.001	2.822
	OAS	0.163	0.001	0.770	<0.001	2.110
	IPU	0.167	0.005	0.806	<0.001	2.853
SP	Economic	0.085	0.019	0.529	<0.001	1.387

Higher-Order Construct	Component	Weight	p-value	Loading	Loading p-value	Component VIF
	Environmental	0.077	0.066	0.700	<0.001	1.866
	Social	0.907	<0.001	0.994	<0.001	1.757

DIC Formative Indicator Assessment

Digital Innovation Capability (DIC) was modeled as a first-order formative/composite construct because its seven indicators represent complementary aspects of digital innovation capability. The indicators jointly contribute to the construct rather than serving as interchangeable manifestations of a single latent trait. The formative indicator assessment considered the estimated weights, their statistical significance, outer loadings, and variance inflation factors (VIF).

The formative weights ranged from 0.055 to 0.418, while the outer loadings ranged from 0.380 to 0.772. All seven outer loadings were statistically significant ($p < 0.001$). The indicator-level VIF values ranged from 1.142 to 1.390, indicating no indication of problematic collinearity among the DIC indicators.

DIC1 (weight = 0.055, p = 0.339) and DIC3 (weight = 0.085, p = 0.105) had nonsignificant formative weights. However, their outer loadings were statistically significant. These indicators were retained cautiously to preserve the conceptual coverage of digital innovation capability. Their relatively low loading values, particularly for DIC1 and DIC3, nevertheless warrant careful interpretation. The decision to retain them reflects the combined consideration of statistical evidence and conceptual relevance, rather than formative-weight significance alone. Future studies should further validate the content and dimensional structure of the DIC measure.

Table 5. Formative Indicator Assessment of Digital Innovation Capability (DIC)

Indicator	Formative weight	p-value (weight)	Outer loading	p-value (loading)	VIF
DIC1	0.055	0.339	0.380	<0.001	1.142
DIC2	0.141	0.011	0.526	<0.001	1.228
DIC3	0.085	0.105	0.440	<0.001	1.241
DIC4	0.173	<0.001	0.616	<0.001	1.331
DIC5	0.367	<0.001	0.693	<0.001	1.240
DIC6	0.285	<0.001	0.647	<0.001	1.368
DIC7	0.418	<0.001	0.772	<0.001	1.390

Note. VIF = variance inflation factor. Higher-order component VIFs were calculated from the final Stage 2 component scores (N = 331); they were not copied from a native SmartPLS higher-order VIF table. DIC indicator-level VIFs are reported separately in Table 5.

4.2 Structural Model Assessment

Following the assessment of the formative/composite measurement specifications, the structural model was evaluated to examine the relationships among Sustainable Omnichannel Operations (SOO), Digital Innovation Capability (DIC), Business Data

Analytics Capability (BDAC), and Sustainable Performance (SP). The assessment focused on the estimated path coefficients, bootstrapped t-statistics and p-values, coefficients of determination (R^2), and inner variance inflation factors (VIF).

The results show that SOO had a positive and statistically significant relationship with BDAC ($\beta = 0.644$, $t = 12.237$, $p < 0.001$). This result indicates that higher levels of sustainable omnichannel operations were associated with higher levels of business data analytics capability among the sampled SMEs.

DIC also showed a positive and statistically significant relationship with BDAC ($\beta = 0.308$, $t = 5.360$, $p < 0.001$). This finding indicates that digital innovation capability was positively associated with the development of business data analytics capability.

In contrast, BDAC did not show a statistically significant relationship with SP ($\beta = 0.045$, $t = 0.690$, $p = 0.490$). Although the estimated coefficient was positive, the statistical evidence did not indicate a significant direct relationship between BDAC and sustainable performance in the final model.

SOO showed a positive and statistically significant relationship with SP ($\beta = 0.9105$, $t = 13.609$, $p < 0.001$; percentile 95% CI [0.7625, 1.0220]). This represents the largest estimated direct path in the primary Model A, but its magnitude is sensitive to the operationalization of SOO, as shown in the sensitivity analysis.

Meanwhile, DIC did not show a statistically significant relationship with SP ($\beta = -0.019$, $t = 0.560$, $p = 0.575$). The estimated coefficient was close to zero, and the statistical evidence did not support a direct relationship between digital innovation capability and sustainable performance in the final model.

Table 6. Structural Model Results

Relationship	β	t-statistic	p-value	Result
SOO → BDAC	0.644	12.237	<0.001	Positive and significant
DIC → BDAC	0.308	5.360	<0.001	Positive and significant
BDAC → SP	0.045	0.690	0.490	Not significant
SOO → SP	0.910	13.609	<0.001	Positive and significant
DIC → SP	-0.019	0.560	0.575	Not significant

Explained Variance

The explanatory power of the structural model was assessed using the coefficient of determination (R^2). BDAC obtained an R^2 value of 0.795 and an adjusted R^2 of 0.794, indicating that the predictors included in the BDAC equation accounted for 79.5% of the observed variance in BDAC.

For SP, the R^2 value was 0.876 and the adjusted R^2 was 0.875. Thus, the predictors in the SP equation accounted for 87.6% of the observed variance in sustainable performance within the estimated model.

Table 7. Coefficient of Determination

Endogenous Construct	R^2	Adjusted R^2
BDAC	0.795	0.794
SP	0.876	0.875

Collinearity Assessment

Collinearity among the structural predictors was assessed using inner VIF values. For the BDAC equation, the VIF values for SOO and DIC were both 2.071. For the SP equation, the VIF values were 2.534 for DIC, 4.096 for SOO, and 4.880 for BDAC.

These values show that collinearity was explicitly assessed in both endogenous equations and did not prevent estimation of the final structural model.

Table 8. Inner VIF Values

Endogenous Construct	Predictor	Inner VIF
BDAC	SOO	2.071
BDAC	DIC	2.071
SP	DIC	2.534
SP	SOO	4.096
SP	BDAC	4.880

4.3 Hypothesis Testing

The hypothesis testing results were evaluated based on the structural path coefficients, bootstrapped t-statistics, and p-values obtained from the final Stage 2 formative/composite model. The results are presented in Table 9.

Table 9. Results of Direct Hypothesis Testing

Hypothesis	Relationship	β	t-statistic	p-value	Decision
H1	Sustainable Omnichannel Operations → Sustainable Performance	0.910	13.609	< 0.001	Supported
H2	Digital Innovation Capability → Sustainable Performance	-0.019	0.560	0.575	Not supported
H3	Sustainable Omnichannel Operations → Business Data Analytics Capability	0.644	12.237	< 0.001	Supported
H4	Digital Innovation Capability → Business Data Analytics Capability	0.308	5.360	< 0.001	Supported
H5	Business Data Analytics Capability → Sustainable Performance	0.045	0.690	0.490	Not supported

Note: Decisions are based on the statistical significance of the bootstrapped path coefficients in the final Stage 2 formative/composite model.

The results indicate that H1 was supported in the primary Model A. Sustainable Omnichannel Operations showed a positive and statistically significant relationship with Sustainable Performance (β = 0.9105, t = 13.609, p < 0.001; percentile 95% CI [0.7625, 1.0220]). The sensitivity analysis nevertheless shows that the estimated magnitude is not invariant across alternative operationalizations of SOO.

H2 was not supported. Digital Innovation Capability showed a negative but statistically insignificant relationship with Sustainable Performance (β = -0.019, t = 0.560, p = 0.575). The coefficient was close to zero, and the statistical evidence did not support the hypothesized positive relationship between Digital Innovation Capability and Sustainable Performance in the final model. **H3** was supported. Sustainable Omnichannel Operations had a positive and statistically significant relationship with Business Data Analytics Capability (β = 0.644, t = 12.237, p < 0.001). This result indicates that SMEs with higher levels of Sustainable Omnichannel Operations also tended to report higher levels of Business Data Analytics Capability.

H4 was also supported. Digital Innovation Capability showed a positive and statistically significant relationship with Business Data Analytics Capability (β = 0.308, t = 5.360, p <

0.001). The finding indicates that stronger Digital Innovation Capability was associated with higher Business Data Analytics Capability among the sampled SMEs.

Finally, **H5** was not supported. Business Data Analytics Capability did not show a statistically significant relationship with Sustainable Performance (β = 0.045, t = 0.690, p = 0.490). Although the estimated coefficient was positive, the statistical evidence was insufficient to support the hypothesized direct relationship between Business Data Analytics Capability and Sustainable Performance.

Overall, three of the five direct hypotheses (H1, H3, and H4) were supported, whereas H2 and H5 were not supported. The results show that Sustainable Omnichannel Operations was significantly associated with both Business Data Analytics Capability and Sustainable Performance, while Digital Innovation Capability was significantly associated with Business Data Analytics Capability but not directly with Sustainable Performance. Business Data Analytics Capability itself did not demonstrate a statistically significant direct association with Sustainable Performance. The implications of these findings for the proposed indirect relationships are examined separately in the statistical mediation analysis.

4.4 Indirect Effects and Statistical Mediation

The indirect effects were examined to assess whether Business Data Analytics Capability (BDAC) was statistically associated with the relationships between Sustainable Omnichannel Operations (SOO), Digital Innovation Capability (DIC), and Sustainable Performance (SP). The analysis used the bootstrapped indirect effects from the final Stage 2 formative/composite model. The results are presented in Table 10.

Table 10. Specific Indirect Effects

Hypothesis	Indirect Relationship	Indirect Effect (β)	STDEV	t-statistic	p-value	95% CI	Bias-Corrected 95% CI	Decision
H6	SOO → BDAC → SP	0.02880	0.04214	0.683	0.494	-0.05543 to 0.11403	-0.05635 to 0.11307	Not supported
H7	DIC → BDAC → SP	0.01377	0.02032	0.678	0.498	-0.02418 to 0.05907	-0.02279 to 0.05958	Not supported

Table 10 presents the specific indirect effects of Sustainable Omnichannel Operations (SOO) and Digital Innovation Capability (DIC) on Sustainable Performance (SP) through Business Data Analytics Capability (BDAC). The indirect effect of SOO on SP through BDAC was positive but not statistically significant (β = 0.02880, t = 0.683, p = 0.494). The 95% confidence interval (-0.05543 to 0.11403) and bias-corrected 95% confidence interval (-0.05635 to 0.11307) both included zero.

Similarly, the indirect effect of DIC on SP through BDAC was positive but not statistically significant (β = 0.01377, t = 0.678, p = 0.498). Both the 95% confidence interval (-0.02418 to 0.05907) and the bias-corrected 95% confidence interval (-0.02279 to 0.05958) included zero. Accordingly, the evidence did not support the proposed indirect relationship, and H7 was not supported.

Taken together, these findings do not provide sufficient evidence that BDAC mediates the relationships of SOO and DIC with SP in the sampled Indonesian SMEs. The results suggest that possessing analytics capability does not necessarily translate into improved

sustainability performance through the proposed indirect pathways. One possible explanation is that analytics capability must be integrated into managerial decision-making, organizational learning, operational implementation, and sustainability strategies before it can contribute to measurable sustainability outcomes. However, these potential mechanisms were not directly tested in this study and should therefore be considered explanations for future investigation rather than established findings. The results highlight the importance of distinguishing between developing an analytics capability and effectively translating that capability into sustainability-related outcomes.

It is important to distinguish these statistical findings from a causal mediation interpretation. The study employed cross-sectional survey data collected from the same respondents at a single point in time. Therefore, the observed indirect effects cannot establish temporal ordering or demonstrate that changes in SOO or DIC cause changes in BDAC, which subsequently cause changes in SP. The results are more appropriately interpreted as evidence concerning statistical indirect associations within the estimated model.

4.5 Predictive Relevance (PLSpredict)

Predictive relevance was assessed using PLSpredict based on the final Stage 2 formative/composite model. The analysis used 10 repetitions and 10 folds with automatic outer weighting. At the latent-variable level, both endogenous constructs exhibited positive predictive relevance. Business Data Analytics Capability (BDAC) had an RMSE of 0.475723, an MAE of 0.362972, and a Q^2_predict value of 0.783474. Sustainable Performance (SP) had an RMSE of 0.364909, an MAE of 0.200794, and a Q^2_predict value of 0.870751.

These results support predictive relevance at the construct level. However, the indicator-level prediction-error statistics in the archived SmartPLS export were inconsistent with the scale of the standardized Stage 2 indicators. Accordingly, the indicator-level RMSE and MAE comparisons are not interpreted as validated results until the discrepancy is resolved. The findings therefore do not support a claim of predictive superiority over the linear-model benchmark based solely on the currently verified construct-level statistics

Table 11. PLSpredict Results at the Latent-Variable Level

Endogenous Construct	RMSE	MAE	Q^2_predict
Business Data Analytics Capability (BDAC)	0.475723	0.362972	0.783474
Sustainable Performance (SP)	0.364909	0.200794	0.870751

Table 12. Indicator-Level PLSpredict Results and Linear Model Benchmark

Endogenous indicator	PLS RMSE	LM RMSE	PLS MAE	LM MAE	Q^2_predict
DAI	0.527168	0.521528	0.390109	0.394343	0.700564
ADU	0.678158	0.618093	0.533787	0.459890	0.505131
OAS	0.710746	0.705786	0.541882	0.528255	0.498203
IPU	0.692556	0.653912	0.540244	0.497608	0.514025
Economic	0.877320	0.823761	0.673153	0.616443	0.229156
Environmental	0.763991	0.729544	0.607892	0.591277	0.407285
Social	0.372870	0.340674	0.220214	0.140551	0.862139

Note: Indicator-level PLS RMSE and PLS MAE are reported on the Stage 2 standardized-score scale after dividing the exported prediction-error summaries by 10^9. LM errors and Q^2_predict are taken from the corresponding SmartPLS prediction summary. Lower

RMSE/MAE indicates lower prediction error; positive Q^2_predict indicates predictive relevance.

The PLSpredict results show that both endogenous constructs produced positive Q^2_predict values. BDAC obtained a Q^2_predict value of 0.783474, while SP obtained a Q^2_predict value of 0.870751. These results indicate that the final model provides predictive relevance for both endogenous constructs.

At the indicator level, all seven endogenous indicators had positive Q^2_predict values, ranging from 0.229 for Economic to 0.862 for Social. However, PLS-SEM RMSE was higher than the linear-model (LM) RMSE for all seven indicators. PLS-SEM MAE was lower only for DAI and higher for the other six indicators. Thus, the results support predictive relevance but do not demonstrate consistent predictive superiority over the LM benchmark.

4.6. Sensitivity Analysis of the SOO–SP Relationship

Table 13. Sensitivity Analysis of the SOO–SP Relationship Across Model Specifications

Model specification	SOO representation	SOO → DIC	SOO → SP β (t; p)	95% CI for SOO → SP	R^2 SP
Model A (primary)	Broader SOO composite	Retained	0.9105 (13.609; <0.001)	[0.7625, 1.0220]	0.8761
Model B-R (narrow SOO; path retained)	SOO1–SOO5	Retained	0.2873 (4.155; <0.001)	[0.1501, 0.4168]	0.6978
Model B (narrow SOO; path excluded)	SOO1–SOO5	Excluded	0.2872 (4.092; <0.001)	[0.1461, 0.4222]	0.6979

Note: Model B-R is a descriptive label for the narrower SOO specification using SOO1–SOO5 while retaining the SOO → DIC path. Model B uses the same SOO indicators but excludes that path. The 95% confidence intervals are percentile intervals from the corresponding SmartPLS bootstrapping outputs. For Model A, the verified percentile 95% CI for SOO → SP is [0.7625, 1.0220].

To distinguish sensitivity to construct operationalization from sensitivity to structural-path specification, two alternative specifications using the narrower SOO representation (SOO1–SOO5) were compared with the primary Model A. Model B-R retained the original six structural paths, including SOO → DIC, whereas Model B excluded SOO → DIC. Both alternative specifications used the same 331 respondents and the same SOO1–SOO5 indicators. Model B-R is used here as a descriptive label for the specification retaining SOO → DIC; it is not a replacement for the original Model A or Model B.

In Model A, the SOO–SP path coefficient was positive and statistically significant ($\beta = 0.9105$, $t = 13.609$, $p < 0.001$; percentile 95% CI [0.7625, 1.0220]; R^2 for SP = 0.8761). Under the narrower SOO specification, the coefficient was 0.2873 when SOO → DIC was retained (Model B-R; $t = 4.155$, $p < 0.001$; 95% CI [0.1501, 0.4168]; R^2 for SP = 0.6978) and 0.2872 when SOO → DIC was excluded (Model B; $t = 4.092$, $p < 0.001$; 95% CI [0.1461, 0.4222]; R^2 for SP = 0.6979). The estimates from Models B-R and B are nearly identical, indicating that removing SOO → DIC does not materially change the SOO–SP estimate under the narrower measurement specification. By contrast, the difference between Model A and Model B-R

indicates substantial sensitivity to the operationalization of SOO. The results should therefore be interpreted as a positive association whose estimated magnitude depends on construct specification, rather than as a specification-invariant estimate or conclusive evidence of an equally large independent SOO effect on SP. Potential conceptual overlap between the broader SOO dimensions of operational efficiency and sustainable resource utilization and the environmental-performance dimensions of SP remains a plausible measurement concern.

4.6 Discussion

4.6.1 Sustainable Omnichannel Operations and Sustainable Performance (H1)

The results support H1 in the primary Model A, showing a positive and statistically significant relationship between Sustainable Omnichannel Operations (SOO) and Sustainable Performance (SP) (β = 0.9105, t = 13.609, $p < 0.001$; percentile 95% CI [0.7625, 1.0220]). However, the sensitivity analysis indicates that the magnitude of this relationship depends substantially on how SOO is operationalized: when SOO was represented using SOO1–SOO5 while retaining the original structural paths, the coefficient was approximately 0.287. Therefore, the primary-model estimate should be interpreted cautiously rather than as invariant across specifications. This caution is reinforced by the supplementary common-method diagnostics: Harman's first component accounted for 39.36% of variance, but the full-collinearity VIF values were 10.785 for SOO, 8.070 for SP, and 4.897 for BDAC. These VIF values do not prove common-method bias, but they mean that shared-source variance and conceptual proximity cannot be ruled out as contributors to the large Model A estimate. Accordingly, β = 0.9105 should not be interpreted as an unambiguous, specification-independent effect.

4.6.2 Digital Innovation Capability and Sustainable Performance (H2)

The results do not support H2, as Digital Innovation Capability (DIC) showed a negative but statistically insignificant relationship with Sustainable Performance (SP) (β = -0.019, t = 0.560, p = 0.575). The coefficient was close to zero, indicating that higher levels of digital innovation capability were not statistically associated with higher sustainable performance in the final model. This finding suggests that the ability of SMEs to generate, develop, implement, and continuously improve digital innovations does not necessarily translate directly into economic, environmental, and social performance. Digital innovation may create new products, services, processes, or business models, but the presence of such innovation alone may not be sufficient to produce broader sustainability outcomes. This result differs from the theoretical expectation developed from Dynamic Capability Theory, which views digital innovation as an organizational capability that enables firms to adapt and reconfigure resources in response to changing environments. It also differs from previous studies cited in the manuscript that associate digitalization and innovation capabilities with SME development and sustainability (Ciampi et al., 2022; Hassan et al., 2024; Avelar et al., 2024). One possible interpretation within the present model is that the contribution of digital innovation may depend on other organizational capabilities that enable SMEs to convert digital activities into measurable performance outcomes. This interpretation is consistent with the role of BDAC examined in the study, although the non-significant BDAC → SP relationship and the non-significant indirect effect indicate that the current data do not provide statistical evidence that BDAC explains this relationship. Therefore, the finding should be interpreted as evidence that DIC was not directly associated with SP in the sampled SMEs, rather than as evidence that digital innovation is irrelevant to sustainability.

Given the cross-sectional design, the result also does not establish whether the effects of digital innovation may emerge over a longer period.

4.6.3 Sustainable Omnichannel Operations and BDAC (H3)

The results support H3, showing a positive and statistically significant relationship between Sustainable Omnichannel Operations (SOO) and Business Data Analytics Capability (BDAC) ($\beta = 0.644$, $t = 12.237$, $p < 0.001$). This finding indicates that SMEs with stronger coordination and integration of online and offline operations tend to report higher capability in acquiring, integrating, analyzing, and using business data. The result is consistent with the Information Processing Theory perspective developed in the study, because integrated omnichannel operations generate information from multiple activities, including transactions, customer interactions, orders, inventory, payments, and distribution. As these activities become more interconnected, SMEs require greater capacity to organize and process the resulting information. The finding is also consistent with Wamba et al. (2017) and Falahat et al. (2023), who emphasize that BDAC develops through the combination of technological, human, and organizational capabilities. In the context of the present study, SOO can therefore be understood as an operational capability that is associated with the development of the information environment in which BDAC operates. The result also complements the significant SOO → SP relationship found in H1, although the present analysis does not establish that the relationship between SOO and SP operates through BDAC because the indirect effect was not statistically significant. Overall, the finding supports the view that integrating online and offline business processes is associated not only with operational coordination but also with a stronger organizational capacity to manage and utilize the data generated by those activities. However, given the cross-sectional design, this relationship should be interpreted as a statistical association rather than as evidence that improvements in SOO necessarily cause improvements in BDAC.

4.6.4 Digital Innovation Capability and BDAC (H4)

The results support H4, showing a positive and statistically significant relationship between Digital Innovation Capability (DIC) and Business Data Analytics Capability (BDAC) ($\beta = 0.308$, $t = 5.360$, $p < 0.001$). This finding indicates that SMEs with stronger capabilities to generate, develop, implement, and continuously improve digital innovations tend to report stronger capabilities to acquire, integrate, analyze, and use business data. The result is consistent with the Information Processing Theory perspective because digital innovation can expand the volume and variety of information generated through digital products, services, customer interactions, marketing activities, and redesigned business processes. As the information environment becomes more complex, the ability to process and utilize business data becomes increasingly relevant. The finding is also consistent with the literature cited in the study. Hassan et al. (2024) highlight the relationship between digitalization and innovation capability in SMEs, while Mikalef et al. (2020) emphasize that BDAC develops through the combination of technological, human, and organizational resources. Avelar et al. (2024) further connect digitalization and innovation with broader SME sustainability. Within the present model, the significant DIC → BDAC relationship therefore indicates that digital innovation capability is associated with the development of an organizational capacity to manage the information generated by digital activities. However, this association does not extend to a significant direct relationship between DIC and Sustainable Performance, as shown by the non-significant DIC → SP path. Thus, the finding supports the role of DIC in relation to BDAC, while the current data do not establish that stronger DIC directly results in

higher Sustainable Performance. Given the cross-sectional design, the relationship should be interpreted as a statistical association rather than evidence of a temporal or causal sequence.

4.6.5 BDAC and Sustainable Performance (H5)

The results do not support H5, as Business Data Analytics Capability (BDAC) showed a positive but statistically insignificant relationship with Sustainable Performance (SP) (β = 0.045, t = 0.690, p = 0.490). Although the coefficient is positive, the statistical evidence does not indicate a significant direct association between the ability to acquire, integrate, analyze, and use business data and sustainable performance in the sampled SMEs. This finding differs from the expectation developed in the hypothesis, which assumed that stronger analytical capability would directly support economic, environmental, and social performance. It also differs from previous studies that have associated BDAC with organizational and sustainability-related outcomes, including Wamba et al. (2017), Mikalef et al. (2020), Falahat et al. (2023), and Khan et al. (2024). One possible interpretation is that having the capability to manage and analyze business data does not necessarily mean that analytical information is converted into actions that improve sustainable performance. The value of analytics may depend on how information is incorporated into operational decisions, resource allocation, innovation activities, and sustainability-oriented practices. In the present study, this interpretation should remain cautious because the model does not directly measure the organizational processes through which analytical information is translated into performance outcomes. The non-significant BDAC → SP relationship also provides an important explanation for the results of the mediation analysis: although SOO and DIC were both significantly associated with BDAC, BDAC did not show a significant association with SP, and consequently neither indirect effect through BDAC was statistically supported. Therefore, the findings indicate that BDAC is significantly related to the digital and operational capabilities examined in the model, but the present data do not provide evidence of a direct statistical relationship between BDAC and Sustainable Performance.

The non-significant relationship between Business Data Analytics Capability (BDAC) and Sustainable Performance (SP) highlights an important distinction between possessing an analytical capability and translating that capability into organizational outcomes. Although BDAC may enable SMEs to collect, integrate, and interpret business information, these activities do not necessarily result in improved economic, environmental, and social performance. Analytical insights may need to be incorporated into managerial decision-making, resource allocation, operational implementation, and sustainability-oriented strategies before they can contribute to measurable outcomes. However, these organizational processes were not directly examined in the present study and therefore represent possible explanations rather than empirically established mechanisms. The findings consequently suggest that BDAC should not automatically be assumed to produce sustainability benefits simply because an organization has developed analytical capabilities.

The present finding also calls for a cautious comparison with prior research linking BDAC to organizational or sustainability-related performance, including Wamba et al. (2017), Mikalef et al. (2020), Falahat et al. (2023), and Khan et al. (2024). Rather than assuming that these relationships must hold in every organizational setting, the current result indicates that the association between analytics capability and sustainable performance may depend on contextual and organizational conditions. Potential boundary conditions include the extent to which analytical insights are incorporated into managerial decisions, the organization's absorptive capacity and learning processes, the alignment of analytics initiatives with

sustainability objectives, and the ability to implement data-informed operational changes. These conditions were not measured in this study; therefore, they should be treated as directions for future research rather than explanations confirmed by the present evidence. Future studies could examine whether these conditions help explain when and how BDAC is associated with sustainability outcomes in SMEs.

4.6.6 Statistical Mediation of BDAC (H6–H7)

The mediation results do not support H6 or H7. The indirect effect of SOO on SP through BDAC was positive but statistically insignificant ($\beta = 0.02880$, $t = 0.683$, $p = 0.494$), with a 95% confidence interval from -0.05543 to 0.11403 and a bias-corrected interval from -0.05635 to 0.11307. Similarly, the indirect effect of DIC on SP through BDAC was positive but statistically insignificant ($\beta = 0.01377$, $t = 0.678$, $p = 0.498$), with a 95% confidence interval from -0.02418 to 0.05907 and a bias-corrected interval from -0.02279 to 0.05958. Both intervals for each indirect effect included zero; therefore, **H6** and **H7** were not supported.

The absence of statistically significant indirect effects is theoretically relevant because it challenges the assumption that BDAC necessarily transmits the relationships of SOO and DIC with SP. Although both SOO and DIC were positively associated with BDAC, neither proposed indirect relationship was statistically supported. This pattern distinguishes the development of analytical capability from the realization of sustainability outcomes. It does not demonstrate that BDAC is ineffective; rather, the present model does not establish BDAC as a statistically supported indirect pathway linking the two capabilities to SP in the sampled SMEs. Potential explanations involving managerial use of analytics, organizational learning, absorptive capacity, or strategic alignment remain open questions because these mechanisms were not directly tested. In addition, the cross-sectional design does not establish temporal ordering or support a causal interpretation of the indirect relationships. Accordingly, H6 and H7 were not supported, and the findings should be interpreted as evidence concerning statistical indirect associations rather than confirmed causal mediation.

4.6.7 Predictive Relevance

The PLSpredict results indicate positive construct-level predictive relevance for Business Data Analytics Capability (BDAC; $Q^2_predict = 0.783474$) and Sustainable Performance (SP; $Q^2_predict = 0.870751$). At the indicator level, all seven indicators had positive $Q^2_predict$ values, but PLS-SEM RMSE exceeded LM RMSE for every indicator and PLS-SEM MAE was lower for only one of the seven indicators. The model therefore shows predictive relevance, but the results do not demonstrate consistent predictive superiority or strong out-of-sample predictive performance relative to the LM benchmark.

5. Conclusion and Implications

This study examined the relationships among Sustainable Omnichannel Operations (SOO), Digital Innovation Capability (DIC), Business Data Analytics Capability (BDAC), and Sustainable Performance (SP) among Indonesian SMEs using both online and offline sales channels. Based on the final formative/composite Model A, SOO was positively and significantly associated with both BDAC and SP. However, the sensitivity analysis showed that the SOO–SP coefficient decreased from 0.910 in the broader primary specification to approximately 0.287 when SOO was represented by SOO1–SOO5 while the original structural paths were retained. Thus, the positive association was consistent in direction but its estimated magnitude was sensitive to SOO operationalization. DIC was positively and

significantly associated with BDAC, but its direct relationship with SP was not statistically significant. BDAC did not show a statistically significant relationship with SP.

The mediation analysis further indicates that BDAC did not provide statistically significant indirect associations between SOO and SP or between DIC and SP. Thus, although SOO and DIC were significantly associated with BDAC, the proposed statistical mediation pathways were not supported because BDAC was not significantly associated with SP. These findings suggest that the presence of data analytics capability alone does not provide sufficient statistical evidence of an indirect association with sustainable performance within the estimated model.

The study contributes empirical evidence on the relationships among omnichannel operations, digital innovation, data analytics capability, and sustainable performance in SMEs. The sensitivity analysis qualifies the interpretation of the SOO–SP relationship: the positive association remains statistically significant under the narrower specification, but its magnitude is substantially smaller. The findings therefore support the relevance of omnichannel operations in relation to sustainable performance while highlighting the need for careful construct operationalization. The relationships involving digital innovation and data analytics capability also require cautious interpretation. The PLSpredict analysis showed positive predictive relevance for BDAC and SP, although the PLS-SEM model did not demonstrate lower prediction errors than the linear benchmark for the reported endogenous indicators.

Because the study used cross-sectional, self-reported data and purposive sampling, the findings should be interpreted as statistical associations within the sampled SMEs rather than as evidence of temporal or causal relationships or population-wide effects.

6. Limitations and Future Research

This study has several limitations that should be considered when interpreting the findings. First, the study used a cross-sectional survey design and collected data from the same respondents at a single point in time. Therefore, the results indicate statistical associations among SOO, DIC, BDAC, and SP but do not establish temporal ordering or causal relationships. Future research could employ longitudinal designs to examine how digital and operational capabilities develop and whether changes in these capabilities are followed by changes in Sustainable Performance.

Another limitation concerns the potential conceptual proximity between SOO and SP. Although SOO represents an operational capability and SP represents sustainability outcomes, aspects such as operational efficiency and resource utilization may be relevant to both constructs. The sensitivity analysis showed that the SOO–SP coefficient decreased from 0.910 in the broader primary specification to approximately 0.287 when SOO was represented using SOO1–SOO5 while retaining the original structural paths. The nearly identical estimate after excluding SOO → DIC indicates that this structural-path change does not materially explain the difference under the narrower SOO specification. These results suggest that the magnitude of the relationship depends partly on the measurement specification and that potential conceptual overlap cannot be ruled out. Future studies should refine indicator wording, conduct an independent assessment of content validity, and consider collecting operational-capability and sustainability-outcome data from different sources or at different points in time.

Second, the study used purposive sampling and included 331 SMEs that met the specified inclusion criteria, including the use of both online and offline sales channels. Therefore, the findings should be interpreted within the context of the sampled SMEs and should not be treated as statistically representative of all Indonesian SMEs. Future studies could use broader or probability-based sampling where feasible and examine SMEs across different regions, sectors, and levels of digital adoption.

Third, the study relied on self-reported survey measures and focused on four main constructs: SOO, DIC, BDAC, and SP. Other organizational and environmental factors may also contribute to Sustainable Performance. Future research could incorporate variables such as organizational learning, digital leadership, financial capability, environmental orientation, supply chain capability, or external market conditions to provide a broader explanation of sustainable SME performance. Future studies could also examine whether the relationships identified in this study vary across different levels of digital adoption or organizational maturity.

A further construct-related limitation concerns Business Data Analytics Capability (BDAC). Although the nine items cover business-data collection, integration, analysis, organizational support, timely information, and performance use, they do not directly measure big-data-specific characteristics such as data volume, velocity, variety, or advanced technical infrastructure. The four component groupings used in this study are study-specific operational groupings and should not be interpreted as a validated general-purpose scale or as a direct reproduction of the dimensions proposed by prior big-data capability studies. Future research should validate the construct and its dimensional structure with SMEs at different levels of digital maturity and, where the research question concerns big data specifically, include direct indicators of big-data resources and technologies.

Two lower-order SOO components—Operational Efficiency (OE) and Sustainable Resource Utilization (SRU) - and the Social component of SP were represented by single questionnaire items in the current instrument. These components were retained to preserve the intended conceptual coverage of the higher-order constructs. However, using a single item limits the ability to assess within-dimension reliability and may make the component more sensitive to item-specific wording. The estimates should therefore be interpreted with this measurement limitation in mind. Future studies should develop and validate multiple indicators for each lower-order dimension before constructing the higher-order composites.

A methodological limitation concerns the potential for common-method bias because the study relied on cross-sectional, self-reported questionnaire data collected from the same key informants. Although procedural measures were applied to encourage candid responses, the possibility of CMB cannot be ruled out. Harman's single-factor test showed that the first component accounted for 39.36% of the total variance. In addition, the supplementary full-collinearity assessment produced VIF values of 4.897 for BDAC, 2.537 for DIC, 10.785 for SOO, and 8.070 for SP. The relatively high values for BDAC, SOO, and SP warrant caution, although they do not independently establish the presence of CMB. This concern is particularly relevant to the large primary-model SOO–SP coefficient, which also decreased substantially under the narrower SOO sensitivity specification. Predictive assessment also requires conservative interpretation: although all reported Q^2_predict values were positive, PLS-SEM RMSE was higher than LM RMSE for all seven indicators, and PLS-SEM MAE was lower only for DAI. The indicator-level RMSE and MAE values were converted from the

exported scale by dividing by 10^9 to match the standardized Stage 2 indicator scale; the source export's error standard deviations reproduce the RMSE values on that scale. These findings support predictive relevance, not predictive superiority. Future studies should use multiple informants or independent data sources where feasible, separate measurements over time, incorporate objective performance indicators, and preserve complete model and prediction-setting records for reproducibility.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to confidentiality and respondent-privacy considerations.

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