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Digital business process integration and sustainability among smes: the mediating role of operational efficiency and the moderating role of credit access

Dedrix Stephenson Bindeeba[1*], Susan Atuhaire[2], Rennie Bakashaba[1] and Eddy Kurobuza Tukamushaba[3]

Abstract

This study investigates the impact of digital business process integration on economic performance and environmental performance among small and medium-sized enterprises in Uganda, a resource-constrained context. It examines operational efficiency as a mediating mechanism and access to credit as a moderating factor. Drawing on the Resource-Based View and Dynamic Capabilities Theory, the research highlights how integrated digital processes and financial support jointly influence the sustainability and competitiveness of these enterprises. Data were collected from 228 enterprises via a structured survey and analyzed using covariance-based structural equation modeling in AMOS. Bootstrapping procedures tested indirect effects, and a multi-group analysis evaluated the moderating role of credit access. The results show that digital business process integration significantly improves both economic and environmental outcomes, with operational efficiency partially mediating these effects by enhancing workflow speed, optimizing resource use, and reducing errors. Furthermore, enterprises with access to credit experience greater operational and financial benefits from digital integration, whereas those without credit rely more heavily on operational efficiency to achieve environmental goals. These findings underscore the importance of robust digital infrastructure, process optimization, and inclusive financing in promoting sustainable development among small and medium-sized enterprises. The study offers actionable recommendations for policymakers and managers aiming to foster digital adoption and resource efficiency in low-income economies.

Keywords Digital business process integration, Operational efficiency, Economic performance, Environmental performance, Credit access

*Correspondence:
Dedrix Stephenson Bindeeba
dedrixbindeeba@gmail.com
[1]Faculty of Business and Management, Mbarara University of Science and Technology, P.O. Box 24985, Mbarara, Uganda
[2]Uganda Martyrs University, Kampala, Uganda
[3]College of Business, University of Doha for Science and Technology, Doha, Qatar

Introduction

Small and medium-sized enterprises (SMEs) are widely recognized as engines of global economic growth, generating employment, driving innovation, and significantly contributing to GDP. According to the Organisation for Economic Co-operation and Development (OECD), SMEs account for over 95% of firms and 60–70% of employment in most countries, making them crucial to inclusive economic development (OECD, 2006). In Uganda, SMEs comprise 96% of all businesses, forming a key foundation of the country's economy (Uganda Investment Authority, 2023). Despite their indispensable role, nearly 75% of Ugandan SMEs fail within their first five years, largely due to insufficient access to finance, poor infrastructure, and inadequate managerial capabilities (Namagembe et al., 2019). This high attrition rate underscores the urgency of identifying strategies that not only enhance Economic Performance (EP) but also strengthen Environmental Performance (EvP) in resource-constrained environments.

A growing global consensus on sustainability, evidenced by the United Nations Sustainable Development Goals (SDGs), intensifies the demand for SMEs to integrate ecological responsibility with economic imperatives. The OECD (2006) strongly advocates for aligning SME development with environmental sustainability, urging policymakers to create enabling frameworks that support both innovation and green growth. Specifically, SDGs 8 (decent work and economic growth), 9 (industry, innovation, and infrastructure), and 13 (climate action) underscore the need for sustainable business models that simultaneously drive profitability and minimize environmental harm (Wang et al., 2024). Meeting these objectives is especially challenging for manufacturing SMEs, which often grapple with resource scarcity and operational inefficiencies (Khin & Ho, 2019). Balancing profitable operations and sound environmental stewardship therefore becomes a complex endeavor, calling for innovative approaches that can address both dimensions.

Digital Business Process Integration (DBPI) offers one such approach. Defined as the strategic utilization of digital tools such as cloud computing, Internet of Things (IoT) platforms, and advanced data analytics, DBPI enables SMEs to streamline workflows, enhance decision-making, and optimize resource allocation (Siswanti et al., 2024; Xie et al., 2023). By automating routine processes, DBPI can significantly reduce errors and inefficiencies, thereby improving productivity and operational cost management. Beyond economic advantages, DBPI also contributes to improved environmental performance (EvP), particularly through enhanced monitoring, energy efficiency, and waste reduction. Recent studies emphasize how IoT technologies and data-driven platforms enable firms to detect inefficiencies, reduce energy consumption, and implement cleaner production systems, thus promoting environmentally sustainable practices even in low-resource settings (Bendig et al., 2023; Chen et al., 2023; Li et al., 2020).

Central to realizing these gains is Operational Efficiency (OE), often described as maximizing outputs while minimizing inputs (Hojnik et al., 2017). In a resource-constrained context like Uganda, DBPI can significantly augment OE by automating labor-intensive tasks, integrating production workflows, and fostering data-driven decision-making (Zahoor & Lew, 2023). For instance, IoT sensors allow SMEs to monitor machinery and inventory in real-time, enabling proactive maintenance and strategic inventory management that cut down on both costs and environmental footprints (Sun & Wang, 2022; Vo Thai et al., 2024). By aligning operational processes with ecological considerations such as energy conservation or pollution reduction, DBPI helps SMEs translate heightened productivity into tangible environmental improvements (Rajala & Hautala-Kankaanpää, 2022). This synergy underscores OE's role as a key mediator that bridges DBPI with EP and EvP.

However, while DBPI holds promise, Access to Credit (CA) remains a substantial obstacle for many Ugandan SMEs, as nearly 70% reportedly face unmet credit needs (MicroSave, 2017). Financial shortfalls inhibit the adoption of sophisticated digital systems and staff training programs required to implement such technologies effectively (Alice Arinaitwe et al., 2015). In turn, limited credit access perpetuates inefficiencies and hampers investment in sustainable practices. Strengthening CA could thus act as a catalyst, enabling SMEs to optimize digital transformation for both economic resilience and environmental stewardship (Wahab Aidoo, 2019; Buyinza et al., 2018). When paired with technology adoption, enhanced credit availability can ease the upfront costs and ongoing operational demands of DBPI, creating a more conducive environment for SMEs to pursue higher levels of efficiency and sustainability.

While DBPI is fundamentally about digitizing processes, its effectiveness can also be influenced by Entrepreneurial Orientation (EO) and Digital Orientation (DO) strategic postures that shape how SMEs innovate, take risks, and adopt technology (Bendig et al., 2023; Nasiri et al., 2022). EO emphasizes the pursuit of novel opportunities and calculated risk-taking, while DO reflects a firm's commitment to leveraging emerging digital tools (Yaseen et al., 2024). The combined effect of these orientations can further accelerate OE by fostering an organizational culture open to new technologies and continuous process improvement. However, OECD reports suggest that such strategic orientations are often underdeveloped in SMEs within low-income countries, pointing to a gap in managerial competencies and institutional support structures. Yet, most empirical studies exploring EO, DO, and performance outcomes focus on developed economies, leaving critical gaps in our understanding of how resource-constrained SMEs like those in Uganda can effectively harness these orientations (Nasiri et al., 2022).

From a theoretical standpoint, this study draws on the Resource-Based View (RBV) and Dynamic Capabilities Theory (DCT) to illuminate how DBPI and related strategic orientations underpin SME competitiveness and sustainability. RBV positions unique firm resources, such as proprietary digital capabilities, as potential sources of sustained competitive advantage (Barney, 1991). However, merely possessing these resources does not guarantee success; DCT posits that firms must continually adapt, integrate, and reconfigure such resources to navigate turbulent environments (Teece et al., 1997). By viewing DBPI as both a strategic resource and a dynamic capability, we capture the broader process through which SMEs integrate technology, refine operations, and respond effectively to evolving market and environmental pressures (Tornatzky & Fleischer, 1990). This dual-framework approach mirrors OECD's guidance on SME competitiveness, which emphasizes both the internal resources and adaptive processes necessary for sustainable growth in developing contexts.

Despite growing interest in digital transformations, research tends to be skewed toward developed markets or rapidly industrializing Asian economies (Rajala & Hautala-Kankaanpää, 2022; Zahoor & Lew, 2023). Furthermore, many studies overlook the mediating role of OE or fail to consider the moderating influence of CA (Bin et al., 2021). These omissions leave critical questions unanswered, particularly in low-income contexts where constraints on capital, infrastructure, and skilled labor are more severe. This study directly addresses these gaps by contextualizing the inquiry within Uganda, an emerging economy where digital adoption is growing but remains uneven, and by critically engaging institutional sources like the OECD to ground the challenges and opportunities confronting SMEs. To address these gaps, the current study examines how DBPI influences both EP and EvP in Ugandan SMEs through OE, and how CA conditions these relationships.

The remainder of this paper is structured as follows: Sect. 2 reviews the literature on DBPI, OE, EP, EvP, and CA, integrating RBV and DCT to develop the conceptual framework and hypotheses. Section 3 outlines the methodology, including sampling, data collection, and SEM-based analysis. Section 4 presents empirical findings, covering descriptive statistics, model fit, and moderation results. Section 5 discusses theoretical, practical, and policy implications. Section 6 concludes the study, emphasizing contributions and practical insights. Section 7 highlights limitations and proposes future research directions.

Literature review and hypotheses development

Theoretical review

This study integrates the RBV and DC Theory to investigate how DBPI enhances EP and EvP performance among SMEs in resource-constrained settings. By examining OE as a mediating factor and credit access (CA) as a moderator, the research presents a dual focus: the inherent value of digital resources via RBV and the adaptability required for reconfiguring such resources via DC Theory.

Resource-based view (RBV)

RBV posits that firms gain competitive advantages by developing and deploying valuable, rare, inimitable, and non-substitutable (VRIN) resources (Barney, 1991). In SMEs, DBPI technologies ranging from IoT-enabled inventory monitoring to cloud-based Enterprise Resource Planning (ERP) tools meet VRIN criteria by optimizing resource allocation, cutting costs, and improving strategic decision-making (Ismail, 2023; Zahoor & Lew, 2023). For instance, IoT-driven systems that track real-time inventory levels and equipment performance can minimize downtime and waste. Meanwhile, cloud-based ERP platforms such as Odoo or QuickBooks streamline accounting and procurement tasks, thereby enhancing transparency and efficiency (Gupta et al., 2020). Although RBV underscores the intrinsic value of DBPI as a resource, it does not fully address the need for firms to adapt swiftly to dynamic market conditions. This limitation is addressed by DC Theory, which emphasizes the continuous transformation and reconfiguration of resources.

Dynamic capabilities theory

DC Theory expands on RBV by stressing the importance of adaptation, integration, and reconfiguration of resources to maintain competitiveness in fast-changing environments (Teece et al., 1997). For SMEs, DBPI facilitates such adaptability by enabling rapid responsiveness to market demands. For example, digital payment solutions like PayPal or mobile money can simplify transactions, thereby broadening customer reach and improving liquidity. IoT-empowered systems further assist SMEs in detecting inefficiencies be it in supply chains or energy usage allowing immediate corrective actions (Joshi & Sharma, 2022; Rahman et al., 2024). Moreover, accessible digital tools such as inventory management apps help reduce waste and align operations with sustainability objectives (Sun & Wang, 2022).

By blending RBV's focus on the strategic potential of DBPI with DC Theory's emphasis on resource reconfiguration, this study provides a comprehensive perspective on how DBPI drives EP and EvP through OE. In addition, CA plays a pivotal enabling role, ensuring SMEs can effectively capitalize on these digital resources and their associated dynamic capabilities.

Hypothesis building

Digital business process integration and firm performance

Digital Business Process Integration refers to the strategic application of digital technologies to streamline organizational workflows, enhance operational efficiency, and drive innovation. Technologies such as Artificial Intelligence (AI), Big Data Analytics (BDA), Cloud Computing, and the Internet of Things (IoT) enable real-time decision-making, resource optimization, and improved agility in operations (Shen et al., 2022; Xi et al., 2024). These tools transform traditional business processes, making them more efficient and responsive to market demands.

In recent years, the integration of digital technologies into business processes has reshaped the way firms operate and compete. As digital tools such as enterprise resource planning (ERP), digital payment systems, and digital workflows become more widespread, understanding their impact on firm performance across economic and environmental dimensions has gained increasing research attention (Escoz Barragan & Becker, 2024; Martínez-Peláez et al., 2024). Previous studies have highlighted the potential of DBPI to enhance firm outcomes by optimizing operations, reducing costs, and fostering innovation, which collectively improve profitability and competitive positioning (Ijaz Baig & Yadegaridehkordi, 2023; Shen et al., 2022).

DBPI also supports environmental sustainability by enabling firms to monitor resource usage, minimize waste, and enhance energy efficiency. These capabilities align with global sustainability goals and help firms embed eco-friendly practices into their operations (Bindeeba et al., 2025; Chen & Hao, 2022). Recent research underscores the importance of digitalization frameworks that integrate economic and environmental objectives, especially in resource-constrained settings like SMEs, where DBPI can promote resilience and sustainability (Chen & Hao, 2022; Li & Lin, 2024; Mishra et al., 2024). By leveraging DBPI, organizations can simultaneously enhance economic and environmental performance, paving the way for sustainable business practices. In short, the discussion leads to the following hypotheses:

H1a *Digital Business Process Integration positively influences Economic Performance.*

H1b *Digital Business Process Integration positively influences Environmental Performance.*

Digital business process integration and operational efficiency

Operational efficiency is a multifaceted concept defined differently across disciplines. In manufacturing, it emphasizes waste reduction and process optimization, while in services, it focuses on improving workflows and customer satisfaction. In financial and managerial contexts, OE is linked to cost minimization and productivity enhancement. Despite this diversity, a unifying definition remains elusive. Lee and Johnson (2013) define OE as the optimal use of resources to achieve desired outcomes, minimizing waste and maximizing productivity without compromising quality.

DBPI plays a transformative role in enhancing OE by automating routine processes, optimizing workflows, and delivering real-time insights. By leveraging tools such as artificial intelligence (AI), the Internet of Things (IoT), and cloud computing, DBPI minimizes resource wastage, streamlines decision-making, and fosters innovation. For example, IoT-enabled monitoring systems improve inventory management by providing accurate, real-time data, while AI-driven analytics enable predictive decision-making to address inefficiencies proactively (Gupta et al., 2020; Luu et al., 2023; Vo Thai et al., 2024).

In resource-constrained settings, such as SMEs, DBPI addresses common operational challenges by reducing production delays, enhancing supply chain coordination, and promoting scalability (Kahraman & Rigopoulos, 2023). For instance, in the manufacturing sector, a small retail distributor can use IoT-based sensors to monitor inventory levels in real-time, avoiding sales interruptions due to shortages. Similarly, AI-powered software can forecast demand trends based on historical sales data, enabling SMEs to optimize production schedules and reduce overstocking. These technologies allow firms to reallocate resources more effectively, foster process innovation, and create competitive advantages by improving efficiency and agility (Chatchawanchanchanakij et al., 2023; Haseeb et al., 2019; Shen et al., 2022).

By integrating digital tools into business processes, DBPI enables firms to not only address inefficiencies but also achieve sustainable and scalable outcomes. These capabilities highlight the critical role of DBPI in driving OE, leading to the following hypothesis:

H2 *Digital Business Process Integration positively influences Operational Efficiency.*

Operational efficiency and firm performance

Economic performance is a fundamental indicator of a firm's financial viability, often assessed through metrics such as profitability, revenue growth, and return on investment (ROI). It reflects the organization's ability to generate consistent financial returns while maintaining long-term strategic sustainability (Nigatu et al., 2024; Nkundabanyanga, 2016; Zhang & Ma, 2021). In parallel, environmental performance (EvP) captures a firm's efforts to minimize its ecological footprint by embracing energy efficiency, waste reduction, and eco-friendly operational practices (Friedman & Miles, 2001; Yusof et al., 2020). Together, EP and EvP form a comprehensive framework for evaluating both economic resilience and environmental responsibility within organizational performance.

Operational efficiency is a key lever through which firms can simultaneously advance economic and environmental goals. By optimizing resource use, streamlining workflows, and lowering operational costs, OE enhances productivity and enables firms to remain agile and financially sound in increasingly competitive markets (Ahmad et al., 2024; Vo Thai et al., 2024). Moreover, OE plays a central role in supporting EvP by reducing energy consumption, minimizing material waste, and enabling the integration of environmentally sustainable routines into daily operations (Kahraman & Rigopoulos, 2023). This dual impact highlights OE as a pivotal conduit linking internal efficiency gains to both economic returns and ecological outcomes.

Achieving this balance requires deliberate alignment of internal processes with strategic objectives. For example, SMEs in the manufacturing sector can adopt IoT-enabled systems that monitor machine performance and energy use in real time, allowing for responsive adjustments that conserve resources and reduce overhead. The use of advanced digital tools such as predictive analytics and cloud-based process controls can further reinforce OE by supporting accurate decision-making and continuous improvement across supply chains and production units (Chin et al., 2024; Tariq et al., 2024). These capabilities are especially valuable in resource-constrained settings, where maximizing output from limited inputs is essential for survival and growth.

Evidence from empirical research confirms that firms that institutionalize OE practices are better positioned to achieve balanced performance outcomes. In such contexts, OE serves not just as an internal driver of efficiency but also as a vehicle for green transformation. By lowering costs and enhancing productivity, OE directly strengthens EP; simultaneously, by embedding sustainability into everyday practices, it fosters improved EvP and alignment with broader global sustainability targets. This theoretical and empirical grounding supports the proposition that operational efficiency is a significant predictor of both economic and environmental performance; thus, we hypothesize that;

H3a *OE positively influences EP.*

H3b *OE positively influences EVP.*

The Mediating Role of Operational Efficiency in the Relationship Between Digital Product Integration and Firm Performance

OE plays a pivotal role in mediating the relationship between DBPI and firm performance by translating DBPI capabilities into measurable economic and environmental performance (EP and EvP) (Ahmad et al., 2024; Alathamneh & Al-Hawary, 2023). DBPI elements such as Enterprise Resource Planning (ERP) systems, Internet of Things (IoT) devices, cloud computing, and data analytics platforms directly enhance OE through automation, real-time monitoring, and process optimization (Awa et al., 2016; Gupta et al., 2020).

For instance, ERP systems like SAP integrate core business functions, reducing redundancies and improving workflow accuracy, which positively impacts EP (Gupta et al., 2020). Similarly, IoT-enabled monitoring systems enhance resource utilization by providing real-time insights into equipment performance, minimizing downtime, and promoting sustainability (Sun & Wang, 2022). Cloud platforms such as Microsoft Azure address cost barriers by offering scalable storage and processing capabilities, critical for SMEs in resource-constrained environments. Moreover, data analytics platforms like Tableau empower firms to optimize operations by uncovering inefficiencies and improving resource allocation (Pham et al., 2024; Yin et al., 2024).

Empirical studies affirm that DBPI facilitates cost savings and waste reduction, particularly in SMEs facing resource limitations (Costa Melo et al., 2023). These tools enable SMEs to align operational practices with sustainability goals, supporting EvP through energy conservation and waste management. By enhancing OE, DBPI bridges the gap between advanced digital tools and firm performance, driving competitive advantages and sustainable growth. This supports the hypotheses that OE positively impacts EP through productivity and cost efficiency and EVP by promoting sustainable practices:

H4a *OE mediates the relationship between DBPI and EP.*

H4b *OE mediates the relationship between DBPI and EVP.*

The moderating role of access to credit

Access to credit plays a pivotal role in enabling SMEs to overcome capital constraints and invest in strategic resources necessary for growth and competitiveness. It allows firms to finance innovation, upgrade technological infrastructure, and build workforce capacity factors that directly influence OE and digital transformation outcomes (Bin et al., 2021; Wahab Aidoo, 2019). In the context of DBPI, AC mitigates financial barriers by providing the capital required to adopt and sustain advanced technologies such as Internet of Things (IoT) devices, cloud computing platforms, and artificial intelligence (AI)-driven systems (Costa Melo et al., 2023). These tools enhance OE by automating workflows, enabling real-time monitoring, and supporting evidence-based decision-making. For instance, SMEs with access to credit can streamline procurement and logistics, reduce material waste, and achieve both economic and environmental performance targets (Buyinza et al., 2018; Alice Arinaitwe et al., 2015).

Empirical studies reinforce the view that financial inclusion is a catalyst for technology-driven sustainability. SMEs with sufficient credit lines are more likely to adopt DBPI solutions that facilitate resource optimization, energy conservation, and cost reduction outcomes that contribute to enhanced EP and EvP (Bin et al., 2021; Alice Arinaitwe et al., 2015). On the other hand, firms lacking credit access often struggle to initiate or scale digital adoption due to high upfront investment costs and limited flexibility in reallocating operational budgets. This financial gap inhibits their capacity to capitalize on the full potential of digital tools, resulting in slower operational improvements and weaker sustainability outcomes.

The moderating role of AC is particularly consequential in resource-constrained settings such as Uganda, where SMEs face structural limitations including underdeveloped digital infrastructure and a shortage of skilled human capital. Credit access acts as a strategic enabler, reinforcing the positive effects of DBPI on OE by easing liquidity constraints and enabling timely investment in necessary digital capabilities. As such, AC not only amplifies performance outcomes but also helps firms adapt more quickly to environmental pressures and market uncertainties. These insights underline the importance of inclusive financial policies and tailored credit schemes aimed at supporting SME digital transformation in developing economies. Thus, we hypothesize the following:

H5a *AC moderates the relationship between DBPI and OE, strengthening it for SMEs with credit access.*

H5b *AC moderates the relationship between OE and EP, strengthening it for SMEs with credit access.*

H5c *AC moderates the relationship between OE and EvP, strengthening it for SMEs with credit access.*

H5d *AC moderates the relationship between DBPI and EP, strengthening it for SMEs with credit access.*

H5e *AC moderates the relationship between DBPI and EvP, strengthening it for SMEs with credit access.*

The conceptual model illustrates the relationships between DBPI and firm performance outcomes

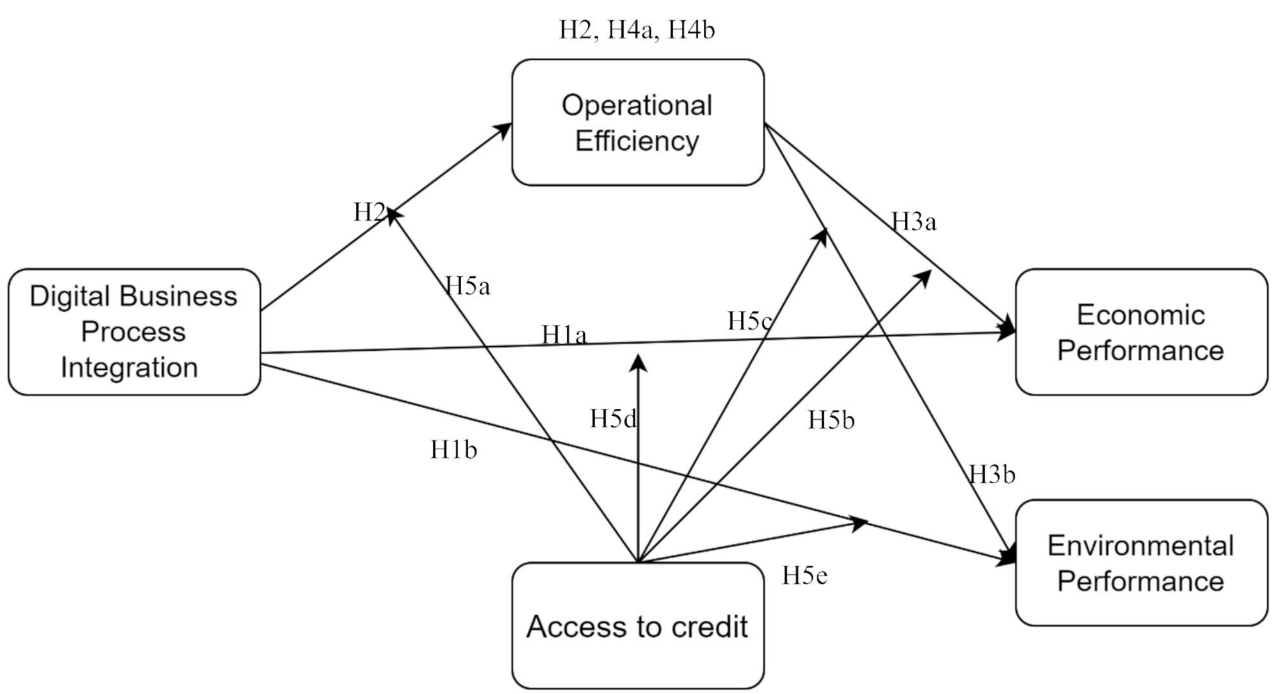

Fig. 1 Conceptual framework of the study

(Economic Performance and Environmental Performance), mediated by Operational Efficiency and moderated by Access to Credit.

Methodology

This study investigates the relationships between DBPI, OE, and the EP and EvP of SME in resource-constrained contexts. Using a explanatory design, the research examines both direct and indirect relationships within the conceptual framework, incorporating Structural Equation Modeling (SEM) to evaluate the proposed mediating and moderating effects.

Sample size determination and sampling method

The required sample size was determined using Krejcie and Morgan's Table for sample size calculation, which recommends a minimum of 306 respondents for a population exceeding 1,000 (Krejcie & Morgan, 1970). Although logistical challenges led to a final sample of 231 responses, three were excluded due to missing data, leaving 228 valid responses. This sample size meets the minimum threshold for SEM analysis, which requires at least 200 cases for reliable parameter estimation (Kline, 2016). Additionally, the ratio of sample size to estimated parameters exceeded the recommended 5:1 ratio, ensuring stability in multi-group analysis.

The study employed a purposive sampling method due to the absence of a centralized database for SMEs in Uganda. The sampling frame was developed using lists from two sources: 1,000 SMEs from the Uganda Revenue Authority (URA) and 495 SMEs listed by the Uganda Investment Authority (UIA). SMEs with clear physical addresses or contact information in Kampala and Wakiso districts were included in the sample. For SMEs with incomplete or unclear address information, Google Maps was used to verify and confirm their locations. This sampling approach addressed the limitations posed by the lack of comprehensive SME registries.

Data collection procedure

To address connectivity challenges and cultural reluctance to participate in surveys, data collection employed a multi-method approach. Initially, an online survey was distributed via Google Forms to 250 SMEs with valid email addresses or phone numbers, resulting in 45 completed responses over 3 months. Recognizing the low uptake of online surveys, face-to-face interviews were conducted at SME premises, ensuring engagement with respondents who lacked internet access or preferred in-person interaction. Additionally, a drop-and-pick method was used, where questionnaires were delivered to SME premises and collected later, providing flexibility for respondents to complete the survey. These methods collectively enhanced participation and addressed logistical barriers, yielding a final response rate of 75%, which is considered acceptable for organizational research surveys that typically report response rates above 50% (Baruch & Holtom, 2008).

Survey instrument and measurement of variables

We adapted our DBPI items from Siswanti et al. (2024) and Xie et al. (2023), who operationalized digital process integration via measures of responsiveness, interoperability, and innovation. OE items speed of operations, decision-making enhancement, resource utilization, and error reduction follow Hojnik et al. (2017) definition of efficiency in eco-innovation contexts. For EP, we drew on Nigatu et al. (2024) validated financial metrics (profitability, retention, revenue, ROI), while EvP measures (energy efficiency, eco-practices, waste reduction) reflect Shahab et al.'s (2018) work linking digitalization to environmental outcomes. To ensure content validity,

Table 1 Survey instrument and variable measurement

Variable	Indicator	Description
Digital Business process integration (DBPI)	DBPI1: Process Responsiveness	Our business processes are designed to utilize digital technologies, enabling timely and effective responses to market demands
	DBPI2: Technological Interoperability	Our business processes integrate seamlessly with other systems and technologies
	DBPI3: Process Innovation	Our firm incorporates advanced digital tools to continuously innovate and improve business processes, delivering superior value
Operational Efficiency (OE)	OE1: Speed of Operations	Digital systems improve the speed and consistency of our business operations.
	OE2: Decision-Making Enhancement	Integration of digital tools into workflows enhances decision-making and planning.
	OE3: Resource Utilization	Automation optimizes resource use, including time, labor, and materials.
	OE4: Error Reduction	Improved workflows enabled by digital tools reduce errors and enhance reliability.
Economic Performance (EP)	EP1: Profitability Improvement	Our business profitability has increased.
	EP2: Customer Retention	Customer retention has improved due to digital tools.
	EP3: Revenue Growth	Internal processes supported by digital tools have boosted our revenue.
	EP4: ROI Growth	Returns on investment (ROI) have significantly improved due to digital product integration.
Environmental Performance (EVP)	EVP1: Energy Efficiency	Digital technologies have reduced energy consumption, enhancing energy efficiency.
	EVP2: Eco-Friendly Practices	Our firm has adopted more eco-friendly practices facilitated by digital tools.
	EVP3: Waste Reduction	Digitization has helped us minimize waste and promote environmental sustainability.

two academic experts and two industry practitioners reviewed and refined wording for clarity and contextual fit. The instrument was pilot-tested with 30 Ugandan manufacturing SMEs, yielding Cronbach's alphas above 0.80 for all constructs. All items use a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), ensuring consistent measurement across variables.

Data analysis

Preliminary data preparation and descriptive analysis

Raw data collected from the survey were cleaned in Microsoft Excel to address duplicates, inconsistencies, and missing values. After excluding three incomplete responses, the final dataset comprised 228 valid cases. The cleaned data were imported into SPSS Version 27 for further analysis. Descriptive statistics, including frequencies, percentages, means, and standard deviations, were computed using SPSS to summarize the background characteristics of SMEs. These statistics provided an overview of variables such as firm size, ownership type, and industry type.

Structural equation modeling

SEM was conducted using IBM SPSS AMOS Version 27 to test the hypothesized relationships between DBPI, OE, EP, and EvP. The analysis incorporated mediation to evaluate the indirect effects of DBPI on performance outcomes through OE. Multi-group analysis was employed to assess the moderating effect of CA by comparing SMEs with and without access to credit. Bootstrapping with 5,000 resamples was applied to test the significance of indirect effects and ensure robustness (MacKinnon et al., 2004). Bias-corrected and percentile confidence intervals at 95% were reported. Model fit indices such as chi-square/df (χ2/df), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA) were evaluated, following thresholds recommended by Hair et al. (2014).

Table 2 Background characteristics of respondents

Characteristic	Categories	Frequency	Percent (%)
Gender of Firm Owner	Female	97	42.5
	Male	131	57.5
Age of Firm Owner	Under 25	3	1.3
	25–34	29	12.7
	35–44	75	32.9
	45–54	88	38.6
	55 and above	33	14.5
Education Level	Primary	2	0.9
	Secondary	7	3.1
	Tertiary	159	69.7
	Vocational/Technical	60	26.3
Firm Size (by Employee Number)	Small (5–49)	183	80.3
	Medium (50–99)	45	19.7
Location	Rural	12	5.3
	Urban	216	94.7
Market Scope	International	32	14.0
	Local	17	7.5
	National	121	53.1
	Regional	58	25.4
Access to Credit	No	175	76.8
	Yes	53	23.2
Ownership Type (A9)	Limited Company	51	22.4
	Partnership	72	31.6
	Sole Trader	105	46.1

Common method bias

Principal Component Analysis (PCA) was conducted to assess common method bias, using the 50% variance threshold recommended by Podsakoff et al. (2003). The cumulative variance explained by the first two components was also reviewed to confirm the robustness of the data.

Reliability and validity testing

Reliability was assessed using Cronbach's alpha, with all constructs exceeding the acceptable threshold of 0.70 (Cronbach, 1951). Convergent validity was confirmed using Composite Reliability (CR ≥ 0.70) and Average Variance Extracted (AVE ≥ 0.50), ensuring the consistency and explanatory power of the constructs (Campbell & Fiske, 1959; Hair et al., 2014). Discriminant validity was evaluated by comparing the square root of the AVE for each construct to the correlations with other constructs. Discriminant validity is established when the square root of the AVE for a construct is greater than the correlations between that construct and all other constructs (Fornell & Larcker, 1981). These assessments verified that the constructs were both conceptually distinct and adequately measured.

Results

Background characteristics

As shown in Table 2, the SMEs in this study are predominantly male-owned (57.5%) and led by middle-aged entrepreneurs, with 38.6% aged 45–54 and 32.9% aged 35–44. Younger business owners (under 25) constitute only 1.3%, highlighting potential barriers for youth in entrepreneurship. Education levels are notably high, with 69.7% of owners holding tertiary qualifications and 26.3% possessing vocational or technical training.

Operationally, the majority of firms are small enterprises (80.3%), with nearly all located in urban areas (94.7%). Ownership structures primarily include sole proprietorships (46.1%) and partnerships (31.6%). These characteristics provide critical demographic and operational context, forming the basis for examining the influence of Digital Business Process Integration and Operational Efficiency on economic and environmental performance.

Measurement model

Common method bias and measurement model evaluation

Common method bias was assessed using Principal Component Analysis (PCA). The analysis revealed that the first component accounted for 47.803% of the total variance, below the commonly accepted threshold of 50% (Podsakoff et al., 2003). This result suggests that common method bias is unlikely to significantly impact the findings. Furthermore, the cumulative variance explained by the first two components, 58.629%, indicates a balanced distribution of variance across multiple factors, providing additional assurance about the robustness of the dataset and minimizing concerns related to bias from a single source.

Table 3 presents the measurement model fit indices, which demonstrate strong alignment with established benchmarks. The chi-square to degrees-of-freedom ratio ($\chi^2/df = 1.926$) falls below the recommended threshold of 3.0, indicating a well-balanced model fit. The RMSEA value of 0.064 meets the acceptable limit of 0.08, further supporting the model's appropriateness for the observed data. Additionally, comparative fit indices (CFI = 0.963, TLI = 0.954, NFI = 0.927) exceed the recommended 0.90 benchmark (Bentler, 1990; Hu & Bentler, 1999), reinforcing the robustness of the measurement model.

Descriptive statistics and reliability indicators

Table 4 provides descriptive statistics and reliability metrics for the core constructs: Digital Business Process Integration, Operational Efficiency, Economic Performance, and Environmental Performance. The mean scores range from 3.76 for Digital Business Process Integration to 4.12 for Environmental Performance, with standard deviations between 0.64 and 0.78, reflecting moderate variability and diverse firm characteristics. Reliability analysis confirmed high internal consistency across all constructs, as evidenced by composite reliability values ranging from 0.87 to 0.92, and Cronbach's alpha values surpassing 0.70 (Nunnally & Bernstein, 1994; Hair et al., 2019). Squared multiple correlations further highlight the explanatory power of the constructs, with Environmental Performance achieving the highest at 89%, followed by Operational Efficiency at 58%.

Table 3 Measurement model fit indices

Fit Index	Value	Threshold
χ^2/df	1.926	< 3.0
RMSEA	0.064	< 0.08
CFI	0.963	> 0.95
TLI	0.954	> 0.90
NFI	0.927	> 0.90

Table 5 Convergent Validity– AVE and factor loadings

Variable	Indicator	Std. Loading (β)	Indicator Reliability (β²)	AVE	CR
DBPI	DBPI1	0.731	0.534		
	DBPI2	0.783	0.613	0.55	0.87
	DBPI3	0.702	0.493		
OE	OE1	0.793	0.629		
	OE2	0.806	0.650	0.64	0.91
	OE3	0.768	0.590		
	OE4	0.827	0.684		
EP	EP1	0.692	0.479		
	EP2	0.864	0.747	0.54	0.90
	EP3	0.635	0.403		
	EP4	0.740	0.548		
EvP	EvP1	0.876	0.768		
	EvP2	0.836	0.699	0.68	0.92
	EvP3	0.757	0.573		

Table 6 Discriminant Validity– Fornell-Larcker criterion

Variable	DBPI	OE	EP	EvP
DBPI	**0.739**			
OE	0.602	**0.799**		
EP	0.602	0.602	**0.737**	
EvP	0.602	0.602	0.602	**0.824**

Note: Bold values represent the square roots of the Average Variance Extracted (AVE). Discriminant validity is affirmed when these values exceed the corresponding inter-construct correlations.

Convergent and discriminant validity

Convergent validity was assessed using Average Variance Extracted (AVE) and standardized factor loadings, as detailed in Table 5. The AVE values ranged from 0.55 to 0.68, surpassing the 0.50 threshold (Fornell & Larcker, 1981), while CR values (0.87 to 0.92) exceeded 0.70, confirming construct reliability and convergent validity. Factor loadings ranged from 0.635 to 0.876, all significant at $p < 0.01$. Discriminant validity, evaluated using the Fornell-Larcker criterion, is summarized in Table 6. Each construct's square root of AVE exceeds its correlations

Table 4 Descriptive statistics and reliability indicators

variable	Mean	Std. Deviation	Min	Max	CR	Cronbach's α	R^2
DBPI	3.76	0.73	1.00	5.00	0.87	0.84	0.55
OE	3.84	0.78	1.00	5.00	0.91	0.89	0.64
EP	4.02	0.64	2.00	5.00	0.90	0.88	0.54
EvP	4.12	0.68	1.00	5.00	0.92	0.90	0.68

Table 7 Direct effects from structural equation modeling

Hypothesis	Path	β (Unstd.)	β (Std.)	SE	*p*-value	Support
H1a	DBPI → EP	0.330	0.434	0.101	***	Supported
H1b	DBPI → EvP	0.489	0.354	0.119	***	Supported
H2	DBPI → OE	0.745	0.758	0.088	***	Supported
H3a	OE → EP	0.200	0.258	0.095	0.035	Supported
H3b	OE → EvP	0.907	0.645	0.123	***	Supported

Note: $p < 0.001$ indicated by ***

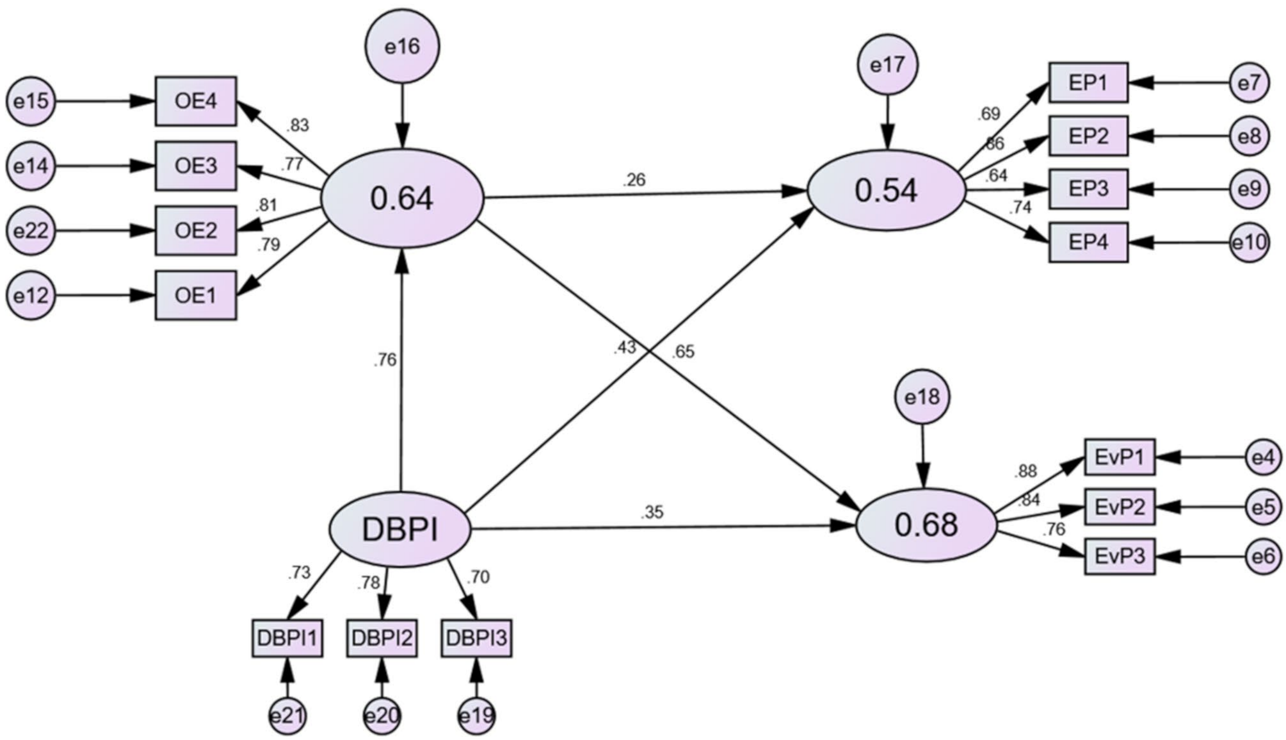

Fig. 2 Structural model– mediation of operational efficiency

with other constructs, confirming their distinctiveness. For example, the square root of AVE for Digital Business Process Integration (0.739) is greater than its correlations with Operational Efficiency (0.602), Economic Performance (0.602), and Environmental Performance (0.602).

The findings presented in Tables 3, 4 and 5, and 6 confirm the measurement model's reliability, convergent validity, and discriminant validity, ensuring its suitability for structural analyses and hypothesis testing related to Digital Business Process Integration, Operational Efficiency, and performance outcomes.

Structural model results

Direct effects

This study evaluated the hypotheses using bootstrapping with 5,000 iterations and sample replacement (Hair et al., 2019). The results, as presented in Table 6, reveal significant direct effects among the study constructs. Specifically, Digital Business Process Integration (DBPI) has a substantial positive impact on OE (β = 0.758, SE = 0.038, $p < 0.001$), indicating that enhanced Digital Business Process Integration directly improves operational processes. Furthermore, DBPI significantly influences Economic Performance (EP) (β = 0.434, SE = 0.072, $p = 0.001$), demonstrating its critical role in driving economic outcomes.

OE also has significant positive effects on performance outcomes. As shown in Table 6, the findings indicate that OE positively impacts EP (β = 0.258, SE = 0.083, $p = 0.035$) and EvP (β = 0.645, SE = 0.045, $p < 0.001$), underscoring the importance of efficient operations in achieving economic and sustainability goals. Additionally, DBPI exerts a significant direct effect on EvP (β = 0.354, SE = 0.058, $p < 0.001$), highlighting its role in advancing environmental performance.

These results confirm Hypotheses H1a through H3b, establishing robust direct relationships among digital product integration, operational efficiency, and performance outcomes. Table 7; Fig. 2 provide a comprehensive

Table 8 Mediation effects of operational efficiency

Hypothesis	Mediated Path	β (Unstd.)	β (Std.)	SE	*p*-value	Support
H4a	DBPI → OE → EP	0.196	0.196	0.027	***	Supported
H4b	DBPI → OE → EvP	0.489	0.354	0.046	***	Supported

*** indicates $p < 0.001$

Table 9 Total effects of DBPI on EP and evp

Path	Direct Effect (Std. β)	Indirect Effect (via OE)	Total Effect (Std. β)
DBPI → EP	0.434	0.196	0.630
DBPI → EvP	0.354	0.354	0.708

representation of these relationships, illustrating the influence of DBPI and OE on EP and EvP.

Mediation analysis

The mediation analysis visualized in Fig. 2 and summarized in Table 8 shows the critical role of OE as an intermediary in the relationships between DBPI and firm performance outcomes. For H4a, OE significantly mediates the relationship between DBPI and Economic Performance (EP), with the indirect effect being $\beta = 0.196$, $SE = 0.027$, $p < 0.001$. Given that the direct effect of DBPI on EP is $\beta = 0.434$, the total effect is $\beta = 0.630$, indicating that DBPI exerts a substantial influence on EP, amplified through operational efficiency gains.

Similarly, for H4b, OE mediates the relationship between DBPI and EvP, with a significant indirect effect of $\beta = 0.354$, $SE = 0.046$, $p < 0.001$. When added to the direct effect of $\beta = 0.354$, the total effect becomes $\beta = 0.708$ (Table 9), highlighting the strong combined impact of DBPI and OE on environmental outcomes. These findings confirm partial mediation, where DBPI contributes directly to both EP and EvP, and OE significantly enhances these contributions by streamlining processes, reducing inefficiencies, and aligning operational workflows with sustainable goals.

Multi-group analysis: the moderating role of credit access

This study conducted a multi-group analysis to explore how access to credit moderates the relationships in the proposed structural model. Using bootstrapping with 5,000 iterations, unstandardized path coefficients were estimated for firms with credit access ("Credit") and those without ("No Credit"). This analysis reveals critical differences in how DBPI and OE influence EP and EVP across these subgroups.

Multi-Group Model Fit Assessment.

The multi-group model demonstrated a good fit to the data, as supported by key fit indices. The χ^2/df ratio of 1.787 fell within the acceptable threshold of less than 3.0, indicating a good balance between model complexity and fit (Byrne, 2016). Additionally, the RMSEA value of 0.059 was below the recommended cutoff of 0.08, while the comparative fit indices ($CFI = 0.941$; $TLI = 0.925$) exceeded the 0.90 benchmark, confirming an adequate model fit for both subgroups (Hu & Bentler, 1999; Hair et al., 2019).

Results of Multi-Group Analysis.

The multi-group analysis, summarized in Table 10 and illustrated in Fig. 3, highlights significant moderating effects of AC on the structural relationships between DBPI, OE, and firm performance outcomes. For the relationship between DBPI and OE, the effect was significant in both subgroups but notably stronger in the Credit subgroup ($\beta = 0.952$, $SE = 0.045$, $p < 0.001$) compared to the No Credit subgroup ($\beta = 0.621$, $SE = 0.062$, $p < 0.001$). This result supports Hypothesis H5a and underscores that credit access enhances firms' ability to optimize digital integration for operational improvements, likely due to increased financial capacity for technology investments and process optimization.

The analysis also reveals divergent effects of OE on EP across the subgroups. In the Credit subgroup, OE significantly positively influenced EP ($\beta = 0.289$, $SE = 0.101$, $p = 0.006$), aligning with Hypothesis H5b. However, in the No Credit subgroup, the relationship was non-significant ($\beta = 0.018$, $SE = 0.112$, $p = 0.908$), indicating that credit access is critical for converting efficiency gains into economic outcomes.

Conversely, the effect of OE on EvP was significant in both subgroups, as proposed in Hypothesis H5c, but stronger for firms without credit access ($\beta = 1.156$, $SE = 0.071$, $p < 0.001$) compared to those with credit access ($\beta = 0.765$, $SE = 0.056$, $p < 0.001$). For the direct effects

Table 10 Multi-Group Analysis– Moderating role of credit access

Hypothesis	Relationship	Credit Estimate (SE)	*p*-value	No Credit Estimate (SE)	*p*-value	Moderation Interpretation
H5a	DBPI → OE	0.952 (0.045)	< 0.001	0.621 (0.062)	< 0.001	Strong effect in both subgroups; stronger for Credit
H5b	OE → EP	0.289 (0.101)	0.006	0.018 (0.112)	0.908	Significant only for Credit
H5c	OE → EvP	0.765 (0.056)	< 0.001	1.156 (0.071)	< 0.001	Significant in both subgroups; stronger for No Credit
H5d	DBPI → EP	0.432 (0.089)	0.002	0.345 (0.098)	0.014	Positive effect in both subgroups
H5e	DBPI → EvP	0.656 (0.078)	< 0.001	0.284 (0.092)	0.048	Significant in both subgroups; stronger for Credit

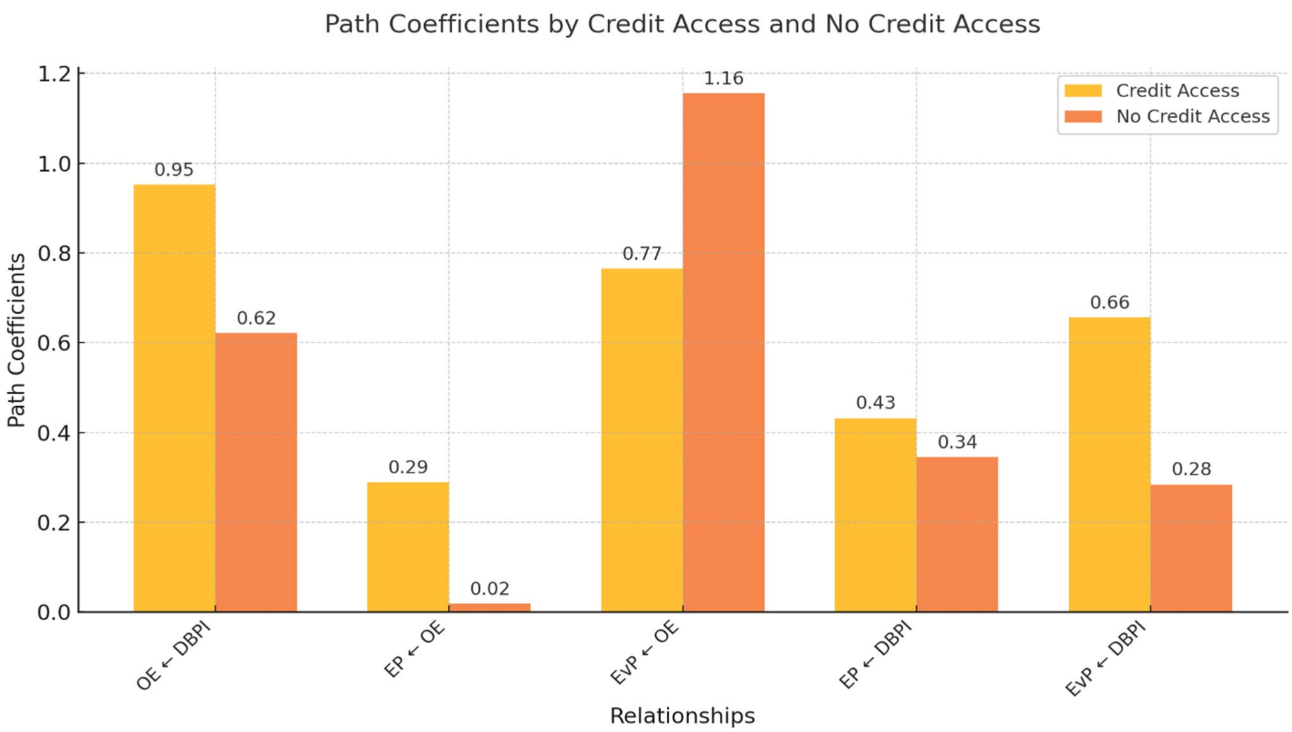

Fig. 3 Multi-group SEM model– SMEs with and without credit access

Table 11 Summary of tested hypotheses

Hypothesis	Hypothesis Statement	Supported?
H1a	DBPI positively influences EP.	Supported
H1b	DBPI positively influences EvP.	Supported
H2	DBPI positively influences OE.	Supported
H3a	OE positively influences EP.	Supported
H3b	OE positively influences EvP.	Supported
H4a	OE mediates the relationship between DBPI and EP	Supported
H4b	OE mediates the relationship between DBPI and EvP.	Supported
H5a	AC moderates the relationship between DBPI and OE, strengthening it for SMEs with credit.	Supported
H5b	AC moderates the relationship between OE and EP, strengthening it for SMEs with credit.	Supported (only for Credit group)
H5c	AC moderates the relationship between OE and EvP, strengthening it for SMEs with credit.	Supported (stronger effect in No Credit group)
H5d	AC moderates the relationship between DBPI and EP, strengthening it for SMEs with credit.	Supported
H5e	AC moderates the relationship between DBPI and EvP, strengthening it for SMEs with credit.	Supported

of DBPI on EP and EvP, significant relationships were observed in both subgroups, supporting Hypotheses H5d and H5e. In the Credit subgroup, DBPI exhibited stronger effects on both EP ($\beta = 0.432$, SE = 0.089, $p = 0.002$) and EvP ($\beta = 0.656$, SE = 0.078, $p < 0.001$) compared to the No Credit subgroup (EP: $\beta = 0.345$, SE = 0.098, $p = 0.014$; EvP: $\beta = 0.284$, SE = 0.092, $p = 0.048$). These results highlight the amplifying role of credit access in maximizing the performance benefits of digital integration. Overall, the findings provide strong support for Hypotheses H5a through H5e, demonstrating that credit access significantly moderates the relationships between DBPI, OE, EP, and EvP.

The results of the structural model, mediation analysis, and multi-group moderation analysis provided robust empirical support for the proposed hypotheses. Table 11 presents a summary of the tested hypotheses, highlighting which relationships were statistically supported based on path estimates and subgroup analyses. All direct paths from DBPI to OE, EP, and EvP were significant. Additionally, OE significantly predicted both EP and EvP, and it mediated the relationship between DBPI and performance outcomes. The moderating role of AC was also confirmed across several pathways, with notable subgroup variations. For example, the effect of OE on EP was significant only among SMEs with credit access, while the OE–EvP path was stronger among firms without credit, reflecting nuanced interactions between digital integration, financial access, and sustainability outcomes. (see Table 11).

Discussion

This study examined how DBPI affects both EP and EvP in resource-constrained SMEs, with OE serving as a mediator and Access to Credit (AC) as a moderator. By employing a correlational design and SEM, the research provides a nuanced picture of how digital transformation efforts, particularly DBPI, can foster sustainability and competitiveness among SMEs in Uganda. The findings offer key insights into the role of technology adoption, operational improvements, and financial resources in driving firm performance under conditions of limited infrastructure and capital.

The results indicate a strong direct effect of DBPI on OE ($\beta = 0.758$, $p < 0.001$), demonstrating that SMEs embracing digital tools such as cloud-based enterprise systems or IoT monitoring are better equipped to streamline workflows, reduce errors, and optimize resource allocation. These improvements align with earlier studies by Hidayat-ur-Rehman and Hossain (2024) and Xi et al. (2024), who found that process and product digitalization substantially boosted operational metrics across different industries and country contexts. In Uganda, where SMEs frequently encounter infrastructural bottlenecks and managerial constraints, DBPI appears to alleviate many day-to-day operational burdens. For instance, real-time tracking of inventories through IoT can prevent stockouts or overproduction, while cloud-based tools such as QuickBooks or Odoo can automate financial reporting. These measures not only lower costs but also create opportunities for more data-driven decision-making an aspect that resonates with Sharma et al. (2024), who highlighted the agility benefits of Industry 4.0 technologies in low-resource environments.

The partial mediation of OE is particularly noteworthy. Its positive impact on both EP ($\beta = 0.258$, $p = 0.035$) and EvP ($\beta = 0.645$, $p < 0.001$) underscores how improvements in speed, accuracy, and resource utilization feed into broader performance outcomes. The mediation tests further reveal that DBPI's influence on EP and EvP is amplified when firms achieve higher OE ($\beta = 0.196$ for EP and $\beta = 0.489$ for EvP, both $p < 0.001$). These results echo the arguments of Li et al. (2020), who underscored how operational enhancements from digital adoption translate into economic and environmental gains. In the Ugandan context, where SMEs often operate on razor-thin margins, even modest efficiency gains can significantly affect overall business viability. Moreover, operational streamlining often has a "green" side effect: cutting unnecessary waste, minimizing energy consumption, and reducing carbon footprints (Bhagat et al., 2022). Hence, OE proves to be the linchpin linking digital transformation initiatives to a firm's economic bottom line and environmental footprint.

Beyond OE, the study finds that DBPI directly predicts both EP ($\beta = 0.434$, $p < 0.001$) and EvP ($\beta = 0.354$, $p < 0.001$). This suggests that digitalization can foster financial resilience and environmental responsibility in tandem a particularly important synergy in emerging economies where SMEs are tasked with contributing to GDP growth while mitigating ecological harm. Such dual outcomes align with Vo Thai et al. (2024) and Lerman et al. (2022), who identified similarly strong relationships between digital transformations and dual performance measures in Vietnam and Brazil, respectively. In Uganda, this translates into tangible strategies such as adopting energy-efficient production lines, deploying real-time sensors to monitor water usage, or optimizing delivery routes to reduce fuel costs and emissions. As Chuang and Huang (2018) found, blending green IT capabilities with digital solutions can be an effective lever for achieving both profitability and sustainability a combination that may hold promise in low- and middle-income countries where firms are compelled to innovate under tight resource constraints.

The multi-group analysis sheds further light on how AC modifies these relationships. Firms with credit access show a stronger link between DBPI and OE ($\beta = 0.952$, $p < 0.001$) than those without ($\beta = 0.621$, $p < 0.001$). This finding affirms that SMEs able to secure external financing are more likely to invest in advanced digital infrastructure and training, thereby maximizing the operational benefits of DBPI (Wahab Aidoo, 2019a). Interestingly, while OE exerts a significant positive effect on EP among credit-access firms ($\beta = 0.289$, $p = 0.006$), this effect is non-significant for those lacking credit ($\beta = 0.018$, $p = 0.908$). It appears that without adequate financing, efficiency gains do not necessarily translate into immediate financial returns possibly because these firms cannot scale their operations or invest in complementary resources that unlock higher revenues.

On the environmental side, however, the reverse pattern emerges. SMEs without credit access report an even stronger link between OE and EvP ($\beta = 1.156$, $p < 0.001$) compared to those with credit ($\beta = 0.765$, $p < 0.001$). This suggests that when funds are limited, SMEs may prioritize low-cost, high-impact operational improvements like lean production, waste reduction, and energy saving that directly support environmental goals. Bhagat et al. (2022) similarly found that resource-scarce SMEs often pursue operational strategies geared toward cost-saving measures that inadvertently benefit the environment. Consequently, the study reveals two distinct pathways based on credit availability: better-funded SMEs channel DBPI into profit-oriented initiatives, whereas those with limited credit utilize DBPI-driven efficiency as a means to offset costs and minimize waste.

Our findings reinforce the assertion that DBPI can be a strong driver of SME competitiveness and sustainability, even in low-income settings with multiple structural constraints. The interplay between OE and AC highlights how crucial financial resources are in unlocking the full potential of digital interventions yet also demonstrates that resource-constrained firms can adapt in creative ways to focus on environmental gains. In global comparisons, the effects of DBPI on Ugandan SMEs may be smaller than in countries like China or Vietnam, which enjoy stronger infrastructural and institutional support (Xi et al., 2024; Vo Thai et al., 2024). However, the fact that Ugandan SMEs still realize notable improvements underscores the adaptability and resilience of these enterprises.

Conclusions, implications, limitations and future research

Conclusions

This study examined the transformative role of DBPI on both EP and EvP performance among resource-constrained SMEs in Uganda. By applying RBV) and DCT, we established DBPI as a strategic resource capable of generating competitive advantages and a dynamic capability that enables agile responses to market and environmental challenges. The results revealed that OE plays a pivotal mediating function, translating DBPI-driven process enhancements into tangible performance gains. SMEs that embraced digital tools such as cloud-based systems or IoT technologies achieved greater cost savings and waste reductions, directly strengthening both EP and EvP.

Additionally, the study underscores credit access (CA) as a significant moderating force, amplifying the positive impact of DBPI on performance outcomes. Firms with credit were more equipped to invest in advanced digital systems and complementary resources, translating operational optimizations into higher profitability. However, SMEs without credit access still found value in DBPI by focusing on lean operations, thereby boosting environmental outcomes while mitigating resource constraints. These findings highlight the resourcefulness and adaptability of SMEs in developing contexts, where even limited digital adoption can yield meaningful improvements.

Overall, the study clarifies DBPI's importance for sustainability, competitiveness, and alignment with global environmental objectives. Although Uganda's underdeveloped infrastructure and restricted financial inclusion present challenges, they also offer opportunities for innovation in cost-effective digital solutions. Policymakers and stakeholders are therefore encouraged to prioritize inclusive financing strategies, digital training, and infrastructural support to maximize the benefits of DBPI. By doing so, SMEs can more effectively harness digital capabilities, forge agile and eco-conscious operations, and sustain growth in increasingly uncertain markets.

Implications

Theoretical implications

This study enriches existing knowledge by merging the RBV with DCT in examining how DBPI influences both EP and EvP in resource-limited SMEs. RBV identifies digital tools as valuable and hard-to-imitate resources that can boost competitiveness, while DCT explains how firms adapt these resources to shifting market conditions. By positioning DBPI as both a strategic resource and a dynamic capability, the study reveals that technology adoption alone is insufficient; instead, firms must continually reconfigure workflows to stay relevant.

A major theoretical contribution is highlighting Operational Efficiency (OE) as the link between DBPI and performance outcomes. While DBPI provides the technological foundation, OE ensures that day-to-day processes fully utilize digital capabilities, leading to better financial returns and reduced environmental impact. In addition, introducing Credit Access (CA) as a moderator expands our understanding of how financial capacity shapes the extent to which SMEs can benefit from digital adoption. This focus on OE and CA provides a holistic view of how technology, operations, and finance converge to drive sustainability and competitiveness, especially important in contexts marked by scarce resources.

Practical implications

For SME managers, the findings underscore that simply installing digital systems does not guarantee success. Managers need to align technology with clear operational goals, such as cutting lead times, reducing material waste, and lowering energy consumption. For example, affordable IoT sensors can track production or inventory in real time, allowing SMEs to adjust resource usage, control costs, and reduce their carbon footprint. However, these tools must be paired with staff training and process redesign to make sure data insights translate into action.

Further, the study suggests that while financially stable SMEs can invest in advanced solutions like cloud-based Enterprise Resource Planning (ERP) firms with limited credit can still implement basic, high-impact digital tools to see measurable gains. Even entry-level platforms can improve record-keeping or automate simple tasks, freeing up resources to focus on product quality and customer experience. For both financially constrained and well-funded SMEs, building internal skills remains vital. Employees who grasp the benefits and usage of digital technologies can turn small-scale trials into far-reaching operational improvements.

In terms of environmental sustainability, the results show that digital transformation can be an effective route for addressing global sustainability goals. By embedding energy efficiency, waste reduction, and eco-friendly practices into everyday activities, SMEs can align business growth with broader environmental objectives, reinforcing both brand reputation and regulatory compliance.

Policy implications

At a broader level, our study highlights financial inclusion as a cornerstone for successful digital adoption. Policymakers can help bridge this gap by offering subsidized loans, microfinance programs, or targeted grants, empowering more SMEs to invest in hardware, software, and staff development. Alongside financial support, governments and development agencies should prioritize digital infrastructure ensuring reliable internet access, fostering technology training centers, and encouraging public-private partnerships that expand the availability of affordable digital solutions.

Moreover, environmental incentives like tax breaks or fast-track approvals for green initiatives can motivate firms to adopt sustainable digital practices. Such measures are particularly valuable in developing regions, where limited capital often forces SMEs to opt for short-term savings over long-term ecological gains. By rewarding eco-friendly decisions, policymakers can shift this cost-benefit calculation, steering enterprises toward more responsible and future-proof strategies.

Overall, these policy recommendations support a thriving ecosystem where SMEs can readily access both the capital, and the technologies needed for digital transformation. Coupled with training and incentives for sustainable operations, such an approach has the potential to spur inclusive economic growth and help emerging markets meet pressing environmental targets. Ultimately, this dual focus on business viability and ecological stewardship can build resilience, enabling SMEs to adapt to evolving global pressures while still contributing to social and economic development.

Limitations

Although this study offers important insights into how Digital Business Process Integration (DBPI) can improve firm performance, several constraints warrant consideration. First, the cross-sectional research design does not allow for definitive causal conclusions. Longitudinal approaches would be beneficial for capturing the evolving effects of DBPI on economic and environmental outcomes over time. Second, while the study focuses on SMEs in Uganda, its findings may not generalize to regions with different financial or technological infrastructures. Comparative research across various countries and industries could illuminate how contextual elements shape the adoption and effectiveness of DBPI. Third, the analysis centers on operational efficiency (OE) and credit access (CA) as key mediating and moderating variables, respectively. Broader constructs such as institutional support, cultural norms, and market volatility could be incorporated in future studies to deepen understanding of the multifaceted factors influencing DBPI's impact on performance.

Future research

Further investigations could employ longitudinal designs to capture how DBPI's contributions evolve in response to technological advancements and shifting market demands. These studies could also examine more diverse populations and settings, offering a clearer picture of the global variance in DBPI adoption. In addition, exploring digital technologies beyond ERP or basic IoT such as blockchain for supply chain transparency or artificial intelligence for data-driven decision-making could shed light on DBPI's broader potential. Finally, while this study highlights the promise of digital transformation for sustainability, questions remain about the long-term environmental and social outcomes in developing economies. Future research could assess how sustained digital innovation impacts global sustainability goals, including climate action, resource efficiency, and social well-being.

Abbreviations

DBPI	Digital Business Process Integration
OE	Operational Efficiency
EP	Economic Performance
EvP	Environmental Performance
CA	Credit Access
SEM	Structural Equation Modeling
SME(s)	Small and Medium-sized Enterprise(s)
ICT	Information and Communication Technology
IoT	Internet of Things
ERP	Enterprise Resource Planning
SDG(s)	Sustainable Development Goal(s)
RBV	Resource-Based View
DCT	Dynamic Capabilities Theory
AVE	Average Variance Extracted
CR	Composite Reliability
CFI	Comparative Fit Index
TLI	Tucker-Lewis Index
NFI	Normed Fit Index
PCA	Principal Component Analysis
ROI	Return on Investment
SPSS	Statistical Package for the Social Sciences

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Author contributions

DSB conceptualized the study, collected and analyzed the data, and led the drafting of the manuscript. EKT contributed to the development of the theoretical framework and provided critical revisions to the manuscript. RB contributed to the research design, data interpretation, and review of the final manuscript. All authors read and approved the final version of the manuscript.

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Data availability
The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Competing interests
The authors declare no competing interests.

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