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From data to green innovation: The role of green organizational learning capability and total quality management

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ABSTRACT

This study aims to look into the role of green organizational learning capability (GOLC) as a mediator between big data analytic capability (BDAC) and the green innovation (GI) of manufacturing SMEs. Importantly, it explores the role of total quality management (TQM) as a moderator between BDAC and GI. A structured questionnaire and a cross-sectional approach were used to gather data from 219 Malaysian SMEs. The structural equation modelling method was used to examine the relationships in the suggested model. The findings reveal a significant positive link between BDAC and GI, emphasizing their crucial role in fostering environmental practices within manufacturing SMEs. Additionally, GOLC mediated the BDAC-GI relationship. Finally, TQM moderated the impact of BDAC and GI. This study provides empirical evidence of the interplay between BDAC, GOLC, TQM, and GI within the context of emerging countries, specifically focusing on Malaysian manufacturing SMEs. Moreover, the insights emphasize the importance for corporations, especially in developing regions, to adopt industry 4.0 technologies with GI to enhance their sustainability.

1. Introduction

In response to escalating environmental concerns and tightening regulatory pressures, green innovation (GI) has become a vital strategic pathway for organizations aiming to enhance sustainability and maintain competitiveness [1,2]. GI refers to "the development of eco-friendly products, processes, and practices that minimize environmental impact and contribute to sustainability" [3]. For small and medium-sized enterprises (SMEs) which form the backbone of many emerging economies pursuing GI is increasingly imperative [4]. Not only are SMEs expected to contribute to national sustainability goals, but their long-term viability increasingly depends on the ability to align operations with environmental expectations [5,6]. However, SMEs often operate with limited strategic resources, underdeveloped technological infrastructures, and fragmented knowledge systems, making the path toward green innovation particularly challenging [7].

Amid this challenge, BDAC has emerged as a strategic enabler that can help firms navigate the complexities of sustainability. It reflects the capability to collect, process, and apply large volumes of structured and unstructured data to support decision-making and innovation [8]. In theory, BDAC should empower SMEs to uncover sustainability opportunities, respond proactively to environmental demands, and foster GI. However, empirical findings remain mixed. Some studies affirm the positive influence of BDAC on sustainability and innovation [9–11], while others report inconsistent or weak effects (e.g., [12]). These discrepancies suggest that BDAC alone may be insufficient for driving GI, and that its effectiveness depends on internal capabilities and contextual factors that shape how analytics insights are interpreted and translated into action. One such capability is green organizational learning capability (GOLC), which reflects a firm's capacity to acquire, assimilate, and apply environmental knowledge in ways that promote sustainable practices and innovation" [13]. While organizational learning has long

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been associated with innovation [14,15], traditional frameworks often lack environmental specificity. GOLC extends this foundation by embedding a green orientation into the firm's learning routines, thereby enabling firms to adapt to environmental changes and develop proactive sustainability strategies. Notably, GOLC consists of two core dimensions: green absorptive capacity (GAC) and green transformative capacity (GTC), which together allow firms to internalize external green knowledge and reconfigure it for strategic use [13,16].

Recent studies have increasingly examined green organizational learning as a mediating mechanism across various contexts. It has been shown to mediate the relationship between regulatory and market pressures and radical GI in China [17], between green transformational leadership and innovation outcomes [18], and between green leadership and competitive edge in Turkey [13]. In Pakistan, GOL has been linked to the effect of green learning orientation on sustainability [19], and in Jordan, it mediates the link between green supply chain integration, BDAC, and GI [20]. Moreover, green entrepreneurship orientation has been identified as another mediating path from BDAC to GI [21]. Despite these contributions, the specific role of GOLC as a mediating mechanism in the BDAC–GI relationship remains underexplored, especially when considered as a multidimensional construct involving both GAC and GTC. From a theoretical standpoint, the dynamic capabilities view (DCV) supports this link, emphasizing that capabilities, such as GOLC, are essential for transforming data-driven insights into strategic innovation [22].

In addition to learning, the internal environment plays an essential role in amplifying the effectiveness of analytics. Here, TQM stands out as a vital contextual enabler. TQM practices, such as data-driven decision-making, continuous improvement, and employee involvement can create the structural and cultural conditions necessary for analytics and learning to generate impactful green outcomes [23]. Moreover, TQM aligns with the sustainability agenda by promoting efficiency, reducing waste, and embedding environmental consciousness into organizational routines [24,25]. Yet, the moderating role of TQM in the BDAC–GI link remains largely unexplored, especially in SMEs where formal systems are less developed, and TQM adoption varies widely [26]. Anchored in the DCV [22], this study advances understanding of how SMEs, particularly in emerging economies, can adapt to environmental challenges by reconfiguring internal capabilities. DCV provides a robust lens for examining how BDAC enables firms to sense sustainability opportunities, seize them through informed decision-making, and reconfigure operations via learning and innovation [27].

By focusing on SMEs in the Malaysian manufacturing sector, an economically vital yet environmentally vulnerable sector, this study provides timely insights into how digital and green capabilities can be harnessed despite institutional and resource constraints [28]. By integrating BDAC, GOLC, and TQM into a unified framework, this research addresses important theoretical and practical gaps at the intersection of digitalization, learning, and sustainability. To address these conceptual and empirical gaps, the study investigates the following research questions:

RQ1. How does BDAC influence GI?

RQ2. Does GOLC mediate the BDAC–GI link?

RQ3. Does TQM moderate the BDAC–GI link?

This research makes three key contributions. First, it develops an integrated framework linking BDAC to GI, with GOLC as a mediator and TQM as a moderator, thereby extending DCV into the GI domain. Second, it contributes to the organizational learning literature by conceptualizing and empirically testing GOLC as a multidimensional construct comprising GAC and GTC which remains underexplored in sustainability contexts [13,29]. Third, it provides novel empirical insights from Malaysian manufacturing SMEs, a setting where GI is increasingly critical yet unevenly supported [30,31].

The remainder of the paper is structured as follows: Section 2 reviews the relevant literature and theoretical foundations; Section 3 outlines the methodology; Section 4 presents the empirical results; Section 5 discusses key findings and implications; and Section 6 concludes with limitations and directions for future research.

2. Literature review

2.1. Theoretical basis

This study draws on DCV to explain how manufacturing SMEs in developing economies can achieve GI by leveraging data-driven, organizational, and quality-enhancing capabilities. As an extension of the resource-based view (RBV), DCV emphasizes that in rapidly changing environments, sustained competitive advantage depends not just on possessing valuable resources but on a firm's ability to sense, seize, and transform them in response to emerging opportunities [32,33]. Within this framework, BDAC is conceptualized as a foundational dynamic capability. BDAC enables companies to sense ecological opportunities through real-time data, seize them via informed decision-making, and transform operational processes toward greener, more sustainable outcomes. Although prior studies have highlighted BDAC's strategic role in general innovation [34,35], its specific application to GI in resource-constrained SMEs has been largely overlooked; this study addresses that gap [36]. DCV also highlights the importance of organizational learning in adapting and evolving capabilities.

Building on this, the study introduces GOLC as a partial mediator in the BDAC–GI relationship. GOLC enables firms to absorb external environmental knowledge and transform it into actionable green practices, reinforcing the transformative phase of dynamic capability development. Drawing on Hsu and Fang [16], GOLC is further divided into GAC, the ability to identify and acquire green knowledge, and GTC, the ability to internalize and reapply that knowledge over time. These components reflect the dynamic learning mechanisms that allow firms to continuously evolve and apply big data insights toward sustainable innovation [13,37,38]. Additionally, this study identifies TQM as a moderating capability that enhances the effectiveness of BDAC in driving GI. Under DCV, TQM can be viewed as an operational dynamic capability that supports continual improvement, standardization, and organizational responsiveness. Through practices such as employee involvement, process control, and defect prevention, TQM creates a structured environment where big data insights can be effectively converted into green solutions [1,39,40]. This interaction reflects the complementarity of digital, learning, and quality-based capabilities in building the organizational agility needed for sustainability. By integrating BDAC, GOLC, and TQM within the DCV framework, this study presents a more nuanced and cohesive model of how dynamic capabilities drive GI. It moves beyond static resource perspectives by showing that the transformation of data into sustainability outcomes requires continual learning and structured quality systems. In sum, this study extends DCV by demonstrating that GI is not a direct outcome of digital resources alone but emerges from the strategic alignment of big data capabilities, learning infrastructure, and quality management practices, all functioning as mutually reinforcing dynamic capabilities in the context of sustainability.

2.2. Big data analytics capability and green innovation

Green innovation refers to "*the development of new products, services, or processes that minimize environmental impact and contribute to sustainability*" [3]. This includes the adoption of eco-friendly technologies, energy-efficient practices, and the design of products that reduce waste and pollution. By integrating green innovation into business strategies, organizations not only meet regulatory demands but also enhance their competitive advantage in a rapidly evolving market focused on environmental stewardship [1].

Recent literature suggests that BDAC can serve as a strong antecedent to GI [41,42]. From the DCV [33], BDAC is considered a strategic resource that enables firms to transform vast amounts of data into actionable insights, thereby fostering innovation [43]. BDAC has been shown to support GI for both product and process. For product innovation, BDAC facilitates idea generation, enhances customer feedback analysis, and helps tailor offerings to environmental needs [21,44–47]. On the process side, BDAC improves operational efficiency, reduces environmental waste, and supports sustainability-driven production systems [48–50].While the general link of BDAC with innovation is well established [51,52], its specific relationship with GI is still evolving and remains under-explored [53]. Nevertheless, studies increasingly suggest that BDAC prompts companies' ability to respond to ecological challenges by enabling more efficient resource use and facilitating data-driven sustainability strategies [47,54,55]. Based on this discussion, we assume that:

H1. BDAC is significantly related to GI.

2.3. *Mediating of green organizational learning capability*

In the era of digital transformation, BDAC has become essential for organizations seeking to navigate complex, data-rich environments. BDAC refers to "*a firm's ability to acquire, process, and utilize massive volumes of structured and unstructured data to generate meaningful insights that support strategic decisions*" [56]. Beyond technical proficiency, BDAC represents a higher-order capability in knowledge processing that prompts a company's ability to discover hidden patterns and generate valuable knowledge that was previously inaccessible [57]. This ability to transform raw data into actionable insights is particularly crucial in the context of GI, where firms must respond swiftly to environmental changes, regulatory pressures, and shifting consumer preferences for sustainability [21,47]. BDAC plays a vital role in supporting GI by enabling firms to identify environmental risks, monitor resource consumption, optimize operations, and assess the ecological performance of products and processes [36]. Through advanced analytics, BDAC assists in improving productivity and reducing waste, thereby directly contributing to both green product and green process innovation [49,50].

However, the conversion of data-driven insights into impactful environmental outcomes requires more than just technical capability; it demands organizational learning. OL refers to a firm's capability to acquire, disseminate, and apply knowledge to enhance adaptability and decision-making [58]. In sustainability contexts, OL evolves into GOLC, which defined as "*a firm's capacity to acquire, assimilate, and apply environmental knowledge in ways that promote sustainable practices and innovation*" [13]. GOLC enables firms to embed environmental values into their learning culture, thus enhancing their ability to innovate sustainably [13,59]. BDAC enhances GOLC by equipping firms with the technological infrastructure and analytical tools needed to interpret and distribute environmental knowledge effectively [60,61]. Through real-time data analysis, organizations can better understand ecological trends, customer expectations, and compliance requirements, fostering green learning and capability development. In turn, GOLC enables firms to integrate green principles into operations, facilitating the generation of eco-friendly products and proactive responses to environmental challenges [62].

Organizations with strong GOLC are more likely to utilize BDAC for GI because they can absorb and apply environmental knowledge in dynamic contexts. Prior studies highlight that OL enhances innovation by helping firms to sense and seize opportunities in both digital and environmental domains [36,63,64]. Thus, GOLC becomes a critical capability that not only supports GI directly but also acts as a conduit through which the benefits of BDAC are realized in sustainable innovation outcomes. The BDAC-GI relationship is therefore not purely direct. While BDAC presents valuable insights, these insights must be transformed into action through effective learning mechanisms. Without GOLC, the data may remain underutilized or disconnected from green strategic goals [65]. GOLC integrates and reconfigures both internal and external knowledge, translating it into capabilities that support innovation aligned with sustainability [38,66]. Based on the above discussion, we assume that:

H2. BDAC is significantly related to GOLC.

H3. GOLC is significantly related to GI.

H4. GOLC mediates the BDAC-GI relationship.

2.4. *Moderating of total quality management*

In the current business landscape, TQM has a crucial role in promoting business performance and productivity [67]. Numerous authors have recognized TQM as a key source of competitive edge [68]. TQM is seen as "*an environmentally friendly approach because it minimizes waste and optimizes resource efficiency*" [1].

Research suggests that while BDAC can improve information quality and business value, its effectiveness heavily relied on the quality of the data being analyzed [69]. Therefore, organizations should prioritize quality before adopting BDAC, as the success of BDAC relies on the quality and speed of operations [31,70,71]. Data quality is a major challenge for organizations aiming to leverage BDAC for better decision-making, more operational efficiency, better customer service, and sustainable manufacturing [71]. TQM, which focuses on continuous improvement and quality assurance, enhances the accuracy and reliability of data utilized in analytics, thereby supporting more effective GI initiatives [72]. Additionally, TQM fosters a culture of employee involvement and continuous improvement, encouraging valuable insights and support for BDAC initiatives. Furthermore, Dubey et al. [73] emphasized the importance of TQM techniques, tools, customer satisfaction, supplier quality, quality standards, and quality management for successfully implementing BDAC in manufacturing. With the support of top management, BDAC can significantly refine the entire system and organizational performance [74]. By moderating the BDAC-GI link, TQM enables firms to leverage their big data capabilities more effectively, which lead to improved GI outcomes. Considering the previously mentioned, we propose that:

H5. TQM moderates the BDAC-GI relationship.

Fig. 1 shows the research model.

3. Methodology

3.1. *Sample*

This study uses a quantitative cross-sectional survey approach to investigate the influence of BDAC, GOLC, and TQM on GI among manufacturing SMEs in Malaysia. The study focuses on SMEs located in the northern states Perlis, Kedah, Penang, and Perak selected for their strategic role in the Northern Corridor Economic Region and high

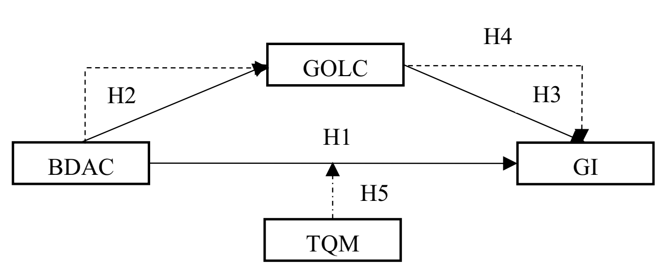

Fig. 1. Research model.

concentration of industrial and SME activity [75,76]. While geographically focused, the sample was stratified by manufacturing sub-sectors to enhance representativeness across Malaysia's SME manufacturing base. A simple random sampling technique was employed to ensure each firm had an equal chance of selection [77]. The sampling frame was developed using two reliable sources "the SME Corporation Malaysia database [78]" and "the Federation of Malaysian Manufacturers [[79] directories (2019)". To mitigate sampling bias, a systematic randomization process was applied, and industry stratification was used to ensure proportional representation of different manufacturing sub-sectors.

Data were collected through a structured questionnaire distributed to top-level managers, including CEOs, R&D heads, quality managers, operations managers, and marketing managers. These roles were selected because of their involvement in innovation strategy, quality initiatives, and organizational learning, ensuring the accuracy and relevance of the information provided ([30], b).

A total of 300 questionnaires were distributed via email, and 219 valid responses were received, surpassing the minimum threshold for structural equation modelling [80]. Using G*Power [81], the minimum required sample size was calculated as 77 (effect size = 0.15, $\alpha = 0.05$, power = 0.80), confirming that the final sample size was sufficient. The response rate of 70 % is much and better than previous SME studies in Malaysia ([82,83], validating the sampling strategy and data adequacy. Furthermore, this sample size is larger than the 100 questionnaires that Hair et al. [80], recommend. Additionally, the sample size and structure align with prior empirical research on Malaysian SMEs [1,4], supporting the credibility and generalizability of the findings.

Prior to utilizing the data for additional analysis, "common method bias (CMB)" was evaluated utilizing Harman's single-factor test, according to Podsakoff et al. [84]. Because the variance explained by a single factor was below the 50 % criterion, the results showed that CMB was absent. CMB is therefore not a problem in this data set.

Table 1 presents the demographic data of the study, showing that most of the companies in the sample have been in the industry for more than ten years (43 %), indicating significant experience. The sample includes both small and medium-sized companies, with small-sized companies making up 48 % of the total sample and medium-sized companies, defined as having fewer than 200 employees, comprising 52 %. This variety in company size is deemed adequate for the study. Table 1 illustrates the industrial structure of the participating companies. According to the results, the majority of companies are in the food and beverage sector (33 %), followed by wood and wood products (21 %). Other companies are distributed across various categories such as "paper products, iron and steel, and textiles".

Table 1
Demographic characteristics.

Category	Number
Position:	
CEO	53
Marketing executive	46
Operation executive	27
R&D executive	48
Quality manager	45
No. of employees:	
Between 5 and 74	105
Between 75 and 200	114
Established (years):	
5–10	70
11–15	94
>15	55
Sub-Sector Industry:	
Food and beverage	73
Paper and paper products	11
Non-metallic mineral products	3
Products and machinery	14
Automobile and motoring products	5
Textile and wearing apparel	15
Wood and wood products	46
Electrical and electronic	22
Iron and steel	30

3.2. Measures

This study utilized a self-administered questionnaire, incorporating validated items from existing literature with slight adjustments to align with the Malaysian SME manufacturing context. To ensure the clarity and ease of understanding of the questionnaire items, face and content validity tests were conducted [85]. The instrument was reviewed by academic experts and pilot-tested with 15 SME managers, with feedback from the pretest leading to minor revisions for better clarity and contextual relevance.

For BDAC, four items were adapted from Al-Khatib [36] for measurement, while GOLC (as a multidimensional construct including GAC and GTC) was measured with six items adapted from Özgül & Zehir [13]. Moreover, four items were adapted from Fikri et al. [86] to measure TQM, and finally, three items were adapted from Azam et al. [87] to measure GI. A five-point Likert scale was used. The finalized measurement items are presented in Appendix 1.

4. Data analysis

For the data analysis, we used PLS-SEM, which is more suitable for analyzing data with nonnormality problems and has been widely utilized in management studies [88–90]. PLS-SEM has more statistical power than covariance-based SEM (CB-SEM) in the context of complicated models with small sample sizes, especially when working with lower sample sizes and concentrating on prediction in research [91]. PLS-SEM consists of two models: measurement and structural model, as follows:

4.1. Measurement model

Indicator loadings with values ≥ 0.70 confirmed internal consistency and reliability [91]. Convergent validity was established by meeting three criteria, including "factor loadings > 0.70, composite reliability > 0.70, and average variance extracted (AVE) > 0.50″ (Ibid).

As shown in Table 2, these standards were met. Discriminant validity was also confirmed using "the Heterotrait-Monotrait ratio of correlations (HTMT)", with coefficients below 0.85, which indicate sufficient validity [92], as shown in Tables 3 and 4.

Table 2
Reliability and convergent validity.

Variable	Code	Loading	CR	AVE
BDAC	BDAC1	0.765	0.910	0.718
	BDAC2	0.899		
	BDAC3	0.899		
	BDAC5	0.818		
GAC	GAC1	0.848	0.895	0.740
	GAC2	0.866		
	GAC3	0.866		
GTC	GTC1	0.911	0.937	0.832
	GTC2	0.920		
	GTC3	0.905		
TQM	TQM2	0.831		
	TQM3	0.851		
	TQM4	0.849		
	TQM5	0.835		
GI	GI1	0.910	0.900	0.750
	GI2	0.898		
	GI4	0.785		

Note: "AVE= average variance extracted; CR=composite reliability; BDAC= big data analytics capability; GAC= Green absorptive capability; GTC= Green transformative capability; TQM= Total quality management; GI= Green innovation".

Table 3
Discriminant validity by HTMT (1st order).

Construct	GAC	GTC
GAC		
GTC	0.681	

Table 4
Discriminant validity by HTMT (2nd order).

Construct	BDAC	GI	GOLC	TQM
BDAC				
GI	0.631			
GOLC	0.762	0.729		
TQM	0.549	0.347	0.655	

4.2. Structural model

The structural model assessed the proposed links in Fig. 1 to validate the psychometric properties of the measurement model. Using R^2 values, Hair et al. [91] found that the model explained 47.1 % of the variance in GI and 34.0 % in GOLC among manufacturing SMEs, which Chin [93] classifies as moderate predictions. The model's predictive capability, evaluated using the Q^2 criterion, showed values of 0.376 for GI and 0.328 for GOLC, indicating satisfactory predictive relevance [94], as shown in Table 5.

Moreover, strong path estimates were obtained using bootstrapping using 5000 resamples. The PLS-SEM analysis confirmed the hypothesized relationships (Tables 6 and 7): BDAC significantly enhanced GI ($\beta = 0.674$, $t = 10.452$, $p < 0.05$), supporting H1, and positively influenced GOLC ($\beta = 0.583$, $t = 9.922$, $p < 0.05$), supporting H2. Additionally, there was a significant positive relationship between GOLC and GI ($\beta = 0.316$, $t = 3.904$, $p < 0.05$), supporting H3.

Additionally, the proposed mediating role of GOLC in the BDAC-GI link in H4 was investigated through the application of Preacher and Hayes' [95] techniques for indirect effects. Hair et al. [96] suggest the PLS-SEM bootstrapping technique for the analysis of mediation, which they believe is more trustworthy than Baron and Kenny's [97] traditional causal process. SEM is a better method since it allows the assessment of variable relationships simultaneously [96]. Table 6 demonstrates the significant indirect effect of BDAC on the GI through GOLC ($\beta = 0.185$, $t = 3.806$, $p < 0.05$). According to our investigation, in SMEs, GOLC serves as a partial mediator in the BDAC-GI link.

Furthermore, the results of this study indicated that TQM may act as a moderator in the BDAC-GI link. The moderation analysis was evaluated using an orthogonalization method, where the absence of zero between the higher and lower confidence intervals supports the moderation hypothesis. The outcomes back up H5 (see Fig. 2), as Table 7 shows that TQM moderates the BDAC-GI link.

5. Discussion

This study explored how BDAC enhances GI in manufacturing SMEs, focusing on the roles of GOLC as a mediator and TQM as a moderator. Rooted in the DCV, the findings shed light on how firms can leverage digital and learning capabilities to innovate sustainably. First, the results confirm that BDAC significantly enhances GI (H1). This supports prior research showing that analytics capabilities help firms identify environmental inefficiencies, reduce waste, and develop eco-friendly products and processes [43,48,55]. BDAC enables SMEs to translate large, complex datasets into actionable insights that inform sustainable decisions [98]. Firms that use BDAC effectively are also better equipped to respond to societal and regulatory pressures, enhance their green image, and demonstrate corporate social responsibility [14,99]. However, the BDAC–GI relationship has not been widely studied in SME contexts, especially in developing economies. This study addresses that gap, highlighting that BDAC is not just a digital tool, but a strategic capability for green transformation [36,100].

Table 5
R^2, Prediction, and Effect Size.

Constructs	R^2	Q^2	f^2	
			BDAC	GOLC
GI	0.471	0.376	0.261	0.104
GOLC	0.340	0.328	0.516	

Table 6
Direct and indirect effects.

Path	β	t-value	p-value	Decision
BDAC→GI	0.674	10.452	0.000	*H1. Supported*
BDAC→GOLC	0.583	9.922	0.000	*H2. Supported*
GOLC→GI	0.316	3.904	0.000	*H3. Supported*
BDAC→GOLC→GI	0.185	3.806	0.000	*H4. Supported*

Table 7
Interactive effects.

Path	β	t-value	p-value	Decision
TQM x BDAC→GI	0.086	1.664	0.000	*H5. Supported*

Second, BDAC is found to positively influence GOLC (H2), indicating that data capabilities contribute to building a learning culture focused on sustainability. This aligns with Ferraris et al. [38], who argued that BDAC enhances a firm's decision-making and innovation by fostering knowledge acquisition and integration. SMEs with strong analytics infrastructures and data-driven mindsets are more capable of interpreting environmental data and learning from it [15,101]. Our findings support the view that GOLC grows out of managerial skill, data systems, and organizational culture key elements also highlighted by Henao-García et al. [102] and Aziz et al. [14]. These capabilities help SMEs turn data into internal knowledge, adapt quickly, and align behavior with green goals [61,63]. Third, the results show that GOLC significantly contributes to GI (H3). This reinforces the role of organizational learning as a key driver of innovation, particularly in sustainability contexts [103,104]. GOLC enables firms to absorb, share, and apply environmental knowledge, which is crucial for developing green products and improving processes [105]. Unlike general learning, GOLC focuses specifically on environmental objectives and allows firms to respond to external pressures with agility and innovation [58,106]. This supports the growing recognition that green learning is a competitive necessity, especially in SMEs facing increasing environmental demands [37,107].

Importantly, GOLC is shown to partially mediate the BDAC-GI link (H4). This means that while BDAC has a direct effect on GI, its impact is stronger when firms develop robust learning capabilities. BDAC provides the data and tools, but GOLC ensures that this information is understood, contextualized, and applied to real-world problems. This mediation effect supports the DCV argument that organizational learning is a dynamic capability essential for adapting to environmental complexity and driving innovation [32,108]. The finding also expands on recent studies showing GOLC's role in linking green leadership, innovation, and competitive advantage [13,37].

Finally, TQM is found to positively moderate the BDAC–GI relationship (H5), indicating that the presence of strong quality management practices enhances the effectiveness of BDAC in driving GI. TQM improves data reliability, promotes continuous improvement, and ensures that environmental objectives are integrated into everyday practices [1]. Without TQM, firms may lack the structure needed to make sense of data or implement data-driven solutions effectively. This is particularly relevant in SMEs, where challenges such as poor data quality and limited digital maturity often hinder the value of BDAC [1,

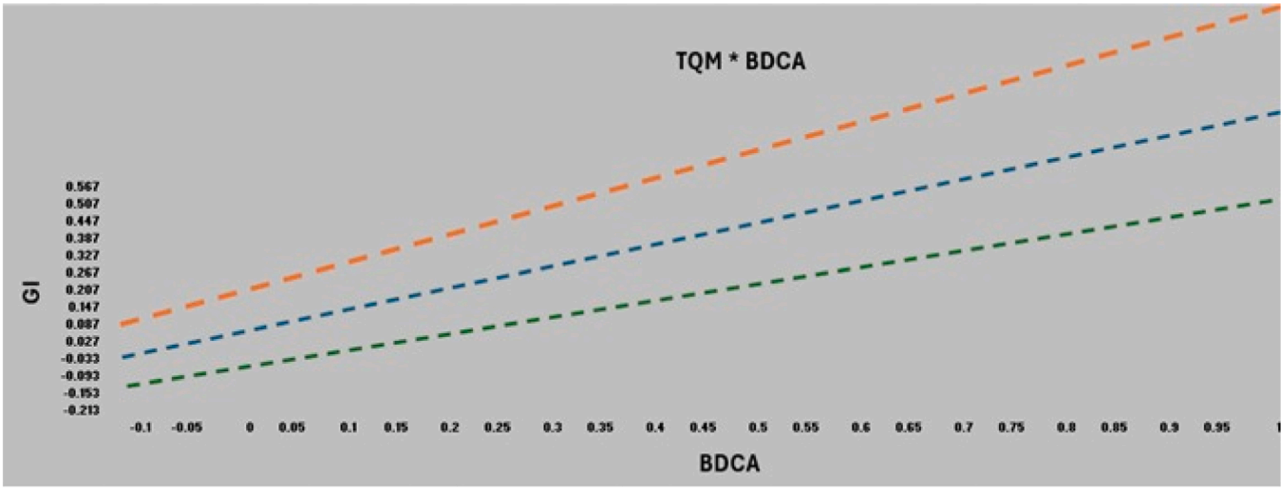

Fig. 2. Moderating effect of TQM on BDAC-GI link.

40]. The interaction of TQM and BDAC thus creates an environment where green insights can be more easily turned into action. In sum, this study offers a comprehensive explanation of how digital, learning, and quality capabilities combine to enable GI in SMEs. BDAC alone is not enough; it must be supported by a culture of environmental learning and structured quality practices. For SMEs in emerging economies like Malaysia where regulatory pressure is increasing but resources are limited these findings offer practical guidance on how to build capabilities that support both competitiveness and sustainability [109,110]. This integrated framework contributes to filling a gap in the literature by showing that the path from data to innovation is neither automatic nor linear, but dependent on how firms learn and manage quality [12,37].

6. Conclusions

6.1. Theoretical implications

The theoretical implications of this study are multifaceted. First, this study extends the DCV by demonstrating how BDAC, GOLC, and TQM simultaneously contribute to GI among manufacturing SMEs. It highlights that dynamic capabilities, specifically the ability to sense sustainability opportunities through BDAC, seize them through organizational learning (i.e., GOLC), and transform them into actionable strategies via TQM, are critical for driving sustainable innovation. This expands our understanding of how firms in resource-constrained contexts can leverage digital, learning, and quality capabilities to develop sustainability-based competitive advantages and how digital transformation supports the circular economy and green growth in emerging economies. Second, the study conceptualizes GOLC as a critical mediating capability in the BDAC-GI link, introducing a multidimensional construct that includes both GAC and GTC. This represents a theoretical development in the organizational learning literature, where previous studies have largely overlooked the environmental aspect of learning. As such, the study provides empirical evidence that GOLC is essential for firms to effectively translate big data insights into sustainable innovation, advancing the theoretical understanding of organizational learning in sustainability contexts. Third, by highlighting the moderating role of TQM in the BDAC-GI link, the study extends the literature on TQM within the context of sustainability and GI, an area that has been somewhat overlooked. Lastly, the study challenges the traditional view that green innovation is solely driven by external pressures or technological resources, instead proposing that internal capabilities, such as data analytics, organizational learning, and quality management, are pivotal to achieving sustainable innovation outcomes.

6.2. Practical implications

This study offers several valuable insights for managers and policymakers in the Malaysian SME manufacturing sector. First, managers should prioritize building strong BDAC as a foundation for GI. This includes investing in essential data infrastructure, recruiting staff with technical and managerial BDA expertise, and embedding data-driven decision-making across operations. A strong data culture one that combines analytical insight with managerial intuition is key for SMEs aiming to compete in fast-changing markets [38]. Second, developing GOLC is essential for leveraging BDAC effectively. This approach is especially relevant for resource-constrained Malaysian SMEs, enabling them to balance long-term innovation with short-term competitiveness [15]. Third, TQM practices can further amplify the impact of BDAC on GI. Managers should reinforce quality-driven cultures that promote cross-functional collaboration, continuous improvement, and customer-focused innovation. Embedding TQM within digital and learning strategies can help Malaysian SMEs meet both domestic and global quality expectations while fostering sustainable innovation.

From a policy standpoint, government agencies in Malaysia, such as SME Corp and MIDA should support capacity-building initiatives that integrate digital skills, organizational learning, and sustainability practices. Tailored funding schemes, training programs, and BDA literacy campaigns would help SMEs better align with the country’s broader Industry 4.0 and green economy goals. Policy incentives should also promote the adoption of quality frameworks that support innovation and sustainability. In sum, this study highlights that for Malaysian manufacturing SMEs, the synergy between BDAC, GOLC, and TQM is crucial for unlocking innovation potential and enhancing competitiveness in a sustainability-driven economy.

6.3. Limitations and future research

Despite offering valuable insights, this study has several limitations that may influence the interpretation and generalizability of its findings. First, the research was confined to manufacturing SMEs in Malaysia. Contextual factors such as national policy, regulatory pressures, and cultural attitudes toward sustainability may limit the applicability of these findings to other sectors or countries. Future studies could adopt cross-country or multi-sectoral comparisons to test the robustness of the proposed relationships under different institutional and economic conditions. Second, the use of cross-sectional data restricts the ability to infer causality between BDAC, GOLC, and GI. For example, it is possible that firms engaging in GI may develop stronger data analytics or learning capabilities over time. Future research should consider longitudinal designs to better capture these temporal dynamics and validate the causal paths proposed, particularly within the framework of the DCV [32]. Third, data were collected exclusively through self-reported questionnaires, which may introduce common method bias or socially desirable responses. Although statistical tests were conducted to minimize this risk, future studies should employ mixed methods such as interviews or case studies to triangulate findings and deepen understanding, particularly of how GOLC manifests in practice. Fourth, the study did not account for respondents' demographic characteristics such as education, age, or managerial experience. These factors may moderate how BDAC and GOLC are perceived and implemented. Future research could explore demographic and organizational heterogeneity through multi-group analysis to enhance contextual relevance. Lastly, GOLC remains a nascent construct in sustainability literature. While this study establishes its mediating role, future work should explore its antecedents (e.g., leadership style, environmental culture) and consequences (e.g., green competitive advantage), using grounded theoretical lenses like DCV or institutional theory to enrich conceptual development.

CRediT authorship contribution statement

Ibraheem Saleh Al Koliby: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Abdullah Kaid Al-Swidi:** Writing – review & editing, Writing – original draft, Resources, Project administration, Methodology, Conceptualization. **Mohammed A. Al-Hakimi:** Writing – review & editing, Writing – original draft, Visualization, Resources, Conceptualization. **Nurul Aini Binti Mehat:** Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Hamid Mahmood Gelaidan:** Funding acquisition, Investigation, Resources, Software, Validation, Writing – review & editing. **Hamood Mohammed Al-Hattami:** Writing – review & editing, Validation, Software, Resources, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.sftr.2025.101191.

Data availability

Data will be made available on request.

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