

Key drivers of green innovation: internal resources, external pressures and dynamic capabilities

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Abstract

Purpose – This study examines the effects of internal resources, external pressures and dynamic capabilities on green innovation and identifies their type-specific factors, focusing on green product innovation and green process innovation in Malaysia.

Design/methodology/approach – Given the presence of multiple potential factors, we employed Bayesian Model Averaging for linear regression, which is effective for handling uncertainty in variable selection using multiple models. In addition, we used ordinary least squares regression for checking the results' robustness.

Findings – By analyzing survey data from 150 firms, the results of Bayesian linear regression indicate that external networks and external knowledge are key drivers of green innovation (GI), both in general and for each type of innovation. However, their relative importance is different, depending on the type - external networks have a strong effect on green product innovation (GPDI), but only a weak effect on green process innovation (GPCI). Technological advantage strongly affects GPDI, while organizational support has a moderate effect on GPCI.

Originality/value – Based on an integrative framework, this study provides a comprehensive understanding of how internal, external and dynamic factors influence green innovation and also highlights the significance of their type-specific dynamics. The results further emphasize the crucial role of government policies in promoting collaboration and strategic partnerships, through initiatives that enhance and support research and development activities.

Keywords Green innovation, Internal resources, External pressures, Dynamic capabilities

Paper type Research article

Introduction

Economic growth is often a catalyst for environmental degradation. In response to growing environmental challenges, green innovation (GI) has become a strategic priority for firms engaging in sustainable development, driven by increasing institutional pressures and dynamic market conditions. As an emerging economy that strongly relies on both manufacturing and service sectors, Malaysia is committed to the United Nations 2030 Agenda for Sustainable Development, whose goals are reflected in various national policies, including the Green Technology Master Plan (2017–2030). However, the country still faces difficulties regarding professional skills, technology and institutional structure, as well as uneven levels of digital adoption, which shows the relevance of understanding the factors that drive GI.

Previous studies examine internal resources or external pressures separately or consider both in a segmented way resulting in an incomplete approach of how these forces jointly shape GI outcomes. Zailani, Iranmanesh, Nikbin, and Jumadi (2014) investigated the effects of



human resources, customer pressure and environmental uncertainty on GI in the transportation sector, while other authors considered both internal and external factors regarding different types of GI. More importantly, firms face distinct barriers concerning innovation in green products, processes and systems. Factors such as managerial attitudes and perceptions, business practices and customer demand are constraints to green product innovation (GPDI) and green process innovation (GPCI) (Abdullah, Zailani, Iranmanesh, & Jayaraman, 2016).

Only internal resources and external pressures cannot explain how firms adapt and reconfigure their capacities in response to a fast-evolving business environment. In the era of Industry 4.0, digital transformation and innovation are crucial for firms' survival (Tajudeen, Nadarajah, Jaafar, & Sulaiman, 2022). Digital technologies, including big data analytics, the Internet of Things (IoT) and cloud computing, are reshaping business operations. Yet, in emerging economies like Malaysia, companies are still resistant to adopting big data technologies (Zian, Zulkarnain, & Kumar, 2024). The inconsistent literature raises an important question about the extent to which internal, external and dynamic factors drive GI, and if the effects of these drivers differ for GPDI and GPCI. To address these gaps, we developed an integrated framework, based on the resource-based view (RBV), institutional theory and dynamic capabilities (DC) theory, in order to explore the effects of internal resources, external pressures and DC on GI and investigate their type-specific factors.

Given the presence of multiple potential factors, we chose to use the Bayesian Model Averaging (BMA) for linear regression in the analysis, since it effectively addresses uncertainty in variable selection by assessing several models. In addition, we carried out an ordinary least squares (OLS) regression to compare the results and make robustness checks. This study provides a comprehensive understanding of GI drivers and emphasizes the importance of type-specific dynamics. Specifically, it extends RBV by explaining how institutional pressures shape GI in the context of environmental sustainability, and DC theory provides a more comprehensive explanation of the dynamic factors that drive it.

Literature review

Theoretical background

Distinct theories have been used as the basis for GI. Among them, RBV is one of the leading ones (Tariq, Badir, Tariq, & Bhutta, 2017), by explaining a firm's internal resources and capabilities, which should be inimitable, irreplaceable, rare and valuable. Such resources act as drivers for innovation, sustaining competitive advantage (Barney, 2001). Therefore, internal resources, such as technological advantage, technological compatibility, organizational culture and organizational support, are crucial drivers for GI.

In addition to RBV, institutional theory is another leading theory for GI (Tariq *et al.*, 2017). In particular, the neo-institutional theory highlights that even quite rigid organizations may be compelled to change under both internal and external pressures. Three isomorphic processes, namely coercive, mimetic and normative, drive this change (DiMaggio & Powell, 1983). Scott (2014) extends the institutional approach by introducing three pillars of institutions that influence organizations: regulative, normative and cognitive. These pillars include formal standards and regulations, values and rules, and the social norms and beliefs that jointly shape firm behavior. Therefore, external pressures from stakeholders, like customers, government bodies, industrial partners and supply chain partners, can strongly influence firms' GI activities, forcing them to achieve legitimacy and enhance business sustainability. Therefore, institutional theory provides a crucial external dimension for GI study. For example, external networks, external customers, external knowledge and external support are important mechanisms to consider.

In addition to RBV and institutional theory, digital transformation has emerged as a key enabler of innovation, with firms leveraging digital technologies more and more to support process innovation (Urbinati, Chiaroni, Chiesa, & Frattini, 2020). Despite its contributions, RBV has limitations, especially in explaining the internal creation and evolution of capabilities

and how firms adapt to fast-changing environments. In response to these shortcomings, DC theory emerged as an alternative perspective (Galvin, Rice, & Liao, 2014), bringing a more comprehensive explanation of the internal mechanisms through which firms develop, deploy, integrate and reconfigure resources over time, in order to address dynamic market conditions (Teece, Pisano, & Shuen, 1997; Teece, 2007, 2020).

Companies with strong DC are not only adaptive but also proactive, shaping their external environments through innovation and collaboration. As such, this theory considers DC a critical determinant of long-term sustainability (Teece, 2007), and the quick advancement of artificial intelligence (AI) is further emphasizing the need for organizational adaptability. Firms must respond to increasingly complex and evolving business environments, particularly as sustainability practices are reshaped by technological progress and AI-driven change. For Nguyen *et al.* (2025), DC theory provides a relevant and strong framework for understanding these emerging challenges.

Hence, by integrating RBV, institutional theory and DC theory, this study proposes an integrative framework to examine the effects of internal resources (I), external pressures (E) and DC (D) on GI. Figure 1 presents the IED framework.

Internal resources

Compared to traditional technology, green technology includes features that support GPDI and GPCI. Technological advantage refers to a firm's superior technological capabilities ahead of its competitors, enabling it to operate more efficiently and contribute to GI. Technological compatibility is the extent to which a new technology aligns with an organization's existing systems, processes and infrastructure. The higher a technology's compatibility, the easier it is for firms to implement GI. Empirical evidence supports this relationship, as green technology plays a critical role in improving environmental quality (Du & Li, 2019). It also improves operational efficiency and decreases costs, helping to reduce environmental degradation in Malaysia (Suki, Suki, Sharif, Afshan, & Jermsittiparsert, 2022). Furthermore, technology readiness shows that both technological advantage and technological compatibility are significant drivers of GI (Zhang, Sun, Yang, & Wang, 2020).

From an organizational perspective, green organizational culture shapes employees' behaviors by gradually internalizing sustainability values and encouraging proactive actions

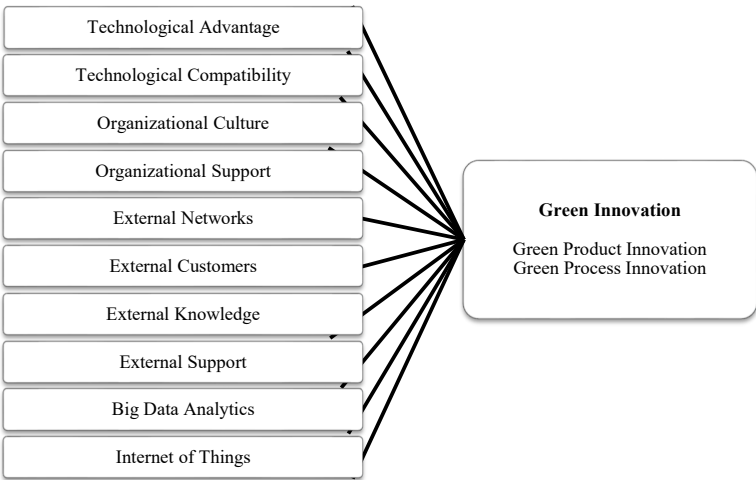


Figure 1. The IED framework

that drive GI. It fosters greater employee commitment, either through a direct relationship with organizational commitment or indirectly, through job satisfaction. Therefore, firms that implement such a culture can enhance both outcomes (Shahriari, Tajmir Riahi, Azizan, & Rasti-Barzoki, 2023). In addition, green organizational culture strongly affects GI (Kiefer, Del Río González, & Carrillo-Hermosilla, 2019), while organizations committed to environmental governance strengthen their capacity for GI (Salihi, Ibrahim, & Baharudin, 2024). Another important factor is organizational support, which is a strong sign of managerial commitment to sustainability initiatives. Managerial support at all levels encourages creative thinking and provides appropriate resources for GI, showing that the organization appreciates employees' contributions and fosters the psychological security required for environmental trial and error, thus enabling employees to do their tasks more effectively. According to Fan, Tang, Chen, and Sun (2022), organizational support is directly related to proactive innovation behavior, thus encouraging GI.

Based on RBV, a firm's internal resources, including technological advantage, technological compatibility, organizational culture and organizational support, are likely to influence GI.

Therefore, the following hypotheses were developed:

- H1. Technological advantage positively influences GI.
- H2. Technological compatibility positively influences GI.
- H3. Organizational culture positively influences GI.
- H4. Organizational support positively influences GI.

External pressures

From an institutional perspective, external networks refer to inter-organizational relationships, such as horizontal collaborations or partnerships with competitors, or firms offering complementary products and services, which are important for GI. Previous studies acknowledge strong external networks as an essential form of social capital that facilitates access to valuable resources and knowledge (Cai & Zhou, 2014), thus supporting GI. In addition, external customers play a significant role in promoting GI; they are increasingly aware of eco-friendly products and tend to switch to less polluting products with longer lifespans (Chen, 2008). Therefore, public demand for green products and services expands market niches and accelerates GI to meet more stringent environmental standards (Fusillo, Orsatti, & Scandura, 2025), while market orientation is considered critical within innovation clusters (Kovács, 2025). Likewise, external knowledge, especially from supply chain partners and customers demanding sustainable practices, creates institutional pressures that influence GI. Medeiros, Vidor and Ribeiro (2018) also highlight the importance of customer expectations for driving GPDI. External support, through government incentives and subsidies, is an important institutional mechanism that supports GI. Solangi, Alyamani and Magazzino (2024) identified government initiatives to support GI as significant drivers for the adoption of renewable energy technologies, thus accelerating the transition toward sustainable development.

Drawing on institutional theory, firms' pressures arising from the institutional environment, including external networks, customers, knowledge and support, are likely to influence GI. Hence, we proposed the following hypotheses:

- H5. External networks have a positive influence on GI.
- H6. External customers have a positive influence on GI.
- H7. External knowledge has a positive influence on GI.
- H8. External support has a positive influence on GI.

Dynamic capabilities

In addition to internal resources and external pressures, the emergence of digital technologies such as AI, big data analytics and IoT brings new opportunities for advancing GI. From DC perspective, big data analytics regards the analysis of large and complex datasets that enable organizations to generate meaningful perceptions for decision-making, particularly for understanding customer needs and market trends. Big data analytics has become an essential tool for enhancing the environmental performance of the production sector, especially for companies facing sustainability challenges. Moreover, the increasing use of big data analytics leads to enhanced GI in manufacturing firms by improving the efficiency of factor allocation for both labor and capital (Waqas, Honggang, Ahmad, Khan, & Iqbal, 2021; Gao, Cheng, & Sun, 2023).

IoT refers to interconnected devices that collect and convey data through sensors and internet connectivity, in order to support real-time operations for GI. Ng and Wakenshaw (2017) showed that IoT is strongly accelerating digitalization by enabling firms to access real-time data from customers, supply chains and production processes, which enhance operational efficiency and facilitate GI. However, the effectiveness of digital technologies may vary across economies; in emerging countries such as Malaysia, capability gaps at the firm level may limit the extent to which firms are able to translate their DC into GI outcomes.

Based on DC theory, firms' DC, including big data analytics and IoT, are likely to influence GI. Hence, we developed the following hypotheses:

H9. Big data analytics positively influences GI.

H10. Internet of Things positively influences GI.

Methodology

The IED model

The IED framework (Figure 1) provides the basis for the research model. However, younger or older firms in different sectors and locations may behave otherwise, potentially affecting the extent of their GI. To account for the heterogeneity in companies' perceptions of GI, characteristics such as firm age, sector and regional dummies were incorporated. Therefore, the IED model was written as the following equations:

$$GI_i = \beta_0 + \beta_1 INT_i + \beta_2 EXT_i + \beta_3 DYN_i + \beta_4 AGE_i + \beta_5 SEC_i + \beta_6 REG_i + \varepsilon_i \quad (1)$$

$$GPDI_i = \beta_0 + \beta_1 INT_i + \beta_2 EXT_i + \beta_3 DYN_i + \beta_4 AGE_i + \beta_5 SEC_i + \beta_6 REG_i + \varepsilon_i \quad (1a)$$

$$GPCI_i = \beta_0 + \beta_1 INT_i + \beta_2 EXT_i + \beta_3 DYN_i + \beta_4 AGE_i + \beta_5 SEC_i + \beta_6 REG_i + \varepsilon_i \quad (1b)$$

Equation (1) represents the model that measures the drivers for overall GI. Equation (1a), in turn, represents the model for measuring the drivers specifically for GPDI, and Equation (1b) for GPCI. GI_i represents the extent of GI in firm i ; $GPDI_i$ represents the extent of GPDI in firm i ; $GPCI_i$ represents the extent of GPCI in firm i . INT_i represents the set of internal resources; EXT_i represents the set of external pressures; DYN_i represents a set of DC; AGE_i represents the characteristic of firm age; SEC_i represents a set of sector dummies; REG_i represents a set of regional dummies and ε_{ij} indicates the error term.

The hypotheses (H1–H10) were first assessed on overall GI using Equation (1) and then re-examined for type-specific factors by replacing GI with GPDI (H1a–H10a) in Equation (1a), and GI with GPCI (H1b–H10b) in Equation (1b).

Data collection and the sample

The population for this study included the manufacturing and eco-friendly product and service sectors listed in the MyHIJAU directory. They were selected for their high relevance to GI activities and have green certifications that comply with global environmental standards.

A total of 644 firms were invited to participate in an online questionnaire survey, focusing on top managers. We received ethical clearance before sharing the survey through Google Forms. All participants were told about the study purpose, and participation was voluntary, through informed consent, and they were assured that answers were anonymous and confidential. The survey was carried out over a period of six months, during which two follow-up reminders were sent to improve the response rate. From the 644 questionnaires sent, 150 firms were selected for analysis after removing missing values, resulting in a response rate of 23.3%.

Variable measurement

The questionnaire was divided into two sections: basic information and GI drivers. Building upon the integrative IED framework and based on the literature (Narver & Slater, 1990; Flint, Larsson, & Gammelgaard, 2008; Chiou, Chan, Lettice, & Chung, 2011; Mina, Bascavusoglu-Moreau, & Hughes, 2014; Zhu, Krikke, & Caniëls, 2018; Xie, Huo, & Zou, 2019; Zhang *et al.*, 2020; Pathak & Sharma, 2022; Chen & Liang, 2023; Rehman, Giordino, Zhang, & Alam, 2023), the three-item scales for each construct were changed to ensure their relevance and suitability for the study. These constructs were operationalized as green product innovation, green process innovation, technological advantage, technological compatibility, organizational culture, organizational support, external networks, external customers, external knowledge, external support, big data analytics and IoT.

All questionnaire items for these constructs were designed to capture firms' perceptions of GI drivers and were measured using a five-point Likert scale, ranging from strongly disagree (1) to strongly agree (5). To continue the analysis, the constructs were validated using a Cronbach's alpha above 0.7, which indicates acceptable internal consistency (Taber, 2018).

Analytical techniques

The BMA approach has been used in economics and political and social science studies (Fragoso, Bertoli, & Louzada, 2018; Tiong & Cheng, 2025). We chose it because BMA includes uncertainty in variable selection by integrating results across multiple models. Compared to a single-model approach, BMA enables inference without the need for prior variable selection, provides better prediction and shows greater robustness against incorrect model specifications (Hinne, Gronau, Van den Bergh, & Wagenmakers, 2020).

The conventional OLS regression is given by

$$Y = \beta_0 + \beta_1 X + \varepsilon$$

where Y is the dependent variable, β is a vector of the parameters, X is the set of independent variables and ε is an error term.

However, rather than using a single model, the BMA approach uses multiple models and addresses the problem of uncertainty in variable selection by calculating the average of the amounts of interest, such as model parameters, across the possible models. We designated the model as M , with $M = (M_1 \dots M_J$ for $j = 1, \dots, J$), representing the set of models under consideration. While the number of potential independent variables is designated as K , the number of possible models is $J = 2^K$. Each model, named as M_j , corresponds to a different set of independent variables and is dependent on parameters, β_j . The posterior probability is given by

$$P(\beta_j|M_j, Y, X) = \frac{P(Y|\beta_j, M_j, X)P(\beta_j|M_j)}{P(Y|M_j, X)}$$

The posterior model probability (PMP) is essential to the BMA framework, by providing the weight to calculate the average of the model coefficients across different possible models. PMP is given by

$$P(M_j|Y, X) = \frac{P(Y|M_j, X) P(M_j)}{P(Y|X)}$$

where $P(Y|M_j, X)$ is the marginal likelihood of the model, or in other words, the probability of the data given in the model M_j ; $P(M_j)$ is the prior model probability; and $P(Y|X)$ is the integrated likelihood, which is constant for all possible models under consideration. Therefore, PMP is determined by the marginal likelihood and the prior probability of the model.

The most important statistical measure for BMA (Beck, 2017) is the posterior inclusion probability (PIP). It is calculated as the sum of the PMPs of all models that include the specific independent variable, and the relative importance of the independent variables is ranked according to their PIP (Raftery, 1995). Hence, PIP is interpreted based on its relevance: weak evidence (PIP 50–75%), moderate evidence (PIP 75–95%), strong evidence (PIP 95–99%) and very strong evidence (PIP >99%). We applied the recommended PIP threshold of above 50%.

Model selection can be sensitive to prior specification. Although it is not easy to identify an appropriate prior, the unit information prior (UIP) generally outperforms other priors (Eicher, Papageorgiou, & Raftery, 2011). To address this limitation, we used UIP for analysis.

Results

Descriptive statistics

Table A1 (listed in Appendix) summarizes the key descriptive statistics for GI drivers. Based on a five-point Likert scale, higher mean scores indicate a greater perceived value of these drivers within firms. “External customers” scores the highest (4.21), while “IoT” scores the lowest (3.52). GI has an overall mean score of 4.12, with GPCI (4.18) higher than GPDI (4.06). In addition, the average firm age is about 15 years.

Robustness checks

Table 1 presents the baseline results for GI (Model 1), GPDI (Model 1a) and GPCI (Model 1b), using Bayesian linear regression. To ensure the robustness of these findings, we employed a different methodological approach to benchmark the results. A comparison of the baseline results (Table 1) with the OLS results (Table A2, listed in Appendix) shows quite consistent findings. However, OLS results may be overfitted in the presence of uncertainty. This is evident from the variance inflation factor (VIF) values for each variable, which range from 1.17 to 10.82. A VIF above 10 requires particular attention, as it indicates a potential multicollinearity problem (Gujarati, 2003). Hence, the baseline results are discussed below.

Discussion

Key drivers for GI

The solid findings from Bayesian linear regression indicate that external networks and external knowledge are key factors, both overall and for each innovation type; however, their relevance varies across the types. External networks have a very strong effect on GPDI, but only a weak effect on GPCI. These networks, comprising industry experts, inventors, research institutions,

Table 1. BMA linear regression results for GI, GPDI and GPCI

	Model 1 GI		Model 1a GPDI		Model 1b GPCI	
	PIP	Post-mean	PIP	Post-mean	PIP	Post-mean
<i>Internal resources</i>						
Technological advantage	0.13	0.01	0.99	0.25	0.03	−0.00
Technological compatibility	0.49	0.09	0.04	0.01	0.29	0.05
Organizational culture	0.25	0.04	0.03	0.00	0.25	0.06
Organizational support	0.47	0.08	0.04	0.00	0.76	0.20
<i>External pressures</i>						
External networks	1.00	0.22	1.00	0.24	0.64	0.11
External customers	0.17	0.03	0.20	0.04	0.13	0.02
External knowledge	0.99	0.29	0.94	0.27	0.97	0.30
External support	0.37	0.04	0.15	0.01	0.30	0.04
<i>Dynamic capabilities</i>						
Big data analytics	0.02	−0.00	0.03	−0.00	0.03	−0.00
Internet of things	0.02	0.00	0.02	0.00	0.01	0.00
<i>Control variables</i>						
Firm age	0.06	0.00	0.08	0.00	0.03	0.00
Sector dummy	1.00	−0.32	1.00	−0.36	0.88	−0.23
Region: central	0.37	0.07	0.12	0.02	0.28	0.06
Eastern	0.03	0.01	0.02	0.00	0.04	0.01
Northern	0.04	−0.00	0.03	−0.00	0.03	−0.00
Southern	0.17	−0.03	0.08	−0.01	0.09	−0.02
Constant	1.00	1.07	1.00	1.01	1.00	1.13
Bayesian info criterion (BIC)	−94.61		−81.05		−70.82	
Posterior model probability (PMP)	0.04		0.28		0.06	

Note(s): PIPs of 50% or higher are in italic. For sector dummy: manufacturing (baseline). For the regional dummy: Sabah and Sarawak (baseline)

collaborations, joint ventures and acquisitions, are crucial for driving technological advances in GPDI. Conversely, GPCI primarily focuses on improving cost-effectiveness, quality and efficiency of internal operations. Hence, the direct impact of external networks on this type of innovation is less noticeable, resulting in a weaker effect on GPCI, compared to GPDI.

Regarding the sector dummy, the service sector shows a very strong effect on GI, which may be caused by its lower capital intensity. In contrast, manufacturing firms often face higher transition costs, technological rigidity and operational constraints, which may limit GI adoption. The stronger effect in the service sector observed for GPDI, compared to GPCI, can be explained by the intangible and flexible nature of service offer, which enables companies to introduce eco-friendly innovations with relatively lower cost and complexity. Furthermore, GPDI in services often reflects digitally enabled and sustainability-oriented improvements, which are more easily implemented than GPCI.

External networks (PIP = 1.00) show a very strong positive effect on GI (Figure 2), thus supporting H5. This finding is consistent with previous studies carried out in different contexts (Arfi, Hikkerova, & Sahut, 2018; Melander & Pazirandeh, 2019; Cheng, Hsu, & Sheu, 2023). Network collaboration is a critical enabler of GI and can take several forms. First, collaboration can be horizontal and vertical (Melander & Arvidsson, 2022). Horizontal collaboration refers to inter-organizational cooperation between firms at the same level of the value chain, while vertical collaboration takes place along the value chain. Second, at a broader level, cross-sectoral collaboration across industrial, political and social spheres facilitates knowledge creation (Tamayo-Orbegozo, Vicente-Molina, & Villarreal-Larrinaga, 2017). Other studies further emphasize the importance of the network of suppliers, suggesting that

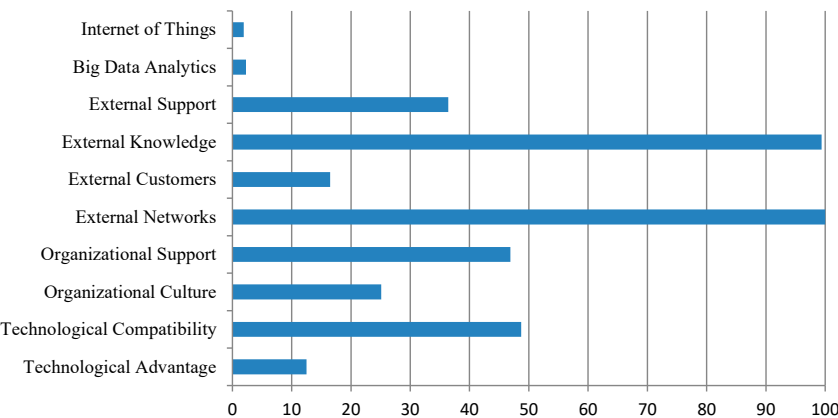


Figure 2. Summary of PIP for GI drivers

bringing together suppliers from different green knowledge domains allows firms to improve their GI performance (Cheng *et al.*, 2023). However, the effectiveness of external networks ultimately depends on a firm’s absorptive capacity – its ability to acquire, assimilate and change external knowledge into internal competencies (Arfi *et al.*, 2018). Therefore, firms should develop business models that enable the effective integration and use of external networks to fully exploit their GI potential. From an institutional perspective, collaborations and networks create external pressures that encourage firms to adopt and strengthen GI, which is consistent with institutional theory.

External knowledge (PIP = 0.99) has a strong positive effect on GI (Figure 2), thus supporting H7 and confirming previous studies (Segarra-Oña, Peiró-Signes, & Payá-Martínez, 2014; Frigon, Doloreux, & Shearmur, 2020). Sharing external knowledge is an important driver of GI and may occur in different ways. For instance, horizontal collaborations across industries enable firms to access extended networks, such as supplier and customer networks in other sectors, acting as relevant drivers of GI (Melander & Pazirandeh, 2019). In addition, firms can access knowledge from formal sources, like universities, public research institutes, private laboratories, academic journals and training programs. Segarra-Oña *et al.* (2014) observe that market information obtained from clients, competitors, external consultants and suppliers is crucial for developing new products and markets, which are key factors leading to GI in environmentally oriented firms. Hence, GI requires stronger knowledge-based competencies compared with conventional innovation (Frigon *et al.*, 2020). Supply chain partners and customers are important sources of external knowledge for enhancing GI, and this finding is consistent with institutional theory, which emphasizes the role of external stakeholder pressures in shaping GI.

Type-specific drivers: GPDI

In addition to external networks (H5a) and external knowledge (H7a), technological advantage (PIP = 0.99) had a strong positive effect on GPDI (Figure 3), thus supporting H1a. GPDI regards the use of eco-friendly or recovered materials and the design of energy-efficient innovative products (Ghisetti & Rennings, 2014), thus requiring energy-efficient technologies. Sáez-Martínez, Díaz-García and Gonzalez-Moreno (2016) highlight the importance of technological capabilities, especially for young and small firms that must develop their innovation capacities in order to adopt advanced technologies, which in turn enable them to achieve technological advantages and contribute to environmental

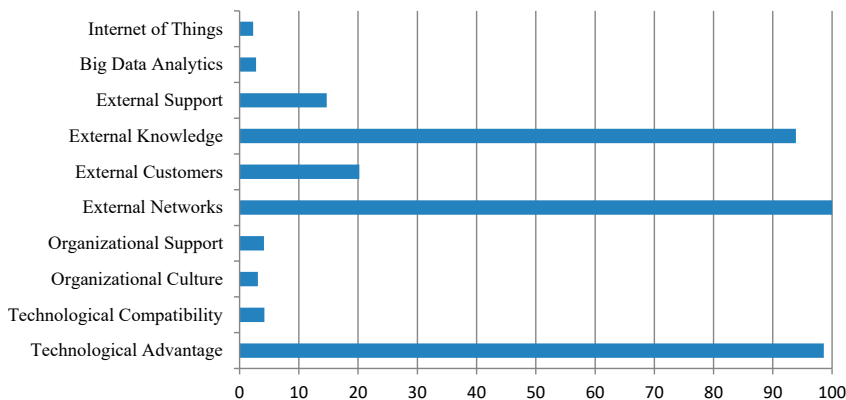


Figure 3. Summary of PIP for GPDI drivers

improvements through GI. Therefore, developing technological capabilities is crucial for leveraging GI and reaching a technological advantage in GPDI, as these skills are firm-specific resources that enhance the effective implementation and integration of GI. From the RBV perspective, such capabilities are valuable and difficult to imitate, allowing firms to change innovation inputs into sustained technological advantages in GPDI.

Type-specific drivers: GPCI

Together with external networks (H5b) and external knowledge (H7b), organizational support (PIP = 0.76) shows a moderate positive effect on GPCI (Figure 4), thus supporting H4b. GPCI is mainly used as an environmental management practice in the production process (Khan, Kaur, Jabeen, & Dhir, 2021); therefore, firms must provide organizational support to invest in such practice and include environmental sustainability concerns in their production processes. Factors like organizational awareness and experts' capacity are crucial for convincing top management of the environmental and financial benefits of GI (Szilagyi, Mocan, Verniquet, Churican, & Rochat, 2018). Previous studies also emphasize the importance of organizational

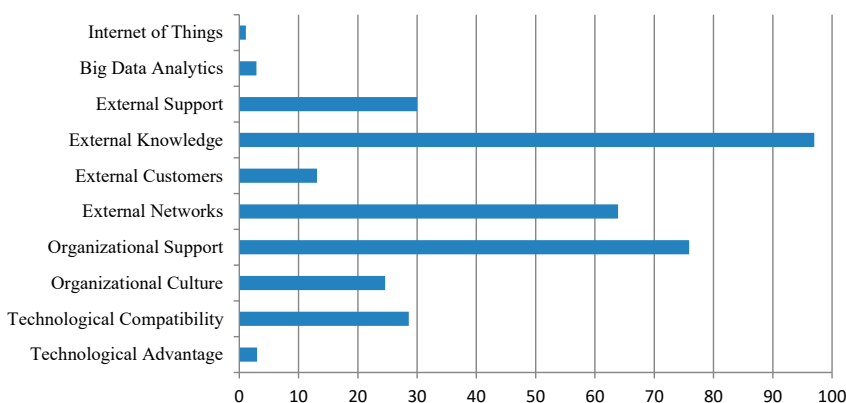


Figure 4. Summary of PIP for GPCI drivers

support for the successful implementation of GPCI. Even firms with strong external networks can lose the benefit of developing integrative capabilities for GI if they remain insensitive to technological changes or resist to develop and acquire new knowledge (Cai & Zhou, 2014). This is particularly relevant in emerging markets, like Malaysia, where research and development (R&D) do not always address GI, because local firms cannot afford the high investment costs associated with R&D (Crespi & Zuniga, 2012). This reality further highlights the importance of strong organizational support for enhancing GPCI, which is aligned with RBV, as it is an important internal resource for starting GPCI.

Conclusions

This study examined how internal resources, external pressures and DC jointly influence GI in Malaysia and if these effects vary depending on the type of GI. Using OLS as a benchmark, BMA linear regression results showed the importance of external pressures in fostering GI, as well as the different effects of internal resources on the various types of GI.

Theoretical implications

External pressures highlight the relevance of institutional theory, while internal resources support the use of RBV for explaining GI. Given the limited significance of DC in Malaysia's emerging market context, firms often present a low or uneven level of digital maturity and remain at an early stage of digital transformation, with poor infrastructure, skills and organizational adaptability. However, DC should not be overlooked, as DC theory remains relevant for explaining companies' long-term ability to respond to changing market conditions. Hence, RBV, institutional theory and DC theory together provide a comprehensive framework for GI. Rather than competing with one another, these perspectives are complementary in explaining GI adoption and its variation in different contexts. This integrated view increases the understanding of GI in emerging economies and aligns with Malaysia's current policy priorities for advancing sustainability within a dynamic environment.

Managerial implications

From a managerial perspective, external networks and external knowledge provide important information for firms in emerging markets, which often face internal gaps in knowledge, skills and technology. This collaboration can help companies overcome these constraints and accelerate GI. Therefore, it is crucial to adopt an integrated approach by expanding external networks, which bring a variety of opportunities for developing green technologies through horizontal and vertical collaborations, and by acquiring external knowledge from supply chains and customers, in order to attain more comprehensive and striking GI outcomes. For instance, managers can actively build strong external links to foster collaboration and open innovation by crowdsourcing ideas and solutions from partners, supply chains and customers. Therefore, firms can gain access to a broader pool of knowledge and creativity, in addition to internal resources.

Among type-specific factors, technological advantage is critical for GPDI, while organizational support is essential for GPCI. To sustain a technological advantage in emerging markets, managers should promote close coordination, both internally and externally, to assimilate and use external networks and knowledge effectively, in order to foster GPDI. In contrast, organizational support, including managerial backing at all levels, promotes creative thinking, ensures availability of resources and encourages investment in training and development of skills, facilitating GPCI. Together, these factors allow emerging-market firms to enhance their GI.

Practical implications

The National Climate Change Policy 2.0 explicitly recognizes the importance of R&D and suggests its increase in order to achieve sustainable development and GI. To foster GI among

firms, policymakers should establish subsidized R&D consortia and innovation clusters that connect firms with manufacturing companies, research institutions and universities or provide tax credits or grants to further encourage participation in networks. In addition, investing in digital platforms that facilitate knowledge exchange and access to external resources would strengthen external networks and external knowledge.

Limitations and future research

Despite the limitation of a moderate-size sample, BMA for linear regression was used to mitigate it. However, future research could benefit from larger and more diverse samples, as well as mixed-method approaches, complemented by focus group discussions, to enhance data robustness and representation. Although DC did not show a significant effect in our study, future papers should extend the analysis beyond digital technologies, by including the role of AI in shaping GI, especially AI-enabled techniques, like predictive analytics, to provide a more up-to-date assessment. This study focused on the direct effects of each driver on GI. Given that external networks and external knowledge were identified as key drivers of GI in Malaysia, new research could examine their mediating or moderating roles, providing stronger information about their impact on fostering GI.

Supplementary material

The supplementary material for this article can be found online.

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Associate editor: Maria Laura Ferranty Mac Lennan