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Tunnelling Innovation: The Impact of Innovative Behavior on BIS Adoption in Malaysian SMEs

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Abstract

The adoption of Business Intelligence Systems (BIS) is critical for enhancing the competitiveness and operational efficiency of Small and Medium-sized Enterprises (SMEs). However, in resource-constrained environments like Malaysia, BIS adoption presents notable challenges. This study explores how Malaysian SMEs navigate these obstacles through Innovative Behavior (IB), with a focus on the mediating role of Competitive Intelligence (CI) and the moderating effect of Innovative Dynamism (ID). Using Structural Equation Modeling (SEM) and Partial Least Squares (PLS) via SmartPLS4, data were analyzed to examine the complex interplay between IB, CI, ID, and BIS adoption. Unexpectedly, results reveal a negative direct relationship between IB and BIS adoption, suggesting that while innovation is often encouraged, it may complicate or delay BIS implementation. However, CI positively mediates this relationship, indicating that strategic use of competitive insights can align innovation with BIS adoption. Conversely, ID negatively moderates the relationship, implying that excessive innovation may destabilize the structured processes required for successful BIS implementation. These findings align with organizational change theory and dynamic capabilities theory. While innovation drives adaptability, it must be synchronized with existing capabilities and structures to avoid resistance and misalignment. Dynamic capabilities theory further suggests that a balance between innovation and operational stability is key to successful technological adoption. This study contributes to both academic literature and practical knowledge by highlighting the nuanced role of innovation in BIS adoption. For policymakers and SME leaders, the findings underscore the importance of channeling innovative efforts through competitive intelligence while avoiding overemphasis on continuous change. A balanced, strategically aligned innovation approach is essential for fostering a conducive environment for BIS adoption in Malaysian SMEs.

Keywords: Innovative Behavior (IB), Competitive Intelligence (CI), Innovative Dynamism (ID), and Business Intelligence Systems (BIS) adoption

Introduction

The adoption of Business Intelligence Systems (BIS) has become increasingly critical for the competitiveness and operational efficiency of Small and Medium-sized Enterprises (SMEs) (Paradza & Daramola, 2021; Trieu, 2017). Despite the recognized benefits, SMEs face significant challenges in the successful adoption and implementation of BIS (Al-Dmour et al., 2023; Caserio & Trucco, 2018; Maguire, 2007). These challenges often caused by limited financial resources, insufficient technical expertise, and resistance to change within organizations. The literature highlights these barriers, indicating that while the potential advantages of BIS are well-documented, the pathway to effective adoption remains uptight with difficulties (Ain et al., 2019; Lim et al., 2013; Maguire, 2007).

Extant literature highlighted that encouraging Innovative Behavior (IB) within organizations presents a promising solution to these challenges (Asurakkody & Shin, 2018; De las Heras-Rosas & Herrera, 2021). IB, characterized by the generation, implementation, and championing of new ideas (Afsar et al., 2021; Janssen, 2003; Nuseir et al., 2021), can potentially enhance the adoption of BIS by fostering a culture that is receptive to technological advancements and change. However, IB alone may not be sufficient to assure the successful BIS adoption. Specifically, other factors, such as the ability to gather and utilize competitive insights (i.e., Competitive Intelligence (CI)) and the overall innovative capacity of the organization (i.e., Innovative Dynamism (ID)), may play crucial roles in this process (Abraheem, 2023; Calof & Wright, 2008; Malerba, 2007; Wu et al., 2023).

In the context of Malaysian SMEs, these additional factors—CI and ID—are particularly relevant and yet underexplored in current research. CI involves the systematic collection and analysis of information about competitors and the broader business environment (Iwu-James et al., 2020; Maritz & Du Toit, 2018). By providing strategic insights and foresight, CI can support the innovative efforts of organizations, making the adoption of BIS more targeted and effective. For Malaysian SMEs, leveraging CI is crucial due to the highly competitive and rapidly evolving market landscape in the region. Despite its importance, the interplay between CI and IB in facilitating BIS adoption has not been adequately addressed in the literature. Similarly, ID, which reflects an organization's capability to continuously innovate and adapt to changing market conditions, is essential for Malaysian SMEs (Amui et al., 2017; Magistretti et al., 2021; Wu et al., 2023). This dynamic capability ensures that firms not only generate innovative ideas but also possess the agility to implement them effectively. Given the diverse and fast-paced business environment in Malaysia, ID can strengthen the impact of IB on BIS adoption by ensuring that innovative initiatives are not only conceived but also executed efficiently. However, the moderating role of ID in the IB-BIS adoption relationship remains insufficiently explored in existing studies.

This study aims to bridge these gaps by exploring the complex relationships between IB and BIS adoption in Malaysian SMEs. Specifically, it investigates: [1] the direct impact of IB on BIS adoption, [2] the role of CI in bridging the direct relationship between IB and BIS adoption, and [3] the role of an organization's adaptive capacity (i.e., ID) in moderating the effectiveness of IB on BIS adoption. In doing so, this study employs a robust methodological approach by utilizing Structural Equation Modeling (SEM) and Partial Least Squares (PLS) techniques with SmartPLS4 to uncover the complex interplay of IB, CI, and ID in the context of BIS adoption.

By examining these relationships, this research attempted to provide a comprehensive understanding of the factors that influence BIS adoption and offer actionable insights for Malaysian SMEs aiming to enhance their technological capabilities through innovative practices. This research contributes to academic discourse and offers practical implications for policymakers and business leaders striving to foster a conducive environment for BIS adoption in Malaysian SMEs.

The following parts of this paper are as follows; literature review focusing on all the variables studied in this paper, underlying theoretical construct, and hypotheses development. Next, methodology discussed about the research design until data analysis. Then, the findings focus on the three-relationship tested in this paper. Followed with discussion and conclusion of this research paper.

Significance of the Study

This study provides new insights into how Malaysian SMEs can overcome key barriers to BIS adoption by leveraging internal behavioural dynamics (IB), environmental scanning capabilities (CI), and organizational adaptability (ID). By exploring the mediating role of CI and the moderating effect of ID in the IB–BIS adoption relationship, the study offers a novel integrative framework not previously addressed in BIS adoption literature. This is particularly timely and relevant for Malaysian SMEs seeking to remain competitive in an increasingly digital and data-driven economy.

In addition, the findings are expected to guide policymakers and business leaders in developing capacity-building programs and innovation strategies to boost BIS usage. The study not only contributes to theoretical advancement in innovation and information systems adoption but also offers practical implications for technology strategy formulation among SMEs in emerging markets.

Literature Review

Business Intelligence Systems (BIS)

BIS comprise a suite of technologies, applications, and methodologies aimed at transforming raw data into actionable insights that support informed decision-making within organizations. The core function of BIS revolves around the collection, integration, analysis, and presentation of business information, enabling organizations to make data-driven decisions.

BIS Adoption

Research by Chen et al. (2012) highlights that the successful adoption of BIS significantly enhances organizational agility and decision-making capabilities. BIS equips organizations to respond rapidly to changing market conditions and capitalize on strategic opportunities, thus gaining a competitive edge. Similarly, Wixom and Watson (2001) emphasize the operational efficiencies and data-driven decision-making capabilities that BIS adoption fosters.

In the context of SMEs, the adoption of BIS has garnered considerable attention in the literature due to its potential benefits and challenges. Studies show that SMEs often face barriers such as financial constraints, limited technical expertise, and organizational resistance to change (Lim et al., 2013; Paradza & Daramola, 2021). These challenges can

hinder the full realization of the strategic benefits that BIS can offer (Maguire, 2007; Paradza & Daramola, 2021).

Challenges Facing BIS Adoption

Despite the potential of BIS to drive transformation, its adoption is frequently fraught with challenges, both technological and organizational. One primary technological challenge is the complexity involved in integrating BIS with existing IT infrastructure, which often entails complex data migration, compatibility issues with legacy systems, and ensuring interoperability across multiple platforms and databases (Paradza & Daramola, 2021; Wixom & Watson, 2001). Moreover, the technical demands of data warehousing, and predictive analytics tools necessitate specialized expertise and resources, making BIS adoption challenging for many organizations (Chen et al., 2012; Maguire, 2007).

To overcome these challenges, strategic planning at both leadership and operational levels is essential. Leadership support, driven by IB, plays a pivotal role in ensuring a dynamic approach to BIS adoption (Afsar et al., 2021; Khraim, 2022). At the operational level, user competence in navigating BIS tools and interpreting data-driven insights is equally crucial. Training programs that cultivate innovation and technological proficiency are imperative to equip users with the skills needed to utilize BIS effectively.

The literature has recognized IB as a key facilitator in overcoming these technological barriers (Afsar et al., 2021; Parzefall et al., 2008). IB involves the generation, promotion, and implementation of novel ideas within organizations (Afsar et al., 2021; Amabile, 1988). Encouraging IB within an organization can create a conducive environment for BIS adoption by fostering readiness for technological advancement and addressing both technological and human challenges (Paradza & Daramola, 2021).

Innovative Behavior (IB)

Innovative behavior (IB) refers to the actions undertaken by individuals within an organization to generate, promote, and implement new ideas aimed at improving products, services, or processes (Asurakkody & Shin, 2018; Nuseir et al., 2021; Parzefall et al., 2008). The construct of IB is inherently multidimensional, encompassing three primary components: idea generation, idea promotion, and idea implementation (Amabile, 1988; Lambriex-Schmitz et al., 2020; Lukes & Stephan, 2017). These dimensions form a continuum that begins with the creative identification of opportunities or problems and ends with the successful realization of innovative ideas in organizational settings.

Component of IB

Idea Generation represents the initial phase of IB, where individuals engage in the development of novel solutions to existing problems or identify potential areas for improvement. This dimension is closely linked to creativity, which acts as a catalyst for innovation by enabling employees to explore new ways of doing things (Asurakkody & Shin, 2018; Lambriex-Schmitz et al., 2020; Parzefall et al., 2008). In the context of BIS adoption, idea generation might involve recognizing the potential of BIS to enhance data-driven decision-making processes or improve operational efficiencies within the organization. Research suggests that fostering a culture of creativity and openness to new ideas is essential for

encouraging idea generation, particularly in resource-constrained environments like SMEs (Behl et al., 2023; Janssen, 2000; Taneja et al., 2016).

Idea Promotion, also known as idea championing, involves advocating for and persuading others to support and adopt new ideas (De las Heras-Rosas & Herrera, 2021; Janssen, 2000; Tian et al., 2021). This dimension is critical in overcoming organizational inertia and resistance to change, which often accompany the introduction of new technologies such as BIS. Effective idea promotion requires individuals to demonstrate the potential value of the innovation to key decision-makers, securing the necessary resources and support for its implementation. In Malaysian SMEs, where hierarchical structures and resource constraints may hinder innovation, the role of idea champions becomes even more significant, as they bridge the gap between conceptualization and realization of innovative projects (Tian et al., 2021).

Idea Implementation is the final phase of IB, wherein the generated and promoted ideas are translated into practical actions and integrated into organizational workflows (Afsar et al., 2021; Amabile, 1988). For BIS adoption, this phase involves the actual deployment of the system, ensuring that the technical infrastructure is in place, employees are adequately trained, and the system aligns with organizational objectives. Successful idea implementation is often seen as the most challenging aspect of IB, as it requires not only technical expertise but also strong leadership and a willingness to adapt existing processes. The literature highlights that organizations with high levels of IB are more likely to successfully implement complex systems like BIS, as they possess the internal capabilities to adapt to technological advancements and overcome operational challenges (Janssen, 2000; Lambriex-Schmitz et al., 2020).

The Role of IB in BIS Adoption

Innovative behavior is increasingly recognized as a critical enabler of technology adoption, particularly in dynamic environments where agility and adaptability are key to sustaining competitive advantage (Taneja et al., 2016; Teece et al., 1997; Tian et al., 2021). Within the context of BIS adoption, IB is hypothesized to play a pivotal role by fostering a proactive organizational climate that is open to technological change. Specifically, IB can facilitate the early identification of opportunities to leverage BIS, enhance stakeholder buy-in, and streamline the implementation process. Several studies have shown that organizations with a strong culture of IB are better positioned to adopt and integrate new technologies, as they are more agile, responsive, and willing to take calculated risks (De las Heras-Rosas & Herrera, 2021; Fatahimilasi et al., 2024).

However, the relationship between IB and BIS adoption is not solely direct. IB alone may not be sufficient to ensure the successful implementation of BIS, as other factors, such as CI and ID, play potential roles of enabling better BIS adoption. CI provides the strategic insights necessary to guide innovation efforts, while ID ensures that the organization possesses the agility to adapt to rapidly changing market conditions. Thus, while IB is a crucial driver of BIS adoption, its effectiveness is enhanced when supported by a broader organizational context that facilitates the collection and application of external intelligence (i.e., CI) and ensures the flexibility to innovate (i.e., ID).

Competitive Intelligence (CI) and Innovative Dynamism (ID)

CI refers to the systematic collection and analysis of information about competitors, markets, and external environmental factors to inform strategic decision-making (Agnihotri & Rapp, 2011; Gaspareniene et al., 2013). In the context of BIS adoption, CI acts as a mediator, enhancing the strategic alignment of IB with organizational goals and market opportunities. By integrating external intelligence, CI improves the effectiveness of IB initiatives, ensuring that BIS adoption is well-informed and strategically aligned with competitive imperatives.

ID, on the other hand, reflects an organization's capacity for innovation and adaptability in response to changing market conditions (Eisenhardt & Martin, 2000; Khan et al., 2022; Malerba, 2007; Nte et al., 2020). ID moderates the relationship between IB and BIS adoption, influencing the extent to which IB drives BIS integration and sustained use. Organizations with high levels of ID are better equipped to generate, implement, and sustain innovative behaviors that enhance BIS adoption, while those with lower levels of ID may struggle to fully leverage the benefits of innovation.

Both CI and ID are critical in understanding the role of IB in BIS adoption. CI provides the strategic insight necessary for guiding IB initiatives towards successful BIS adoption, while ID ensures that organizations have the internal capabilities to adapt and evolve through the adoption of new technologies. Together, CI and ID enable organizations to navigate the challenges of BIS adoption, ensuring that innovation efforts are both strategically aligned and operationally feasible.

Underlying Theories

The relationships between IB, CI, ID, and BIS adoption have been grounded in several established theoretical frameworks. Among the most relevant are Organizational Change Theory and Dynamic Capabilities Theory. These theories provide the foundation for understanding how firms navigate technological innovation and adoption, especially within the context of complex systems like BIS.

Organizational Change Theory

Organizational Change Theory offers a lens through which to examine the processes by which organizations adapt to new technologies such as BIS. Rooted in Lewin's three-stage model (see Burnes, 2020) of organizational change—unfreeze, change, refreeze—this theory posits that organizations must first disrupt established patterns and overcome resistance to change before successfully adopting new technologies. The unfreezing stage often involves breaking down old routines or cultural barriers, which can generate resistance among employees or within the organization as a whole. In the context of BIS adoption, the unfreezing stage would involve questioning traditional decision-making processes and the technological infrastructure that supports them.

The change stage is characterized by the active adoption of new practices, such as BIS, where IB plays a critical role in driving innovation and facilitating the transition (Hanelt et al., 2021; Myers et al., 2012). IB can either accelerate or hinder this change process depending on the degree of employee engagement and leadership support. Lastly, the refreezing stage focuses on stabilizing the organization around the new BIS technologies, embedding them into daily operations. IB's role extends into this phase, as continuous innovation ensures that the

changes are not only adopted but also optimized for long-term performance. Nevertheless, IB can significantly influence all phases of this model, impacting the effectiveness of BIS adoption.

Dynamic Capabilities Theory

Dynamic Capabilities Theory, introduced by Teece et al. (1997), provides a framework for understanding how organizations adapt and evolve in response to changing external conditions (Cheng et al., 2020). This theory suggests that firms' ability to renew, reconfigure, and integrate internal and external competencies is critical to sustaining a competitive advantage in dynamic environments. The theory is highly relevant to BIS adoption, as it addresses how organizations mobilize their resources, such as IB, CI, and ID, to embrace technological advancements and changes.

CI, as a key dynamic capability, enables organizations to systematically acquire, analyze, and utilize external market intelligence, which can then be integrated with internal innovations (Conboy et al., 2020; Eisenhardt & Martin, 2000). This strategic alignment of external information with internal innovation processes facilitates more effective BIS adoption, allowing organizations to make informed decisions regarding technological investments. Additionally, CI serves as an essential mechanism for filtering relevant data that supports the implementation of BIS, which in turn enhances decision-making capabilities.

ID, from the dynamic capabilities perspective, reflects an organization's ability to adapt and evolve its innovation processes in response to internal and external shifts (Eisenhardt & Martin, 2000; Malerba, 2007). ID helps to navigate the complexities and uncertainties that often accompany the introduction of new technologies such as BIS. By fostering an environment where innovation can thrive, ID not only amplifies the effects of IB but also acts as a moderating force that shapes the relationship between IB and BIS adoption. This suggests that organizations with high ID may experience a stronger, more positive relationship between IB and BIS adoption, while those with lower ID may face greater challenges in leveraging innovation to drive technological adoption.

Conceptual Framework

Based on the theories above, the conceptual framework presented in Figure 1 illustrates the relationships between IB, CI, ID, and BIS adoption. In this model, IB—which is broken down into three dimensions: idea generation, idea championing, and idea implementation—acts as the independent variable, directly influencing the adoption of BIS. The framework introduces CI as a mediating variable, which means that CI plays a critical role in translating innovative behavior into the successful adoption of BIS. Additionally, ID serves as a moderating variable, suggesting that the dynamic capabilities of an organization can strengthen the impact of IB on BIS adoption.

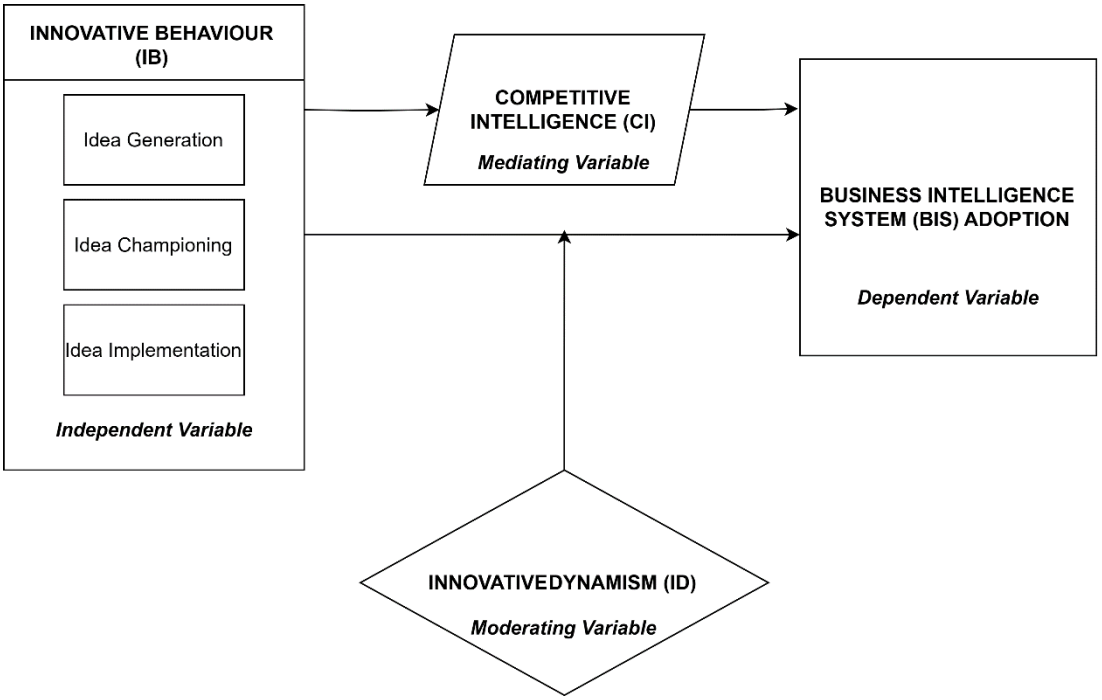

Figure 1 Conceptual Framework

The framework in Figure 1 highlights the complex interactions between innovation processes, intelligence practices, and technology adoption in SMEs, with particular focus on how these elements interact to enhance organizational effectiveness and competitive advantage.

Hypothesis Development

Grounded in the theoretical frameworks outlined above and building on existing literature, this study develops the following hypotheses:

Hypothesis 1 (H1): IB has a positive influence on BIS adoption in Malaysian SMEs.

This hypothesis is based on the expectation that IB, through the generation and implementation of innovative ideas, fosters a culture conducive to the successful adoption of advanced systems like BIS (Scott & Bruce, 1994). IB promotes the exploration of new technologies and supports the organizational changes necessary for their integration.

Hypothesis 2 (H2): CI positively mediates the relationship between IB and BIS adoption in Malaysian SMEs.

CI, which involves the systematic gathering and analysis of external intelligence (Calof & Wright, 2008), is posited to enhance the effectiveness of IB by providing critical insights and strategic guidance during the adoption of BIS. The mediation effect suggests that CI strengthens the IB-BIS link by ensuring that innovative behaviors are informed by external competitive factors, making the adoption process more effective.

Hypothesis 3 (H3): ID positively moderates the relationship between IB and BIS adoption in Malaysian SMEs.

ID is expected to influence the strength and direction of the relationship between IB and BIS adoption, with the moderating effect contingent upon the organization's capacity for continuous innovation and adaptation (Danneels, 2016). Firms with higher levels of ID are likely to benefit more from IB in terms of BIS adoption, as their dynamic capabilities allow

them to swiftly integrate new systems and processes. Conversely, firms with lower ID may struggle to harness the potential of IB for BIS adoption due to their less adaptive structures and cultures.

Methodology

Research Design

This study adopted a quantitative, cross-sectional research design to test the proposed relationships between IB, CI, ID, and BIS adoption. A cross-sectional design was appropriate for this research, as it allowed the collection of data at a single point in time, ideal for examining the patterns and relationships among the variables.

The unit of analysis for this study was SMEs in Malaysia, and data collection was performed using a structured questionnaire. The population for this study comprised SMEs in Malaysia that had adopted BIS. A purposive sampling technique was employed to ensure that the sample adequately represented SMEs with BIS adoption. According to (Sarker & AL-Muaalemi, 2022), purposive sampling enabled the selection of participants who met specific criteria, ensuring the inclusion of only SMEs with BIS adoption, thereby enhancing the relevance and applicability of the findings. The sample size was predicted using G*Power software (Kang, 2021; Rahman, 2023), with a final sample size of 408 respondents, ensuring sufficient statistical power for the analysis.

Measurement Instrument

The survey instrument was designed to measure the key constructs based on well-established scales from prior research. Following past studies (Nicolaidis et al., 2020; Tsai et al., 2024) recommendation, pre-existing validated scales were adapted to suit the context of Malaysian SMEs, with slight modifications to ensure cultural relevance and clarity.

Innovative Behavior (IB)

IB was measured using a scale adapted from Lambriex-Schmitz et al. (2020), which assessed three dimensions: idea generation, idea promotion, and idea implementation. This scale had been validated in previous research, making it suitable for assessing the innovative behaviors of SMEs.

Competitive Intelligence (CI)

CI was assessed using a scale adapted from (Saayman et al., 2008), capturing the systematic collection, analysis, and utilization of competitor information to inform strategic decision-making.

Innovative Dynamism (ID)

ID was measured using items adapted from Mohsin (2015), focusing on the firm's capacity to innovate and adapt to changing market conditions. This dynamic capability was essential for understanding how firms responded to technological advancements such as BIS.

Business Intelligence Systems (BIS) Adoption

BIS adoption was measured using items adapted from Popovič et al. (2019), capturing the extent of BIS implementation and usage across various business functions, such as decision support, operational efficiency, and competitive advantage.

The questionnaire was pre-tested through a pilot study with 30 SME owners and managers to ensure clarity, validity, and reliability of the items. The feedback from the pilot study was incorporated to refine the survey instrument further.

Data Collection and Analysis

Data collection was conducted using an online survey distributed to SME owners, managers, and key decision-makers across Malaysia. This method was efficient and ensured broader geographical coverage (Memon et al., 2021). The online survey was hosted on a secure platform to ensure data integrity and confidentiality. Multiple reminders were sent at regular intervals to improve response rates. Respondents were informed of the purpose of the study, the voluntary nature of participation, and the confidentiality of their responses. To encourage participation, SMEs were also given a summary of key findings as an incentive.

The data collected was analyzed using SEM with PLS, a robust statistical technique suitable for testing complex models in management research (Hair et al., 2019; Ramayah et al., 2017). SEM-PLS was particularly suited for this study as it allowed for the simultaneous estimation of multiple relationships, including direct, mediating (i.e., CI), and moderating effects (i.e., ID). In line with ethical research practices, informed consent was obtained from all participants before they proceeded with the survey. They were assured that their responses were anonymous and confidential, and participation was voluntary. Ethical approval was sought from the relevant institutional review board, ensuring that the study adhered to all ethical standards for research involving human subjects. Data privacy and security were strictly maintained throughout the research process.

Data Analysis

The results of the SEM analysis provide insights into the relationships among IB, CI, ID and BIS adoption in Malaysian SMEs. We utilized PLS modeling through SmartPLS 4.1.0.0 (Ringle et al., 2015) to test the proposed model. PLS is particularly suitable for this study as it is robust to violations of normality, a common issue in survey-based data collection (Chin et al., 2003). Given that the data was collected from a single source, we addressed the issue of Common Method Bias (CMB) following the approach suggested by extant literature (Kock, 2015; Kock & Lynn, 2012). A full collinearity test was conducted by regressing all variables against a common variable. The results, shown in Table 1, indicate that all Variance Inflation Factors (VIFs) were below the threshold of 3.3, suggesting that CMB is not a significant issue in this study.

Table 1
Full Collinearity Testing

ID	IB	CI	BIS
1.728	1.585	2.805	3.033

Note: ID = Innovative Dynamism, IB = Innovative Behaviour, CI = Competitive Intelligence, BIS = Business Intelligence System (BIS) Adoption

Measurement Model

This paper used two-step approach (Anderson & Gerbing, 1988), we first evaluated the measurement model to assess the reliability and validity of the constructs. Following past

literature (Hair et al., 2019; Ramayah et al., 2018), the measurement model was assessed for indicator reliability, internal consistency, convergent validity, and discriminant validity.

For convergent validity, we examined the factor loadings, Average Variance Extracted (AVE), and Composite Reliability (CR). According to Hair et al. (2019), factor loadings should be ≥ 0.5, AVE ≥ 0.5, and CR ≥ 0.7. As shown in Table 2, all constructs demonstrated AVE values above 0.5 and CR values greater than 0.7, confirming convergent validity. Most loadings were acceptable, with only a few slightly below 0.708.

In addition, for second-order constructs, such as IB, the validity and reliability of the higher-order constructs were assessed. As indicated in Table 3, the second-order construct measurement was also valid and reliable.

We further assessed discriminant validity using the Heterotrait-Monotrait (HTMT) criterion (Franke & Sarstedt, 2019; Henseler et al., 2015). As shown in Table 4, all HTMT values were below the stricter threshold of 0.85, confirming that the constructs were distinct from each other.

Table 2
Measurement Model for the First Order Constructs

First order Constructs	Items	Loadings	AVE	CR
IDEA GENERATION	IB1IG	0.847	0.781	0.97
	IB2IG	0.845		
	IB3IG	0.88		
	IB4IG	0.89		
	IB5IG	0.938		
	IB6IG	0.879		
	IB7IG	0.935		
	IB8IG	0.832		
	IB9IG	0.902		
IDEA CHAMPIONING	IB10IC	0.876	0.82	0.948
	IB11IC	0.898		
	IB12IC	0.939		
	IB13IC	0.907		
IDEA IMPLEMENTATION	IB14II	0.903	0.835	0.953
	IB15II	0.924		
	IB16II	0.93		
	IB17II	0.899		
INNOVATIVE DYNAMISM	ID3	0.741	0.573	0.841
	ID4	0.601		
	ID5	0.83		
	ID6	0.832		
COMPETITIVE INTELLIGENCE	CI1	0.649	0.63	0.966
	CI2	0.741		
	CI3	0.667		
	CI4	0.837		
	CI5	0.763		
	CI6	0.715		

	CI7	0.796		
	CI8	0.826		
	CI9	0.739		
	CI10	0.746		
	CI11	0.907		
	CI12	0.887		
	CI13	0.913		
	CI14	0.932		
	CI15	0.774		
	CI16	0.565		
	CI17	0.924		
BUSINESS INTELLIGENCE SYSTEM_ADOPTION	BIS1	0.722	0.838	0.992
	BIS2	0.878		
	BIS3	0.818		
	BIS4	0.741		
	BIS5	0.873		
	BIS6	0.811		
	BIS7	0.875		
	BIS8	0.932		
	BIS9	0.946		
	BIS10	0.959		
	BIS11	0.916		
	BIS12	0.958		
	BIS13	0.954		
	BIS14	0.982		
	BIS15	0.968		
	BIS16	0.941		
	BIS17	0.945		
	BIS18	0.929		
	BIS19	0.948		
	BIS20	0.942		
	BIS21	0.962		
	BIS22	0.989		
	BIS23	0.958		
	BIS24	0.962		

Table 3
Measurement Model for the Second Order Constructs

Second Order Constructs	Indicator	Loadings	AVE	CR
Innovative Behaviour	IC	0.991	0.962	0.987
	IG	0.980		
	II	0.971		

Table 4
Discriminant Validity (HTMT)

	1	2	3	4
1. Business Intelligence System (BIS) Adoption				
2. Competitive Intelligence	0.75			
3. Innovative Behaviour	0.443	0.622		
4. Innovative Dynamism	0.675	0.527	0.318	

Structural Model

We assessed the structural model following the guidelines provided by past literature (Cain et al., 2017; Hair et al., 2019). The data was found to be non-multivariate normal, as indicated by Mardia's multivariate skewness ($\beta = 26.89727$, $p < 0.01$) and Mardia's multivariate kurtosis ($\beta = 67.97667$, $p < 0.01$).

Using a 5,000-sample bootstrapping procedure, we evaluated the path coefficients, standard errors, t-values, and p-values. We also incorporated confidence intervals and effect sizes to test the developed hypotheses, as per Hahn and Ang's (2017) recommendations. The R^2 value for BIS was 0.720, indicating that 72% of the variance in BIS was explained by the predictors. The direct relationship between IB and BIS was found to be negative and significant ($\beta = -0.061$, $p < 0.001$), rejecting H1.

To test the mediation effect, we followed Preacher and Hayes (2008) bootstrapping method for indirect effects. The results confirmed that CI mediates the relationship between IB and BIS ($\beta = 0.100$, $p < 0.01$), supporting H2.

We also examined the moderating effect of ID on the relationship between IB and BIS adoption. The interaction effect was negative and significant ($\beta = -0.28$, $p < 0.01$), indicating that ID diminishes the positive effect of IB on BIS adoption, rejecting H3.

Table 5
Hypothesis Testing Direct Effects

Hypothesis	Relationship	Std Beta	Std Error	t-values	p-values	BCI LL	BCI UL
H1	Innovative Behavior -> Business Intelligence System Adoption	-0.061	0.032	11.046	p<.001	-0.302	-0.408

Note: We use 95% confidence interval with a bootstrapping of 5,000

Table 6
Hypothesis Testing Indirect Effects

Hypothesis	Relationship	Std Beta	Std Error	t-values	p-values	BCI LL	BCI UL
H2	Innovative Behaviour -> Competitive Intelligence -> Business Intelligence System_Adoption	0.462	0.038	12.089	p<.001	0.403	0.526
H3	Innovative Dynamism X Innovative Behaviour -> Business Intelligence System_Adoption	-0.282	0.032	8.637	p<.001	-0.337	-0.223

Note: We use 95% confidence interval with a bootstrapping of 5,000

For the moderating effect of IB and ID on BIS adoption, interestingly, the slope for low ID is steeper compared to high ID, indicating a more pronounced effect on BIS adoption. Additionally, within the spectrum of low IB, the disparity between low and high ID is substantial, gradually narrowing as IB increases. This suggests a negative moderating effect of IB x ID, even though both IB and ID individually exhibit positive associations with BIS adoption. These findings imply that while both IB and ID positively contribute to BIS adoption, their interaction introduces complexities, with the magnitude of this effect varying across different levels of IB and ID, as illustrated in Figure 2.

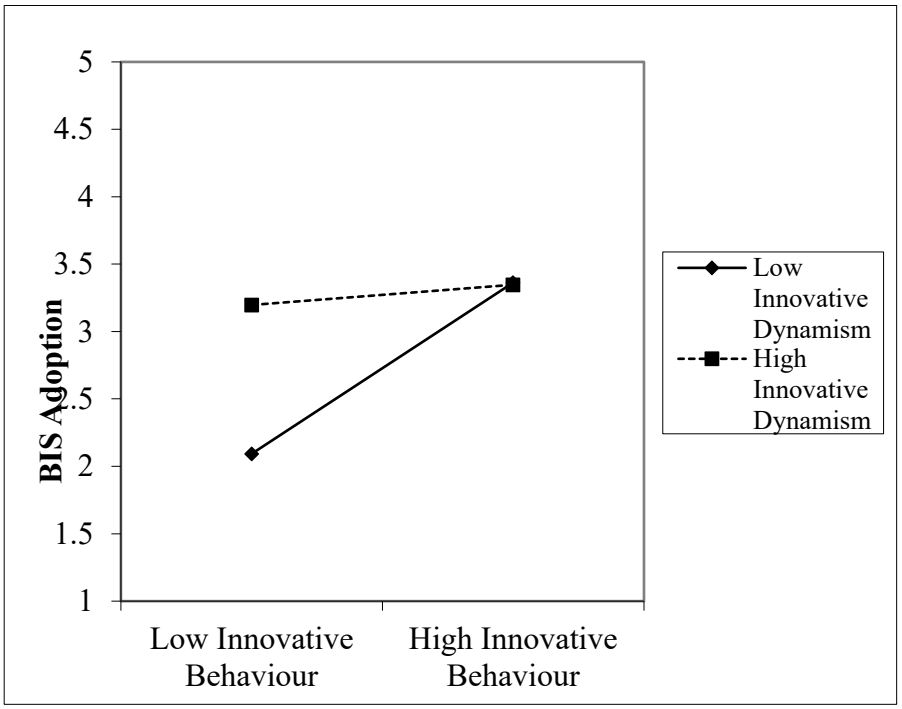

Figure 2 Moderation Analysis

Additionally, we employed the PLSpredict procedure, as suggested by Shmueli et al. (2019), to assess the predictive relevance of the model. The errors from the PLS model were consistently higher than those of the Linear Model (LM), indicating that our model lacks predictive power.

Table 7
PLSpredict Evaluation

Construct/Item	PLS Error	LM Error	Prediction
BIS	Higher	Lower	No predictive relevance

Discussion

The results of this study offer intriguing insights into the relationships between IB, CI, ID and BIS adoption in Malaysian SMEs. These findings challenge conventional expectations and enrich the understanding of how innovation and competitive dynamics interact in the context of technology adoption and organizational behavior.

Direct Relationship between IB and BIS Adoption

The negative relationship between IB and BIS adoption ($\beta = -0.061$, $p < 0.05$) presents a significant deviation from the expected positive association often found in the literature. Previous studies generally argue that fostering IB enhances the organizational capacity to embrace and implement new technologies like BIS (Nuseir et al., 2021; Parzefall et al., 2008). However, our findings suggest that in Malaysian SMEs, high levels of IB may not directly contribute to BIS adoption.

This result aligns with theories of organizational change, which suggest that significant innovations can often encounter resistance or operational challenges (Afsar et al., 2021; De las Heras-Rosas & Herrera, 2021). Malaysian SMEs, typically facing resource constraints and conservative business practices, might find it difficult to integrate BIS, despite fostering innovation. The negative coefficient indicates that promoting IB may simultaneously introduce organizational complexities that hinder effective BIS adoption, such as resistance to change, misalignment with strategic needs, or insufficient resources for technology implementation.

The negative relationship between IB and BIS adoption highlights the importance of assessing organizational readiness when introducing technological innovations. It suggests that while fostering innovation is critical, Malaysian SMEs must also address the barriers to BIS adoption, such as improving change management, enhancing alignment with strategic objectives, and investing in the necessary capacity-building initiatives.

Mediated Relationship through CI on BIS Adoption

The positive and significant mediation effect of CI ($\beta = 0.413$, $p < 0.001$) between IB and BIS adoption supports the literature's view on the role of competitive intelligence in enhancing decision-making and organizational alignment (Agnihotri & Rapp, 2011; De las Heras-Rosas & Herrera, 2021; Gaspareniene et al., 2013). CI allows SMEs to collect and utilize market insights, thereby aligning innovation activities with strategic goals and facilitating BIS adoption.

This finding underlines the role of CI as a strategic intermediary that transforms IB efforts into actionable outcomes, reducing risks and improving decision-making. CI's contribution reflects dynamic capabilities theory, emphasizing that organizational learning and adaptation are key to responding to market dynamics (Eisenhardt & Martin, 2000; Ye et al., 2022).

As a result, the finding from this paper supports the view that CI enhances the effectiveness of IB by aligning innovation with market realities, thereby facilitating BIS adoption. By investing in CI capabilities, such as information systems and training, SMEs can improve strategic alignment and competitiveness, ensuring innovation leads to practical technology adoption.

Moderated Relationship by ID on IB and BIS Adoption

The negative moderation effect of ID ($\beta = -0.209$, $p < 0.01$) on the relationship between IB and BIS adoption is unexpected, as ID typically suggests greater organizational adaptability and innovation potential. This finding contrasts with the expectation that ID would enhance the positive effects of IB on BIS adoption (Conboy et al., 2020; Wu et al., 2023).

High levels of ID may shift focus away from BIS adoption, leading to a dilution of efforts towards technological integration. While ID is crucial for maintaining competitiveness, excessive dynamism without strategic focus can result in organizational misalignments and inefficiencies (Teece et al., 1997; Ye et al., 2022).

This finding on the moderating role of ID highlights the importance of balancing innovation with strategic focus. While IB fosters creative ideation, high levels of ID may challenge the structured implementation of BIS. Malaysian SMEs need a strategic approach to innovation management that ensures technological initiatives like BIS are aligned with long-term goals and organizational capacity, optimizing the impact of both IB and ID.

Conclusion

This study provides important insights into the relationships between IB, CI, ID and BIS adoption in Malaysian SMEs. The findings challenge conventional assumptions and offer a deeper understanding of how organizational dynamics influence technology adoption and innovation management.

The study contributes by revealing several unexpected findings that deviate from traditional perspectives. First, IB shows a negative direct effect on BIS adoption, suggesting that while IB promotes innovation within Malaysian SMEs, it may also introduce complexities that hinder effective BIS adoption. This contrasts with the common expectation that IB facilitates technological adoption. Second, CI emerges as a key mediator between IB and BIS adoption, with a significant positive mediation effect. This finding underscores the strategic role of CI in translating innovative ideas into actionable insights that support BIS adoption. It highlights the importance of strategic information management in enhancing decision-making and achieving competitive advantage. Third, ID negatively moderates the relationship between IB and BIS adoption, indicating that excessive organizational agility and adaptability may divert resources and attention away from BIS implementation, despite fostering innovation.

From a practical standpoint, these findings have several implications for SMEs and organizational leaders. First, improving CI capabilities is essential to optimizing the impact of IB on BIS adoption. Investments in CI systems, employee training, and strategic partnerships can help align innovation efforts with technology integration goals. Additionally, a balanced approach to innovation is critical. While IB stimulates creativity and idea generation, organizations must ensure these initiatives are supported by structured frameworks that

facilitate BIS adoption. Clear strategies, cross-functional collaboration, and targeted change management efforts are vital to streamlining technological integration. Moreover, organizations should carefully manage ID to prevent disruptions to BIS adoption. Although dynamic capabilities provide competitive advantages, overly high levels of ID may detract from strategic technology initiatives. Balancing agility with stability ensures that dynamic capabilities positively contribute to BIS adoption.

Despite its contributions, the study acknowledges several limitations. The cross-sectional design limits the ability to make causal inferences about the observed relationships. Future longitudinal studies could offer deeper insights into how IB, CI, ID, and BIS adoption evolve over time and interact causally. Additionally, the findings are context-specific to Malaysian SMEs and may not generalize across industries or countries. Replication studies in different contexts would enhance external validity and offer broader insights. Furthermore, while validated scales were used, context-specific factors may not have been fully captured. Future research could develop more tailored measurement instruments to increase accuracy and relevance in similar contexts.

Future research should explore several avenues to expand upon these findings. Longitudinal studies could clarify the causal mechanisms between IB, CI, ID, and BIS adoption, providing insights into their evolutionary dynamics. Sector-specific analyses would uncover industry-specific factors that influence BIS adoption, enriching the understanding of contextual variables and implications for technology integration strategies. Examining additional moderators (e.g., organizational culture, leadership styles) and mediators (e.g., knowledge management practices) would offer a comprehensive view of the factors influencing technology adoption outcomes in SMEs. Comparative studies across different countries or regions would highlight cross-cultural differences in innovation and technology adoption practices, enhancing the generalizability of the findings.

In conclusion, this study offers valuable insights into the complex dynamics of IB, CI, ID, and BIS adoption in Malaysian SMEs. Addressing the study's limitations and pursuing future research directions will advance knowledge in technology adoption and innovation management, ultimately enhancing organizational competitiveness and sustainability in dynamic market environments.

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