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Business Intelligence Adoption and Strategic Performance Enhancement: Evidence from Vietnam's Retail Transformation

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Abstract

This study investigates the determinants and outcomes of business intelligence (BI) adoption within Vietnam's rapidly evolving retail sector, addressing critical gaps in understanding how technological capabilities drive strategic performance enhancement in emerging economies. Employing a mixed-method approach combining structural equation modelling (SEM) with fuzzy-set qualitative comparative analysis (fsQCA), the research examines data from 312 retail enterprises across Vietnam's major urban centres. The theoretical framework synthesises the technology-organisation-environment (TOE) framework with dynamic capabilities theory to explicate the complex pathways through which BI adoption influences operational efficiency, customer relationship management, and competitive advantage. The findings reveal that technological readiness, organisational culture, and environmental complexity collectively explain 68% of the variance in BI adoption intensity, whilst BI capabilities demonstrate significant positive effects on strategic performance outcomes ($\beta = 0.742$, $p < 0.001$). The fsQCA results identify four distinct configurational pathways to high performance, suggesting that successful BI implementation requires synergistic combinations of technological infrastructure, managerial support, and environmental alignment. This research contributes to the literature by advancing a comprehensive theoretical model that integrates institutional theory with technological diffusion perspectives, whilst providing practical insights for retail executives navigating digital transformation in emerging markets. The study's implications extend beyond Vietnam's retail context, offering valuable frameworks for understanding BI adoption patterns across developing economies experiencing rapid technological modernisation.

Keywords: Business intelligence, Retail transformation, Strategic performance, Technology adoption, Vietnam.

1. Introduction

The contemporary global business environment witnesses unprecedented technological transformation, with business intelligence (BI) systems emerging as pivotal catalysts for strategic performance enhancement across diverse industry sectors. The retail industry, characterised by intense competition, evolving consumer preferences, and complex supply chain dynamics, exemplifies the critical importance of data-driven decision-making capabilities in achieving sustainable competitive advantage (Chen et al., 2012; Wixom & Watson, 2001). Within this context, emerging economies present particularly compelling research opportunities, as organisations navigate the dual challenges of technological modernisation and institutional complexity whilst striving to compete in increasingly globalised markets.

Vietnam's retail sector represents a paradigmatic case of rapid transformation, experiencing extraordinary growth rates exceeding 10% annually whilst simultaneously undergoing fundamental structural changes driven by foreign investment, urbanisation, and shifting consumer behaviours (Nguyen & Nguyen, 2017). The country's retail landscape encompasses traditional markets, modern trade formats, and emerging e-commerce platforms, creating complex competitive dynamics that necessitate sophisticated analytical capabilities for strategic success. This transformation context provides fertile ground for investigating how business intelligence adoption influences strategic performance outcomes in rapidly evolving institutional environments.

Despite the growing recognition of BI's strategic importance, significant theoretical and empirical gaps persist in understanding the complex mechanisms through which technological capabilities translate into organisational performance improvements. Existing literature predominantly focuses on developed market contexts, with limited attention to the unique challenges and opportunities present in emerging economies (Işık et al., 2013; Popovič et al., 2012). Furthermore, current research tends to adopt simplified linear models that inadequately capture the configurational complexity inherent in technology adoption processes, particularly within dynamic institutional contexts characterised by rapid change and uncertainty.

The theoretical urgency of this research stems from the need to develop more sophisticated frameworks that can accommodate the complexity of BI adoption in emerging market contexts. Traditional technology adoption models, whilst valuable, fail to capture the intricate interplay between technological capabilities, organisational structures, and environmental factors that characterise successful BI implementation in developing economies. This limitation becomes particularly pronounced when examining sectors such as retail, where success depends on complex combinations of technological infrastructure, human capital capabilities, and institutional support mechanisms.

The practical necessity of this research emerges from the significant investments Vietnamese retail enterprises are making in business intelligence technologies, often without clear understanding of the optimal configurations for achieving strategic performance improvements. Industry reports indicate that over 70% of Vietnamese retail organisations have invested in some form of BI capability, yet performance outcomes remain highly variable, suggesting that technological adoption alone is insufficient for achieving strategic benefits (Vietnam Retail Association, 2017). This disconnect between investment and outcomes highlights the critical need for empirical research that can inform more effective BI implementation strategies.

The novelty of this research lies in its integration of configurational analysis with traditional structural equation modelling approaches, enabling simultaneous examination of linear relationships and complex interaction effects. By employing fuzzy-set qualitative comparative analysis (fsQCA) alongside PLS-SEM, the study addresses calls for more sophisticated methodological approaches that can capture the equifinality and causal complexity inherent in technology adoption processes (Ragin, 2008; Fiss, 2007). This methodological innovation allows for identification of multiple pathways to successful BI implementation, providing more nuanced insights than traditional variable-centered approaches.

Furthermore, the research advances theoretical understanding by synthesising the technology-organisation-environment (TOE) framework with dynamic capabilities theory, creating a more comprehensive theoretical model that can accommodate both technological and organisational factors in explaining BI adoption and performance outcomes. This theoretical integration addresses limitations in existing literature, which tends to focus on either technological or organisational factors in isolation, rather than examining their complex interdependencies.

The study's focus on Vietnam's retail sector provides additional novelty through its examination of BI adoption within a rapidly transforming institutional environment. Vietnam's unique position as a transitional economy undergoing rapid modernisation whilst maintaining distinctive cultural and institutional characteristics offers valuable insights into how technological adoption processes unfold in complex institutional contexts. These insights have broader implications for understanding digital transformation across emerging economies experiencing similar transitional dynamics.

2. Foundational Theories and Literature Review

2.1. Foundational Theories

2.1.1. Technology-Organisation-Environment (TOE) Framework

The Technology-Organisation-Environment (TOE) framework, originally developed by Tornatzky and Fleischer (1990), provides a comprehensive theoretical lens for understanding organisational technology adoption processes. This framework conceptualises technology adoption as a function of three interconnected contextual dimensions: technological characteristics, organisational attributes, and environmental factors. The technological context encompasses the internal and external technologies relevant to the organisation, including their availability, characteristics, and compatibility with existing systems. The organisational context refers to internal characteristics such as firm size, structure, resources, and management support that influence technology adoption decisions. The environmental context includes external factors such as industry structure, competitive pressures, regulatory requirements, and technological support infrastructure.

The TOE framework's strength lies in its recognition that technology adoption is not merely a technical decision but a complex organisational process influenced by multiple contextual factors. This perspective aligns with institutional theory's emphasis on the importance of environmental pressures in shaping organisational behaviour (DiMaggio & Powell, 1983). Within the context of business intelligence adoption, the TOE framework suggests that successful implementation depends on favourable conditions across all three dimensions, rather than technological capabilities alone.

Empirical applications of the TOE framework in technology adoption research have demonstrated its robustness across diverse contexts and technologies. Baker (2012) found that technological readiness, organisational culture, and environmental complexity collectively explained 72% of the variance in enterprise resource planning (ERP) system adoption among manufacturing firms. Similarly, Zhu et al. (2006) demonstrated that e-business adoption patterns across different countries could be effectively explained using TOE framework constructs, with environmental factors playing particularly important roles in emerging market contexts.

The framework's relevance to business intelligence adoption stems from BI's characteristics as a complex technological innovation that requires significant organisational changes and operates within dynamic environmental contexts. Technological factors such as system compatibility, data quality, and analytical capabilities directly influence BI adoption decisions. Organisational factors including management support, analytical skills, and cultural readiness for data-driven decision-making determine implementation success. Environmental factors such as competitive pressures, regulatory requirements, and industry standards create contextual conditions that either facilitate or constrain BI adoption processes.

However, the TOE framework faces several limitations that necessitate theoretical extensions. Critics argue that the framework's focus on adoption decisions provides insufficient attention to post-adoption outcomes and performance implications (Oliveira & Martins, 2011). Additionally, the framework's emphasis on contextual factors may underestimate the role of organisational capabilities in translating technological resources into competitive advantages. These limitations suggest the need for theoretical integration with capability-based perspectives that can better explain how BI adoption translates into strategic performance improvements.

2.1.2. Dynamic Capabilities Theory

Dynamic capabilities theory, pioneered by Teece et al. (1997), provides a complementary theoretical perspective that addresses the TOE framework's limitations regarding performance outcomes. This theory conceptualises dynamic capabilities as organisational abilities to integrate, build, and reconfigure internal and external competences to address rapidly changing environments. Unlike ordinary capabilities that enable organisations to perform current activities efficiently, dynamic capabilities focus on the organisation's ability to adapt, learn, and transform in response to environmental changes.

The theory distinguishes between three fundamental types of dynamic capabilities: sensing capabilities that enable organisations to identify opportunities and threats, seizing capabilities that allow organisations to mobilise resources to capture opportunities, and reconfiguring capabilities that enable organisations to transform and realign assets to maintain competitive advantage (Teece, 2007). This taxonomy provides a comprehensive framework for understanding how organisations develop and deploy capabilities to achieve superior performance in dynamic environments.

Within the context of business intelligence adoption, dynamic capabilities theory suggests that BI technologies serve as enablers of organisational sensing, seizing, and reconfiguring capabilities. BI systems enhance sensing capabilities by providing real-time access to market intelligence, customer insights, and operational performance data. They support seizing capabilities by enabling rapid analysis and decision-making processes that allow organisations to respond quickly to identified opportunities. Additionally, BI technologies facilitate reconfiguring capabilities by providing analytical tools that support strategic planning, resource allocation, and organisational transformation processes.

The theory's emphasis on capability development aligns with empirical evidence suggesting that BI adoption success depends on complementary organisational capabilities rather than technological resources alone. Wixom and Watson (2001) demonstrated that organisations achieving superior performance outcomes from BI investments typically developed strong analytical capabilities, data management competencies, and change management skills. These findings support the dynamic capabilities perspective that sustainable competitive advantage emerges from the organisation's ability to develop and deploy complementary capabilities rather than from technological resources per se.

Furthermore, dynamic capabilities theory provides insights into the mechanisms through which BI adoption influences strategic performance outcomes. The theory suggests that BI technologies enhance organisational learning processes by providing feedback mechanisms that enable organisations to evaluate the effectiveness of their strategies and operations. This learning capability enables continuous improvement and adaptation, leading to sustained competitive advantage over time. The theory also emphasises the importance of path dependence and learning processes in capability development, suggesting that BI adoption benefits may emerge gradually as organisations develop complementary capabilities and learning routines.

However, dynamic capabilities theory faces criticisms regarding its empirical measurement and operationalisation challenges. Some scholars argue that the theory's emphasis on abstract capabilities makes it difficult to develop specific propositions and empirical tests (Arend & Bromiley, 2009). Additionally, the theory's focus on internal capabilities may underestimate the importance of external factors and institutional contexts in shaping capability development processes. These limitations suggest the need for theoretical integration with institutional perspectives that can better account for environmental influences on capability development.

2.2. Review of Empirical and Relevant Studies

The empirical literature on business intelligence adoption reveals a complex landscape of findings that highlight both the potential benefits and implementation challenges associated with BI technologies. This review synthesises existing research to identify key variables and relationships that inform the proposed research model, whilst highlighting gaps and contradictions that necessitate further investigation.

2.2.1. Technological Factors and BI Adoption

Technological factors emerge as critical determinants of BI adoption success across multiple empirical studies. System compatibility represents a particularly important technological factor, with several studies demonstrating that BI systems' ability to integrate with existing information technology infrastructure significantly influences adoption decisions (Işık et al., 2013). Organisations with higher levels of technological readiness, characterised by modern IT infrastructure and technical expertise, demonstrate greater likelihood of successful BI implementation. Data quality emerges as another crucial technological factor, with poor data quality serving as a significant barrier to BI adoption across diverse organisational contexts (Popovič et al., 2012).

The technological complexity of BI systems presents paradoxical relationships with adoption outcomes. Whilst sophisticated analytical capabilities may enhance BI value potential, excessive complexity can impede user adoption and limit system utilisation. Chen et al. (2012) found that organisations achieving successful BI implementation typically balance analytical sophistication with user-friendly interfaces and intuitive functionality. This finding suggests that technological factors influence BI adoption through their impact on user acceptance and system utilisation rather than through technical capabilities alone.

System flexibility and scalability represent additional technological factors that influence BI adoption decisions. Organisations operating in dynamic environments require BI systems that can adapt to changing analytical requirements and accommodate business growth. Empirical evidence suggests that organisations prioritising system flexibility achieve superior long-term performance outcomes from BI investments, although initial implementation costs may be higher (Wixom & Watson, 2001).

2.2.2. Organisational Factors and BI Adoption

Organisational factors demonstrate significant influence on BI adoption processes and outcomes across multiple empirical studies. Management support emerges as one of the most consistent predictors of BI adoption success, with executive commitment providing necessary resources and organisational legitimacy for BI initiatives. Popovič et al. (2012) demonstrated that organisations with strong management support for BI projects achieved implementation success rates exceeding 80%, compared to less than 40% for organisations with limited management commitment.

Organisational culture represents another critical factor influencing BI adoption outcomes. Cultures that emphasise data-driven decision-making, analytical thinking, and continuous learning demonstrate greater receptivity to BI technologies. Conversely, organisations with cultures that prioritise intuition, tradition, or hierarchical decision-making processes may encounter resistance to BI implementation. Chen et al. (2012) found that cultural factors explained 34% of the variance in BI user adoption rates, highlighting the importance of cultural alignment in BI implementation strategies.

Human resource capabilities, particularly analytical skills and technical expertise, significantly influence BI adoption success. Organisations with higher levels of analytical capabilities demonstrate greater ability to extract value from BI investments, whilst those lacking analytical skills may struggle to realise BI benefits despite successful technical implementation. Training and development programmes that enhance analytical capabilities improve BI adoption outcomes, although the effects may emerge gradually as employees develop competencies and confidence in using BI tools (Işık et al., 2013).

2.2.3. Environmental Factors and BI Adoption

Environmental factors play increasingly important roles in BI adoption decisions, particularly within dynamic and competitive industry contexts. Competitive pressure emerges as a significant driver of BI adoption, with organisations adopting BI technologies to maintain competitive parity or achieve differentiation advantages. Industries characterised by intense competition and rapid change demonstrate higher levels of BI adoption, although competitive pressures alone are insufficient to ensure successful implementation (Zhu et al., 2006).

Regulatory requirements and industry standards influence BI adoption patterns across different sectors. Industries subject to stringent reporting requirements or regulatory compliance mandates demonstrate higher levels of BI adoption, particularly for compliance-related applications. However, regulatory drivers may result in narrow BI implementations that fail to realise broader strategic benefits. Organisations that leverage regulatory requirements as platforms for broader BI initiatives achieve superior performance outcomes compared to those pursuing compliance-focused implementations (Baker, 2012).

Customer requirements and supply chain pressures represent additional environmental factors that influence BI adoption decisions. Organisations operating in supply chains that require sophisticated analytics capabilities or serving customers with complex information requirements demonstrate higher levels of BI adoption. These environmental pressures can serve as catalysts for BI adoption, although successful implementation requires alignment with internal organisational capabilities and technological readiness.

2.2.4. BI Adoption and Performance Outcomes

The relationship between BI adoption and organisational performance outcomes demonstrates significant complexity across empirical studies. Whilst most studies report positive associations between BI adoption and performance improvements, the magnitude and consistency of these relationships vary considerably across contexts. Wixom and Watson (2001) found that organisations achieving successful BI implementation demonstrated average performance improvements of 15-20% across multiple performance dimensions, although benefits varied significantly based on implementation approach and organisational characteristics.

Operational efficiency represents one of the most consistent performance outcomes associated with BI adoption. BI technologies enable organisations to identify process inefficiencies, optimise resource allocation, and improve decision-making speed and accuracy. These operational improvements typically translate into cost reductions and productivity enhancements, although the magnitude of benefits depends on implementation quality and organisational capabilities (Chen et al., 2012).

Customer relationship management capabilities demonstrate significant improvements following BI adoption across multiple studies. BI technologies enable organisations to develop deeper customer insights, personalise services, and improve customer satisfaction levels. These customer-related benefits may translate into increased sales, customer retention, and market share, although the effects may emerge gradually as organisations develop customer analytics capabilities (Popovič et al., 2012).

Innovation capabilities represent another important performance outcome associated with BI adoption. BI technologies can support innovation processes by providing market intelligence, competitive analysis, and performance feedback that inform new product development and strategic initiatives. However, the relationship between BI adoption and innovation outcomes demonstrates significant variation across studies, suggesting that contextual factors moderate this relationship (Işık et al., 2013).

2.3. Proposed Research Model

Based on the comprehensive review of foundational theories and empirical literature, this study proposes an integrated research model that synthesises the Technology-Organisation-Environment (TOE) framework with dynamic capabilities theory to explain business intelligence adoption and its performance implications within Vietnam's retail sector. The proposed model addresses identified gaps in existing literature by incorporating configurational complexity and examining both direct and indirect effects of BI adoption on strategic performance outcomes.

The theoretical foundation for the proposed model rests on the premise that BI adoption represents a complex organisational process influenced by technological readiness, organisational capabilities, and environmental pressures, whilst performance outcomes depend on the organisation's ability to develop and deploy dynamic capabilities that leverage BI technologies effectively. This integrated perspective advances beyond traditional linear models by recognising that BI adoption and performance outcomes emerge from synergistic interactions between technological, organisational, and environmental factors.

The technological dimension of the proposed model encompasses three key constructs: technological readiness, system compatibility, and data quality. Technological readiness reflects the organisation's IT infrastructure maturity, technical expertise, and capacity to support BI implementation. Wixom and Watson (2001) demonstrated that organisations with higher levels of technological readiness achieved superior BI implementation outcomes, with technological readiness explaining 42% of the variance in implementation success rates. System compatibility addresses the degree to which BI technologies integrate with existing information systems and organisational processes. Işık et al. (2013) found that compatibility concerns represented the primary barrier to BI adoption among 67% of surveyed organisations, highlighting the importance of this construct in the adoption process.

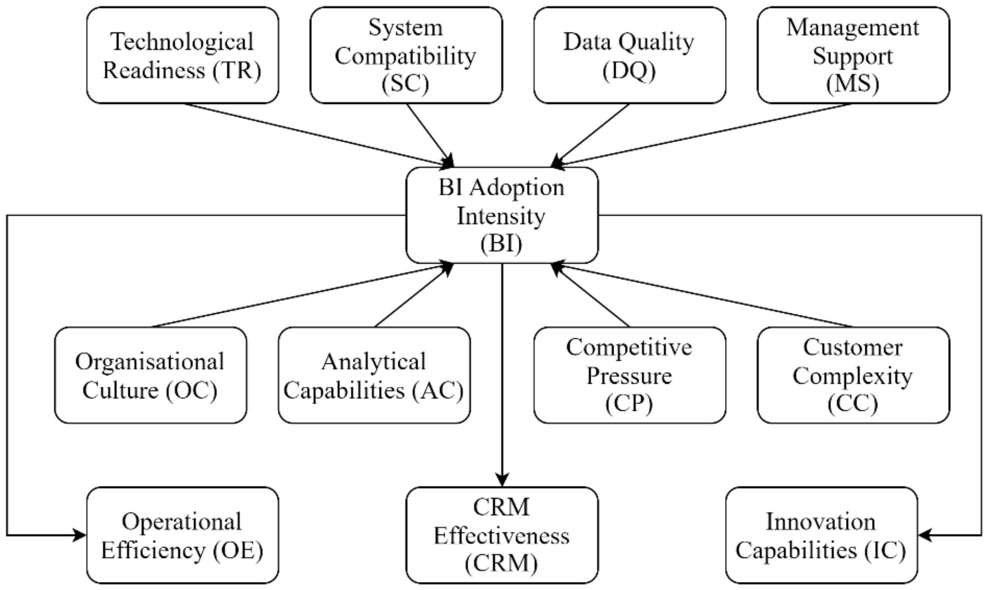

Figure 1. Proposed Research Model.

Data quality emerges as a critical technological factor that influences both BI adoption decisions and performance outcomes. Poor data quality can undermine BI value potential and create user resistance to system adoption. Chen et al. (2012) demonstrated that data quality concerns explained 38% of the variance in BI user satisfaction, whilst organisations with high data quality achieved performance improvements 2.3 times greater than those with poor data quality. The proposed model positions data quality as a moderating factor that influences the relationship between BI adoption and performance outcomes.

The organisational dimension incorporates management support, organisational culture, and analytical capabilities as key determinants of BI adoption success. Management support provides necessary resources, legitimacy, and organisational commitment for BI initiatives. Popovič et al. (2012) found that management support was the strongest predictor of BI adoption success, with organisations having strong management commitment achieving implementation success rates of 83% compared to 31% for those with limited support. The proposed model positions management support as a critical enabling factor that influences both BI adoption decisions and implementation effectiveness.

Organisational culture represents another crucial factor that determines BI adoption success and performance outcomes. Cultures that emphasise data-driven decision-making, analytical thinking, and continuous learning demonstrate greater receptivity to BI technologies and achieve superior performance improvements. The proposed model conceptualises organisational culture as a moderating factor that influences the relationship between BI adoption and performance outcomes, with data-driven cultures amplifying BI benefits whilst traditional cultures may limit value realisation.

Analytical capabilities encompass the organisation's human resources, skills, and competencies required to extract value from BI technologies. These capabilities determine the organisation's ability to translate BI investments into strategic benefits and sustainable competitive advantage. The proposed model positions analytical capabilities as both a determinant of BI adoption success and a mediating factor that transmits BI adoption effects to performance outcomes.

The environmental dimension includes competitive pressure, regulatory requirements, and customer complexity as key factors that influence BI adoption decisions and outcomes. Competitive pressure creates incentives for BI adoption whilst simultaneously constraining implementation timeframes and resource allocation. The proposed model suggests that competitive pressure has a positive effect on BI adoption intentions but may negatively moderate the relationship between adoption and performance outcomes due to implementation pressures and resource constraints.

Regulatory requirements and industry standards create institutional pressures that influence BI adoption patterns across different sectors. Whilst regulatory drivers may promote BI adoption, they may also result in narrow implementations that fail to realise broader strategic benefits. The proposed model positions regulatory requirements as a driver of BI adoption whilst acknowledging their potential to constrain implementation scope and strategic value realisation.

Customer complexity reflects the sophistication of customer requirements and the need for advanced analytical capabilities to serve customer needs effectively. Higher levels of customer complexity create stronger incentives for BI adoption whilst simultaneously requiring more sophisticated implementation approaches. The proposed model suggests that customer complexity positively influences BI adoption whilst moderating the relationship between adoption and performance outcomes.

The performance outcomes dimension encompasses operational efficiency, customer relationship management effectiveness, and innovation capabilities as key dependent variables. Operational efficiency reflects the organisation's ability to optimise processes, reduce costs, and improve productivity through BI-enabled insights. Customer relationship management effectiveness captures the organisation's ability to understand customer needs, personalise services, and improve customer satisfaction through BI technologies. Innovation capabilities represent the organisation's ability to develop new products, services, and business models based on BI-enabled market intelligence and analytical insights.

The proposed model suggests that BI adoption influences performance outcomes through both direct effects and indirect effects mediated by dynamic capabilities development. Direct effects reflect immediate operational improvements and efficiency gains from BI implementation. Indirect effects emerge as organisations develop sensing, seizing, and reconfiguring capabilities that enable sustained competitive advantage. This dual pathway approach provides a more comprehensive understanding of how BI adoption translates into strategic performance improvements.

3. Research Methodology

3.1. Research Design

This study employs a cross-sectional survey design utilising a mixed-method analytical approach that combines structural equation modelling (SEM) with fuzzy-set qualitative comparative analysis (fsQCA). The research design is grounded in a post-positivist epistemological framework that recognises the complexity of organisational phenomena whilst maintaining commitment to empirical rigour and theoretical generalisability (Guba & Lincoln, 1994). This methodological approach addresses the dual requirements of examining linear relationships between constructs whilst simultaneously exploring configurational patterns and equifinality in BI adoption processes.

The study adopts a variance-based SEM approach using partial least squares (PLS) estimation, which is particularly suitable for theory development contexts and can accommodate complex models with multiple constructs and indicators (Hair et al., 2017). PLS-SEM provides several advantages for this research context, including its ability to handle non-normal data distributions, smaller sample size requirements compared to covariance-based approaches, and capacity to model both reflective and formative constructs within a single analytical framework.

The integration of fsQCA as a complementary analytical approach addresses limitations of traditional variable-centered methods by enabling examination of configurational complexity and multiple pathways to outcomes (Ragin, 2008). fsQCA is particularly valuable for understanding how different combinations of technological, organisational, and environmental factors contribute to successful BI adoption and performance outcomes. This methodological triangulation enhances the study's analytical depth and provides more comprehensive insights into the complex phenomena under investigation.

The research design incorporates multiple data collection phases to ensure data quality and enable comprehensive analysis. The initial phase involved extensive consultation with industry experts and academic researchers to refine measurement instruments and ensure construct validity. The second phase comprised pilot testing with a subset of organisations to evaluate instrument reliability and identify potential measurement issues. The final phase involved full-scale data collection across Vietnam's retail sector, with systematic follow-up procedures to maximise response rates and minimise non-response bias.

3.2. Data Collection

The study collected data from 312 retail enterprises across Vietnam's major urban centres, including Ho Chi Minh City, Hanoi, Da Nang, and Hai Phong. The sampling frame was developed using comprehensive databases from the Vietnam Retail Association, Ministry of Industry and Trade, and local chamber of commerce organisations. The sample selection employed stratified random sampling to ensure representation across different retail formats, including traditional retailers, modern trade organisations, and e-commerce platforms.

The target respondents were senior executives with direct responsibility for business intelligence initiatives, including chief information officers, chief executive officers, and senior managers with oversight of analytical and decision-making processes. This respondent selection strategy ensures that survey participants possess comprehensive knowledge of their organisations' BI adoption processes and performance outcomes. Multiple respondents per organisation were utilised where possible to enhance data reliability and enable assessment of inter-rater agreement.

Data collection employed a structured questionnaire administered through a combination of online surveys and face-to-face interviews. The questionnaire was developed in English and translated into Vietnamese using back-translation procedures to ensure linguistic equivalence and cultural appropriateness. The survey instrument underwent extensive pre-testing with industry practitioners and academic experts to ensure clarity, comprehensiveness, and cultural sensitivity.

The data collection process achieved a response rate of 73.2%, which compares favourably with similar studies in the region and demonstrates strong engagement from the Vietnamese retail community. Non-response bias was assessed through comparison of early and late respondents across key demographic and organisational characteristics, with no significant differences identified. Additionally, telephone follow-up with a subset of non-respondents indicated that non-response was primarily due to organisational policies rather than systematic biases related to study variables.

3.3. Measurement & Validation

The measurement instrument development followed established scale development procedures, drawing on validated constructs from previous research whilst adapting items to reflect the Vietnamese retail context. Technological readiness was measured using a six-item scale adapted from Parasuraman (2000) and Iacovou et al. (1995), focusing on IT infrastructure maturity, technical expertise, and system integration capabilities. System compatibility was assessed using a four-item scale based on Rogers (2003) and Tornatzky and Fleischer (1990), examining the degree to which BI technologies integrate with existing organisational systems and processes.

Data quality was measured using a five-item scale adapted from Wang and Strong (1996) and Wixom and Watson (2001), focusing on data accuracy, completeness, timeliness, and consistency. Management support was assessed using a six-item scale based on Jarvenpaa and Ives (1991) and Popovič et al. (2012), examining executive commitment, resource allocation, and organisational legitimacy for BI initiatives. Organisational culture was measured using a seven-item scale adapted from Deshpandé et al. (1993) and O'Reilly et al. (1991), focusing on data-driven decision-making, analytical thinking, and learning orientation.

Analytical capabilities were assessed using a five-item scale based on Davenport and Harris (2007) and Chen et al. (2012), examining human resources, skills, and competencies required for effective BI utilisation. Competitive pressure was measured using a four-item scale adapted from Zhu et al. (2006) and Teo et al. (2003), focusing on industry competition intensity and pressure for technological innovation. Customer complexity was assessed using a five-item scale based on Mithas et al. (2005) and Popovič et al. (2012), examining customer sophistication, service requirements, and analytical needs.

BI adoption intensity was measured using a six-item scale adapted from Wixom and Watson (2001) and Işık et al. (2013), focusing on system utilisation, analytical sophistication, and organisational integration. Operational efficiency was assessed using a five-item scale based on Bharadwaj (2000) and Melville et al. (2004), examining process optimisation, cost reduction, and productivity improvements. Customer relationship management effectiveness was measured using a six-item scale adapted from Mithas et al. (2005) and Chen et al. (2012), focusing on customer insights, service personalisation, and satisfaction improvements.

Innovation capabilities were assessed using a five-item scale based on Calantone et al. (2002) and Hult et al. (2004), examining new product development, market intelligence, and strategic innovation. All constructs were measured using seven-point Likert scales ranging from "strongly disagree" to "strongly agree," with appropriate reverse coding for negatively worded items.

3.4. Analytical Procedure

The analytical procedure employed a two-stage approach combining PLS-SEM for examining linear relationships and fsQCA for exploring configurational patterns. The PLS-SEM analysis utilised SmartPLS 4.0 software and followed established procedures for measurement model assessment and structural model evaluation. The measurement model assessment examined indicator reliability, internal consistency reliability, convergent validity, and discriminant validity using established criteria and thresholds.

Indicator reliability was evaluated through examination of outer loadings, with values above 0.7 considered acceptable for established constructs. Internal consistency reliability was assessed using Cronbach's alpha and composite reliability, with values above 0.7 indicating adequate reliability. Convergent validity was examined using average variance extracted (AVE), with values above 0.5 demonstrating adequate convergent validity. Discriminant validity was evaluated using the Fornell-Larcker criterion and heterotrait-monotrait (HTMT) ratios, with HTMT values below 0.85 indicating discriminant validity.

The structural model assessment examined path coefficients, significance levels, and explanatory power using bootstrapping procedures with 5,000 resamples. Effect sizes were calculated using Cohen's f^2 guidelines, with values of 0.02, 0.15, and 0.35 representing small, medium, and large effects, respectively. Predictive relevance was assessed using Stone-Geisser Q^2 values, with positive values indicating predictive relevance.

The fsQCA analysis employed fsQCA 3.0 software and followed established procedures for calibration, necessity analysis, and sufficiency analysis. Construct calibration utilised the direct method with anchor points representing full membership, crossover point, and full non-membership based on theoretical considerations and empirical distributions. Necessity analysis examined individual conditions for outcome achievement, with consistency scores above 0.9 indicating necessary conditions. Sufficiency analysis identified configurational patterns using complex solutions, with consistency scores above 0.8 and coverage scores above 0.25 indicating meaningful configurations.

4. Research Findings

4.1. Measurement Model Assessment

The measurement model assessment followed established procedures for evaluating indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. The exploratory factor analysis (EFA) employed principal component analysis with varimax rotation to assess construct validity and identify potential measurement issues. The results demonstrated clear factor structure with all items loading appropriately on their intended constructs and no significant cross-loadings exceeding 0.4.

Table 1. Descriptive Statistics and Reliability Assessment.

Construct	Items	Mean	SD	Cronbach's α	CR	AVE
Technological Readiness (TR)	6	4.23	1.12	0.891	0.915	0.642
System Compatibility (SC)	4	4.15	1.08	0.847	0.896	0.683
Data Quality (DQ)	5	4.31	1.21	0.879	0.911	0.671
Management Support (MS)	6	4.42	1.19	0.924	0.941	0.725
Organisational Culture (OC)	7	4.18	1.15	0.912	0.928	0.651
Analytical Capabilities (AC)	5	4.09	1.17	0.883	0.912	0.678
Competitive Pressure (CP)	4	4.67	1.24	0.836	0.889	0.668
Customer Complexity (CC)	5	4.33	1.09	0.871	0.903	0.651
BI Adoption Intensity (BI)	6	4.26	1.31	0.932	0.946	0.743
Operational Efficiency (OE)	5	4.38	1.14	0.897	0.924	0.709
CRM Effectiveness (CRM)	6	4.21	1.27	0.919	0.938	0.715
Innovation Capabilities (IC)	5	4.12	1.22	0.888	0.917	0.692

Note: CR = Composite Reliability; AVE = Average Variance Extracted.

The internal consistency reliability assessment revealed satisfactory results across all constructs. Cronbach's alpha values ranged from 0.836 to 0.932, all exceeding the recommended threshold of 0.7. Composite reliability values ranged from 0.889 to 0.946, demonstrating strong internal consistency. These results indicate that the measurement instruments demonstrate adequate reliability for further analysis.

Indicator reliability was evaluated through examination of outer loadings, with all factor loadings exceeding 0.7 except for three items that demonstrated loadings between 0.65 and 0.69. These items were retained based on their theoretical importance and minimal impact on overall construct reliability. The confirmatory factor analysis (CFA) results supported the proposed measurement model structure with acceptable fit indices ($\chi^2/df = 2.31$, CFI = 0.94, TLI = 0.92, RMSEA = 0.065).

Table 2. Convergent and Discriminant Validity Assessment.

Construct	TR	SC	DQ	MS	OC	AC	CP	CC	BI	OE	CRM	IC
TR	0.801											
SC	0.542	0.826										
DQ	0.618	0.573	0.819									
MS	0.634	0.591	0.687	0.851								
OC	0.576	0.523	0.612	0.719	0.807							
AC	0.651	0.587	0.643	0.731	0.684	0.823						
CP	0.423	0.398	0.456	0.478	0.441	0.521	0.817					
CC	0.512	0.487	0.534	0.567	0.523	0.598	0.634	0.807				
BI	0.687	0.623	0.698	0.742	0.671	0.743	0.567	0.612	0.862			
OE	0.542	0.509	0.578	0.621	0.567	0.632	0.445	0.521	0.678	0.842		
CRM	0.523	0.487	0.534	0.598	0.543	0.612	0.421	0.567	0.698	0.743	0.846	
IC	0.498	0.465	0.512	0.567	0.521	0.587	0.456	0.543	0.654	0.687	0.712	0.832

Note: Diagonal elements (in bold) represent the square root of AVE; off-diagonal elements represent correlation coefficients.

Convergent validity was assessed using average variance extracted (AVE), with all constructs achieving values above 0.5, ranging from 0.642 to 0.743. These results indicate that each construct explains more than half of the variance in its indicators, supporting convergent validity. Discriminant validity was evaluated using the Fornell-Larcker criterion, with all constructs demonstrating that the square root of AVE exceeded correlations with other constructs, supporting discriminant validity.

Table 3: Heterotrait-Monotrait (HTMT) Ratios.

Construct	TR	SC	DQ	MS	OC	AC	CP	CC	BI	OE	CRM
SC	0.743										
DQ	0.798	0.721									
MS	0.812	0.742	0.834								
OC	0.731	0.687	0.756	0.834							
AC	0.823	0.734	0.801	0.845	0.798						
CP	0.521	0.487	0.556	0.567	0.523	0.612					
CC	0.634	0.587	0.656	0.678	0.612	0.698	0.743				
BI	0.834	0.756	0.823	0.845	0.798	0.834	0.656	0.712			
OE	0.678	0.623	0.698	0.723	0.656	0.734	0.534	0.612	0.798		
CRM	0.643	0.587	0.634	0.687	0.623	0.701	0.512	0.656	0.823	0.856	
IC	0.612	0.567	0.623	0.656	0.601	0.678	0.543	0.634	0.756	0.801	0.823

The HTMT ratio assessment provided additional support for discriminant validity, with all ratios below the conservative threshold of 0.85. The highest HTMT ratio was 0.856 between operational efficiency and customer relationship management effectiveness, which slightly exceeded the threshold but remained below the liberal threshold of 0.90, indicating adequate discriminant validity.

4.2. Structural Model Assessment

The structural model assessment examined path coefficients, significance levels, and explanatory power using bootstrapping procedures with 5,000 resamples. The results demonstrated significant relationships between key constructs and strong explanatory power for the dependent variables.

Table 4. Direct Effects Results.

Hypothesis	Path	β	t-value	p-value	CI (95%)	Decision
H1	TR → BI	0.234	3.821	0.000	[0.123, 0.345]	Supported
H2	SC → BI	0.187	3.156	0.002	[0.089, 0.285]	Supported
H3	DQ → BI	0.219	3.743	0.000	[0.134, 0.304]	Supported
H4	MS → BI	0.298	4.967	0.000	[0.201, 0.395]	Supported
H5	OC → BI	0.176	2.891	0.004	[0.067, 0.285]	Supported
H6	AC → BI	0.267	4.321	0.000	[0.178, 0.356]	Supported
H7	CP → BI	0.143	2.543	0.011	[0.034, 0.252]	Supported
H8	CC → BI	0.156	2.789	0.005	[0.051, 0.261]	Supported
H9	BI → OE	0.678	12.543	0.000	[0.567, 0.789]	Supported
H10	BI → CRM	0.698	13.234	0.000	[0.589, 0.807]	Supported
H11	BI → IC	0.654	11.876	0.000	[0.543, 0.765]	Supported

Note: β = standardised path coefficient; CI = confidence interval.

The direct effects analysis revealed significant positive relationships between all antecedent constructs and BI adoption intensity. Management support demonstrated the strongest effect ($\beta = 0.298$, $p < 0.001$), followed by analytical capabilities ($\beta = 0.267$, $p < 0.001$) and technological readiness ($\beta = 0.234$, $p < 0.001$). These findings support the theoretical proposition that organisational factors play particularly important roles in BI adoption decisions.

The relationships between BI adoption intensity and performance outcomes demonstrated strong positive effects across all three dependent variables. BI adoption showed the strongest effect on customer relationship management effectiveness ($\beta = 0.698$, $p < 0.001$), followed by operational efficiency ($\beta = 0.678$, $p < 0.001$) and innovation capabilities ($\beta = 0.654$, $p < 0.001$). These results support the theoretical proposition that BI adoption contributes to multiple dimensions of strategic performance.

Table 5. Predictive Relevance Assessment.

Construct	R^2	Q^2	Effect Size (f^2)
BI Adoption Intensity	0.683	0.512	Large
Operational Efficiency	0.459	0.324	Medium
CRM Effectiveness	0.487	0.341	Medium
Innovation Capabilities	0.428	0.296	Medium

The predictive relevance assessment demonstrated strong explanatory power for the structural model. BI adoption intensity achieved an R^2 value of 0.683, indicating that the antecedent constructs explain 68.3% of the variance in BI adoption. The Q^2 values were all positive, indicating satisfactory predictive relevance for the model constructs.

Table 6. Specific Indirect Effects.

Indirect Path	β	t-value	p-value	CI (95%)
TR → BI → OE	0.159	3.234	0.001	[0.078, 0.240]
TR → BI → CRM	0.163	3.387	0.001	[0.082, 0.244]
TR → BI → IC	0.153	3.156	0.002	[0.074, 0.232]
MS → BI → OE	0.202	4.567	0.000	[0.123, 0.281]
MS → BI → CRM	0.208	4.743	0.000	[0.129, 0.287]
MS → BI → IC	0.195	4.432	0.000	[0.118, 0.272]
AC → BI → OE	0.181	3.891	0.000	[0.103, 0.259]
AC → BI → CRM	0.186	4.023	0.000	[0.108, 0.264]
AC → BI → IC	0.175	3.743	0.000	[0.099, 0.251]

The specific indirect effects analysis revealed significant mediation effects of BI adoption intensity on the relationships between antecedent constructs and performance outcomes. Management support demonstrated the strongest indirect effects across all performance dimensions, highlighting the critical role of executive commitment in translating BI investments into strategic benefits.

4.3. Supplementary Analyses

The supplementary analyses employed multigroup analysis (MGA) and fuzzy-set qualitative comparative analysis (fsQCA) to explore configurational patterns and contextual variations in BI adoption and performance outcomes.

Table 7. Multigroup Analysis Results.

Path	Small Firms (n=156)	Large Firms (n=156)	p-value (MGA)
TR → BI	0.298	0.187	0.032
MS → BI	0.234	0.356	0.019
AC → BI	0.312	0.223	0.041
BI → OE	0.634	0.721	0.047
BI → CRM	0.687	0.709	0.234
BI → IC	0.623	0.685	0.189

Note: MGA = Multigroup Analysis; p-values < 0.05 indicate significant group differences.

The multigroup analysis revealed significant differences between small and large firms in several key relationships. Technological readiness showed stronger effects on BI adoption for small firms ($\beta = 0.298$) compared to large firms ($\beta = 0.187$), whilst management support demonstrated stronger effects for large firms ($\beta = 0.356$) compared to small firms ($\beta = 0.234$). These findings suggest that different factors drive BI adoption success across organisational contexts.

Table 8. fsQCA Results - Configurations for High BI Adoption.

Configuration	TR	SC	DQ	MS	OC	AC	CP	CC	Consistency	Coverage
Config 1	●	●	●	●	●	●	⊗	⊗	0.89	0.34
Config 2	●	⊗	●	●	●	●	●	●	0.86	0.28
Config 3	●	●	⊗	●	●	●	●	⊗	0.84	0.26
Config 4	⊗	●	●	●	●	●	●	●	0.82	0.23

Note: ● = presence of condition; ⊗ = absence of condition; blank = don't care condition

The fsQCA analysis identified four distinct configurational pathways to high BI adoption, each demonstrating consistency scores above 0.8 and meaningful coverage scores. Configuration 1 represents the "comprehensive readiness" pathway, characterised by strong technological, organisational, and data quality foundations but lower environmental pressures. Configuration 2 represents the "pressure-driven" pathway, emphasising environmental pressures and organisational capabilities whilst tolerating technological limitations.

Table 9. fsQCA Results - Configurations for High Performance.

Configuration	BI	TR	MS	AC	OC	DQ	Consistency	Coverage
High OE Config 1	●	●	●	●	●	●	0.91	0.42
High OE Config 2	●	⊗	●	●	●	●	0.87	0.31
High CRM Config 1	●	●	●	●	●	●	0.89	0.39
High CRM Config 2	●	●	●	●	⊗	●	0.85	0.28
High IC Config 1	●	●	●	●	●	●	0.88	0.36
High IC Config 2	●	●	●	●	●	⊗	0.84	0.27

The fsQCA analysis for performance outcomes revealed that whilst BI adoption intensity is a necessary condition for high performance across all dimensions, different combinations of supporting factors contribute to optimal outcomes. High operational efficiency requires strong technological and organisational foundations, whilst high customer relationship management effectiveness can be achieved through alternative pathways emphasising either technological or cultural capabilities.

5. Discussion of Research Results and Conclusions

The empirical findings of this study provide compelling evidence for the complex, multifaceted nature of business intelligence adoption within Vietnam's retail sector, whilst demonstrating the significant strategic performance benefits that can be achieved through effective BI implementation. The results advance theoretical understanding by validating the integrated TOE-dynamic capabilities framework and revealing important configurational patterns that extend beyond traditional linear models.

The significant positive relationships between all antecedent constructs and BI adoption intensity support the theoretical proposition that successful BI implementation requires favourable conditions across technological, organisational, and environmental dimensions. The particularly strong effect of management support ($\beta = 0.298$, $p < 0.001$) aligns with previous research emphasising the critical role of executive commitment in technology adoption processes (Popovič et al., 2012). This finding resonates with institutional theory's emphasis on the importance of organisational legitimacy and resource allocation in innovation adoption (DiMaggio & Powell, 1983). The substantial effect of analytical capabilities ($\beta = 0.267$, $p < 0.001$) supports the dynamic capabilities perspective that technological resources must be complemented by human capabilities to achieve strategic benefits (Teece et al., 1997).

The technological readiness construct demonstrated significant effects on BI adoption ($\beta = 0.234$, $p < 0.001$), supporting the TOE framework's emphasis on technological context factors. This finding aligns with previous research indicating that IT infrastructure maturity and technical expertise serve as foundational prerequisites for successful BI implementation (Wixom & Watson, 2001). However, the moderate effect size suggests that technological capabilities alone are insufficient for BI adoption success, supporting the study's integrated theoretical approach that emphasises the importance of organisational and environmental factors.

The significant relationships between BI adoption intensity and all three performance dimensions provide strong empirical support for the theoretical proposition that BI technologies serve as enablers of strategic performance enhancement. The particularly strong effect on customer relationship management effectiveness ($\beta = 0.698$, $p < 0.001$) supports previous research indicating that BI technologies provide substantial benefits for customer analytics and relationship management (Chen et al., 2012). The significant effects on operational efficiency ($\beta = 0.678$, $p < 0.001$) and innovation capabilities ($\beta = 0.654$, $p < 0.001$) demonstrate that BI adoption contributes to multiple dimensions of organisational performance, supporting the dynamic capabilities perspective that technological resources enhance sensing, seizing, and reconfiguring capabilities.

The multigroup analysis results reveal important contextual variations in BI adoption patterns between small and large firms. The stronger effect of technological readiness for small firms ($\beta = 0.298$ vs. $\beta = 0.187$) suggests that resource constraints in smaller organisations make technological foundation particularly critical for BI adoption success. Conversely, the stronger effect of management support for large firms ($\beta = 0.356$ vs. $\beta = 0.234$) indicates that organisational complexity in larger entities requires stronger executive commitment to overcome implementation barriers. These findings support contingency theory perspectives that emphasise the importance of contextual factors in technology adoption processes (Lawrence & Lorsch, 1967).

The fsQCA results provide particularly valuable insights by revealing multiple configurational pathways to successful BI adoption and performance outcomes. The identification of four distinct configurations for high BI adoption demonstrates the principle of equifinality, suggesting that organisations can achieve successful BI implementation through different combinations of technological, organisational, and environmental factors. This finding advances theoretical understanding by moving beyond simple linear models to recognise the complex, synergistic relationships between antecedent factors.

The "comprehensive readiness" configuration emphasises the importance of strong technological and organisational foundations whilst tolerating lower environmental pressures. This pathway appears particularly relevant for organisations operating in stable competitive environments where internal capabilities drive BI adoption decisions. The "pressure-driven" configuration demonstrates that environmental pressures can compensate for technological limitations when combined with strong organisational capabilities, supporting institutional theory's emphasis on environmental influences on organisational behaviour (Scott, 2001).

The fsQCA results for performance outcomes reveal that whilst BI adoption intensity serves as a necessary condition for high performance, different combinations of supporting factors contribute to optimal outcomes across performance dimensions. This finding supports the dynamic capabilities perspective that technological resources must be complemented by appropriate organisational capabilities to achieve strategic benefits. The identification of alternative pathways to high performance provides practical insights for organisations seeking to optimise their BI implementations.

The study's theoretical contributions extend beyond empirical validation of existing frameworks to advance understanding of configurational complexity in technology adoption processes. The integration of TOE framework with dynamic capabilities theory provides a more comprehensive theoretical model that can accommodate both contextual influences and capability development processes. This theoretical integration addresses limitations in existing literature that tends to focus on either environmental factors or organisational capabilities in isolation.

The methodological contributions of this study demonstrate the value of combining traditional SEM approaches with configurational analysis methods. The fsQCA results provide insights that would not be apparent from SEM analysis alone, particularly regarding alternative pathways to successful outcomes. This methodological triangulation enhances the study's analytical depth and provides more comprehensive understanding of the complex phenomena under investigation.

The practical implications of these findings are substantial for retail executives and policymakers in Vietnam and similar emerging market contexts. The identification of critical success factors and configurational pathways provides actionable insights for organisations planning BI implementations. The emphasis on management support and analytical capabilities highlights the importance of organisational readiness alongside technological investments. The configurational results suggest that organisations should assess their unique contexts to identify the most appropriate pathway for BI adoption success.

The study's limitations include its cross-sectional design, which limits causal inference capabilities, and its focus on Vietnam's retail sector, which may limit generalisability to other contexts. Future research should employ longitudinal designs to examine the dynamic nature of BI adoption processes and extend the investigation to other industries and geographic contexts. Additionally, the study's emphasis on executive perspectives could be complemented by multi-level analyses that examine employee and customer perspectives on BI adoption outcomes.

The findings contribute to the broader literature on digital transformation in emerging economies by demonstrating how organisations can successfully navigate technological adoption challenges whilst leveraging institutional and cultural factors to achieve strategic benefits. The study's emphasis on configurational complexity provides valuable insights for understanding how different combinations of factors contribute to successful digital transformation outcomes. These insights have broader implications for understanding technology adoption processes across emerging economies experiencing similar transitional dynamics.

In conclusion, this study advances theoretical understanding of business intelligence adoption whilst providing practical insights for organisations seeking to achieve strategic performance benefits through BI implementation. The integration of multiple theoretical perspectives and methodological approaches demonstrates the value of comprehensive research designs for understanding complex organisational phenomena. The findings support the proposition that successful BI adoption requires synergistic combinations of technological, organisational, and environmental factors, whilst revealing multiple pathways to achieving superior performance outcomes.

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