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# Leveraging business intelligence for competitive advantage: The mediating role of innovation in the Thai hotel industry

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ABSTRACT

This study investigates how business intelligence capabilities (BIC) influence competitive performance (COP) in the Thai hotel industry, with a particular focus on the mediating role of innovation capability (INC). Drawing on the Resource-Based View and Dynamic Capabilities Theory, the study develops a structural model proposing that BIC improves COP both directly and indirectly through INC. Using stratified random sampling based on classifications from the Tourism Grading Council of Thailand, data were collected from 180 hotel managers through a structured questionnaire. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to test the proposed relationships. The results show that BIC does not directly affect COP, but has a strong and significant indirect effect through INC, indicating that innovation capability fully mediates this relationship. These findings highlight the importance of strengthening innovation to convert business intelligence insights into a competitive advantage. The study adds to the literature on business intelligence and innovation management by providing empirical evidence from the hospitality sector in an emerging market. It also stresses the strategic need to align business intelligence systems with innovation activities to achieve sustainable performance. The study offers originality by demonstrating that innovation capability fully mediates the link between business intelligence capabilities and competitive performance in the underexplored context of Thai hotels.



## 1. Introduction

Emerging as a critical field, business intelligence (BI) is an essential tool for organizations to support data collection, extraction, and analysis from both internal and external sources. It generates information that underpins strategic decision-making (Torres et al., 2018). Organizations equipped with modern technology can better keep pace with competitors, accurately meet customer needs, and respond promptly, thereby enhancing their chances of achieving competitive advantage and improving operational efficiency (Alnoukari and Hanano, 2017).

The hotel industry, as part of the service sector, emphasizes flexibility, agility, and responsiveness, all of which contribute to strategic advantage. Applying BI—an information system that produces critical insights and adds value to products and services—enables organizations to leverage valuable and scarce resources to improve efficiency and effectiveness. The ability to manage IT resources empowers firms to acquire relevant knowledge for decision-making, set strategic directions, and optimize business processes. This ability is referred to as business intelligence capabilities.

The capacity of an organization to leverage BI is a key driver of competitiveness through improved access to business data. BI capabilities also expand the knowledge base available to entrepreneurs and managers by gathering and transforming information into actionable knowledge (Colombelli et al., 2013). The intelligence embedded in information systems fosters the generation of new ideas and collaboration in innovative ways across the supply chain. Consequently, the hotel service industry must harness these capabilities to advance operations and adapt to external changes.

Moreover, political and social changes worldwide have intensified global competition and accelerated technological progress. As uncertainty increases, businesses require data to support operations, which, in turn, stimulate innovation activities. BI capabilities have been shown to influence business

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innovation and positively affect enterprise competitiveness. Nevertheless, organizations must recognize that creative products and novel business models cannot succeed without dynamic capabilities, which enhance innovation management capacity beyond that of market rivals.

Research on BI systems has grown in significance in recent years. A key theoretical gap lies in the absence of a cohesive framework integrating dynamic capabilities, organizational factors, and clear empirical measures of the impact BI has on firm performance. This gap stems from the lack of a unified explanation of how BI capabilities contribute to organizational performance. While BI is recognized as vital for improving efficiency, its implementation often fails for unclear reasons (Olszak, 2014). Theoretical foundations such as the Resource-Based View (RBV) and Dynamic Capabilities Theory could provide a stronger explanatory basis for these failures. Furthermore, there remains no consensus on the most effective measures of BI capabilities (Chen and Lin, 2021), underscoring the need for clearer frameworks linking BI capabilities to competitive performance.

From this perspective, BI capabilities, innovation capability, and competitive performance are causally interrelated. Therefore, the purpose of this study is to provide empirical evidence on BI capability management and innovation management in Thai hotel businesses. The research seeks to determine whether, and how, BI capabilities and innovation capability drive competitive performance by increasing the efficiency and effectiveness of business operations. Ultimately, the findings are expected to guide Thai hotel businesses in adapting to dynamic environments, ensuring survival, and recognizing the critical importance of preparing strategic resources—particularly data and information. These considerations form the foundation of this research.

## 2. Theoretical framework

### 2.1. Competitive performance view

Competitiveness and competitive advantage, while closely related, differ in scope. Competitiveness refers to the ability of an organization to consistently outperform its rivals in the marketplace (Lin et al., 2020), whereas competitive advantage represents the foundation for assessing competitive performance and forms the core link between performance and market positioning (Gyemang and Emeagwali, 2020; Mahdi et al., 2019).

In contemporary markets, competitive advantage is essential for survival and long-term success. It is achieved when a firm offers goods or services that are perceived as superior or distinct compared to its competitors, whether through differentiation or cost leadership (Langlois and Chauvel, 2017; Seufert and Schiefer, 2005; Zucca, 2013). This positional advantage may be reflected in higher customer lifetime value, lower relative costs, greater market share, or superior business performance (Amarakoon et al., 2018).

Within the hotel industry, competitive performance is both a prerequisite for and an outcome of competitive advantage. Hotels must develop distinctive capabilities that deliver greater value than competitors to secure and sustain a strong market position (Hossain et al., 2022). Achieving this requires more than operational efficiency; it demands strategic agility, market intelligence, and the capacity to innovate service offerings. Competitiveness in service-based industries is driven by exceptional customer satisfaction, differentiated service strategies, and adaptability to changing conditions. Thus, in the hospitality sector, competitive performance (COP) serves as a critical measure of how effectively a hotel leverages its unique resources and capabilities to maintain leadership and achieve sustainable success.

### 2.2. Business intelligence capabilities view

Business intelligence (BI) encompasses the technological and organizational capabilities that allow firms to collect, process, and exploit data to support strategic decision-making, enabling analytics-driven planning and operational efficiency in data-intensive sectors such as hospitality. However, despite its widespread adoption, empirical evidence shows that the performance impact of BI varies significantly across contexts, often depending on the degree of strategic integration and alignment with organizational objectives (Popovič et al., 2019).

Rather than being viewed as a static system, BI should be understood as a dynamic capability that adapts to evolving business needs. While BI systems generate data-driven insights, their true value lies in translating these insights into adaptive and innovative actions that improve competitiveness (Chen and Lin, 2021). The Resource-Based View (RBV) and Dynamic Capabilities Theory reinforce this perspective, framing BI as a strategic resource whose value emerges through its interaction with complementary capabilities and assets (Elbashir et al., 2008).

Business intelligence capability (BIC) is further enhanced when supported by organizational learning, managerial commitment, and an innovation-oriented culture. In dynamic markets, firms that leverage BI not only for monitoring operations but also for exploration and innovation achieve superior competitive outcomes (Torres et al., 2018; Wang et al., 2022). Accordingly, BI should be developed as a core strategic asset—embedded across functional areas and decision-making hierarchies—to strengthen organizational agility, responsiveness, and long-term performance.

### 2.3. Innovation capability view

Innovation capability (INC) refers to the capacity of an organization to transform creative ideas into new or improved products, services, or processes that enhance performance. Beyond RandD investments, it encompasses organizational culture, leadership, employee engagement, and adaptive learning processes (Forsman, 2011). In hospitality, innovation capability is reflected in a hotel being able to personalize customer experiences, streamline operations, and respond to evolving consumer preferences. Firms with strong innovation capabilities are better equipped to address competitive pressures by introducing new service models, adopting digital tools, and implementing customer-driven improvements (Hjalager, 2010).

Empirical studies consistently link innovation capability to strategic renewal, long-term growth, and competitive differentiation (Calantone et al., 2002; Rajapathirana and Hui, 2018). However, the extent to which innovation contributes to performance depends on the organizational context and the capacity to effectively operationalize innovative ideas. Without the right structures, leadership support, and processes, innovation may fail to deliver measurable results.

Importantly, innovation capability interacts synergistically with other organizational capabilities, particularly business intelligence (BI). BI provides insights into customer behavior, operational inefficiencies, and market trends, enabling evidence-based innovation strategies. This interaction forms a layered capability framework in which data-driven insights inform action, and innovation translates these actions into competitive outcomes.

To sustain these benefits, innovation capability must be cultivated as a continuous, embedded process rather than as an ad hoc initiative. This requires committed leadership, strategic resource allocation, and a culture willing to embrace calculated risk. In this sense, innovation capability functions not only as a performance enhancer but also as a resilience mechanism that equips firms to adapt to uncertainty and maintain long-term competitiveness (Behl et al., 2023).

### 2.4. Mediating role of innovation capability

Innovation capability serves as a critical mediator between business intelligence capabilities and competitive performance. Rather than operating as separate constructs, business intelligence and competitiveness are interconnected through a firm being able to convert data into actionable, value-generating innovations. This mediating role emphasizes that simply possessing business intelligence capabilities does not ensure superior performance—what matters is their application in creative problem-solving and service innovation

Firms with strong innovation capabilities are better positioned to leverage business intelligence in adapting to market dynamics and evolving customer needs. By channeling business intelligence insights into the development of novel products, services, and processes, innovation enhances organizational responsiveness and differentiation. This is particularly vital in the hotel industry, where rapidly changing customer expectations make service differentiation essential for sustaining competitive performance. In hospitality, business intelligence delivers its greatest performance benefits when integrated with innovation-driven strategies. BI-enabled innovations, such as personalized guest experiences, process automation, and data-driven marketing, are linked to higher customer satisfaction, greater market share, and stronger competitive positioning. Similarly, advancements in booking platforms, revenue management, and guest services demonstrate how business intelligence insights, when transformed into innovative solutions, can differentiate hotels operating in highly competitive markets. Collectively, these findings suggest that without innovation capability, business intelligence investments are likely to produce only incremental operational improvements rather than strategic differentiation.

The mediating role of innovation capability also highlights the importance of an enabling organizational environment—marked by a supportive culture, committed leadership, and cross-functional collaboration. While business intelligence provides the analytical foundation, innovation capability activates the creative capacity of the organization, converting raw data into strategic outcomes. Cultivating innovation as a mediating mechanism enables hotels to bridge the gap between information and competitive value, ensuring business intelligence capabilities are fully leveraged to achieve sustainable competitive performance.

### 2.5. Hypothesis development

Based on the literature reviewed, the following hypotheses are proposed:

**H1:** Business intelligence capabilities (BIC) positively influence innovation capability (INC).
**H2:** Innovation capability (INC) positively influences competitive performance (COP).
**H3:** Business intelligence capabilities (BIC) positively influence competitive performance (COP).
**H4:** Innovation capability (INC) positively mediates the relationship between business intelligence capabilities (BIC) and competitive performance (COP).

However, based on the literature reviewed and the research hypotheses, the research conceptual framework can be illustrated as shown in Fig. 1.

## 3. Methodology

### 3.1. Research design

A stratified random sampling design was employed to ensure proportional representation of hotels across different star ratings and geographical locations. The sampling frame was obtained from the official registry provided by the Tourism Grading Council of Thailand, which categorizes hotels from one to five stars. Strata were defined by star rating (1–2 stars, 3 stars, 4 stars, and 5 stars), and proportional allocation was used to select respondents from each stratum. This approach minimized selection bias by including both upscale and non-upscale hotels, capturing a more diverse range of business intelligence and innovation practices. The study was conducted across the Bangkok Metropolitan Region and other major tourist destinations, including Chiang Mai, Phuket, and Pattaya, to reflect varying competitive and environmental contexts.

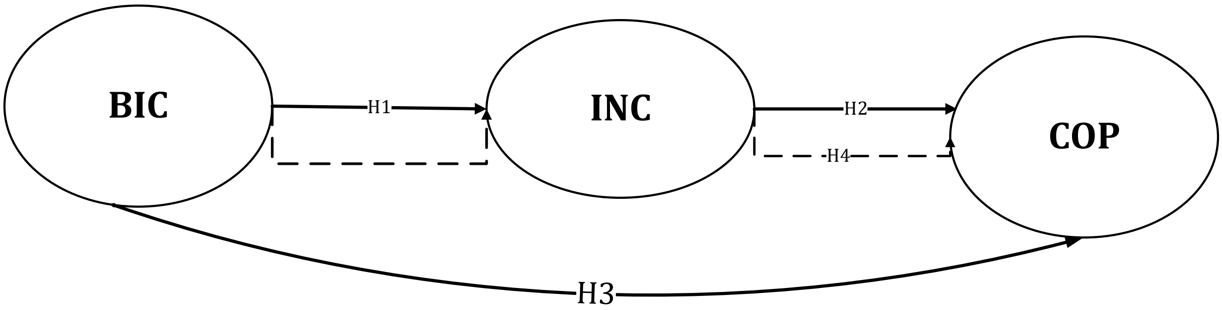


**Fig. 1:** Research model

### 3.2. Population and sample sizes

The target population consisted of top managers of accommodation establishments across Thailand, as recorded in the 2020 Accommodation Survey by the National Statistical Office, Ministry of Digital Economy and Society, which reported 6,054 registered hotel locations nationwide. The unit of analysis was the hotel manager, selected for their comprehensive strategic and operational knowledge.

In determining the sample size, the study followed Hair et al. (2017), who recommend that PLS-SEM studies consider the "10-times rule" (i.e., ten times the maximum number of structural paths directed at any construct in the model) and conduct a priori power analysis to ensure statistical adequacy. The sample size for this research, using the largest number of indicators of any latent variable in the model (BIC=18 items) and the maximum number of predictors for a single endogenous variable (COP has 2 predictors), was calculated as $n \geq 10 \times \max(18,2) = 180$. In addition, a power analysis was conducted using G*Power ($\alpha = .05$, power = .80, $f^2 = 0.15$, predictors = 2), which indicated that a minimum of approximately 70–85 samples would be required for adequate statistical power. Therefore, this study set the sample size above these thresholds and allowed for an additional 10–20% to account for potential missing data.

To ensure representativeness, a stratified random sampling approach was employed, proportionally selecting hotel managers from different star-rating categories (three-, four-, and five-star hotels) and from diverse geographical regions, thereby minimizing sampling bias and ensuring that the sample structure accurately reflected the composition of the Thai hotel industry. Of the 180 invitations distributed, all yielded valid responses, resulting in an effective response rate of 100.0%, which meets the minimum threshold required for PLS-SEM analysis.

### 3.3. Data collection and bias

The questionnaire comprised four main sections: (1) demographic information, (2) business intelligence capability, (3) innovation capability, and (4) competitive performance. A detailed list of questionnaire items is provided in the appendix.

Business intelligence capability (BIC) was measured across three dimensions—BI_technology, BI_structure, and BI_culture—using 18 items adapted from Ramakrishnan et al. (2016). Innovation capability (INC) was assessed through three sub-dimensions—Tech_inno, Proc_inno, and Mar_inno—measured using 11 items adapted from Zhou et al. (2019). Competitive performance (COP) was evaluated through three constructs—Lg_pref, St_pref, and Cd_pref—using 10 items adapted from Tajeddini et al. (2020) and Tajeddini and Trueman (2014).

All measurement items were rated on a five-point Likert scale, ranging from 1 ("strongly disagree") to 5 ("strongly agree"). To minimize potential bias, established and validated measurement scales were adopted from the prior literature, and the questionnaire was pre-tested with hotel managers to ensure clarity and contextual relevance.

### 3.4. Reliability and validity

Content validity was established through expert review to ensure that the questionnaire items adequately represented the intended constructs. The panel of experts—comprising three academics specializing in hospitality management and two senior hotel executives—assessed each item for relevance, clarity, and representativeness. Based on their feedback, minor modifications were made to improve wording and contextual appropriateness.

A pilot test was then conducted with 30 hotel professionals to further refine the instrument. Feedback from the pilot participants was used to revise ambiguous items and confirm the suitability of the questionnaire for the target respondents.

Reliability was assessed using Cronbach's alpha and composite reliability (CR). Cronbach's alpha coefficients for all constructs exceeded the minimum threshold of 0.70, indicating acceptable internal consistency reliability. Composite reliability values were also above the recommended cut-off of 0.70, confirming that the items within each construct consistently measured the same underlying concept.

Convergent validity was evaluated by examining the average variance extracted (AVE) for each construct, with all AVE values exceeding 0.50, thereby demonstrating that the constructs captured more than half of the variance of their indicators (Fornell and Larcker, 1981). Discriminant validity was confirmed using the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT), ensuring that each construct was empirically distinct from the others. These procedures collectively confirmed that the measurement instrument possessed both strong reliability and validity, supporting its suitability for subsequent data analysis.

### 3.5. Analysis method

This study utilized Partial Least Squares Structural Equation Modeling (PLS-SEM) as the primary analytical technique due to its distinct advantages. PLS-SEM is particularly well-suited for research with relatively small sample sizes and does not impose strict assumptions regarding measurement scales or data normality. Moreover, it is appropriate for analyzing complex models and is widely recommended in social science research for its robust procedures in assessing both reliability and validity (Henseler et al., 2012; Hair et al., 2019).

In this research, PLS-SEM was applied to examine two primary components: The measurement model and the structural model. The measurement model was evaluated to confirm construct validity and indicator reliability through the assessment of convergent and discriminant validity. The structural model was subsequently tested to evaluate the hypothesized relationships among constructs (Hair et al., 2017).

All statistical analyses were conducted using SmartPLS 4.0 (Hair et al., 2017), which provides comprehensive tools for implementing PLS-SEM analysis effectively.

## 4. Results and discussions

### 4.1. Measurement model assessment

In general, the measurement model to be evaluated requires conducting a validity test of the indicators to ensure their ability to measure the respective constructs. Hair et al. (2017) suggested the process of testing these indicators can be performed through reliability, which is calculated by a common approach called AVE, Composite Reliability (CR), and Cronbach's Alpha (α) in this analysis (Afthanorhan et al., 2020). The reliability of the variable is a critical aspect of the measurement model analysis. Thus, this study utilizes SmartPLS for checking the reliability and validity of the measurement model, and the results are presented in Table 1.

The findings indicate that the α coefficient test results range from 0.933 to 0.946, demonstrating that all variables possess good conceptual reliability (Henson, 2001). The values of CR and AVE exceed the specified thresholds, acceptable ranges of >0.50 and > 0.70, respectively, of convergent validity (Fornell and Larcker, 1981). Moreover, to check for multicollinearity, the variance inflation factor (VIF) of each variable was assessed. Statistics for all variables were lower than 10, indicating the absence of multicollinearity. Finally, the results of the measurement model confirmed the reliability and validity of the variable.

**Table 1:** Descriptive statistics, validity, and reliability

| Construct | Items | Mean | S.D. | Factor loading | Alpha (α) | C.R. (rho_a) | C.R. (rho_c) | AVE |
|---|---|---|---|---|---|---|---|---|
| Business intelligence capability (BIC) | BI_tech | 4.489 | .567 | .952 | .932 | .934 | .956 | .880 |
| | BI_struct | 4.341 | .668 | .935 | | | | |
| | BI_culture | 4.378 | .630 | .926 | | | | |
| Innovation capability (INC) | Tech_inno | 4.208 | .731 | .937 | .932 | .935 | .957 | .881 |
| | Proc_inno | 4.344 | .657 | .958 | | | | |
| | Mar_inno | 4.346 | .683 | .920 | | | | |
| Competitive performance (COP) | Lg_Pref | 4.189 | .750 | .957 | .952 | .956 | .969 | .912 |
| | St_Pref | 4.237 | .760 | .965 | | | | |
| | Cd_Pref | 4.324 | .690 | .944 | | | | |

This study examined an issue related to validity using another type of validity called discriminant validity, which is generally used to evaluate how the research constructs are correlated or represent unique concepts. Henseler et al. (2012) stated that this validity procedure is performed to check the validity through a cross-loading approach. The study also conducted criterion analysis, namely Fornell-Larcker and the Heterotrait-Monotrait ratio (HTMT), which are important as they indicate the construct correlations. The findings given in Table 2 were calculated by taking the square root of the AVE; these are shown in boldface in a left-to-right descending diagonal slope and are higher than correlations with other constructs (Fornell and Larcker, 1981).

Further, the study utilized HTMT as another analytical approach to assess the discriminant validity. The findings given in Table 3 show that the HTMT achieved a good threshold of (≤0.90).

Therefore, this meets the requirements for the correct analysis of the discriminant validity by HTMT. The results indicate that the square root of the AVE values (diagonal values) is greater than the correlation values between that construct and other constructs. Therefore, the discriminant validity among the variables is consistent with the research requirements.

### 4.2. Structural model assessment

To further validate the hypotheses, this study employed PLS-SEM for further analysis and measurement. The results of the path analysis are illustrated in Fig. 2.

#### 4.2.1. Hypothesis testing

This study depends on the main common findings conducted in this analysis, like path estimates, t-values, and p-values, to review the research hypotheses in terms of accepting or rejecting them. The analysis used a bootstrapping test to examine the significance of the model, and the hypothesis testing results for H1, H2, H3, and H4 are presented in Tables 4-6.

**Table 2:** Comparison of square root AVE with correlation between constructs (Fornell-Larcker Criterion)

| Variables | BIC | INC | COP |
|---|---|---|---|
| Business Intelligence capability (BIC) | .938 | | |
| Innovation capability (INC) | .859 | .938 | |
| Competitive performance (COP) | .555 | .642 | .955 |

**Table 3:** The discriminant validity of the HTMT ratio

| Variables | BIC | INC | COP |
|---|---|---|---|
| Business Intelligence capability (BIC) | | .899 | .587 |
| Innovation capability (INC) | | | .676 |
| Competitive performance (COP) | | | |

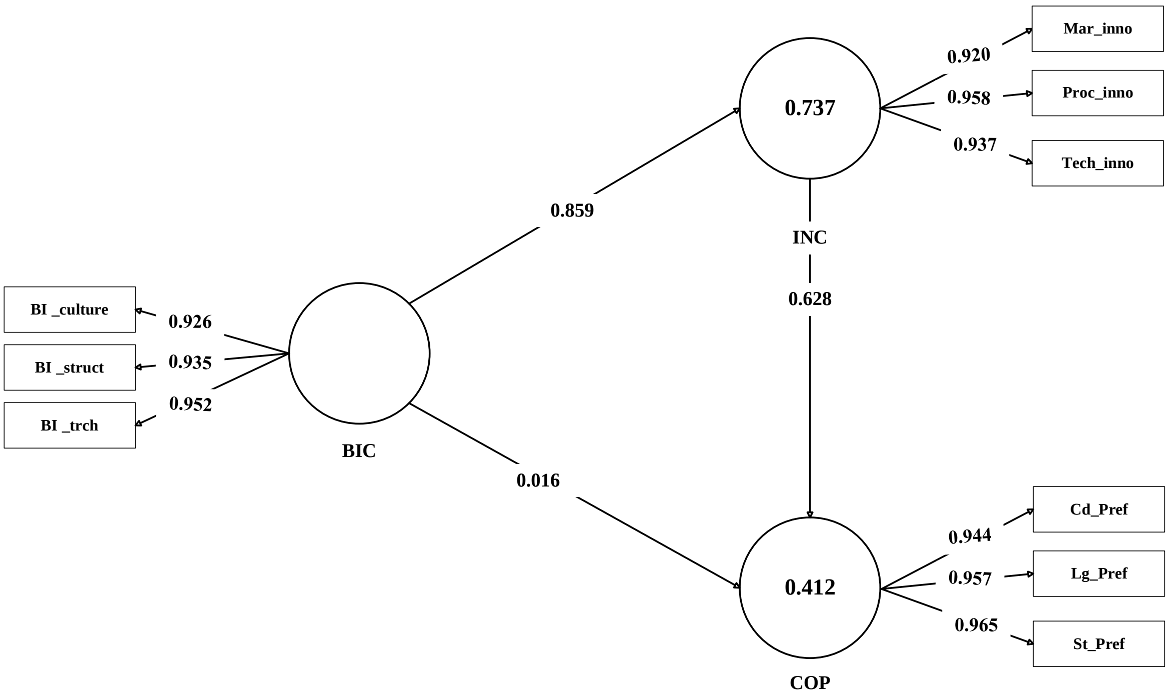


**Fig. 2:** Path analysis results

**Table 4:** Results of the hypothesis testing

| Hypothesis | Full sample | Bootstrap mean | t-values | Boot 95% CI (lower) | Boot 95% CI (upper) | Result |
|---|---|---|---|---|---|---|
| H1: BIC → INC | .859 | .859 | 42.903*** | .816 | .894 | Supported |
| H2: INC → COP | .628 | .628 | 5.778*** | .415 | .844 | Supported |
| H3: BIC → COP (direct) | .016 | .015 | .152 | -.205 | .221 | Not supported |
| $R^2$ of INC | | | .737 | | | |
| $R^2$ of COP | | | .412 | | | |

***: Significant level at 0.001

**Table 5:** Results of model quality

| Endogenous | Predictor | $R^2$ included | $R^2$ excluded | $f^2$ | VIF |
|---|---|---|---|---|---|
| INC | BIC | .737 | 0 | 2.805 | 1 |
| COP | BIC | .412 | .412 | 0 | 3.758 |
| COP | INC | .412 | .355 | .176 | 3.758 |
| COP | — (Model $R^2$) | .412 | | | |

To evaluate the proposed hypotheses (H1–H3), the structural model was assessed using PLS-SEM with 5,000 bootstrap samples. Table 4 presents the path coefficients (β), t-values, p-values, and 95% bias-corrected and accelerated (BCa) confidence intervals for each hypothesized relationship, alongside model quality indicators ($R^2$, $f^2$, and VIF).

H1 hypothesized that BIC positively influences INC. The results supported this hypothesis (β=0.859, t = 42.903, p < .001, 95% CI [0.816, 0.894]), indicating a very strong and statistically significant effect. H2 proposed that INC positively influences COP. The results confirmed this relationship (β=0. 628, t = 5.778, p < .001, 95% CI [0.415, 0.844]), suggesting that firms with higher INC achieve better COP. H3 posited that BIC has a direct positive effect on COP. The direct path coefficient was small and statistically non-significant (β = 0.016, t = 0.152, p = .910, 95% CI [−0.205, 0.221]). This indicates that the influence of BIC on COP may operate primarily through innovation capability rather than directly, which is further corroborated by the mediation analysis results. Regarding model quality in Table 5, the $R^2$ value for INC was 0.737, indicating that BIC explains 73.7% of its variance. The $R^2$ for COP was 0.412, meaning that the combination of BIC and INC explains 41.2% of its variance. Effect sizes ($f^2$) indicated a large effect of BIC on INC ($f^2$ = 2.805) and a small-to-medium effect of INC on COP ($f^2$ = 0.176), while the effect of BIC on COP was negligible ($f^2$=0.000). All variance inflation factor (VIF) values were below the threshold of 5, indicating no multicollinearity concerns.

In summary, Fig. 2 provides details about the parameter estimates for the model, and Table 4 reports the results of the hypothesis tests, which are as follows: H1 and H2 were supported, whereas H3 was not supported. This conclusion indicates that business intelligence capability (BIC) and innovation capability (INC) are antecedent variables that influence competitive performance (COP). However, business intelligence capability (BIC) does not have a direct effect on competitive performance but may have an indirect effect through innovation capability (INC).

### 4.2.2. Robustness check (bootstrap resampling)

To examine the stability of the structural results, we performed a bootstrap resampling robustness check with 5,000 resamples. For each resample, the model was re-estimated, and the distributions of path coefficients and $R^2$ statistics were obtained. Table 4 summarizes the robustness outcomes with bootstrapping with an increased resample approach. The results showed that the significance levels (p-values) of all hypothesized paths remained consistent with the original analysis, confirming the stability of the findings.

However, the bootstrap robustness tests collectively indicate that the estimated path relationships are stable and not driven by sample peculiarities. Increasing the bootstrap samples did not materially change coefficient magnitudes or significance. These results enhance the credibility of the model findings despite the relatively small sample size.

### 4.3. Mediating analysis

Our model hypothesizes that innovation capability (INC) mediates the relationship between business intelligence capability (BIC) and competitive performance (COP). To evaluate mediation, we followed the procedure recommended by Hair et al. (2017) for PLS-SEM, which involves the following steps.

- Assessment of the indirect effect: The significance of the indirect path BIC → INC → COP was tested using a bias-corrected bootstrapping procedure with 5,000 resamples. Mediation is considered present when the indirect effect is statistically significant, and the 95% bias-corrected confidence interval does not include zero.
- Assessment of the direct effect: We examined the significance of the direct path BIC → COP after including the mediator in the model.
- Determination of mediation type: According to Hair et al. (2017), if both the direct and indirect effects are significant, partial mediation is indicated; if the indirect effect is significant but the direct effect is not, full mediation is indicated.

**Table 6:** Mediating bootstrapping test: Significance analysis of the direct and indirect effects

| Hypothesis | Relationship | Coefficient/effect | t-values (indirect) | Boot 95% CI (lower) | Boot 95% CI (upper) | Result |
|---|---|---|---|---|---|---|
| H4 | BIC → INC | .859 | | .816 | .894 | Supported |
| | INC → COP | .628 | | .415 | .844 | |
| | BIC → COP (direct, c') | .016 | .152 | -.205 | .221 | |
| | BIC → COP (total, c) | .555 | 9.441*** | .430 | .662 | |
| | BIC -> INC -> COP | .539 | 5.441*** | .350 | .738 | |

***: Significant level at 0.001

The results of testing the proposed hypothesis (H4) are presented in Table 6. The indirect effect of BIC on COP via INC was positive and statistically significant (β = 0.539, t = 5.441, 95% CI [0.350, 0.738], p < 0.001). The total effect of BIC on COP was also significant (β = 0.555, t = 9.441, 95% CI [0.430, 0.662], p < 0.001). However, the direct effect of BIC on COP, when controlling for INC, was small and non-significant (β = 0.016, t = 0.152, 95% CI [−0.205, 0.221], p = 0.880). The variance accounted for (VAF) value was 93.4%, exceeding the 80% threshold suggested by Hair et al. (2017) for full mediation. Therefore, these findings indicate that INC fully mediates the relationship between BIC and COP, suggesting that the influence of BIC on COP operates entirely through INC.

Therefore, it is confirmed that innovation capability (INC) plays a role as a mediating variable in the relationship between business intelligence capabilities (BIC) and competitive performance (COP). These results emphasize the pivotal role of innovation capability as a conduit through which business intelligence capability translates into competitive performance, reinforcing the theoretical stance that capabilities are most valuable when they enable and enhance innovation.

## 5. Conclusion

The primary objective of this study was to examine the effects of business intelligence capabilities (BIC), innovation capability (INC), and competitive performance (COP), with a particular focus on the mediating role of innovation capability in the relationship between BIC and COP. The findings indicate a strong and statistically significant positive relationship between BIC and INC, suggesting that higher levels of BIC substantially enhance innovation capability. Moreover, the results reveal that innovation capability has a significant positive effect on COP, highlighting its critical role in driving competitive outcomes.

The mediation analysis further confirms that innovation capability fully mediates the relationship between BIC and COP, as the direct effect of BIC on COP was not significant, while the indirect effect through INC was positive and significant. These findings are consistent with prior research, which emphasizes that innovativeness serves as a key mechanism for transforming organizational capabilities into competitive performance. The results underscore the importance of fostering innovation capability to effectively leverage business intelligence investments and achieve sustainable competitive advantage.

### 5.1. Theoretical implications

This study advances the understanding of competitive performance and organizational learning in the hospitality sector by integrating the Resource-Based View (RBV) and Dynamic Capabilities Theory. The contributions emerge from two key perspectives.

First, the findings confirm that business intelligence capabilities (BIC) serve as a strong predictor of innovation capability (INC). The results demonstrate a robust and statistically significant positive correlation between BIC and INC, indicating that greater adoption and effective utilization of BI systems substantially enhance classifications published by organizational capacity for innovation. This aligns with prior empirical evidence, which reported that higher levels of BI adoption were associated with superior innovation performance (Wang et al., 2022).

Second, the results establish that innovation capability plays a full mediating role in the relationship between BIC and competitive performance (COP), acting as the causal mechanism through which BI insights are transformed into competitive advantage. This is consistent with earlier research emphasizing the pivotal role of innovation in driving firm performance and sustaining long-term competitiveness (Calantone et al., 2002; Gunday et al., 2011). By enabling the creation of new products, services, and processes, innovation capability allows firms to adapt to dynamic market environments, differentiate themselves, and outperform competitors. Consequently, the findings reinforce the theoretical proposition that innovation capability is a primary enabler linking strategic resources, such as BI, to superior competitive performance outcomes.

### 5.2. Managerial implications

The results of this study provide several actionable insights for hotel managers and decision-makers in the hospitality industry.

First, the findings emphasize the necessity of developing strong Business Intelligence Capabilities (BIC). Hotel managers should invest in advanced BI systems and cultivate a data-driven culture throughout the organization. Such capabilities enable timely access to accurate, relevant information, which supports evidence-based strategic decision-making and improves operational efficiency.

Second, the study highlights innovation capability (INC) as a critical driver of competitive performance. Managers should actively foster a culture of innovation by encouraging experimentation, investing in employee training, and facilitating the adoption of relevant technologies. Hotels with stronger innovation capabilities are better equipped to meet evolving customer needs, design distinctive service offerings, and adapt swiftly to market changes—factors essential for maintaining long-term competitive advantage.

Third, given that the study found that innovation capability fully mediates the relationship between BIC and competitive performance, managers should recognize that possessing BI systems alone is insufficient to drive superior performance. Instead, BI insights must be strategically applied to inspire and guide innovation initiatives. For example, customer analytics can be used to identify unmet needs, service gaps, or emerging market trends, which can then inform the development of new, value-added services that differentiate the hotel from its competitors.

Finally, in an era of heightened environmental and competitive pressures, the strategic integration of BIC and INC should be viewed as a cornerstone for sustainable growth. Hotel executives are advised to align technology investments with long-term innovation strategies, thereby building dynamic capabilities that not only enhance current operations but also ensure adaptability, resilience, and sustained success in the future.

### 5.3. Limitations

Despite its contributions, this study has several limitations that should be acknowledged. First, the data were collected from a single industry (hospitality) within one national context (Thailand), which may limit the generalizability of the findings to other sectors or geographic regions. Cross-industry comparisons could provide a more nuanced understanding of how business intelligence capabilities and innovation capabilities interact under different environmental conditions.

Second, the use of self-reported survey data may introduce common method bias, even though validated measurement scales and pre-testing were employed to mitigate this risk. Incorporating objective performance indicators, such as financial records or customer satisfaction scores, could improve measurement accuracy.

Third, the study employed a cross-sectional design, which limits the ability to establish causal relationships. While the structural model provides theoretical justification for the proposed causal pathways, longitudinal studies would allow researchers to capture the dynamic evolution of business intelligence capabilities, innovation capability, and competitive performance over time.

### 5.4. Future research directions

To address these limitations and advance the literature, several avenues for future research are proposed.

- Cross-Industry and cross-country studies: Expanding the research to include different service sectors (e.g., airlines, retail, healthcare) and diverse geographic contexts would allow for greater external validity and insights into cultural or market-specific variations.
- Integration of moderating variables: Future models could incorporate moderators such as environmental turbulence, firm size, or strategic orientation to explore whether the BIC–INC–COP relationship is contingent on external or internal conditions.
- Longitudinal and mixed-methods approaches: Combining longitudinal data with qualitative case studies could reveal how business intelligence enabled innovation processes unfold over time and how managerial practices influence these dynamics.
- Deeper investigation into innovation types: Differentiating between product, process, and marketing innovation could clarify which forms of innovation most effectively translate business intelligence insights into competitive gains.
- Linking business intelligence and customer-centric outcomes: Exploring how business intelligence-driven innovation impacts customer satisfaction, loyalty, and brand perception could provide more actionable insights for practitioners.

In conclusion, this study underscores that business intelligence capabilities are a necessary but insufficient condition for competitive performance. It is the effective transformation of business intelligence insights into innovative actions—supported by a conducive organizational culture and dynamic capabilities—that ultimately drives sustained competitive advantage in the hospitality industry.

## List of abbreviations

| | |
|---|---|
| AVE | Average variance extracted |
| BCa | Bias-corrected and accelerated confidence interval |
| BI | Business intelligence |
| BI_culture | Business intelligence culture dimension |
| BI_struct | Business intelligence structure dimension |
| BI_tech | Business intelligence technology dimension |
| BIC | Business intelligence capabilities |
| CB-SEM | Covariance-based structural equation modeling |
| CI | Confidence interval |
| COP | Competitive performance |
| CR | Composite reliability |
| $f^2$ | Effect size |
| HTMT | Heterotrait–Monotrait ratio |
| INC | Innovation capability |
| Lg_pref | Long-term preference |
| Mar_inno | Marketing innovation |
| PLS-SEM | Partial Least Squares Structural Equation Modeling |
| Proc_inno | Process innovation |
| RBV | Resource-Based View |
| S.D. | Standard deviation |
| SEM | Structural equation modeling |
| St_pref | Strategic preference |
| Tech_inno | Technological innovation |
| VIF | Variance inflation factor |

## Compliance with ethical standards

## Ethical considerations

The Ethical Committee of the Institutional Review Board, Association of Legal and Political Studies, Thailand, has granted approval for this study (Ref. No. Exp 37/67).

## Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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