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Data-Driven Decision Systems and Organizational Ambidexterity: The Moderating Role of Strategic Vigilance

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Abstract: In technology-intensive and dynamic environments, organizations must simultaneously achieve efficiency and innovation, a duality captured by organizational ambidexterity. Despite widespread adoption of business intelligence (BI), its association with combined organizational ambidexterity remains underexplored, particularly under varying contextual conditions. This study examines the association between BI capability and combined organizational ambidexterity and assesses whether strategic vigilance moderates this association within the telecommunications sector. Using a quantitative, cross-sectional design, data were collected from 200 senior and middle-level managers in a single major telecommunications firm in Jordan. BI capability was operationalized through data collection, data reliability, and data analysis, and tested using hierarchical multiple regression after controlling for six respondent characteristics. BI capability was positively associated with combined organizational ambidexterity and explained an additional 54.2% of the variance in it beyond the control variables. Strategic vigilance was also positively associated with ambidexterity, and the BI × strategic vigilance interaction was statistically significant ($B = 0.42$, $p < 0.001$), explaining an additional 2.5% of variance beyond the main-effects model. While data collection exhibited the highest reported mean, data analysis had the lowest, indicating comparatively weaker perceived analytical capability. The findings distinguish BI, as a technical information-processing capability, from strategic vigilance, as a managerial interpretive capability, and highlight the importance of connecting BI outputs to strategic decision processes. The results reflect cross-sectional managerial perceptions within one organization and do not establish causality or sector-wide generalizability.

Keywords: Business intelligence capability; organizational ambidexterity; strategic vigilance; dynamic capabilities; data analytics; environmental scanning; telecommunications sector; emerging markets.

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1. Introduction

In today's highly competitive and rapidly changing marketplaces, fueled by increasing amounts of technology, companies have a growing need to both increase their overall operational performance and to create an environment that supports continuous innovation. This dual objective can be especially true for industries with high rates of technological advancement and strong levels of competition (e.g., telecommunications). For this type of industry, it is essential that firms continually optimize their operations and capitalize on new opportunities as they arise; therefore, developing organizational ambidexterity, defined as the simultaneous pursuit of exploitation and exploration, is critical (O'Reilly and Tushman, 2013). An organization's ability to exhibit both adaptability and innovation stems from its engineering and operational management systems. Organizational ambidexterity is not just a strategic goal; rather, it reflects how the organization operates through its data infrastructure, information systems, and decision-making routines. Business intelligence (BI), informed by extensive empirical studies, has emerged as one of the most essential tools for conducting data-driven decision-making. Businesses can currently analyze massive volumes of structured and unstructured data, derive insights from them, and leverage these insights to optimize operations and gain foresight (Alzghoul et al., 2024). Studies have recently shown that the use of artificial intelligence and business analytics in telecommunication companies has contributed immensely to their digital transformations (Hanandeh and Hajij, 2022; Rana et al., 2022). In the current research, "data-driven decision systems" refers to the BI capability, as reflected in data collection, data reliability, and data analysis for organizational decision-making.

However, despite the emergence of BI as a strategic resource, its association with organizational ambidexterity remains insufficiently theorized and empirically examined, particularly in emerging economies and infrastructure-intensive industries. Although previous studies have addressed the relationships between BI and organizational performance, innovation, agility, and digital transformation (Yan et al., 2023; Wamba et al., 2024), comparatively little attention has been paid to whether BI capability is associated with the simultaneous presence of exploration and exploitation.

Strategic Vigilance is defined as an organization's ability to maintain awareness of environmental changes by continuously monitoring developments that could affect the company's future. It is viewed as an active sensory mechanism for organizations, providing early warning systems for detecting potential opportunities or threats and enabling them to respond to changing conditions (Wamba et al. 2024; Khan et al. 2024). While BI and strategic vigilance both relate to the use of information within an organization, they are two different concepts. BI focuses on how an organization collects, verifies, organizes, analyzes, and manages data from internal and external sources. Strategic vigilance, on the other hand, refers to managerial attentiveness to and interpretation of signals, anticipation of changes and preparedness to link information to strategic decision-making and resource allocation. Although strategic vigilance is theoretically relevant to understanding the relationship between BI capability and organizational ambidexterity, prior research has examined it only as a moderator of this relationship. Much of the prior research has focused on intelligence, environmental scanning, or the rate of environmental change as direct predictors of organizational performance rather than examining whether these constructs moderate the association between data-processing capability and organizational ambidexterity. This gap is particularly important in industries characterized by rapid technological change. Thus, this research contributes to the literature by integrating BI, vigilance strategy and ambidexterity at the organizational level, specifically in telecommunications. Ambidexterity is operationalized as combined ambidexterity, meaning simultaneously engaging in exploration and exploitation. It is not operationalized as a difference, balance or multiplication interaction between those dimensions. BI capability is calculated as a composite of data collection, data reliability, and data analysis, while strategic vigilance is examined as a moderator of the BI–ambidexterity association. The present study focuses on Orange Jordan, a major telecommunications operator. The evidence is based on responses from 200 senior- and middle-level managers employed within this single organization. The observations, therefore, represent individual managerial perceptions within one shared organizational context rather than data from 200 independent firms. Accordingly, the findings cannot be generalized to the Jordanian telecommunications sector as a whole.

The conceptual relationships are presented in Fig. 1. data collection, reliability, and analysis constitute the dimensions of composite BI capability. BI capability is positively associated with combined organizational ambidexterity, while strategic vigilance moderates this association. The model contains a one-directional BI–ambidexterity path, and the moderation path is directed toward that relationship rather than toward development independently. The six respondent-level control variables are gender, age, educational qualification, managerial level, years of experience, and organizational tenure.

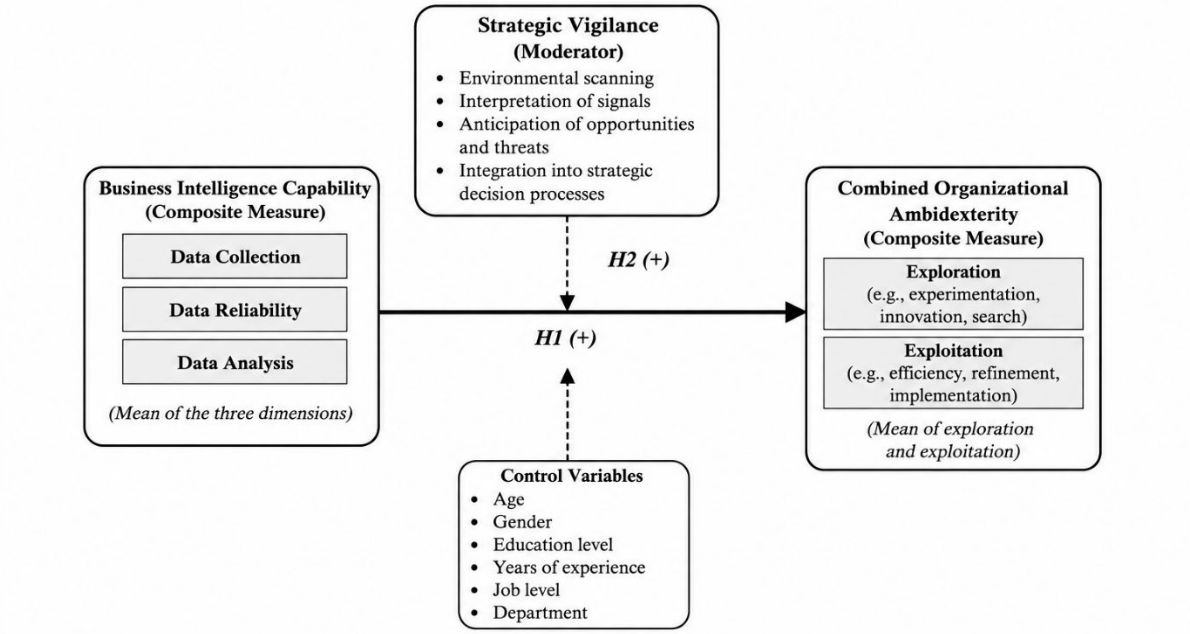

Fig. 1. Conceptual model of BI capability, strategic vigilance, and combined organizational ambidexterity
Note: The solid arrow indicates the direct effect in H1.The dashed arrow from strategic vigilance to the relationship indicates the moderating effect in H2. The dashed arrow coming from the control variables to the dependent variable indicates that the control variables were included in the regression models.

Thus, the current study will explore the relationship between BI capabilities and organizational ambidexterity in a volatile telecommunications industry, and whether this association is conditional on strategic vigilance. This research will be aimed at the following questions:

RQ1. To what extent is BI capability associated with combined organizational ambidexterity?

RQ2. To what extent does strategic vigilance moderate the association between BI capability and combined organizational ambidexterity?

2. Literature Review

2.1. BI as a Data-Driven Capability

The concept of BI in contemporary literature is increasingly seen as an organization's capability to leverage data rather than as a technology-driven phenomenon. For instance, recent studies suggest that BI helps organizations translate data into knowledge that improves decision-making, responsiveness, and performance (Alzghoul et al., 2024). More empirical studies suggest that BI capability enables rapid and holistic decision-making, which is necessary for effective performance in rapidly changing business environments, such as the telecommunications sector (Alzghoul et al., 2024). Drawing on the principles of dynamic capabilities theory, BI may be viewed as an information-processing capability that helps organizations identify changes in their environment (Teece, 2007). Recent empirical literature further develops this concept, suggesting that BI and analytics capabilities contribute to organizational agility and competitiveness by facilitating innovation and knowledge sharing (Wamba et al., 2024; Yan et al., 2023). Similarly, the study by Khan et al. (2024) concludes that business analytics capabilities facilitate organizational agility and performance. Additionally, it is important to highlight that, according to research, BI capability works in tandem with complementary organizational capabilities, such as absorptive capacity and knowledge management, to affect performance (Wamba et al., 2024; Garmaki et al., 2023). The results suggest that BI should be considered not only a tool but also part of a broader capability ecosystem. This paper views BI as an operational information-processing capability that, in combination with interpretative managerial practices, may contribute to organizational adaptation. BI is not treated as a complete dynamic capability because the routines through which information is converted into strategic action were not directly measured.

2.2. Organizational Ambidexterity in Dynamic Environments

Ambidexterity continues to be one of the key concepts in organizational strategy formulation. According to March (1991) and O'Reilly and Tushman (2013), ambidexterity entails the capability of organizations to concurrently undertake exploration and exploitation. Ambidexterity can be seen as a composite ability, that is, engaging in both activities at once, rather than achieving a balance between the two. Ambidexterity, in this case, is viewed as an aggregation of the abilities to explore and exploit. More specifically, the present study adopts a combined organizational ambidexterity approach, representing the simultaneous presence of exploration and exploitation. It is not measured as the difference, balance, or multiplicative interaction between the two dimensions. In recent years, ambidexterity has gained greater recognition for its association with organizational agility and innovation performance through digitalization. It is evident from various studies that there is a strong relationship between ambidexterity and firms' performance in terms of adaptability and responsiveness, especially through the use of digital technology (Hwang et al., 2023; Raisch and Birkinshaw, 2008). Further, according to Tongtong and Xinhang (2024), data analytics facilitates ambidextrous innovation performance through organizational agility. Organizational ambidexterity is another recent development used in studies to demonstrate the connection between big data analytics and supply chain resilience (Kong and Feng, 2025; Shi and Feng, 2024), alongside paradoxical cognition and ambidexterity (Gao et al., 2026). According to dynamic capabilities theory, ambidexterity can be viewed as a means through which organizations can adapt their resources to address conflicting issues under conditions of uncertainty (O'Reilly and Tushman, 2008; Teece, 2007). Current studies have confirmed this perception, illustrating that ambidexterity serves as an intermediary linking data-based capabilities to organizational performance (Raisch and Birkinshaw, 2008). The integration of BI with strategic vigilance represents a capability configuration that may be associated with organizational adaptation; however, the underlying reconfiguration processes were not directly measured in this study.

2.3. BI and Organizational Ambidexterity

The link between BI and ambidexterity has increasingly become popular among academics. BI may support ambidexterity by equipping organizations with the information base needed to simultaneously pursue exploration and exploitation. Research findings indicate that BI capability is associated with organizational agility and innovation, two important aspects of ambidexterity (Al-Maaitah et al., 2026; Mbima and Tetteh, 2023). More importantly, BI assists organizations in identifying opportunities through data analysis while streamlining operations. Moreover, current research indicates that BI may support ambidexterity through knowledge integration and learning processes, enabling firms to effectively integrate knowledge from both internal and external sources (Wamba et al., 2024; Garmaki et al., 2023). According to the knowledge-based approach, BI is a vital factor in helping organizations adapt to using information and knowledge management. Besides, Medeiros and Maçada (2022) note that the ability to conduct data analytics can be a significant source of competitive advantage through enhanced agility, thereby confirming that BI is a vital element of ambidexterity. There are many ways in which different aspects of BI can be related to exploration or exploitation, but these have been poorly defined. It is suggested, based upon the knowledge-based view of organizations, that data collection and reliability provide a foundation for exploitation by providing a basis for process improvement and operational standardization, while data analysis may support exploration since this enables the discovery of patterns, forecasts, and the testing of hypotheses (Tongtong and Xinhang, 2024). All three, however, should enhance ambidexterity. These differentiated relationships are theoretically plausible but are not tested separately in the present study. Data collection, data reliability, and data analysis are instead treated as dimensions contributing to the composite BI capability measure. The preceding discussion suggests that BI capability is positively related to combined organizational ambidexterity by improving data-driven decision-making, organizational learning, and adaptive responsiveness. Accordingly, the following hypothesis is proposed:

H1. BI capability is positively associated with combined organizational ambidexterity.

The principal hypothesis concerns composite BI capability; therefore, separate hypotheses for data collection, data reliability, and data analysis are not proposed.

2.4. Strategic Vigilance as a Moderating Capability

Strategic vigilance is another important capability associated with organizational adaptation, as it allows the organization to decipher environmental signals and assess their strategic relevance. While BI enables the organization to analyze data effectively, strategic vigilance concerns managerial interpretation of information and readiness to connect it with appropriate decisions. While BI data collection primarily focuses on the technological collection and storage of both internal and external data, strategic vigilance includes managerial interpretation of opportunities and threats, anticipation of potential developments, and preparedness to reallocate resources (Khan et al., 2024). The raw information infrastructure is provided by BI, while the interpretive and attentional mechanisms for assessing the strategic significance of information are supplied through strategic vigilance. Accordingly, strategic vigilance is treated as a distinct complementary capability rather than as an additional dimension of BI.

Recent research on environmental scanning and competitive intelligence indicates that more vigilant organizations can use information technology effectively to make strategic decisions, especially in times of uncertainty and change (Khan et al., 2024; Wamba et al., 2024). Strategic vigilance may strengthen the organizational value of BI by enabling managers to interpret their environment and prioritize relevant information. Using a dynamic capabilities framework, strategic vigilance may support sensing and seizing activities that are important for organizational adaptation (Teece 2007). Consequently, organizations are better placed to detect opportunities early, respond to threats and match their capabilities to the demands of the environment. Worth pointing out that current literature also highlights moderating effects of environmental and contextual factors on linkages between capabilities and performance (Hossain et al. 2022). Therefore, it would be reasonable to argue that the association between BI capability and ambidexterity is moderated by organizations' ability to understand environmental signals, which is the very essence of strategic vigilance. This complementarity may operate through cross-functional intelligence reviews, signal-escalation procedures, scenario assessments, decision rights, and routines that link interpreted information to resource-allocation decisions. However, these mechanisms were not directly measured. The study, therefore, tests a conditional statistical association rather than demonstrating the organizational processes through which BI outputs are converted into action**.** Strategic vigilance is thus likely to positively moderate the association between BI capability and combined organizational ambidexterity, especially in uncertain environments and amid technological change. Accordingly, the following hypothesis is proposed:

H2. Strategic vigilance positively moderates the association between BI capability and combined organizational ambidexterity, such that the positive association is stronger at higher levels of strategic vigilance.

3. Methodology

3.1. Research Design and Justification

The research design chosen for this study is quantitative, cross-sectional, and associative. Quantitative methods of analysis make it possible to analyze hypotheses using statistics. The cross-sectional design is adequate for researching managers' perceptions at a particular point in time (Creswell, 2014; Saunders et al., 2019). Hierarchical multiple regression analysis and mean centering were used to examine the association between BI capability and combined organizational ambidexterity and to test the moderating role of strategic vigilance following the methodology used to explore interaction effects (Aiken and West, 1991; Hayes, 2018). As the analysis is based on cross-sectional data, causal inferences are precluded; the reported associations are correlational. Accordingly, the regression coefficients are interpreted as statistical associations rather than causal effects.

3.2. Population and Sampling

The target population comprised senior- and middle-level managers employed by Orange Jordan, totaling 286 individuals. The rationale for choosing these respondents was their role in organizational decision-making, BI, operational planning, and strategy. For sampling purposes, simple random sampling was used. In total, 240 questionnaires were sent to respondents, and 204 were returned. After applying data-screening techniques, including checking for missing values and response inconsistencies, only 200 questionnaires were available, resulting in a response rate of 83.3%, which is acceptable for organizational research according to Hair et al. (2019). An a priori power analysis was conducted to assess the incremental contribution of a single predictor in a final regression model containing nine predictors. With a medium anticipated effect size of $f^2 = 0.15$, statistical power of 0.80, and α=0.05, the minimum required sample was 55 respondents (Faul et al., 2009). The final sample of 200, therefore, exceeded the minimum requirement. Nevertheless, the results obtained are relevant only to the investigated organization and should not be generalized to other organizational environments. Potential non-response bias was assessed by comparing 150 early respondents with 50 late respondents using independent-samples t-tests. No statistically significant differences were identified in BI capability, strategic vigilance, exploration, exploitation, or combined organizational ambidexterity, with p-values ranging from 0.599 to 0.641. The complete results are reported in Supplementary Table S3. This diagnostic does not completely eliminate the possibility of non-response bias. Six respondent-level variables were included as statistical controls: gender, age, educational qualification, managerial level, years of experience, and organizational tenure. Gender was coded as 0 for female and 1 for male, and managerial level as 0 for middle management and 1 for senior management. Age and years of experience were coded into four questionnaire categories, and organizational tenure was entered as a continuous variable. Educational qualification was included only as a statistical adjustment variable because the “Other” category does not represent a clearly ordered qualification level. Firm-level controls could not be included because all respondents were employed by the same organization.

3.3. Measurement Instrument and Variable Operationalization

The data collection tool consisted of a structured questionnaire containing 33 substantive questions and six demographic questions measured using a scale on a five point Likert scale from "strongly disagree" (1) to "strongly agree" (5). Constructs were defined operationally and measured reflectively using reliable scales based on previously validated sources. In this study, BI capability was assessed along three dimensions: data collection, data reliability and data analysis. Items were adapted from Alzghoul et al. (2024) and Wamba et al. (2024). Six items measured each of the three dimensions, and separate mean scores were calculated for each dimension. The composite capability of BI was calculated as shown in Eq. (1).

$$\text{BI capability} = (\text{Mean data collection} + \text{Mean data reliability} + \text{Mean data analysis})/3 \quad (1)$$

Strategic vigilance was measured by assessing the firm's capacity to observe, analyze, and predict the environment using an eight-item scale adapted from Khan et al. (2024), which captures environmental monitoring, threat anticipation, and interpretive capacity. A mean score was calculated across the eight strategic vigilance items. BI and strategic vigilance were treated as distinct constructs: BI represented technical and operational information processing, whereas strategic vigilance represented managerial attention, interpretation, anticipation, and readiness to respond. Organizational ambidexterity was operationalized using the core distinction between exploration and exploitation, as defined by March (1991) and O'Reilly and Tushman (2013). Both exploration and exploitation were defined as separate dimensions, and a total ambidexterity score was also calculated. The seven ambidexterity items were developed by the researchers and reviewed by nine experts before questionnaire administration. Exploration was measured using four items, and exploitation using three. Combined organizational ambidexterity was calculated as shown in Eq. (2).

$$\text{Combined organizational ambidexterity} = (\text{Mean exploration} + \text{Mean exploitation})/2 \quad (2)$$

This score represents the simultaneous presence of exploration and exploitation. It does not represent ambidexterity based on differences, balance, or multiplicative interactions between the two dimensions. The questionnaire included reverse-scored items on certain scales to reduce response bias. Reverse scoring was applied to DC5, DR6, and SV1 based on negative wording. Scores were recorded using the following formula: Revised score = 6 − original score. Supplementary File S1 contains a complete version of the questionnaire, including the original wording, sequence, construct allocation, and scoring procedure. No substantive item was added, removed, or reworded after data collection. The analysis was done using IBM SPSS Statistics version 26 for regression and summary statistics and IBM SPSS Amos version 26 for confirmatory factor analysis.

3.4. Validity and Reliability

Content validity was determined through an expert assessment conducted by nine experts in management, BI, and information systems. In line with their comments, items were modified to improve clarity and enhance construct validity prior to questionnaire administration. The construct validity of each variable was assessed using confirmatory factor analysis. The measurement model specified six distinct first-order constructs: data collection, data reliability, data analysis, strategic vigilance, exploration, and exploitation. The results showed acceptable fit of the model according to the following indicators: $\chi^2/df = 2.14$; CFI = 0.94; TLI = 0.92; RMSEA = 0.076; and SRMR = 0.058, all of which were within acceptable model-fit thresholds (Hu and Bentler, 1999). All standardized factor loadings ranged from 0.71 to 0.86 and were statistically significant ($p < 0.001$). The complete item-level loadings and item-to-construct mapping are presented in Table 1. Finally, discriminant validity was tested using the heterotrait–monotrait ratio. The analysis was based on the six first-order constructs specified in the CFA model. The complete matrix contains all 15 pairwise comparisons and is reported in Supplementary Table S2b. HTMT values ranged from 0.52 to 0.82 and were all below the recommended value of 0.85 (Henseler et al., 2015), supporting discriminant validity among the six first-order constructs. All the values for reliability and validity of the constructs are presented in Table 1. The composite reliability ranged from 0.83 to 0.92, exceeding the 0.70 threshold. The average variance extracted ranged from 0.59 to 0.68, exceeding the 0.50 threshold. Cronbach's alpha values were between 0.82 and 0.91.

Table 1. Reliability and validity statistics

Construct	Cronbach's α	Composite Reliability (CR)	Average Variance Extracted (AVE)
Data Collection	0.91	0.92	0.66
Data Reliability	0.88	0.90	0.59
Data Analysis	0.85	0.89	0.59
Strategic Vigilance	0.82	0.92	0.60
Exploration	0.87	0.89	0.68
Exploitation	0.84	0.83	0.62

3.5. Common Method Bias Assessment

Given the study's one-source cross-sectional design, the issue of common method bias was assessed using both procedural and statistical methods. On the procedural side, the questionnaire guaranteed participants' confidentiality, was organized into construct-specific sections, and used three negatively worded, reverse-scored items to reduce acquiescence bias. The statistical analysis using Harman's single-factor test showed that the first factor accounted for 26.8% of the total variance, below the recommended 50% threshold (Podsakoff et al., 2003). This result indicates that one general factor did not dominate the covariance structure, but it does not establish that common method bias was eliminated. A latent common-method-factor CFA-based test was also performed. The addition of a latent common-method factor to the original CFA model produced only limited changes in model fit (ΔCFI = 0.010, ΔRMSEA = 0.002). These diagnostics do not indicate a dominant general method factor. Nevertheless, residual same-source variance remains possible because all focal constructs were measured from the same respondents at the same point in time.

3.6. Diagnostic Testing and Assumption Checks

Before hypothesis testing, several important regression assumptions were examined. The normality assumption was satisfied, as indicated by appropriate values of skewness and kurtosis. The linearity assumption was confirmed by plotting residual plots, which showed no substantial departures from linearity. Homoscedasticity was examined using the Breusch–Pagan test, which produced $\chi^2(9) = 12.34$, $p = 0.195$. The nonsignificant result did not indicate a statistically detectable violation of homoscedasticity. Multicollinearity was assessed using variance inflation factors (VIFs), which ranged from 1.08 to 1.95 and were all below the threshold of 5. The independence assumption of errors was checked using the Durbin–Watson statistic, which was satisfactory at 1.96. Mean centering of BI capability and strategic vigilance was performed before interaction testing.

3.7. Data Analysis Procedures

The data analysis was done in a stepwise process. First, there was a need to determine the central tendencies and spread of variables under study using descriptive statistics. Second, means, standard deviations, and inter-construct correlations were calculated for the principal model variables. Third, hierarchical multiple regression analysis was conducted. Model 0 included gender, age, educational qualification, managerial level, years of experience, and organizational tenure. Model 1 added composite BI capability, Model 2 added strategic vigilance, and Model 3 added the BI × strategic vigilance interaction term. The models were specified as shown in Eqs. (3)-(6).

$$\text{Model 0: } OA = \beta_0 + \Sigma\gamma_k \text{Control}_k + \varepsilon \tag{3}$$

$$\text{Model 1: } OA = \beta_0 + \Sigma\gamma_k \text{Control}_k + \beta_1 BIc + \varepsilon \tag{4}$$

$$\text{Model 2: } OA = \beta_0 + \Sigma\gamma_k \text{Control}_k + \beta_1 BIc + \beta_2 SVc + \varepsilon \tag{5}$$

$$\text{Model 3: } OA = \beta_0 + \Sigma\gamma_k \text{Control}_k + \beta_1 BIc + \beta_2 SVc + \beta_3 (BIc \times SVc) + \varepsilon \tag{6}$$

In these equations, OA denotes combined organizational ambidexterity. BIc denotes mean-centered BI capability. SVc denotes mean-centered strategic vigilance. Control_k denotes the six respondent-level controls, and ε denotes the residual term**.** Lastly, a post hoc analysis using conditional BI coefficients was conducted to determine the moderating effect of strategic vigilance at one standard deviation below its mean, at its mean, and at one standard deviation above its mean (Aiken and West, 1991). No individual regression analyses were performed for the separate BI dimensions because the principal model examined composite BI capability and combined organizational ambidexterity.

4. Results

4.1. Descriptive Statistics and Respondent Profile

Respondents' demographic data are shown in Table 2. Most were middle managers (68%), while senior managers accounted for 32% of respondents. Mean organization tenure was 12.4 years (SD = 6.2). Most respondents were male (71.0%), the largest age category was 30–39 years (38.0%), and nearly half held a bachelor's degree (49.0%). Potential non-response bias was assessed by comparing the 150 early respondents with the 50 late respondents. No statistically significant differences were detected in BI capability, strategic vigilance, exploration, exploitation, or combined organizational ambidexterity, with p-values ranging from 0.599 to 0.641. These findings provide no evidence of systematic early–late response differences, although they do not eliminate the possibility of non-response bias. The complete results are reported in Table 3**.** Table 3 depicts the means, standard deviations, and inter-construct correlations for the variables included in the principal moderation model. It was found that all constructs had significant correlations in the anticipated direction. The strongest correlation was observed between BI and combined organizational ambidexterity ($r = 0.781$, $p < 0.001$). The descriptive statistics for the six first-order constructs are reported in Supplementary Table S2a. Among the BI dimensions, data collection had the highest reported mean (M = 3.98, SD = 0.92), followed by data reliability (M = 3.35, SD = 0.88) and data analysis (M = 2.83, SD = 0.95). The lower reported mean for data analysis indicates that managers perceived analytical capability as comparatively less developed within the investigated organization**.**

4.2. Testing H1: Association between BI Capability and Combined Organizational Ambidexterity

Hierarchical multiple regression was conducted to examine the association between BI capability and combined organizational ambidexterity, controlling for respondent-level variables. Model 0 included gender, age, educational qualification, managerial level, years of experience, and organizational tenure. Model 1 added BI capability, Model 2 added strategic vigilance, and Model 3 added the BI × strategic vigilance interaction term. The hierarchical regression results for Models 0–3 are presented in Table 4. Adding BI capability increased the explained variance to 61.0%, $R^2 = 0.610$, adjusted $R^2 = 0.596$. The increase of 54.2 percentage points was statistically significant, $\Delta R^2 = 0.542$, $\Delta F(1, 192) = 266.83$, $p < 0.001$. This result supports H1 and indicates that BI capability was positively associated with combined organizational ambidexterity after accounting for the six respondent-level controls**.**

Table 2. Respondent demographic profile (N = 200)

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	142	71.0
	Female	58	29.0
Age	Less than 30 years	28	14.0
	30–39 years	76	38.0
	40–49 years	62	31.0
	50 years and above	34	17.0
Educational Qualification	Bachelor's Degree	98	49.0
	Master's Degree	72	36.0
	Doctorate Degree	18	9.0
	Other	12	6.0
Managerial Level	Senior Management	64	32.0
	Middle Management	136	68.0
Years of Experience	Less than 5 years	22	11.0
	5–10 years	54	27.0
	11–15 years	78	39.0
	More than 15 years	46	23.0
Organizational Tenure	Mean = 12.4 years	SD = 6.2	–

Table 3. Descriptive statistics and correlations for the principal model variables

Construct	Mean	SD	1	2	3
1. BI Capability	3.39	0.76	1.000		
2. Strategic Vigilance	3.52	0.91	0.660***	1.000	
3. Combined Organizational Ambidexterity	3.72	0.84	0.781***	0.703***	1.000

Notes: N = 200. Values are Pearson product–moment correlations. BI capability was calculated as the arithmetic mean of data collection, data reliability, and data analysis. Combined organizational ambidexterity was calculated as the arithmetic mean of exploration and exploitation. ***p<0.001, two-tailed.

Table 4. Hierarchical regression results

Model	Variables Entered	R²	Adjusted R²	ΔR²	F	ΔF	p for ΔF
0	Control variables	0.068	0.039	0.068	F(6, 193) = 2.35	2.35	0.033
1	Controls and BI capability	0.610	0.596	0.542	F(7, 192) = 42.90	266.83	<0.001
2	Controls, BI capability, and strategic vigilance	0.672	0.658	0.062	F(8, 191) = 48.91	36.10	<0.001
3	Controls, BI capability, strategic vigilance, and BI × strategic vigilance	0.697	0.683	0.025	F(9, 190) = 48.56	15.68	<0.001

Note: BI capability and strategic vigilance were mean-centered before calculating the interaction term. The control-only model explained 6.8% of the variance in combined organizational ambidexterity, $R^2 = 0.068$, adjusted $R^2 = 0.039$, $F(6, 193) = 2.35, p = 0.033$.

4.3. Testing H2: Moderating Role of Strategic Vigilance

Hierarchical multiple regression analysis was performed to assess the moderating role of strategic vigilance. BI capability and strategic vigilance were centered around their means before calculating the interaction term. Adding strategic vigilance in Model 2 increased the explained variance to 67.2%, $R^2 = 0.672$, adjusted $R^2 = 0.658$. The increase was statistically significant, $\Delta R^2 = 0.062, \Delta F(1, 191) = 36.10, p < 0.001$. In the final model, strategic vigilance was positively associated with combined organizational ambidexterity, $B = 0.32$, $SE = 0.053$, $t = 6.04$, $p < 0.001$, 95% CI [0.22, 0.42]. The complete final-model coefficients, confidence intervals, and VIF values are reported in Table 4. The interaction effect BI × Strategic Vigilance proved to be statistically significant ($B = 0.42$, $SE = 0.106$, $t = 3.96$, $p < 0.001$, 95% CI [0.21, 0.63])and accounted for an additional explained variance of $\Delta R^2 = 0.025$. The final interaction model explained 69.7% of the variance in combined organizational ambidexterity, $R^2 = 0.697$, adjusted $R^2 = 0.683$, while the interaction produced $\Delta F(1, 190) = 15.68$, $p < 0.001$. This result supports H2.

Conditional BI coefficients were calculated at one standard deviation below the mean of strategic vigilance, at the mean, and at one standard deviation above the mean. The association between BI capability and combined organizational ambidexterity was $B = 0.56$at low strategic vigilance, $B = 0.94$at the mean level, and $B = 1.32$at high strategic vigilance. The corresponding moderator values and conditional BI coefficients are reported in Supplementary Table S5. The increasing coefficients indicate that the positive BI–ambidexterity association was stronger at higher reported levels of strategic vigilance. This pattern indicates a conditional statistical association. It does not demonstrate that strategic vigilance directly converts analytical insights into strategic action because the relevant managerial routines were not measured. The relationship between BI capability and ambidexterity is depicted in Fig. 2, which presents conditional BI regression coefficients across varying levels of strategic vigilance, followed by Table 5, which summarizes the results of hypothesis testing for the direct and moderating associations examined in this study.

5. Discussion

5.1. Interpreting the Role of BI in Combined Organizational Ambidexterity

The results of the current study indicate that BI capability is positively associated with combined organizational ambidexterity. This finding addresses the first research question by confirming the association between BI and combined organizational ambidexterity after accounting for the six respondent-level control variables. It would help to understand this relationship through the lens of dynamic capabilities theory, in which Teece (2007) argued that organizations become adaptable by sensing, interpreting, and responding to environmental changes. BI may provide an information-processing foundation for organizational sensing by increasing managerial awareness and supporting evidence-based decision-making. Particularly, BI may serve as an operational information-processing capability that supplies data, while strategic vigilance may help managers interpret the strategic relevance of that information. However, the study did not directly measure sensing, seizing, reconfiguration, or the routines through which information is converted into strategy. This interpretation, therefore, represents a theoretical explanation of the observed associations rather than a demonstrated causal mechanism.

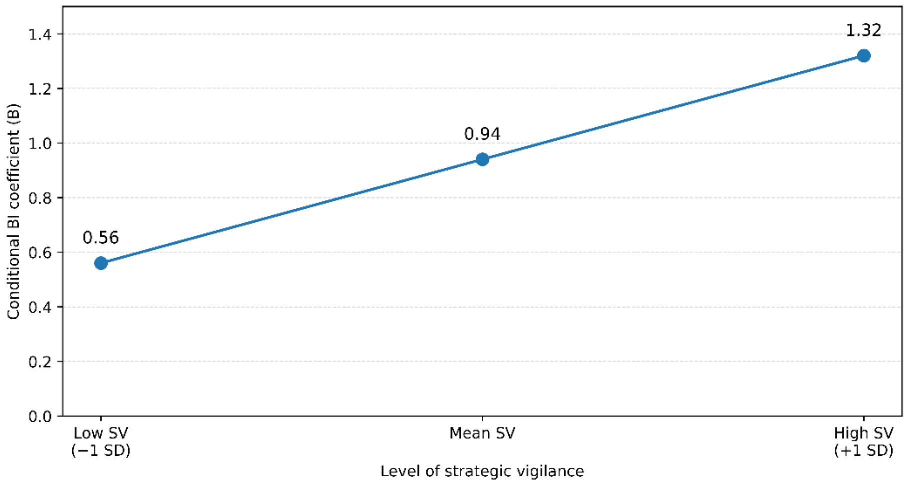

Fig. 2. Conditional BI regression coefficients at low, mean, and high levels of strategic vigilance
Note: Conditional coefficients were calculated at one standard deviation below the mean, at the mean, and at one standard deviation above the mean of strategic vigilance. Higher coefficients indicate a stronger positive association between BI capability and combined organizational ambidexterity.

Table 5. Summary of hypothesis testing

Hypothesis	Tested Association	Statistical Evidence	p	Supported?
H1	BI capability and combined organizational ambidexterity	$r = 0.781$; $\Delta R^2 = 0.542$; $\Delta F(1, 192) = 266.83$	<0.001	Yes
H2	BI × strategic vigilance interaction and combined organizational ambidexterity	$B = 0.42$; $t = 3.96$; $\Delta R^2 = 0.025$	<0.001	Yes

The observed result supports H1, indicating that managers who reported stronger BI capability also reported higher simultaneous levels of exploration and exploitation. Data gathering may help organizations identify new opportunities, while data analysis may help managers interpret complex patterns for experimentation and innovation. Meanwhile, quality data may support consistency and operational efficiency, thus contributing to exploitation efforts. Therefore, the combination mentioned above is consistent with the theory that ambidexterity can be achieved by integrating the two processes rather than separating them (March, 1991; O'Reilly and Tushman, 2013). It is worth noting that the results are similar to those of recent empirical studies on analytics capabilities and their associations with organizational outcomes (Medeiros and Maçada, 2022). Previous literature has shown that BI capabilities are associated with better decision-making in terms of speed, accuracy, and responsiveness, thereby supporting organizational adaptability (Alzghoul et al., 2024). Therefore, the current study supports the view that BI capability is strategically relevant to combined organizational ambidexterity. Nevertheless, reverse ordering remains possible because organizations with stronger exploratory and exploitative activities may be more likely to invest in BI systems and analytical tools.

5.2. Strategic Vigilance as a Capability-Enhancing Mechanism

A central contribution of the research is highlighting strategic vigilance as a moderator that strengthens the positive association between BI and combined organizational ambidexterity. The findings provide support for H2, showing that the association between BI and ambidexterity is stronger when strategic vigilance is high. In this regard, the findings address the second research question by indicating that the organizational relevance of BI varies with managers' reported strategic vigilance. BI and strategic vigilance play different but complementary roles. While BI entails processing and analyzing data, strategic vigilance involves contextualizing findings and assessing their strategic relevance (Khan et al., 2024; Al-Rikabi and Ibrahim, 2021). More importantly, Model 3 shows that strategic vigilance has a positive direct association with ambidexterity ($B = 0.32$, $p < 0.001$). This means that strategic vigilance is associated with combined ambidextrous activity independently of its interaction with BI. Interpretive and anticipatory skills may therefore represent important resources for ambidexterity. Strategic vigilance may help organizations sift through relevant signals, prioritize information, and connect analytical results with possible strategic decisions. According to dynamic capabilities theory, strategic vigilance may support sensing and seizing by helping managers recognize strategic insights and respond to them promptly (Teece, 2007; Khan et al., 2024). BI coefficients increased from $B = 0.56$ at low vigilance for strategic matters to $B = 0.94$ at average levels and $B = 1.32$ at high levels of vigilance. This pattern suggests that the association between BI and ambidexterity is stronger at reported high levels of strategic vigilance. However, interaction should not be taken as proof that high vigilance turns BI outputs into concrete organizational actions. Review processes across functions, escalation procedures, decision-making rights, and resource allocation are plausible mechanisms, but were not measured directly. Previous research generally conflated scanning with analytical processing; results here support distinguishing vigilance from BI as related but distinct capabilities. Key points are preserved, including the increase in BI coefficients with higher vigilance levels, the conclusion that this does not prove that vigilance turns BI into action, plausible mechanisms for this association, and support for distinguishing vigilance from BI.

5.3. Theoretical and Practical Implications

Conceptually, current research adds value to the literature by synthesizing BI (BI) and vigilance strategy, and combining organizational ambidexterity into a coherent framework. The results show a conditional association between data-driven capability and ambidexterity, consistent with the dynamic capabilities approach (Teece, 2007). According to this approach, BI represents technical and operational processing of information, while strategic vigilance represents managerial attention and interpretation. Results do not show either construct as a complete dynamic capability, nor do they directly show sensing opportunities, reconfiguring resources or mobilizing resources. In practical terms, the results show that management should focus on implementing systems that integrate data analysis with strategic insight. Specifically, telecommunications companies should invest in warehouses and dashboards and develop routine processes that connect ongoing environmental scanning with organizational decisions. Steps include forming cross-functional vigilance committees that review competitive intelligence and link it to BI outputs; embedding predictive analytics in network centers to anticipate capacity issues, and establishing formal feedback loops from market intelligence into product development pipelines. Managers may also use demand forecasting and usage patterns in their capacity planning to determine appropriate times to make capital investments and allocate an organization's resources. For capital expenditure decisions, managers can combine data from analyses with results from environmental assessments to identify priorities such as specific technologies, geographic areas and/or service offerings. For customer retention decision-making, indicators may be used alongside escalation rules that specify which customer actions (increased complaint levels, decreased engagement, switching behavior) indicate escalating dissatisfaction and require managerial intervention. Cross-functional reviews should specify who validates the information, when a signal should be escalated, what evidence is required before action, and which managers have authority to reallocate resources. The development of high-quality data sources, improvement of analysts' skills, and establishment of regular monitoring processes are needed for the organization to support both efficiency and innovation (Wamba et al., 2024; Khan et al., 2024). Additionally, managers should prioritize closing the perceived gap in analytical capability by investing in advanced analytics training and decision-support tools, as data collection alone does not guarantee strategic value.

5.4. Limitations and Acknowledgment of Reverse Causality

The comparatively high explained variance may partly reflect the shared organizational setting, same-source measurement, and conceptual proximity of the constructs. Several limitations are recognized. The first limitation is that the study employs a cross-sectional design, which does not establish causality or temporal ordering. It may also be the case that ambidextrous organizations invest more heavily in BI, thus providing a plausible reverse-ordering explanation. Longitudinal or instrumental-variable designs would provide a better way to determine the direction of the relationship. The second limitation is that the sample was drawn from a single organization. The 200 observations represent individual managers within that organization rather than independent firms. Without multiple organizations, aggregated evidence, or multilevel analysis, the findings cannot support organizational-level or sector-wide conclusions. A third limitation is that although six respondent-level controls were included, gender, age, educational qualification, managerial level, years of experience, and organizational tenure, firm-level controls could not be included. Variables such as organizational culture, digital maturity, previous technology investment, regulatory exposure, and competitive position may have contributed to the results. Residual omitted-variable bias, therefore, remains possible. The fourth limitation is that all focal measures were based on self-reports. Therefore, although procedural and statistical methods were used to assess response and common-method concerns, they cannot demonstrate that socially desirable responding or residual same-source variance was eliminated. Educational qualification was included using the original questionnaire coding. Because the “Other” category does not represent a clearly ordered qualification level, its coefficient was included only as a statistical adjustment and was not interpreted substantively. Finally, combined organizational ambidexterity was used as the dependent variable. The study did not examine balanced or multiplicative ambidexterity, separate relationships with exploration and exploitation, or the relative statistical importance of the individual BI dimensions. Lastly, the positive coefficient for strategic vigilance ($B = 0.32$, $p < 0.001$) indicates that strategic vigilance was directly associated with combined organizational ambidexterity in addition to its moderating role. Future models should therefore examine both their direct and conditional associations using longitudinal, multi-source, and multi-firm designs.

6. Conclusion

Consequently, the results of this study confirm the positive association between BI capability and combined organizational ambidexterity, and show that this association strengthens at higher reported levels of strategic vigilance, an interpretive and anticipatory capability. BI is related to ambidexterity because it supports the gathering and processing of information relevant to both exploration and exploitation. The gathering of data may increase organizational awareness of existing opportunities, while data reliability may increase managers’ confidence in available information, and data analysis may transform information into decision-relevant knowledge. However, the lower reported mean for data analysis is descriptive and does not establish that it is statistically less important than the other BI dimensions. From a theoretical perspective, the paper contributes to the dynamic capabilities approach by integrating BI, strategic vigilance, and organizational ambidexterity. Specifically, the paper treats BI as a technical and operational information-processing capability, strategic vigilance as a managerial attentional and interpretive capability, and ambidexterity as the simultaneous presence of exploration and exploitation. The study does not directly demonstrate sensing, seizing, reconfiguration, or resource-allocation routines; these remain theoretical interpretations of the observed associations. From a practical standpoint, telecommunications firms need not only to acquire data but also to develop sound data management, analysis, and environmental monitoring. Managers should connect BI outputs with decisions concerning network planning, capital investment, product development, customer retention, and competitive response.

Future studies will need to conduct this study across multiple telecommunications organizations in a longitudinal design. Future studies should conduct this study across multiple telecommunications organizations using a longitudinal design and multiple data sources. In addition, future studies should examine exploration and exploitation separately. Furthermore, studies should determine whether the same associations exist across the dimensions of BI (BI) and explore how BI information is interpreted and utilized by managers within their respective organizational environments. This research was based on cross-sectional, self-reported perceptions from only one organization. As such, these results represent association rather than causation and are not directly generalizable to the wider telecommunications industry.

Author Contributions

Maryam Khalid Obeidat contributed to conceptualization, methodology, investigation, data collection, formal analysis, visualization, draft preparation, and manuscript writing. Mahmoud Ali Alrousan contributed to conceptualization, supervision, validation, methodology review, manuscript editing, project administration, and final approval of the manuscript. All authors reviewed and approved the final version of the manuscript.

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Institutional Review Board Statement

Approval for this study was obtained from the Institutional Research Ethics Committee of Irbid National University on 11 May 2026 under approval number IRB-2026-0511. All participants provided informed consent before participating in the study.

Declaration of Artificial Intelligence (AI) Tools

Grammarly was used for minor language editing and proofreading purposes only. The authors reviewed all suggested changes and assume full responsibility for the final content of the manuscript.

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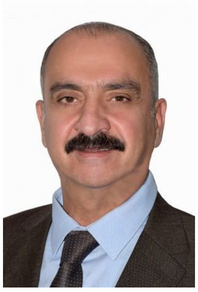

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