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Designing a Business Intelligence Model Based on Systems Thinking

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ABSTRACT

The purpose of this study is to design and validate a business intelligence model grounded in systems thinking for small and medium-sized manufacturing enterprises, particularly within the oil and gas industry. The model aims to elucidate the dynamic interaction among technology, human resources, and processes, thereby facilitating improvements in organizational performance and agility. This research is applied in purpose and employs a mixed-methods approach with a predominance of qualitative analysis. In the qualitative phase, using comparative content analysis and semi-structured interviews with experts and managers in business intelligence and information technology, the components and dimensions of the model were extracted and enriched. Sampling was purposive and continued until theoretical saturation was achieved. In the quantitative phase, the conceptual model derived from the qualitative analysis was tested using a researcher-made questionnaire among managers and specialists of small and medium-sized manufacturing enterprises in the oil and gas sector. Data were analyzed through confirmatory factor analysis and structural equation modeling using LISREL software, and the model's validity and reliability were assessed. Qualitative findings indicated that business intelligence is a multidimensional and systematic phenomenon, not limited solely to technology, but emerging from the interaction of human, technological, and knowledge factors. Accordingly, eleven principal dimensions were identified, including reporting technologies, online analytical processing, analytics, data mining, process mining, complex event processing, business performance management, benchmarking, text mining, predictive analytics, and multidimensional analysis. Quantitative results demonstrated that the proposed model possesses appropriate validity, reliability, and fit, with all model paths exerting significant positive effects on business intelligence. Among these, benchmarking, complex event processing, and analytics contributed most substantially to explaining business intelligence. The findings suggest that business intelligence represents a dynamic organizational capability based on systems thinking, which can enhance decision-making, organizational agility, and performance through the synergy of data analysis, organizational learning, and data-driven culture. The presented model can serve as a practical framework for implementing, evaluating, and developing business intelligence in small and medium-sized enterprises for managers and policymakers.

Keywords: Business intelligence, systems thinking, structural equation modeling, data analysis, small and medium-sized enterprises, oil and gas industry.

Introduction

In contemporary business environments, organizations are increasingly required to transform dispersed, heterogeneous, and rapidly changing data into reliable knowledge for decision-making, strategic adaptation, and operational control. Business intelligence has therefore moved beyond its earlier technical meaning as a set of

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reporting tools and has become a multidimensional organizational capability through which firms collect, integrate, analyze, interpret, and use data to improve responsiveness and performance. This transformation is particularly important for small and medium-sized enterprises because these firms usually operate with limited financial, technological, and human resources while facing intense competitive pressure, market uncertainty, and the need for rapid decision-making. In such conditions, business intelligence can function as a strategic mechanism for reducing ambiguity, strengthening managerial cognition, improving customer-oriented processes, and supporting evidence-based action. Literature on the strategic impact of business intelligence has emphasized that the value of business intelligence lies not merely in data storage or technological deployment, but in its ability to align information resources with organizational goals, competitive priorities, and managerial decision structures (1).

The increasing strategic relevance of business intelligence should be understood within the wider context of digital transformation. Digital platforms, artificial intelligence, and data-driven infrastructures have reconfigured entrepreneurial processes and reshaped how organizations identify opportunities, mobilize resources, and create value (2). Artificial intelligence has also accelerated the transformation of enterprise business processes by enabling automation, predictive reasoning, adaptive workflows, and intelligent process redesign (3). These developments have changed the logic of competition from resource possession alone to data interpretation, learning speed, analytical capability, and systemic coordination. In this context, business intelligence becomes a bridge between digital technologies and organizational outcomes, because it enables managers to extract meaning from data and translate analytical insights into decisions, actions, and performance improvement. The strategic utilization of business intelligence is therefore associated with the capacity to create managerial insight, improve organizational alignment, and generate measurable value from information systems (4).

Business intelligence is especially significant for manufacturing enterprises because manufacturing activities are embedded in complex relationships among suppliers, production processes, technologies, customers, regulations, and market signals. In the oil and gas industry, this complexity is even more pronounced due to capital intensity, operational risk, fluctuating demand, technological dependency, safety requirements, environmental considerations, and the need for coordination across upstream, midstream, and downstream processes. Small and medium-sized manufacturing enterprises active in this sector must respond to changes in supply chains, maintenance needs, quality standards, customer requirements, and competitive pressures. However, many such enterprises still rely on fragmented information systems, experience-based decision-making, delayed reporting, and weak integration between operational data and strategic analysis. Business intelligence can help these firms move from reactive decision-making to proactive and predictive management by integrating reporting technologies, analytical processing, data mining, process mining, performance management, benchmarking, text processing, predictive analytics, and multidimensional analysis into an integrated decision-support architecture.

Prior research has shown that business intelligence can improve organizational performance through several mechanisms. The capacity for business intelligence, when combined with network learning and innovation, has been linked to better organizational performance because it strengthens the firm's ability to interpret environmental signals and convert knowledge into value-creating action (5). Similarly, business intelligence can improve customer-oriented and competitive processes by enabling firms to analyze customer behavior, identify process weaknesses, and align operational decisions with market demands (6). In the competitive domain, business intelligence contributes to firm competitiveness, and entrepreneurial orientation can mediate the relationship between business intelligence and competitive outcomes by transforming analytical knowledge into opportunity-seeking behavior (7).

These findings suggest that business intelligence is not simply an information technology investment; rather, it is a managerial and strategic capability that becomes valuable when it is embedded in learning, innovation, entrepreneurial orientation, and performance-oriented decision-making.

The importance of business intelligence for small and medium-sized enterprises has also been emphasized in studies on adoption, maturity, and performance. Evidence on business intelligence systems adoption in small and medium-sized enterprises indicates that the use of such systems can contribute to firm performance when the organization is able to justify adoption, ensure system use, and align technological functions with managerial needs (8). Adoption is shaped by technological, individual, and supply-chain-related factors, meaning that the effectiveness of business intelligence depends on the simultaneous readiness of infrastructure, users, and interorganizational processes (9). This issue is crucial for small and medium-sized manufacturing enterprises in the oil and gas sector because they must not only acquire analytical tools but also develop the human competencies, data governance routines, and supply-chain integration mechanisms needed to use those tools effectively. Therefore, a business intelligence model for such enterprises must include both technological and non-technological dimensions.

The maturity perspective provides another important foundation for understanding business intelligence development. Business intelligence maturity models help organizations evaluate their current analytical capabilities, identify developmental gaps, and plan improvement paths. Studies on business intelligence maturity among Iranian organizations have shown that maturity is a gradual and multidimensional process involving infrastructure, data quality, analytical capability, managerial support, and organizational culture (10). A hybrid model for evaluating business intelligence maturity also highlights the need to combine multiple criteria rather than assessing business intelligence through isolated technical indicators (11). These insights are highly relevant for small and medium-sized enterprises because such firms often need practical models that can diagnose their current position and guide them toward higher levels of data-driven decision-making. Without a maturity-oriented and systemic view, business intelligence implementation may remain limited to software installation and fail to create sustained organizational value.

Implementation studies further demonstrate that business intelligence success depends on organizational, technical, managerial, and environmental factors. Research on the Iranian banking industry has identified several factors influencing business intelligence implementation, including managerial support, information technology infrastructure, data quality, organizational readiness, and user acceptance (12). Although the banking sector differs from oil and gas manufacturing, the underlying implication is transferable: business intelligence implementation requires alignment between technology, structure, people, and strategy. Likewise, organizational intelligence models developed in manufacturing companies indicate that intelligence at the organizational level emerges from coordinated capabilities such as knowledge acquisition, information processing, communication, learning, and adaptation (13). These findings support the argument that business intelligence should be modeled as an integrated organizational phenomenon rather than as a narrow technological subsystem.

From a theoretical perspective, systems thinking provides a powerful lens for designing a comprehensive business intelligence model. Systems thinking focuses on interdependence, feedback loops, dynamic relationships, nonlinear effects, and the interaction between parts and wholes. In the context of business intelligence, this means that reporting, analytics, data mining, process monitoring, performance management, and strategic learning should not be treated as separate components, but as mutually reinforcing elements of an organizational intelligence system. The value of systems thinking is evident in dynamic modeling research, where the analysis of social capital through system dynamics demonstrates how organizational phenomena can be understood through interactions among multiple variables over time (14). Applying this logic to business intelligence implies that the effectiveness of analytical technologies depends on feedback relationships among data quality, user interpretation, managerial action, organizational learning, and performance outcomes.

Systems thinking is also consistent with the knowledge-based dynamic capabilities perspective. Competitive intelligence formation in small and medium-sized enterprises has been examined through the lens of knowledge-based dynamic capabilities, emphasizing that firms need sensing, learning, integration, and reconfiguration capabilities to respond to environmental change (15). Business intelligence can be considered one of the central mechanisms through which these dynamic capabilities are operationalized, because it enables organizations to sense market and operational signals, interpret patterns, and reconfigure processes accordingly. Recent research has also shown that business intelligence can influence performance through innovation ambidexterity and dynamic capabilities, indicating that the impact of business intelligence is mediated by the organization's ability to simultaneously exploit existing knowledge and explore new opportunities (16). Therefore, the design of a business intelligence model should account for the dynamic interaction between analytical capability, innovation, learning, and adaptive performance.

Technological advances have expanded the functional scope of business intelligence. Machine learning has strengthened the movement from data mining to strategic insights by enabling automated pattern recognition, predictive modeling, and advanced decision support (17). Artificial intelligence-based data mining mechanisms have also shown how behavioral data can be analyzed for quality monitoring and adaptive management in network-based environments (18). Customer review analytics illustrates another important dimension of business intelligence, because unstructured textual data can be processed to reveal customer perceptions, satisfaction drivers, complaints, and emerging market expectations (19). These developments show that modern business intelligence must include structured and unstructured data, descriptive and predictive analysis, and both operational and strategic forms of knowledge extraction. For manufacturing enterprises in the oil and gas sector, such capabilities can support demand forecasting, maintenance prediction, supplier evaluation, risk analysis, and customer-oriented process improvement.

The emergence of advanced technologies such as artificial intelligence and virtual reality has also introduced new opportunities and challenges for business intelligence in organizations. The use of virtual reality and artificial intelligence in business contexts can improve simulation, visualization, training, and decision-making, but it also creates challenges related to implementation cost, user readiness, technical complexity, and organizational adaptation (20). These challenges are particularly relevant for small and medium-sized enterprises, which may recognize the value of advanced technologies but lack the resources or managerial frameworks needed for effective adoption. In addition, the growing role of intelligence and business wargaming in developing foresight shows that organizations increasingly need structured methods for anticipating future scenarios, competitive moves, and strategic uncertainties (21). Therefore, business intelligence should not be limited to retrospective reporting; it should support foresight, scenario analysis, strategic preparedness, and continuous adaptation.

Business intelligence has also been connected with corporate performance management, a field that emphasizes the translation of strategic objectives into measurable indicators, monitoring systems, feedback cycles, and corrective actions. Studies on the impact of business intelligence on corporate performance management indicate that analytical systems can improve performance monitoring and managerial control when they are integrated with planning, measurement, and evaluation processes (22). This connection is essential from a systems-thinking perspective because decision-making is not complete when data are analyzed; it must be followed by action, feedback, evaluation, and learning. In small and medium-sized manufacturing enterprises, performance management supported by business intelligence can help managers identify bottlenecks, evaluate process efficiency, compare performance against benchmarks, and implement corrective measures. Thus, performance management represents the feedback mechanism through which business intelligence becomes a continuous improvement system.

Sector-specific and emerging studies further confirm that business intelligence is relevant across diverse business contexts. Research on online sports enterprises has identified key factors influencing business intelligence and shown that digital business environments require systematic attention to data, technology, users, and managerial processes (23). Although online sports enterprises differ from manufacturing firms, the general insight is that business intelligence must be contextualized according to the operational logic, market structure, and technological maturity of each sector. For oil and gas manufacturing small and medium-sized enterprises, contextualization requires attention to production processes, industrial supply chains, safety-sensitive operations, maintenance systems, and competitive benchmarking. Therefore, a generic business intelligence model may not be sufficient; a tailored model based on systems thinking is needed to explain how technological, human, analytical, and process-oriented components interact in this specific industrial environment.

Despite the growing body of research on business intelligence, several gaps remain. First, many studies emphasize business intelligence adoption, maturity, performance, or competitiveness, but fewer studies offer an integrated model that combines technological functions with systems thinking for small and medium-sized manufacturing enterprises. Second, previous models often focus on either technical infrastructure or organizational outcomes, while the interaction among reporting technologies, online analytical processing, analytics, data mining, process mining, complex event processing, business performance management, benchmarking, text processing, predictive analytics, and multidimensional analysis has not been sufficiently conceptualized as a coherent system. Third, in industrial contexts such as oil and gas manufacturing, business intelligence must operate across complex process networks and uncertain environments, which requires a model capable of reflecting feedback, interdependence, adaptation, and dynamic decision-making. These gaps justify the need for a systems-thinking-based model that treats business intelligence as a dynamic organizational capability rather than a fragmented set of tools.

Accordingly, the present study aimed to design and validate a business intelligence model based on systems thinking for small and medium-sized manufacturing enterprises in the oil and gas industry.

Methods and Materials

This study was conducted with the aim of presenting a conceptual model for business intelligence in small and medium-sized manufacturing enterprises in the oil and gas industry, with an emphasis on systems thinking. In terms of purpose, the study is applied, and in terms of method, it is based on a mixed-methods approach with a qualitative predominance. In the qualitative phase, relying on qualitative content analysis with a deductive approach and using existing theoretical frameworks, data were collected through semi-structured interviews with managers and experts familiar with business intelligence and information technology. Qualitative sampling was conducted purposively and theoretically, and the data collection process continued until theoretical saturation was achieved. Qualitative data analysis was carried out through the stages of immersion in the data, deductive coding, code refinement, category formation, and final interpretation. While adhering to the initial conceptual framework, the analysis also allowed for the modification and expansion of the model based on empirical data. To enhance the credibility of the findings, methods such as participant review, co-coding, and transparency in reporting the results were taken into account.

In the quantitative phase, the statistical population included managers and experts of small and medium-sized manufacturing enterprises in the oil and gas sector that had information technology infrastructure. After screening, simple random sampling was conducted. The main research instrument was a researcher-made questionnaire based on the conceptual model of Jiang and Dong (2020), which includes eleven main dimensions of business intelligence: reporting, online analytical processing, data analytics, data mining, process mining, complex event processing, performance management, benchmarking, text processing, predictive analytics, and multidimensional analysis. The validity and reliability of the instrument were examined using content validity, confirmatory factor analysis, composite reliability, and Cronbach's alpha. The conceptual model was tested through structural equation modeling using LISREL software. Finally, the model fit indices indicated that the proposed model had an appropriate fit with the empirical data and could be used as a valid framework for implementing and evaluating business intelligence in small and medium-sized enterprises in the oil and gas industry.

Findings and Results

In qualitative content analysis with a deductive approach, the researcher initially has a theoretical framework or a set of predetermined concepts and codes and analyzes the data based on them. In this approach, the analytical path begins from theory and moves toward data; that is, the conceptual structure is first determined, and then the data are examined to identify instances and evidence of those concepts. This method is applicable when the researcher intends to test, complete, or enrich an existing theoretical model. Finally, by examining the relationships among categories, verbal evidence, and the degree of alignment between the data and the initial theoretical framework, the researcher formulates the final findings. In this section, it becomes clear which parts of the theory are confirmed, which parts require revision, and which new concepts have been added to the model. The result of this analysis is an enriched model based on empirical evidence that has a clear and logical relationship with the initial theoretical structure.

The business intelligence model based on systems thinking consists of several fundamental dimensions. Each dimension or main category is associated with a set of subcategories that represent the functions, processes, and technologies that shape organizational intelligence in practice. This classified structure indicates that business intelligence is a multidimensional and network-based concept that is systematically formed through the layers of reporting, analytics, data mining, process orientation, forecasting, and performance management.

Application of Reporting Technologies: The subcategories of this section include scheduled report generation, standardization of formats, integration of data sources, and report-sharing capability. These elements indicate that the reporting component functions as the primary infrastructure of business intelligence and is responsible for the integration, order, and flow of basic information within the organization.

Online Analytical Processing: The presence of categories such as the construction of analytical cubes and data exploration indicates that organizations require multidimensional analyses for decision-making across different levels. This dimension enables managers to view and analyze data from multiple perspectives.

Analytics: Descriptive analysis, diagnostic analysis, trend analysis, and scenario analysis are included in this section. This category reflects the organization's capability to convert data into operational insights and covers dimensions such as examining causes, forecasting trends, and analyzing the current situation.

Data Mining: Clustering, association rules, anomaly detection, and predictive algorithms indicate that this category focuses on discovering hidden patterns and non-obvious relationships in data. This dimension helps the organization better understand customer behavior, products, and processes.

Process Mining: Identifying bottlenecks, analyzing deviations, and redesigning processes indicate that the integration between data and the actual workflow within the organization has been examined. This category emphasizes that performance improvement is not possible without understanding real processes.

Complex Event Processing: The subcategories of this section include real-time event detection and rapid response to abnormal events. This indicates that the model also considers the "real-time" dimension as a key element of organizational intelligence.

Business Performance Management: The feedback cycle and corrective actions indicate that decision-making does not end at the analysis stage but must lead to follow-up and continuous improvement. This section has a direct relationship with systems thinking.

Benchmarking: Comparison with competitors, gap analysis, and extraction of best practices indicate the importance of learning from the external environment and adapting to competitive standards. This category demonstrates the role of the environment in system dynamics.

Text Processing: Sentiment analysis, topic extraction, and text classification represent the role of unstructured data in intelligent decision-making. This category strengthens the model's capacity to integrate complex data.

Predictive Analytics: Demand forecasting, failure prediction, and risk analysis indicate that the system is not merely descriptive but also future-oriented and capable of modeling the probability of events.

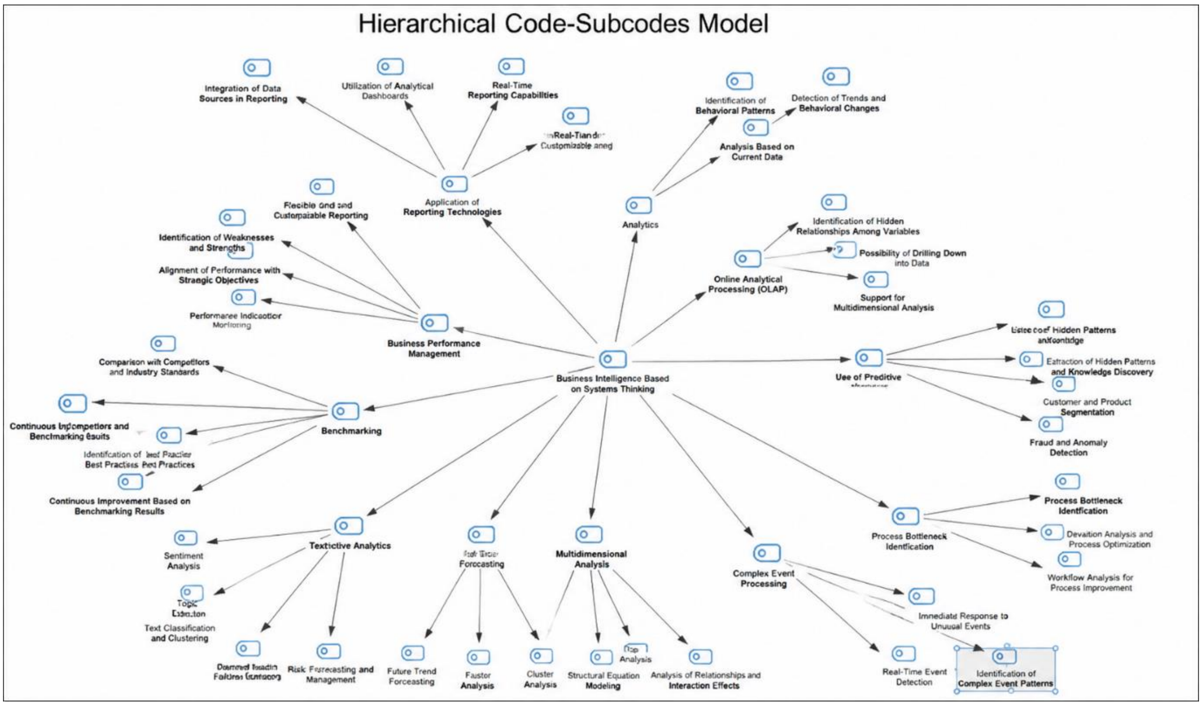

Figure 1. Business Intelligence Model Based on Systems Thinking

This section, through tools such as factor analysis, cluster analysis, and structural modeling, reveals complex relationships among variables and enables the organization to conduct high-level analyses and examine interaction effects.

Table 1 presents the descriptive indices, including mean, standard deviation, minimum score, and maximum score of the participants in the variables under study.

Table 1. Descriptive Indices of the Research Variables

Variable	N	Minimum Score	Maximum Score	Mean	Standard Deviation
Application of reporting technologies	368	1.00	5.00	3.682	0.819
Online analytical processing	368	1.00	5.00	3.511	0.827
Analytics	368	1.00	5.00	3.455	0.789
Data mining	368	1.00	5.00	3.566	0.796
Process mining	368	1.00	5.00	3.483	0.861
Complex event processing	368	1.00	5.00	2.954	0.904
Business performance management	368	1.00	5.00	3.099	0.876
Benchmarking	368	1.00	5.00	3.366	0.859
Text processing	368	1.00	5.00	3.577	0.827
Predictive analytics	368	1.00	5.00	3.608	0.727
Multidimensional analysis	368	1.00	5.00	3.531	0.872

An examination of the descriptive indices in Table 1 shows that the mean scores of all variables on the 1-to-5 scale are above the midpoint of 3, indicating a desirable and relatively strong status in the use of reporting technologies and data analytics. The highest means are related to “application of reporting technologies” (3.682) and “predictive analytics” (3.608), indicating that organizations have greater mastery of reporting tools and future-oriented analytics. In contrast, “complex event processing,” with the lowest mean (2.954) and the highest standard deviation (0.904), was the most challenging area for users, and respondents’ opinions in this area showed greater variability. Lower standard deviations in variables such as predictive analytics (0.727) indicate homogeneity of views and similar performance in that area. Overall, the data indicate that although basic analytical and reporting infrastructures have been well institutionalized, processing complexities and business performance management still require greater attention and development in order to reduce the gap with more successful areas.

Table 2 presents the distribution indices of the research variables, including skewness, kurtosis, and multivariate kurtosis.

Table 2. Distribution Indices of the Research Variables

Variable	Skewness	Kurtosis	Kolmogorov–Smirnov Test	Significance Level (Sig.)
Application of reporting technologies	-0.316	-0.334	0.098	0.084
Online analytical processing	-0.493	0.246	0.099	0.083
Analytics	-0.351	0.127	0.094	0.087
Data mining	-0.498	-0.037	0.095	0.087
Process mining	-0.385	-0.335	0.103	0.079
Complex event processing	0.003	-0.448	0.108	0.074
Business performance management	0.014	-0.629	0.105	0.077
Benchmarking	-0.452	-0.049	0.103	0.079
Text processing	-0.153	-0.569	0.099	0.083
Predictive analytics	-0.404	0.153	0.087	0.095
Multidimensional analysis	-0.457	-0.082	0.104	0.077

The results of the data normality test show that all research variables are within the acceptable range in terms of skewness and kurtosis, and their values are close to zero; therefore, no substantial deviation from normality is observed. Moreover, the Kolmogorov–Smirnov test values for all variables range from 0.087 to 0.108, and more importantly, the significance level (Sig.) for all variables is greater than 0.05. This indicates that the assumption of data normality is not rejected, and the distribution of the variables is statistically considered normal. Therefore, the data meet the necessary conditions for using parametric methods and more advanced analyses.

The evaluation of the measurement model, or confirmatory factor analysis (CFA), is one of the main stages in structural equation modeling and is conducted to ensure the validity and reliability of the constructs. At this stage, it is examined whether the indicators/items properly measure the intended theoretical constructs. A summary of the CFA evaluation is as follows:

At this stage, the factor loadings of the indicators measured for each latent variable, that is, the observed variables, were examined. Factor loadings greater than 0.50 are desirable, and values below this threshold should be removed.

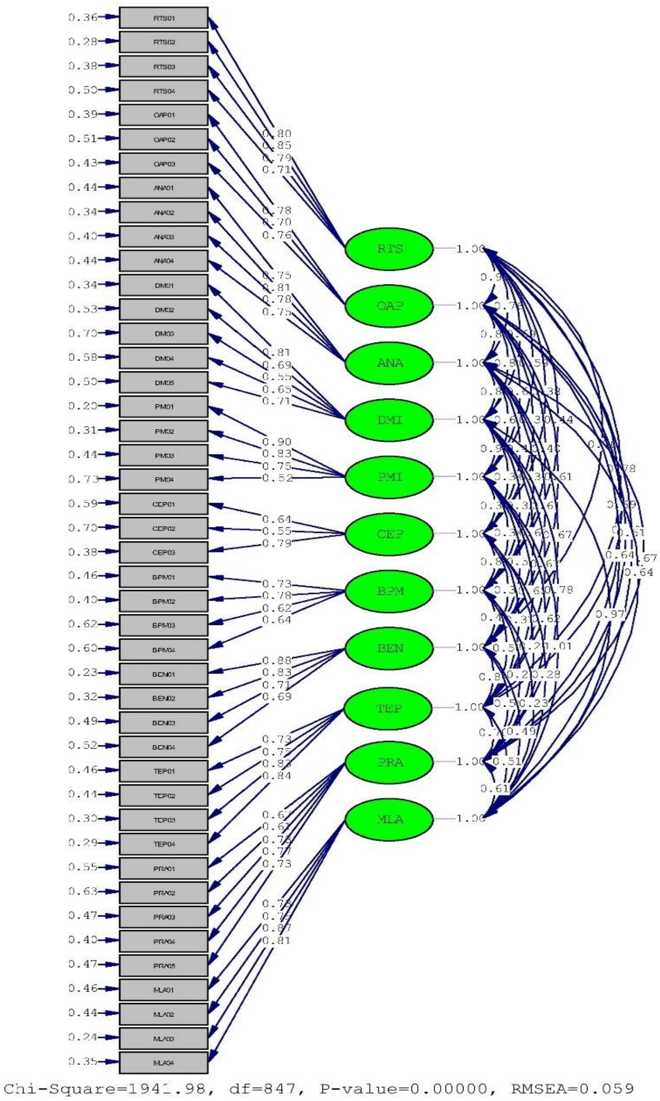

Figure 2. Confirmatory Factor Loadings of the First-Order Model

As observed in the figure, the factor loadings of the items are greater than 0.50, confirming that the items can be used in the model.

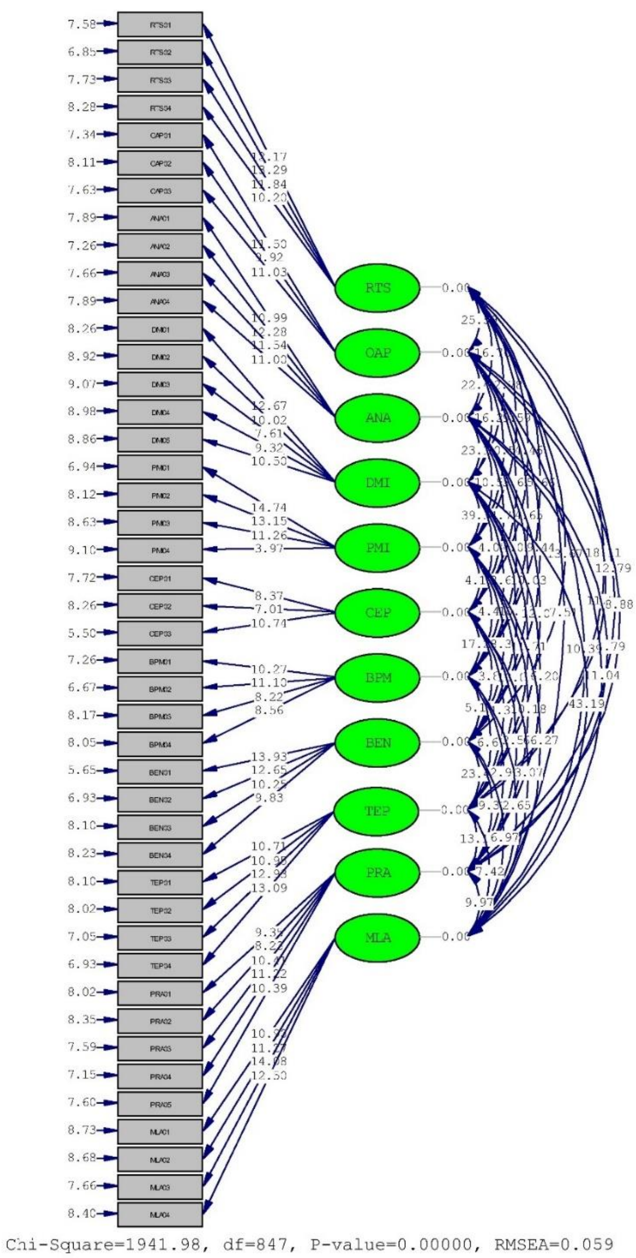

Figure 3. t-Statistic Values of the First-Order Confirmatory Model

The overall research model was examined using model fit indices.

Table 3. Goodness of Fit of the Confirmatory Model

Symbol	Value	Index Title
Chi-square	1941.98	Chi-square statistic
Degrees of freedom	847	Model degrees of freedom
P value	0.001	Significance level of the chi-square test
ChiSqr/df	2.29	Chi-square to degrees of freedom ratio
RMSEA	0.05	Root mean square error of approximation
GFI	0.96	Goodness-of-fit index
AGFI	0.94	Adjusted goodness-of-fit index
PGFI	0.95	Parsimony goodness-of-fit index
SRMR	0.065	Standardized root mean square residual
NFI	0.93	Normed fit index
CFI	0.97	Comparative fit index

Based on the results presented, the measurement model has an acceptable fit. Although the chi-square value (1941.98) with 847 degrees of freedom is significant (P = 0.001), due to the sensitivity of this test to sample size, alternative criteria are of greater importance. The ratio ChiSqr/df = 2.29 falls within the acceptable range, that is, below 3, and indicates an appropriate model fit. The RMSEA value of 0.05 is also below 0.08, indicating a good model fit. In addition, the values of GFI = 0.96 and AGFI = 0.94 indicate a highly desirable overall model fit. The NFI = 0.93 and CFI = 0.97 indices also show that the model has strong comparative fit. The SRMR value of 0.06 is below 0.08 and confirms the appropriate quality of the residuals. Finally, the high PGFI value of 0.95 indicates that the principle of parsimony has been observed in the model. Overall, all indices indicate that the proposed structural model has desirable and reliable fit.

At this stage, the factor loadings of the indicators measured for each latent variable, that is, the observed variables, were examined. Factor loadings greater than 0.50 are desirable, and values below this threshold should be removed.

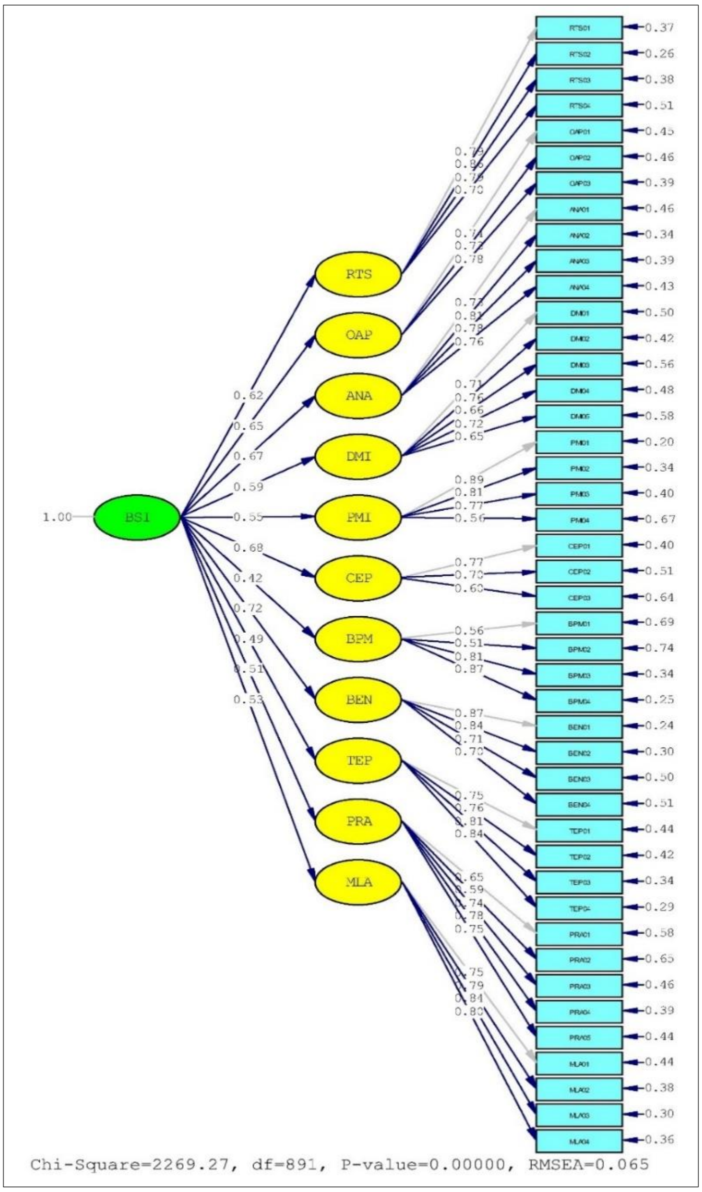

Figure 4. Confirmatory Factor Loadings of the Second-Order Model

As observed in the figure, the factor loadings of the items are greater than 0.50, confirming that the items can be used in the model.

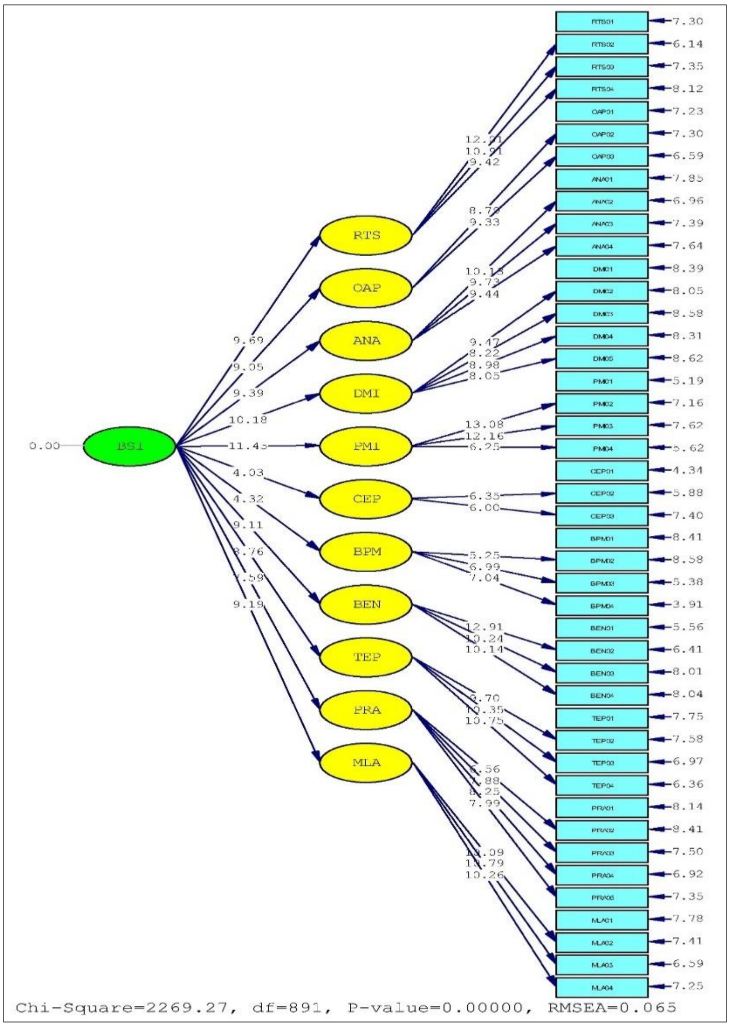

Figure 5. t-Statistic Values of the Second-Order Confirmatory Model

The overall research model was examined using model fit indices.

Table 4. Goodness of Fit of the Confirmatory Model

Symbol	Value	Index Title
Chi-square	2269.27	Chi-square statistic
Degrees of freedom	891	Model degrees of freedom
P value	0.001	Significance level of the chi-square test
ChiSqr/df	2.54	Chi-square to degrees of freedom ratio
RMSEA	0.065	Root mean square error of approximation
GFI	0.96	Goodness-of-fit index
AGFI	0.93	Adjusted goodness-of-fit index
PGFI	0.94	Parsimony goodness-of-fit index
SRMR	0.07	Standardized root mean square residual
NFI	0.92	Normed fit index
CFI	0.96	Comparative fit index

The presented results show that the structural model has an appropriate and acceptable fit. Although the chi-square value = 2269.27 with 891 degrees of freedom is significant (P = 0.001), given the sensitivity of this test to sample size, alternative indices are of greater importance. The ratio ChiSqr/df = 2.54 is lower than the criterion value of 3 and confirms the desirable fit of the model. The RMSEA value = 0.06 is lower than 0.08 and indicates an acceptable model fit. The GFI = 0.96 and AGFI = 0.93 indices are also above the criterion value of 0.90 and indicate a very good overall fit. The SRMR value = 0.07 is below 0.08 and indicates the appropriateness of the residual pattern. In addition, the NFI = 0.99 and CFI = 0.964 indices, both of which exceed the desirable value of 0.90, indicate the strong fit of the model compared with the independent model. Finally, the high PGFI value of 0.94 also shows that the model is in a desirable condition in terms of parsimony. Overall, all indices indicate that the proposed model has an appropriate and reliable fit.

In studies based on structural equation modeling, three indices, namely composite reliability (CR), Cronbach's alpha, and average variance extracted (AVE), are used to evaluate construct reliability and validity. Typically, Cronbach's alpha and composite reliability values should be greater than 0.70 for construct reliability to be considered acceptable, although values above 0.80 indicate stronger reliability. In addition, the AVE value should be greater than 0.50 to indicate that the construct explains more than half of the variance of its indicators and that convergent validity is established. If CR is higher than 0.70 and greater than AVE, and AVE also exceeds 0.50, it can be concluded that the construct has desirable validity and reliability.

Table 5. Construct Reliability

Variable	Composite Reliability	Cronbach's Alpha Coefficient	Average Variance Extracted
Application of reporting technologies	0.78	0.77	0.64
Online analytical processing	0.80	0.80	0.60
Analytics	0.70	0.72	0.64
Data mining	0.75	0.72	0.61
Process mining	0.83	0.80	0.65
Complex event processing	0.87	0.82	0.67
Business performance management	0.81	0.84	0.66
Benchmarking	0.81	0.78	0.64
Text processing	0.78	0.76	0.65
Predictive analytics	0.69	0.67	0.60
Multidimensional analysis	0.82	0.82	0.61

The composite reliability values of the research variables were confirmed because they are greater than the standard value of 0.70. This indicates that the model is acceptable in terms of external validity and that the structural dimensions of the model can be relied upon. According to the table above, Cronbach's alpha coefficients for all intended constructs are above 0.70, indicating the appropriate reliability of the model. It should also be noted that the convergent validity of the research model was confirmed because the AVE values for the variables were greater than 0.50.

The following model shows the path coefficient values and the coefficient of determination related to the structural relationships among the variables.

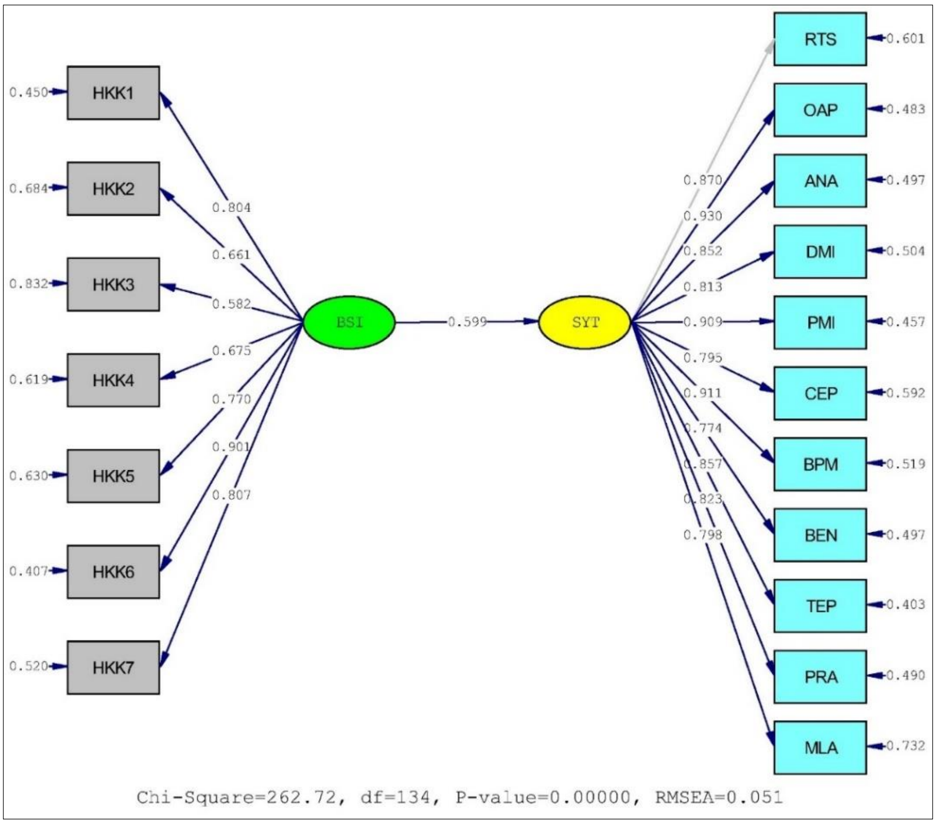

Figure 6. Path Coefficients of the Model

As observed, the factor loadings of the items are greater than 0.50, confirming that the items can be used in the model. The following figure shows the t-statistic values related to the structural relationships among the research variables.

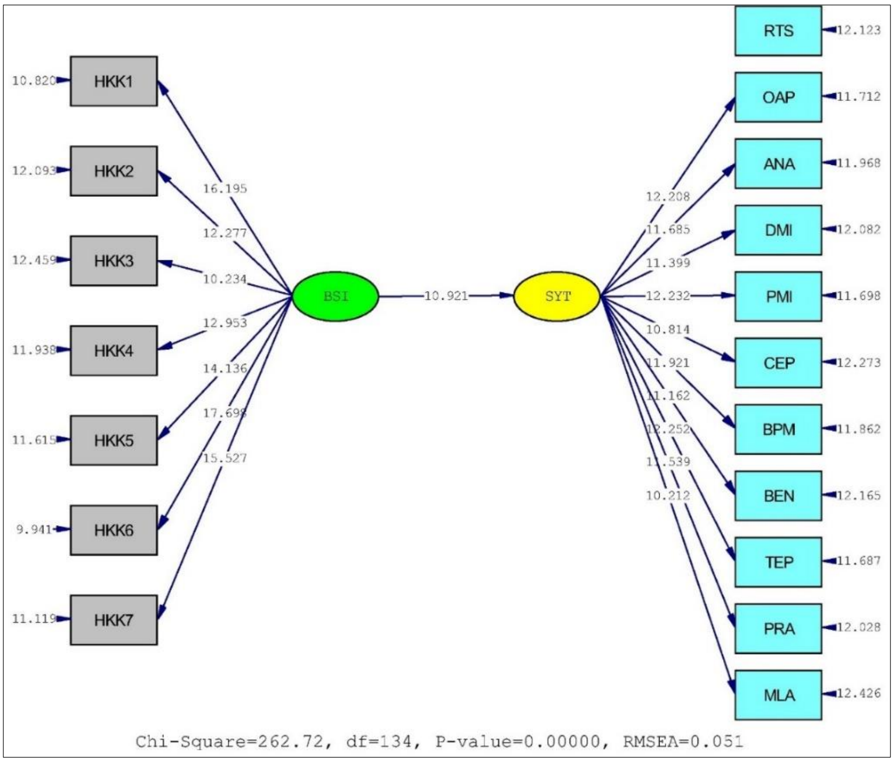

Figure 7. t-Statistic Values of the Model

The t-statistic value related to the path is greater than 1.96, confirming that the path coefficient values of the model are statistically significant.

The overall research model was examined using model fit indices.

Table 6. Goodness of Fit of the Structural Model

Symbol	Value	Index Title
Chi-square	262.72	Chi-square statistic
Degrees of freedom	134	Model degrees of freedom
P value	0.001	Significance level of the chi-square test
ChiSqr/df	1.961	Chi-square to degrees of freedom ratio
RMSEA	0.051	Root mean square error of approximation
GFI	0.98	Goodness-of-fit index
AGFI	0.92	Adjusted goodness-of-fit index
PGFI	0.91	Parsimony goodness-of-fit index
SRMR	0.073	Standardized root mean square residual
NFI	0.93	Normed fit index
CFI	0.94	Comparative fit index

The results of the fit indices show that the proposed model has an appropriate and acceptable status. The chi-square value = 262.72 with 134 degrees of freedom is significant (P = 0.001), which is expected given the sensitivity of this test to sample size. The ratio ChiSqr/df = 1.961 is lower than 2 and indicates a very good model fit. The RMSEA index = 0.051 is also below 0.08 and is on the boundary of excellent fit. The GFI = 0.98 and AGFI = 0.92 indices both exceed the criterion value of 0.90 and indicate a strong model fit. The SRMR value = 0.073 is below 0.08 and shows that the residuals are within the acceptable range. In addition, the NFI = 0.93 and CFI = 0.94 indices, which exceed the minimum acceptable value of 0.90, indicate the desirable comparative fit of the model. Finally, the PGFI value = 0.91 shows that the model follows the principle of parsimony and structural simplicity. Overall, all indices confirm that the model has an appropriate and reliable fit.

Unlike measurement models, the structural model section is not concerned with items or observed variables and examines only latent variables and the relationships among them.

R^2 is a criterion used to connect the measurement section and the structural section of structural equation modeling and indicates the effect that an exogenous variable has on an endogenous variable. The essential point is that the R^2 value is calculated only for dependent, or endogenous, constructs in the model, and for exogenous constructs, the value of this criterion is zero. The higher the R^2 value for the endogenous constructs of a model, the better the model fit. The value of this coefficient ranges from zero to one, with larger values being more desirable. Jain (1988) evaluates values close to 0.67 as desirable, values close to 0.33 as moderate, and values close to 0.19 as weak.

Table 7. Coefficient of Determination R^2

Variable	Coefficient of Determination R^2	Adjusted Coefficient of Determination R^2
Business intelligence	0.359	0.352

According to the table above, it can be stated that the R^2 values for all variables are at a moderate and acceptable level.

Predictive relevance (Q^2) determines the predictive power of the model. Models with acceptable structural fit must be capable of predicting the indicators related to the endogenous constructs of the model. Henseler et al. (2009) defined the three values of 0.02, 0.15, and 0.35 to indicate weak, moderate, and strong predictive power of the relevant exogenous construct or constructs. It is necessary to mention that this value is calculated only for the endogenous constructs of the model whose indicators are reflective.

Table 8. Predictive Relevance (Q^2)

Variable	Statistic Level 1-SSE/SSO
Business intelligence	0.476

According to the table above, the Q^2 value for the construct indicates that the model has strong predictive power regarding its indicators.

Table 9. Direct Effects Indices

Path	Path Coefficient	Standard Estimation Error	t-Statistic	p-value
Application of reporting technologies → Business intelligence	0.62	0.06	9.69	0.001
Online analytical processing → Business intelligence	0.65	0.07	9.05	0.001
Analytics → Business intelligence	0.67	0.07	9.39	0.001
Data mining → Business intelligence	0.59	0.06	10.18	0.001
Process mining → Business intelligence	0.55	0.05	11.45	0.001
Complex event processing → Business intelligence	0.68	0.17	4.03	0.001
Business performance management → Business intelligence	0.42	0.10	4.32	0.001
Benchmarking → Business intelligence	0.72	0.08	9.11	0.001
Text processing → Business intelligence	0.49	0.06	8.76	0.001
Predictive analytics → Business intelligence	0.51	0.07	7.59	0.001
Multidimensional analysis → Business intelligence	0.53	0.06	9.19	0.001

Based on the results of the direct effects table, the contribution of each factor affecting business intelligence based on systems thinking can be analyzed according to its standardized path coefficient. The larger the path coefficient, the greater the contribution and role of that factor in explaining business intelligence. According to the coefficients presented, the greatest effect belongs to benchmarking, with a coefficient of 0.72; this means that this component has the greatest contribution to strengthening business intelligence compared with other factors. It is followed by complex event processing (0.68) and analytics (0.67), both of which play strong and considerable roles. Online analytical processing (0.65) and the application of reporting technologies (0.62) also have a high contribution to this process. At the moderate level, data mining (0.59), process mining (0.55), multidimensional analysis (0.53), predictive analytics (0.51), and text processing (0.49) are placed. Finally, business performance management, with a path coefficient of 0.42, has the lowest contribution among the factors, although its effect is still significant and positive. Overall, all components have a significant and positive effect on business intelligence, but the intensity of their effects differs, with some analytical and comparative elements playing a more prominent role.

Discussion and Conclusion

The present study aimed to design and validate a business intelligence (BI) model grounded in systems thinking for small and medium-sized manufacturing enterprises in the oil and gas sector. The findings indicate that BI is a multidimensional organizational capability that extends beyond technological infrastructure to encompass human, analytical, and process-oriented components. Descriptive and inferential analyses demonstrated that all eleven model dimensions—reporting technologies, online analytical processing, analytics, data mining, process mining, complex event processing, business performance management, benchmarking, text processing, predictive analytics, and multidimensional analysis—positively and significantly contribute to the overall construct of business intelligence. Among these dimensions, benchmarking, complex event processing, and analytics exhibited the highest path coefficients, suggesting their relatively stronger role in enhancing organizational intelligence within small and medium-sized enterprises. This finding is consistent with prior research emphasizing the centrality of comparative analysis and process optimization for leveraging BI capabilities in performance improvement (5, 7).

The qualitative phase revealed that business intelligence operates as a systemically interconnected phenomenon, where technological, human, and knowledge-related factors interact to shape organizational decision-making and agility. The identification of eleven principal dimensions aligns with earlier theoretical propositions regarding the multidimensional nature of BI, where the integration of operational and strategic analytics, process management, and predictive capability creates an actionable intelligence system (1, 16, 17). The prominence of benchmarking in our results underscores the importance of external comparison and organizational learning as mechanisms for enhancing intelligence capacity. This is in line with the findings of Rezaei et al. (2018), who highlighted that organizational performance improvement is facilitated not merely by internal analysis but by aligning internal processes with external best practices. The high influence of complex event processing and analytics suggests that the ability to monitor, detect, and interpret real-time operational events is critical for manufacturing firms in volatile environments such as oil and gas, corroborating the emphasis on real-time monitoring and data-driven decision-making highlighted in studies on artificial intelligence-supported enterprise processes (3, 18).

The role of reporting technologies and online analytical processing, while slightly lower in effect compared to benchmarking and complex event processing, remains substantial, indicating the foundational importance of accurate data capture, structured reporting, and multidimensional analysis in supporting higher-order BI capabilities. This supports the assertion by Lim and Teoh (2020) that organizations with robust reporting frameworks and OLAP tools are better positioned to translate raw data into managerial insights. Moreover, predictive analytics emerged as a moderate yet significant contributor, confirming that anticipatory capabilities, such as forecasting demand, assessing potential failures, and risk modeling, are integral to a comprehensive BI system. These results align with Popovič et al. (2019), who noted that predictive and prescriptive analytics allow small and medium-sized enterprises to move from descriptive to forward-looking intelligence, thereby improving strategic decision-making.

The study's quantitative results, particularly confirmatory factor analysis and structural equation modeling outcomes, confirmed the reliability and validity of the proposed model. Composite reliability indices, Cronbach's alpha values, and average variance extracted all exceeded recommended thresholds, indicating that the constructs measured the intended latent variables effectively. These psychometric findings resonate with prior studies on BI measurement, emphasizing the need for reliable instruments to capture the multidimensional and systemic nature of organizational intelligence (12, 22). The high model fit indices (GFI, AGFI, CFI, NFI, RMSEA, SRMR, PGFI) further reinforce the adequacy of the systems-thinking-based framework, providing evidence that the interrelationships among technological, analytical, and process-oriented dimensions reflect real organizational patterns observed in SMEs operating under complex operational constraints.

The alignment of our results with previous research highlights the interplay between business intelligence, innovation, and dynamic capabilities. As indicated by Sartipzade et al. (2025), BI contributes to organizational performance when coupled with innovation ambidexterity and dynamic capabilities, enabling firms to exploit existing knowledge while exploring new opportunities. Our findings echo this view, as the interplay among data mining, process mining, analytics, and performance management illustrates how BI facilitates both operational efficiency and strategic adaptation. Additionally, the significance of BI in small and medium-sized manufacturing firms aligns with studies showing that even resource-constrained organizations can achieve competitive advantage when analytical systems are integrated with managerial decision-making, process monitoring, and external benchmarking (5, 6).

The findings also illustrate the practical implications of integrating artificial intelligence, machine learning, and real-time analytics into business intelligence systems. Dimensions such as complex event processing and predictive analytics directly incorporate AI-based insights to enhance responsiveness and foresight. This is consistent with contemporary literature emphasizing the transformative role of AI in enterprise intelligence, particularly in operationally complex sectors like oil and gas (3, 17, 18). Moreover, the moderate contribution of text processing highlights the increasing relevance of unstructured data in organizational decision-making, which aligns with Khedkar and Shinde (2018), who demonstrated that textual data analysis can reveal hidden customer insights and operational trends that support informed strategic choices.

Overall, the proposed model confirms that business intelligence in small and medium-sized enterprises is not an isolated technological implementation but a systemic capability requiring the integration of multiple dimensions. The results demonstrate that firms can enhance decision-making quality, operational agility, and performance outcomes by synergistically combining reporting, analytics, data mining, process monitoring, and predictive tools. These findings reinforce the perspective that business intelligence is both a strategic and operational capability that translates digital and human inputs into actionable insights (1, 2, 21). Furthermore, the identification of key dimensions and their relative contributions provides a roadmap for prioritizing resource allocation and technology adoption, especially in environments characterized by complexity, volatility, and competitive intensity.

Despite its contributions, this study has several limitations. First, the research was conducted in the context of small and medium-sized manufacturing enterprises in the oil and gas industry, which may limit the generalizability of the findings to other sectors or larger firms with different operational dynamics. Second, the study relied on cross-sectional data collection for the quantitative phase, which precludes strong causal inference and longitudinal assessment of business intelligence development over time. Third, while the qualitative phase employed purposive sampling and achieved theoretical saturation, the number of interviews and organizational contexts may have been insufficient to capture all variations in BI implementation practices, particularly in different geographic regions or organizational cultures. Fourth, the study focused on eleven dimensions identified through literature and expert interviews; other emergent factors, such as organizational culture, leadership, or regulatory compliance, may also influence BI effectiveness but were not explicitly included in the model.

Future research could address these limitations by conducting longitudinal studies to investigate the evolution of business intelligence capabilities over time and their impact on firm performance. Comparative studies across multiple sectors, including service-oriented and technology-intensive industries, would provide insight into the generalizability of the model and the relative importance of different dimensions in varying operational contexts. Additionally, incorporating organizational culture, leadership style, and regulatory influences as moderating variables could enrich the model and reveal contextual contingencies affecting BI effectiveness. Future studies might also examine the integration of emerging technologies such as the Internet of Things, blockchain, and cloud-based analytics into business intelligence systems, exploring their influence on real-time decision-making and predictive capacity. Mixed-methods designs could be further utilized to combine rich qualitative insights with largescale quantitative data, providing a holistic understanding of how small and medium-sized enterprises develop, implement, and leverage BI capabilities.

Practitioners in small and medium-sized enterprises should recognize that business intelligence is a systemic capability rather than a set of isolated tools. Firms should prioritize establishing robust reporting infrastructures and analytical platforms while investing in human capital development to interpret, integrate, and act upon data effectively. Benchmarking, complex event processing, and analytics should be strategically emphasized, as these dimensions were found to have the greatest impact on BI capability. Organizations should integrate predictive analytics and process monitoring into their decision-making routines to anticipate operational challenges and opportunities. Furthermore, the adoption of artificial intelligence and machine learning tools should be complemented by training and change management practices that enable employees to leverage these technologies for actionable insights. Continuous evaluation, feedback loops, and alignment with strategic objectives will ensure that business intelligence becomes a dynamic, performance-enhancing capability rather than a static technical implementation. Finally, managers should foster a data-driven organizational culture, encourage cross-functional collaboration, and maintain alignment between technological investments and strategic priorities to maximize the value derived from business intelligence systems.

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Authors’ Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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