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Identification and Prioritization of Factors Influencing AI- and Blockchain-Based Business Innovation in Golgohar Sirjan Iron Ore Company

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ABSTRACT

The purpose of this study was to identify and prioritize the factors influencing business innovation based on Artificial Intelligence (AI) and Blockchain Technology in Golgohar Sirjan Iron Ore Company. In terms of purpose, the study was applied research, and in terms of methodology, it employed an exploratory mixed-methods design. In the qualitative phase, data were collected through library research and semi-structured interviews with experts and specialists in relevant fields, leading to the extraction of the study's main components. Based on the findings of this phase, a researcher-developed questionnaire was designed for the quantitative phase and distributed among 384 employees of Golgohar Sirjan Iron Ore Company. Construct validity was assessed using factor analysis, as well as convergent and discriminant validity measures. The reliability of the instrument was confirmed through Cronbach's alpha, composite reliability, and the Rho coefficient. The results indicated that Cronbach's alpha values for all constructs exceeded 0.70, while the Average Variance Extracted (AVE) values for all variables were greater than 0.50. Data analysis was conducted using Structural Equation Modeling (SEM) through SPSS and SmartPLS software packages. In addition, the Fuzzy DEMATEL method was employed to prioritize the identified factors. The prioritization results revealed that several indicators related to the diversity of innovation resources, legal requirements and support mechanisms, risk assessment, intelligent managerial dashboards, and legal adaptability were among the most influential factors affecting the development of AI- and blockchain-based business innovation in Golgohar Sirjan Iron Ore Company. Overall, the findings demonstrate that the successful development of AI- and blockchain-driven business innovation in Golgohar Sirjan requires simultaneous attention to causal, contextual, intervening, strategic, and consequential factors. Such an approach can enhance decision-making processes, increase organizational agility, improve productivity, and strengthen the company's competitive advantage.

Keywords: Business Innovation, Artificial Intelligence, Blockchain Technology, Golgohar Sirjan Iron Ore Company, Fuzzy DEMATEL.

Introduction

In contemporary business environments, innovation is increasingly shaped by the convergence of digital technologies, intelligent analytics, distributed infrastructures, and data-driven decision-making systems. Organizations operating in capital-intensive and strategically important industries, such as mining and iron ore production, are under growing pressure to enhance productivity, improve operational transparency, reduce uncertainty, optimize resource allocation, and strengthen their competitive position through advanced technological transformation. Business innovation is no longer limited to the development of new products or services; rather, it includes the redesign of business models, decision-making processes, interorganizational relationships, value-chain mechanisms, and organizational learning systems. From this perspective, artificial intelligence and blockchain technology have emerged as two transformative technological domains that can fundamentally reshape the logic of business innovation by enabling intelligent prediction, secure information exchange, automation, transparency, decentralization, and trust-based coordination across organizational processes [1-3].

Artificial intelligence has become one of the core drivers of digital transformation because it enables organizations to transform large volumes of structured and unstructured data into actionable knowledge. Through machine learning, deep learning, predictive analytics, natural language processing, and intelligent decision-support systems, artificial intelligence allows firms to identify hidden patterns, predict market and operational trends, automate complex processes, and improve the quality and speed of managerial decisions. In business strategy, artificial intelligence is particularly important because it connects data infrastructure with strategic agility and innovation capability. Organizations that effectively integrate artificial intelligence into their strategic processes are better able to respond to environmental turbulence, personalize services, improve customer relationship management, and develop evidence-based business models [1, 4, 5].

The role of artificial intelligence in business innovation is also evident in its ability to strengthen customer-centered decision-making and enhance organizational responsiveness. For instance, intelligent systems can analyze online behavior, customer preferences, purchasing patterns, and sentiment data to support more accurate decision-making in marketing, service design, and product development. Research on sentiment-based systems has shown that hybrid fuzzy and deep neural network approaches can be used to measure customer satisfaction and generate more precise insights for managerial action [5]. Similarly, studies on intelligent online shopping behavior have demonstrated that artificial intelligence and Internet of Things-based decision systems can improve the interpretation of consumer behavior and support more adaptive e-business strategies [4]. Although these studies have mainly focused on service and retail settings, their implications are relevant to industrial organizations as well, because customer orientation, market responsiveness, and data-based decision-making are increasingly central to innovation in all sectors.

Blockchain technology represents another major pillar of digital business innovation. Unlike centralized information systems, blockchain provides a distributed, immutable, transparent, and cryptographically secured infrastructure for recording and sharing transactions. These features make blockchain highly relevant for organizations that require traceability, trust, accountability, and secure data exchange across complex networks. In business model innovation, blockchain can alter how firms create, deliver, and capture value by enabling decentralized coordination, smart contracts, tokenized assets, secure supply chains, and transparent interorganizational transactions [2, 6, 7]. Accordingly, blockchain is not merely a technical infrastructure but a strategic mechanism that can transform organizational governance, information sharing, and value-chain relationships.

One of the most important contributions of blockchain to business innovation concerns trust and security. In digital business ecosystems, organizations increasingly exchange sensitive operational, financial, technological, and customer-related data. Traditional centralized systems are vulnerable to manipulation, unauthorized access, and single points of failure. Blockchain-based architectures can reduce these risks by providing tamper-resistant records, decentralized validation, and enhanced data integrity. Research on privacy protection in blockchain systems has emphasized the importance of privacy-preserving mechanisms, secure protocols, and careful governance in distributed environments [7]. Similarly, studies on blockchain convergence with multimedia and Internet of Things systems have shown that blockchain can strengthen security, authentication, and data reliability, while also creating new research challenges related to scalability, interoperability, and system complexity [8]. These issues are highly relevant for industrial firms that depend on secure and continuous flows of operational data.

The integration of blockchain with Internet of Things infrastructures is especially significant for smart industries. In industrial environments, sensors, machines, enterprise platforms, and decision-support systems continuously generate and exchange data. This creates opportunities for real-time monitoring, predictive maintenance, automated quality control, and intelligent resource management, but it also creates risks related to cybersecurity, data ownership, and system reliability. Blockchain-assisted secure data-sharing models have been proposed as a way to improve trust and reliability in Internet of Things-based smart industries [9]. In addition, blockchain-based security mechanisms have been examined in advanced communication environments, indicating that distributed ledger technologies can support reliable service delegation and secure communication in future digital infrastructures [10]. These capabilities are particularly important for mining and iron ore companies, where large-scale operations, dispersed assets, and high-value supply chains require secure, transparent, and reliable data ecosystems.

The business value of blockchain is not restricted to cybersecurity. Blockchain can also support accessibility, traceability, transparency, and decentralization in commerce and supply-chain systems. For example, decentralized accessibility of e-commerce products through blockchain technology has been examined as a way to improve transparency and trust in digital transactions [6]. Blockchain applications in hospitality operations have also been discussed in relation to transaction transparency, operational efficiency, customer trust, and service innovation [11]. Although the hospitality and e-commerce sectors differ from the mining industry, the underlying managerial logic is transferable: blockchain can reduce information asymmetry, strengthen stakeholder trust, and create new forms of digitally enabled business processes. Therefore, blockchain-based innovation has the potential to support industrial companies in areas such as procurement, logistics, contract management, supply-chain traceability, quality assurance, and regulatory compliance.

The interaction between artificial intelligence and blockchain creates even broader possibilities for business innovation. Artificial intelligence provides analytical intelligence, prediction, automation, and decision optimization, while blockchain provides secure, transparent, decentralized, and traceable data infrastructures. When integrated, these technologies can help organizations develop intelligent and trustworthy business systems. Artificial intelligence depends on reliable and high-quality data, while blockchain can enhance the credibility, traceability, and security of data used by intelligent algorithms. Conversely, artificial intelligence can improve blockchain-based systems through fraud detection, anomaly identification, smart contract optimization, and predictive governance. In smart industrial contexts, the combination of these technologies can support intelligent decision-making, secure data sharing, automated risk assessment, and more resilient innovation ecosystems [1, 8, 9].

Digital business innovation also requires attention to organizational strategy and transformation frameworks. Technological adoption alone does not guarantee innovation unless it is aligned with enterprise architecture, managerial capabilities, organizational culture, and strategic objectives. Business transformation frameworks emphasize the need for holistic models that integrate technology, process redesign, governance structures, human resources, and strategic alignment [3]. This is particularly important in organizations such as Golgohar Sirjan Iron Ore Company, where innovation must be integrated into existing industrial processes, managerial routines, technological infrastructures, and regulatory requirements.

Without a coherent transformation framework, artificial intelligence and blockchain initiatives may remain isolated technical projects rather than becoming drivers of sustainable business innovation.

Innovation is also shaped by cooperation, networks, and institutional support. In many organizations, especially those operating in complex and resource-intensive sectors, innovation depends on collaboration with technology providers, research institutions, suppliers, customers, start-ups, and regulatory bodies. Cooperation for innovation provides opportunities for resource sharing, knowledge exchange, risk reduction, and joint value creation, but it also involves challenges such as coordination costs, capability gaps, and institutional barriers [12]. Therefore, identifying the factors that facilitate or hinder AI- and blockchain-based business innovation requires attention not only to technological variables but also to organizational, environmental, legal, cultural, and strategic conditions.

The importance of environmental and operational intelligence has also been highlighted in studies of Internet of Things-based business models. IoT-based e-business models in intelligent greenhouses, for example, demonstrate how connected technologies can support operational management, real-time data collection, process optimization, and intelligent business decision-making [13]. In industrial settings, similar principles can be applied to production monitoring, equipment management, energy consumption, logistics, and supply-chain control. Moreover, research on cloud datacenter support and renewable energy instability indicates that intelligent systems are increasingly needed to manage complex technological infrastructures and resource fluctuations [14]. For mining companies, where energy consumption, operational continuity, and resource optimization are central concerns, intelligent and secure digital systems can provide substantial strategic value.

Another important dimension of digital innovation concerns information integrity and misinformation control. In digital networks, misinformation, inaccurate data, and unreliable information flows can undermine decision-making and organizational trust. Research on multi-topic misinformation blocking in online social networks has shown that controlling unreliable information under resource constraints is a complex but necessary task [15]. Although this literature focuses on social networks, its implications extend to organizational decision systems, where inaccurate, incomplete, or manipulated data can produce serious operational and strategic consequences. For AI- and blockchain-based business innovation, the quality, credibility, and governance of information are critical because intelligent decisions are only as reliable as the data on which they are based.

Security-related applications of blockchain have also been examined in other connected environments, such as vehicular named data networks, where blockchain-based architectures have been proposed to enhance secure communication and data exchange [16]. Such studies demonstrate that blockchain can be adapted to diverse technical contexts in which distributed trust, authentication, and secure data transmission are required. For industrial organizations, these capabilities are relevant to machine-to-machine communication, logistics tracking, autonomous systems, and secure operational networks. As industrial firms move toward smart operations, the need for secure and interoperable digital infrastructures becomes increasingly important.

At the same time, business innovation must be evaluated from the perspective of market relationships and stakeholder value. The study of consumer-brand relationships in the hospitality industry indicates that customer perceptions, trust, emotional attachment, and relational quality influence business outcomes and competitive advantage [17]. Although the present study is situated in the iron ore industry rather than hospitality, the broader implication is that technological innovation must eventually contribute to value creation for stakeholders. In industrial companies, stakeholders may include customers, suppliers, employees, regulators, investors, and local communities. Therefore, AI- and blockchain-based business innovation should not be assessed only in technical terms; it should also be evaluated in relation to organizational performance, market responsiveness, transparency, trust, and long-term stakeholder relationships.

Despite the growing literature on artificial intelligence, blockchain, smart industries, and digital transformation, several gaps remain. First, many studies have examined artificial intelligence and blockchain separately, while fewer have addressed their combined role in business innovation. Second, existing research has often focused on service industries, e-commerce, smart cities, healthcare, communication networks, and Internet of Things systems, while less attention has been paid to mining and iron ore companies. Third, technological studies frequently emphasize technical architecture, security, or system performance, whereas management research requires a broader understanding of causal, contextual, intervening, strategic, and consequential factors. Fourth, organizations need not only to identify relevant factors but also to prioritize them in order to allocate resources, design implementation roadmaps, and develop effective innovation policies.

In this regard, Golgohar Sirjan Iron Ore Company provides a meaningful context for examining AI- and blockchain-based business innovation. As a major industrial organization, it operates in an environment characterized by large-scale production, complex supply chains, high capital intensity, technological requirements, market uncertainty, regulatory pressures, and increasing expectations for productivity and competitiveness. The successful implementation of artificial intelligence and blockchain in such a context requires the identification of technological, managerial, organizational, legal, cultural, infrastructural, and strategic factors. It also requires prioritization, because not all factors have the same level of influence or interaction within the innovation system. Therefore, a systematic model can help managers understand which factors should receive greater attention in planning and implementing AI- and blockchain-based business innovation.

Accordingly, the aim of this study is to identify and prioritize the factors influencing business innovation based on artificial intelligence and blockchain technology in Golgohar Sirjan Iron Ore Company.

Methodology

The data collection method in the qualitative phase was library-based. In this study, semi-structured interviews were used to collect data in order to identify the components of business innovation based on artificial intelligence and blockchain technology in Golgohar Sirjan Iron Ore Company. The statistical population in the quantitative phase consisted of the employees of Golgohar Sirjan Iron Ore Company. Considering the intended statistical population, the sampling method was non-probability random sampling, and the sample size was determined as 384 participants using G*Power software. In the quantitative phase, a researcher-developed questionnaire was designed for field data collection based on the criteria obtained from the qualitative phase. Moreover, in this study, a questionnaire was used to collect data for presenting customers' online purchasing behavior using artificial intelligence tools in the retail industry. This questionnaire was developed according to the number of indicators extracted from the characteristics of the influencing factors and was sent online to the participants. After confirming validity, including construct validity using factor analysis, and reliability, through the calculation of Cronbach's alpha coefficient, the questionnaire was provided to the respondents, and they were asked to answer the questions voluntarily if they were willing and interested.

Findings and Results

In the quantitative phase, by considering maximum variance and a 5% error level, it was determined that, in order to increase the questionnaire return rate and facilitate the research process, more than 400 questionnaires were distributed electronically. Of these, 384 respondents completed the questionnaire, and this number was used as the basis for analysis and hypothesis testing. In this study, the selected variables were examined based on a conceptual model. The normality of the data was assessed using skewness and kurtosis indices. The sample consisted of 384 respondents. The validity and reliability of the constructs were assessed using the measurement model and hypothesis testing, and model fit was evaluated through covariance-based structural equation modeling using SPSS version 20 and SmartPLS version 2. The use of structural equation modeling in measuring latent variables provided a better representation of the conceptual relationships. Cronbach's alpha and composite reliability were used to assess the reliability of the questionnaire. The reliability results for each variable showed that all values were greater than 0.70, indicating desirable reliability. Convergent and discriminant validity were used to assess validity. Table 1 presents the findings related to convergent validity. The results obtained for the convergent validity of the latent variables in the model were greater than 0.50; therefore, it can be stated that the convergent validity of the measurement models was desirable.

Table 1

Convergent Validity and Reliability of the Research Variables

Variable	Cronbach's Alpha	AVE	CR	Rho
Causal Factors	0.761	0.600	0.833	0.781
Contextual Factors	0.736	0.687	0.825	0.744
Intervening Factors	0.769	0.651	0.828	0.769
Strategies	0.793	0.678	0.734	0.731
Consequences	0.774	0.659	0.833	0.778
Core Phenomenon	0.736	0.682	0.845	0.745

According to the results presented in the table above, Cronbach's alpha values for all variables were greater than 0.70; therefore, all variables were confirmed in terms of reliability. The Average Variance Extracted (AVE) values were consistently greater than 0.50; thus, convergent validity was also confirmed. The Composite Reliability (CR) values were greater than both AVE and 0.70, indicating that each construct in the model had appropriate validity and reliability. Moreover, the homogeneous reliability coefficient, Rho, was also found to be higher than 0.70.

On the other hand, discriminant validity refers to the extent of the relationship between a construct and its indicators compared with the relationship between that construct and other constructs. In other words, acceptable discriminant validity in a model indicates that a construct has stronger interactions with its own indicators than with other constructs. Discriminant validity is acceptable when the AVE value for each construct is greater than the shared variance between that construct and other constructs, that is, the squared correlation coefficients between constructs in the model. This issue is examined using a matrix in which the cells contain the correlation coefficients between constructs and the square roots of the AVE values for each construct. The model has acceptable discriminant validity when the values on the main diagonal are greater than the values below them. The main characteristic of this matrix is that the main diagonal is initially equal to one. Then, the values on the main diagonal are replaced with the square roots of the AVE values, and finally Table 2 is presented.

Table 2

Fornell–Larcker Method

Variable	Causal Factors	Contextual Factors	Intervening Factors	Strategies	Consequences	Core Phenomenon
Causal Factors	0.774					
Contextual Factors	0.551	0.828				
Intervening Factors	0.478	0.598	0.806			
Strategies	0.418	0.474	0.536	0.823		
Consequences	0.513	0.509	0.587	0.470	0.811	
Core Phenomenon	0.613	0.591	0.480	0.401	0.503	0.825

As shown in Table 2, the values on the main diagonal of the matrix are greater than all the values in their corresponding columns, indicating that the model has appropriate discriminant validity. Recent research by Henseler et al. (2015) showed that the Fornell–Larcker criterion does not perform well when the factor loadings of the constructs differ only slightly from one another. Therefore, Henseler et al. proposed the HTMT criterion as an alternative. If all values reported in the columns using this method are less than 0.90, the model has appropriate discriminant validity.

Table 3

Results of the HTMT Method for Assessing Discriminant Validity

Variable	Causal Factors	Contextual Factors	Intervening Factors	Strategies	Consequences	Core Phenomenon
Causal Factors						
Contextual Factors	0.737					
Intervening Factors	0.620	0.797				
Strategies	0.430	0.573	0.711			
Consequences	0.748	0.684	0.485	0.739		
Core Phenomenon	0.414	0.710	0.638	0.592	0.630	

According to Table 3, since the obtained values are less than 0.90, HTMT-based discriminant validity is accepted.

After ensuring the adequacy of the measurement models through reliability, convergent validity, and discriminant validity tests, the results of the structural model can be presented. In the structural section of the model, unlike the measurement models, the questions and observed variables are not considered, and only the latent variables and the relationships among them are examined. To assess model fit, structural model fit indices, including the (R^2) criterion, the (F^2) effect size criterion, and the (Q^2) criterion, are used.

This criterion is related to the overall section of structural equation models. This means that through this criterion, after examining the fit of both the measurement and structural sections of the model, the researcher can also assess the overall fit of the research model. The GOF criterion was introduced by Tenenhaus et al. (2005) and is calculated using the following formula:

$$GOF = \sqrt{Avg(Communalities) \times R^2}$$

In this formula, Communalities represents the mean of the communality values of each construct, and R^2represents the mean value of the explained variance of the endogenous constructs in the model.

Wetzels et al. (2009) introduced three values, namely 0.01, 0.25, and 0.36, as weak, moderate, and strong values for GOF, respectively. The GOF criterion was calculated as follows:

$$Avg(R^2) = 0.374$$

$$GOF = \sqrt{0.856 \times 0.20} = 0.413$$

Therefore, based on the GOF index, the model is also confirmed.

The second category of findings in this study examined the structural model test. After confirming validity and reliability, the structural model of the research was evaluated. Using this model, the research models can be examined. Figure 1 presents the results obtained from the output of SmartPLS 2 software. According to this model, the factor loadings were significant at the 95% confidence level, and all t-statistic values were outside the interval of $-1.96$to $+1.96$.

Figure 1

Structural Model of the Research in the Significance State

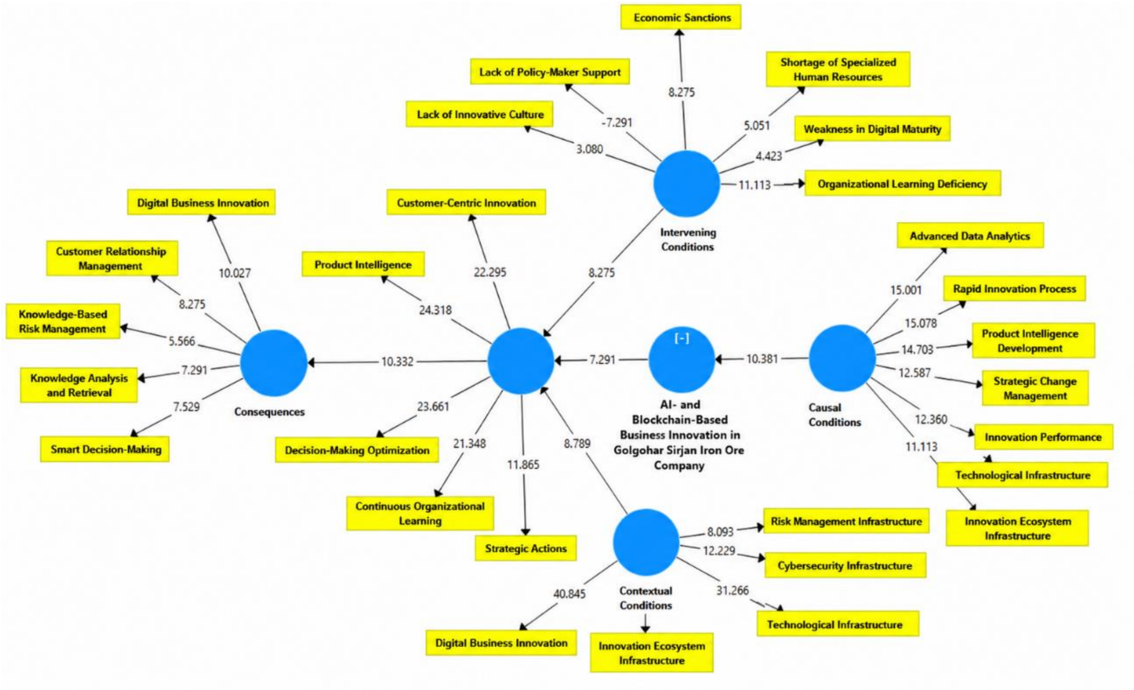
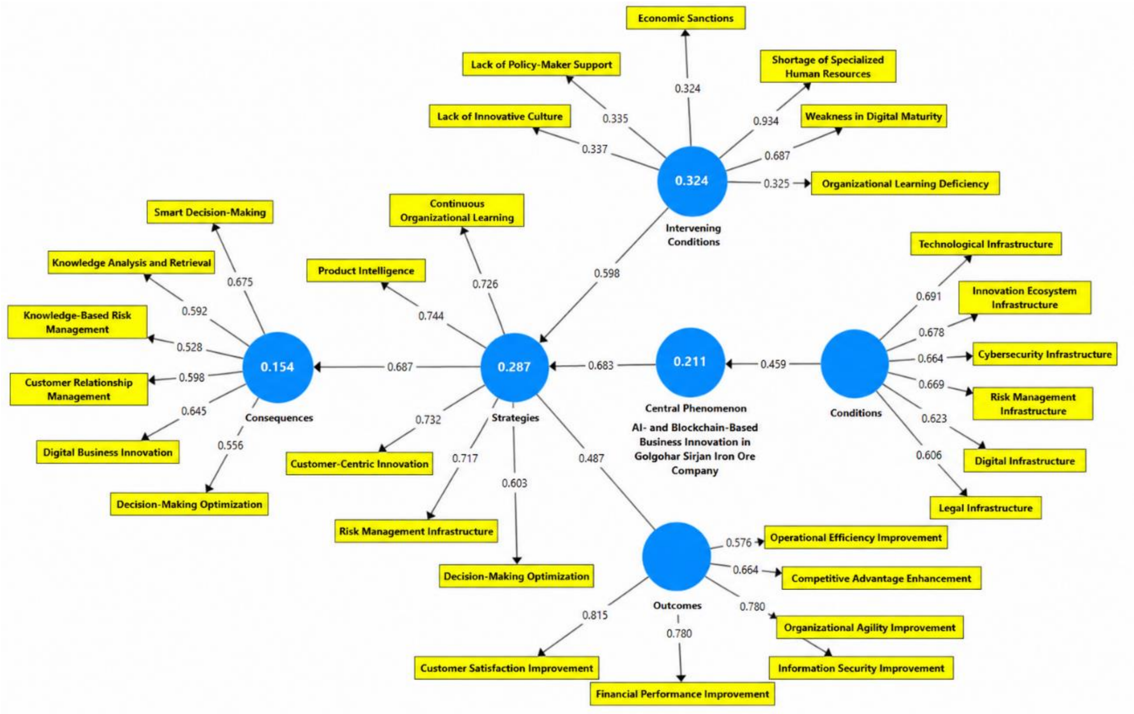


Figure 2

Structural Model of the Research in the Standardized State



The quantitative findings of the study showed that all relationships proposed in the conceptual model were positive and significant. Based on the results of structural equation modeling, causal conditions had a positive and significant effect on the core phenomenon. In addition, the core phenomenon affected strategies, and this relationship was also statistically confirmed as significant. Furthermore, the results showed that strategies had a positive and significant effect on the research consequences. Moreover, the effect of intervening conditions on strategies was positive and significant. Contextual conditions also had a positive and significant effect on strategies. Therefore, considering the significance of the relationships among the variables, it can be concluded that the main research hypotheses were confirmed. On the other hand, the overall model fit index also indicated the desirable fit of the research model, showing that the proposed model had adequate explanatory power for examining business innovation based on artificial intelligence and blockchain technology in Golgohar Sirjan Iron Ore Company.

Table 3

Results of the Hypotheses

Row	Hypothesis	Path Coefficient	t-Statistic	Significance Level	Status
1	Causal conditions have a significant effect on the main category.	0.459	10.381	0.000	Confirmed
2	The main category has a significant effect on strategies.	0.663	7.291	0.000	Confirmed
3	Strategies have a significant effect on consequences.	0.687	10.332	0.000	Confirmed
4	Intervening conditions have a significant effect on strategies.	0.598	8.275	0.000	Confirmed
5	Contextual conditions have a significant effect on strategies.	0.467	8.789	0.000	Confirmed

To identify the pattern of relationships among $n$criteria, an $n \times n$matrix is first constructed. The influence of the element in each row on the elements in the columns is entered into this matrix as a fuzzy number. If the viewpoints of more than one expert are used, each expert must complete the matrix. Then, the simple average of the opinions is used, and the direct-relation matrix $Z$is formed.

$$Z = \begin{bmatrix} 0 & \cdots & \tilde{z}_{n1} \\ \vdots & \ddots & \vdots \\ \tilde{z}_{1n} & \cdots & 0 \end{bmatrix}$$

The following table presents the direct-relation matrix, which represents the experts' pairwise comparisons. If several experts were used in the evaluation, the matrix below represents the arithmetic mean of all experts' judgments.

The fuzzy scale used in Table 4 is also presented below.

Table 4

Fuzzy Scale

Code	Linguistic Term	L	M	U
1	No influence	0	0	0.25
2	Very low influence	0	0.25	0.50
3	Low influence	0.25	0.50	0.75
4	High influence	0.50	0.75	1
5	Very high influence	0.75	1	1

Step 2: Normalizing the fuzzy direct-relation matrix

The following equation is used to normalize the fuzzy direct-relation matrix:

$$\tilde{x}_{ij} = \frac{\tilde{z}_{ij}}{r} = \left(\frac{l_{ij}}{r}, \frac{m_{ij}}{r}, \frac{u_{ij}}{r}\right)$$

where:

$$r = \max_{i,j}\left\{\max_{i} \sum\nolimits_{j=1}^{n} u_{ij}, \max_{j} \sum\nolimits_{i=1}^{n} u_{ij}\right\}, i, j \in \{1,2,3, \dots, n\}$$

Step 3: Calculating the fuzzy total-relation matrix

In this step, the fuzzy total-relation matrix is formed using the following equation:

$$\tilde{T} = \lim_{k \to +\infty} (\tilde{x}^1 \oplus \tilde{x}^2 \oplus \cdots \oplus \tilde{x}^k)$$

If each fuzzy element of the total-relation matrix is expressed as:

$$\tilde{t}_{ij} = \left(l''_{ij}, m''_{ij}, u''_{ij}\right)$$

then it is calculated as follows:

$$[l''_{ij}] = x_l \times (I - x_l)^{-1}$$
$$[m''_{ij}] = x_m \times (I - x_m)^{-1}$$
$$[u''_{ij}] = x_u \times (I - x_u)^{-1}$$

In other words, first the inverse of the normalized matrix is calculated, then it is subtracted from matrix I, and finally the normalized matrix is multiplied by the resulting matrix. The following table shows the fuzzy total-relation matrix.

Fuzzy Total-Relation Matrix

Step 4: Defuzzification of the values of the total-relation matrix

The CFCS method proposed by Opricovic and Tzeng was used for defuzzification. The stages of the defuzzification method are as follows:

$$l^n_{ij} = \frac{l^t_{ij} - \min l^t_{ij}}{\Delta_{\min}}$$
$$m^n_{ij} = \frac{m^t_{ij} - \min l^t_{ij}}{\Delta_{\min}}$$
$$u^n_{ij} = \frac{u^t_{ij} - \min l^t_{ij}}{\Delta_{\min}}$$

where:

$$\Delta_{\min} = \max u^t_{ij} - \min l^t_{ij}$$

Calculation of the upper and lower bounds of the normalized values:

$$l^s_{ij} = \frac{m^n_{ij}}{1 + m^n_{ij} - l^n_{ij}}$$
$$u^s_{ij} = \frac{u^n_{ij}}{1 + u^n_{ij} - l^n_{ij}}$$

The output of the CFCS algorithm is a matrix with crisp values.

Calculation of the total normalized crisp values:

$$x_{ij} = \frac{l_{ij}^{s}(1 - l_{ij}^{s}) + u_{ij}^{s} \times u_{ij}^{s}}{1 - l_{ij}^{s} + u_{ij}^{s}}$$

The following table shows the defuzzified values of the total-relation matrix.

Table 5

Crisp Total-Relation Matrix

Criterion Name	Criterion Type	Criterion Weight
Level of use of machine learning algorithms	+	(1.000, 1.000, 1.000)
Accuracy of predictive analytical models	+	(1.000, 1.000, 1.000)
Diversity of business innovation resources used	+	(1.000, 1.000, 1.000)
Response time of analytical systems	+	(1.000, 1.000, 1.000)
Level of intelligence of managerial dashboards	+	(1.000, 1.000, 1.000)
Number of commercialized business innovations per year	+	(1.000, 1.000, 1.000)
Average time from development to product launch	+	(1.000, 1.000, 1.000)
Percentage of investment in research and development	+	(1.000, 1.000, 1.000)
Product adaptability index to market changes	+	(1.000, 1.000, 1.000)
Number of ongoing business innovation-based projects	+	(1.000, 1.000, 1.000)
Percentage of process automation using business innovation	+	(1.000, 1.000, 1.000)
Organizational maturity level in using business innovation	+	(1.000, 1.000, 1.000)
Cost savings resulting from the application of business innovation	+	(1.000, 1.000, 1.000)
Percentage of key decisions based on business innovation	+	(1.000, 1.000, 1.000)
Extent of organizational business innovation documentation	+	(1.000, 1.000, 1.000)
Number of interactions on business innovation exchange platforms	+	(1.000, 1.000, 1.000)
Rate of business innovation retrieval during decision-making	+	(1.000, 1.000, 1.000)
Extent of business innovation training based on internal experiences	+	(1.000, 1.000, 1.000)
Average obsolescence time of the technologies used	+	(1.000, 1.000, 1.000)
Number of technology updates per year	+	(1.000, 1.000, 1.000)
Compatibility index with emerging technologies	+	(1.000, 1.000, 1.000)
Dependence rate on legacy technologies	+	(1.000, 1.000, 1.000)
Costs arising from adaptation to new technologies	+	(1.000, 1.000, 1.000)
Percentage of customized products/services relative to total production	+	(1.000, 1.000, 1.000)
Ability to adapt products to individual customer needs	+	(1.000, 1.000, 1.000)
Percentage of customer satisfaction with customized services	+	(1.000, 1.000, 1.000)
Percentage of processes based on modular design	+	(1.000, 1.000, 1.000)
Exchange rate volatility	+	(1.000, 1.000, 1.000)
Annual inflation of goods and services	+	(1.000, 1.000, 1.000)
Volatility of the stock market and investment index	+	(1.000, 1.000, 1.000)
Organizational credit and financial risk	+	(1.000, 1.000, 1.000)
Unemployment rate of skilled labor	+	(1.000, 1.000, 1.000)
Lack of specialized training	+	(1.000, 1.000, 1.000)
Migration of skilled labor	+	(1.000, 1.000, 1.000)
Gap between business innovation knowledge and industry	+	(1.000, 1.000, 1.000)
Weakness in soft skills	+	(1.000, 1.000, 1.000)
Limitation in talent attraction	+	(1.000, 1.000, 1.000)
Lack of digital infrastructure	+	(1.000, 1.000, 1.000)
Lack of a digital roadmap	+	(1.000, 1.000, 1.000)
Limited use of technology	+	(1.000, 1.000, 1.000)
Resistance to digital change	+	(1.000, 1.000, 1.000)
Traditional technology management	+	(1.000, 1.000, 1.000)
Lack of financial incentives	+	(1.000, 1.000, 1.000)
Ambiguous laws	+	(1.000, 1.000, 1.000)
Weakness in innovation policies	+	(1.000, 1.000, 1.000)
Lack of support for start-ups	+	(1.000, 1.000, 1.000)

Political instability	+	(1.000, 1.000, 1.000)
Bureaucratic structure	+	(1.000, 1.000, 1.000)
Lack of continuous updating	+	(1.000, 1.000, 1.000)
Lack of learning motivation	+	(1.000, 1.000, 1.000)
Lack of business innovation	+	(1.000, 1.000, 1.000)
Lack of team learning	+	(1.000, 1.000, 1.000)
Fear of failure	+	(1.000, 1.000, 1.000)
Failure to reward innovation	+	(1.000, 1.000, 1.000)
Conservative decision-making	+	(1.000, 1.000, 1.000)
Lack of employee participation	+	(1.000, 1.000, 1.000)
Exclusive focus on productivity	+	(1.000, 1.000, 1.000)
Access to high-speed internet	+	(1.000, 1.000, 1.000)
Business innovation and cloud computing centers	+	(1.000, 1.000, 1.000)
Organizational smart equipment	+	(1.000, 1.000, 1.000)
Business innovation-based platforms	+	(1.000, 1.000, 1.000)
Technological compatibility	+	(1.000, 1.000, 1.000)
Business innovation protection laws	+	(1.000, 1.000, 1.000)
Ethical framework for business innovation	+	(1.000, 1.000, 1.000)
Legal adaptability	+	(1.000, 1.000, 1.000)
Transparency of intellectual property rights	+	(1.000, 1.000, 1.000)
Regulatory legal structure	+	(1.000, 1.000, 1.000)
Availability of venture capital	+	(1.000, 1.000, 1.000)
Tolerance of failure in organizational culture	+	(1.000, 1.000, 1.000)
Entrepreneurship support policies	+	(1.000, 1.000, 1.000)
Risk management training	+	(1.000, 1.000, 1.000)
Risk prediction systems	+	(1.000, 1.000, 1.000)
Business innovation encryption systems	+	(1.000, 1.000, 1.000)
Digital security training	+	(1.000, 1.000, 1.000)
Intrusion detection tools	+	(1.000, 1.000, 1.000)
Information security policies	+	(1.000, 1.000, 1.000)
Continuous backup system	+	(1.000, 1.000, 1.000)
Open innovation networks	+	(1.000, 1.000, 1.000)
Culture of participation and team orientation	+	(1.000, 1.000, 1.000)
Policies supporting collaborative innovation	+	(1.000, 1.000, 1.000)
Accelerators and innovation centers	+	(1.000, 1.000, 1.000)
Prediction accuracy of the model	+	(1.000, 1.000, 1.000)
Process automation	+	(1.000, 1.000, 1.000)
Adaptive learning of the algorithm	+	(1.000, 1.000, 1.000)
Reduction of human error	+	(1.000, 1.000, 1.000)
Increased speed of business innovation analysis	+	(1.000, 1.000, 1.000)
Rapid circulation of business innovation	+	(1.000, 1.000, 1.000)
Continuous updating of information	+	(1.000, 1.000, 1.000)
Sharing of digital business innovation	+	(1.000, 1.000, 1.000)
Learning from error	+	(1.000, 1.000, 1.000)
Business innovation agility	+	(1.000, 1.000, 1.000)
Design based on user experience	+	(1.000, 1.000, 1.000)
Use of customer feedback	+	(1.000, 1.000, 1.000)
Use of customer feedback	+	(1.000, 1.000, 1.000)
Customized development	+	(1.000, 1.000, 1.000)
Customer sentiment analysis	+	(1.000, 1.000, 1.000)
Open innovation with customers	+	(1.000, 1.000, 1.000)
Cost calculation of e-learning systems	+	(1.000, 1.000, 1.000)
Culture of lifelong learning	+	(1.000, 1.000, 1.000)
Constructive internal feedback	+	(1.000, 1.000, 1.000)
Documentation of business innovation	+	(1.000, 1.000, 1.000)
Environmental adaptive learning	+	(1.000, 1.000, 1.000)
Decision-making based on business innovation	+	(1.000, 1.000, 1.000)
Cost calculation rate of business innovation assistant algorithms	+	(1.000, 1.000, 1.000)
Analysis of different scenarios	+	(1.000, 1.000, 1.000)
Business innovation decision-making	+	(1.000, 1.000, 1.000)
Product differentiation	+	(1.000, 1.000, 1.000)
Protection of innovation	+	(1.000, 1.000, 1.000)

Increased customer loyalty	+	(1.000, 1.000, 1.000)
Higher productivity	+	(1.000, 1.000, 1.000)
Rapid market response	+	(1.000, 1.000, 1.000)
Rapid structural changeability	+	(1.000, 1.000, 1.000)
Process flexibility	+	(1.000, 1.000, 1.000)
Real-time decision-making	+	(1.000, 1.000, 1.000)
Cross-functional collaboration	+	(1.000, 1.000, 1.000)
Rapid learning from the environment	+	(1.000, 1.000, 1.000)
Production of new business innovation	+	(1.000, 1.000, 1.000)
Commercialization of business innovation	+	(1.000, 1.000, 1.000)
Continuous process improvement	+	(1.000, 1.000, 1.000)
Effective transfer of business innovation	+	(1.000, 1.000, 1.000)
Innovation in the business model	+	(1.000, 1.000, 1.000)
Identification of emerging risks	+	(1.000, 1.000, 1.000)
Assessment of probability and consequences	+	(1.000, 1.000, 1.000)
Continuous risk monitoring	+	(1.000, 1.000, 1.000)
Cost calculation of customer satisfaction	+	(1.000, 1.000, 1.000)
Retention of key customers	+	(1.000, 1.000, 1.000)
Rapid response to requests	+	(1.000, 1.000, 1.000)
Customer preference orientation	+	(1.000, 1.000, 1.000)
Customer behavior analysis	+	(1.000, 1.000, 1.000)
Rapid recovery from crisis	+	(1.000, 1.000, 1.000)
Security of business innovation and systems	+	(1.000, 1.000, 1.000)
Compatibility with modern technologies	+	(1.000, 1.000, 1.000)
Continuity of digital business innovation operations	+	(1.000, 1.000, 1.000)
Strengthening the culture of business innovation acceptance	+	(1.000, 1.000, 1.000)

Step 5: Threshold calculations

All values in the crisp total-relation matrix that are lower than the mean of the total-relation matrix are identified and set to zero using the following equation. In other words, that causal relationship is not considered.

$$TS = \frac{\sum_{i=1}^{n} \sum_{j=1}^{m} V_{ij}}{m \times n}$$

$$U_{ij} = \begin{cases} V_{ij}, & V_{ij} \geq TS \\ 0, & \text{otherwise} \end{cases}$$

The following table presents the total-relation matrix after removing the values below the threshold. Based on the table below, causal relationships among the elements are drawn. The threshold value (TS)in this study was equal to 0.05.

Step 6: Final output and development of the causal diagram

The next step is to obtain the sums of the rows and columns of matrix T. The row sums $(D)$and column sums $(R)$are obtained using the following formulas:

$$D = \sum_{j=1}^{n} T_{ij}$$

$$R = \sum_{i=1}^{n} \tilde{T}_{ij}$$

Then, based on $D$and R, the values of $D + R$and $D - R$are calculated. These values indicate the degree of interaction and the influence power of the factors, respectively. The final output is presented in Table 6.

Table 6

Final Output

R	D	D + R	D – R	Criterion Name
1.943	2.329	4.272	0.386	Level of use of machine learning algorithms
1.858	1.931	3.789	0.073	Accuracy of predictive analytical models
1.956	2.551	4.508	0.595	Diversity of business innovation resources used
1.982	2.342	4.324	0.360	Response time of analytical systems
2.556	2.363	4.919	-0.193	Level of intelligence of managerial dashboards
1.985	1.757	3.742	-0.228	Number of commercialized business innovations per year
1.918	1.779	3.698	-0.139	Average time from development to product launch
2.160	2.450	4.610	0.290	Percentage of investment in research and development
2.287	2.439	4.726	0.153	Product adaptability index to market changes
2.161	2.027	4.188	-0.134	Number of ongoing business innovation-based projects
2.197	2.076	4.273	-0.121	Percentage of process automation using business innovation
1.840	2.112	3.953	0.272	Organizational maturity level in using business innovation
2.286	2.252	4.538	-0.034	Cost savings resulting from the application of business innovation
2.187	2.181	4.369	-0.006	Percentage of key decisions based on business innovation
2.551	2.306	4.858	-0.245	Extent of organizational business innovation documentation
2.100	1.886	3.986	-0.214	Number of interactions on business innovation exchange platforms
2.293	2.162	4.455	-0.131	Rate of business innovation retrieval during decision-making
2.157	2.262	4.419	0.105	Extent of business innovation training based on internal experiences
2.361	2.235	4.596	-0.126	Average obsolescence time of the technologies used
2.300	1.928	4.228	-0.372	Number of technology updates per year
2.175	1.888	4.063	-0.287	Compatibility index with emerging technologies
2.371	2.063	4.435	-0.308	Dependence rate on legacy technologies
1.872	2.276	4.148	0.404	Costs arising from adaptation to new technologies
2.097	1.999	4.096	-0.098	Percentage of customized products/services relative to total production
2.100	1.886	3.986	-0.214	Ability to adapt products to individual customer needs
2.293	2.162	4.455	-0.131	Percentage of customer satisfaction with customized services
2.157	2.262	4.419	0.105	Percentage of processes based on modular design
2.361	2.235	4.596	-0.126	Exchange rate volatility
2.300	1.928	4.228	-0.372	Annual inflation of goods and services
2.175	1.888	4.063	-0.287	Volatility of the stock market and investment index
2.371	2.063	4.435	-0.308	Organizational credit and financial risk
1.872	2.276	4.148	0.404	Unemployment rate of skilled labor
2.040	2.283	4.322	0.243	Lack of specialized training
2.027	2.146	4.173	0.119	Migration of skilled labor
2.404	2.224	4.628	-0.181	Gap between business innovation knowledge and industry
2.149	1.911	4.059	-0.238	Weakness in soft skills
1.806	1.947	3.753	0.141	Limitation in talent attraction
2.023	1.998	4.021	-0.025	Lack of digital infrastructure
1.877	1.789	3.666	-0.088	Lack of a digital roadmap
2.036	1.878	3.914	-0.158	Limited use of technology
2.106	1.953	4.059	-0.154	Resistance to digital change
1.991	2.022	4.013	0.030	Traditional technology management
2.025	2.146	4.172	0.121	Lack of financial incentives
1.695	1.980	3.675	0.285	Ambiguous laws
2.208	1.861	4.069	-0.347	Weakness in innovation policies
2.006	2.093	4.099	0.087	Lack of support for start-ups
2.128	2.066	4.193	-0.062	Political instability
1.691	1.821	3.512	0.130	Bureaucratic structure
1.848	1.936	3.784	0.088	Lack of continuous updating
2.050	2.056	4.106	0.006	Lack of learning motivation
2.027	2.146	4.173	0.119	Lack of business innovation
2.404	2.224	4.628	-0.181	Lack of team learning
2.149	1.911	4.059	-0.238	Fear of failure
1.806	1.947	3.753	0.141	Failure to reward innovation
2.023	1.998	4.021	-0.025	Conservative decision-making
1.877	1.789	3.666	-0.088	Lack of employee participation
2.036	1.878	3.914	-0.158	Exclusive focus on productivity

2.106	1.953	4.059	-0.154	Access to high-speed internet
1.991	2.022	4.013	0.030	Business innovation and cloud computing centers
2.025	2.146	4.172	0.121	Organizational smart equipment
1.943	2.329	4.272	0.386	Business innovation-based platforms
1.858	1.931	3.789	0.073	Technological compatibility
1.956	2.551	4.508	0.595	Business innovation protection laws
1.982	2.342	4.324	0.360	Ethical framework for business innovation
2.556	2.363	4.919	-0.193	Legal adaptability
1.985	1.757	3.742	-0.228	Transparency of intellectual property rights
1.918	1.779	3.698	-0.139	Regulatory legal structure
2.160	2.450	4.610	0.290	Availability of venture capital
2.287	2.439	4.726	0.153	Tolerance of failure in organizational culture
2.161	2.027	4.188	-0.134	Entrepreneurship support policies
2.197	2.076	4.273	-0.121	Risk management training
1.840	2.112	3.953	0.272	Risk prediction systems
2.286	2.252	4.538	-0.034	Business innovation encryption systems
2.187	2.181	4.369	-0.006	Digital security training
2.551	2.306	4.858	-0.245	Intrusion detection tools
2.100	1.886	3.986	-0.214	Information security policies
2.293	2.162	4.455	-0.131	Continuous backup system
2.157	2.262	4.419	0.105	Open innovation networks
2.361	2.235	4.596	-0.126	Culture of participation and team orientation
2.300	1.928	4.228	-0.372	Policies supporting collaborative innovation
2.175	1.888	4.063	-0.287	Accelerators and innovation centers
2.371	2.063	4.435	-0.308	Prediction accuracy of the model
1.872	2.276	4.148	0.404	Process automation
2.097	1.999	4.096	-0.098	Adaptive learning of the algorithm
2.100	1.886	3.986	-0.214	Reduction of human error
2.293	2.162	4.455	-0.131	Increased speed of business innovation analysis
2.157	2.262	4.419	0.105	Rapid circulation of business innovation
2.361	2.235	4.596	-0.126	Continuous updating of information
2.300	1.928	4.228	-0.372	Sharing of digital business innovation
2.175	1.888	4.063	-0.287	Learning from error
2.371	2.063	4.435	-0.308	Business innovation agility
1.872	2.276	4.148	0.404	Design based on user experience
2.040	2.283	4.322	0.243	Use of customer feedback
2.027	2.146	4.173	0.119	Use of customer feedback
2.404	2.224	4.628	-0.181	Customized development
2.149	1.911	4.059	-0.238	Customer sentiment analysis
1.806	1.947	3.753	0.141	Open innovation with customers
2.023	1.998	4.021	-0.025	Cost calculation of e-learning systems
1.877	1.789	3.666	-0.088	Culture of lifelong learning
2.036	1.878	3.914	-0.158	Constructive internal feedback
2.106	1.953	4.059	-0.154	Documentation of business innovation
1.991	2.022	4.013	0.030	Environmental adaptive learning
2.025	2.146	4.172	0.121	Decision-making based on business innovation
1.695	1.980	3.675	0.285	Cost calculation rate of business innovation assistant algorithms
2.208	1.861	4.069	-0.347	Analysis of different scenarios
2.006	2.093	4.099	0.087	Business innovation decision-making
2.128	2.066	4.193	-0.062	Product differentiation
1.691	1.821	3.512	0.130	Protection of innovation
1.848	1.936	3.784	0.088	Increased customer loyalty
2.050	2.056	4.106	0.006	Higher productivity
2.027	2.146	4.173	0.119	Rapid market response
2.404	2.224	4.628	-0.181	Rapid structural changeability
2.149	1.911	4.059	-0.238	Process flexibility
1.806	1.947	3.753	0.141	Real-time decision-making
2.023	1.998	4.021	-0.025	Cross-functional collaboration
1.877	1.789	3.666	-0.088	Rapid learning from the environment
2.036	1.878	3.914	-0.158	Production of new business innovation
2.106	1.953	4.059	-0.154	Commercialization of business innovation
1.991	2.022	4.013	0.030	Continuous process improvement

2.025	2.146	4.172	0.121	Effective transfer of business innovation
1.943	2.329	4.272	0.386	Innovation in the business model
1.858	1.931	3.789	0.073	Identification of emerging risks
1.956	2.551	4.508	0.595	Assessment of probability and consequences
1.982	2.342	4.324	0.360	Continuous risk monitoring
2.556	2.363	4.919	-0.193	Cost calculation of customer satisfaction
1.985	1.757	3.742	-0.228	Retention of key customers
1.918	1.779	3.698	-0.139	Rapid response to requests
2.160	2.450	4.610	0.290	Customer preference orientation
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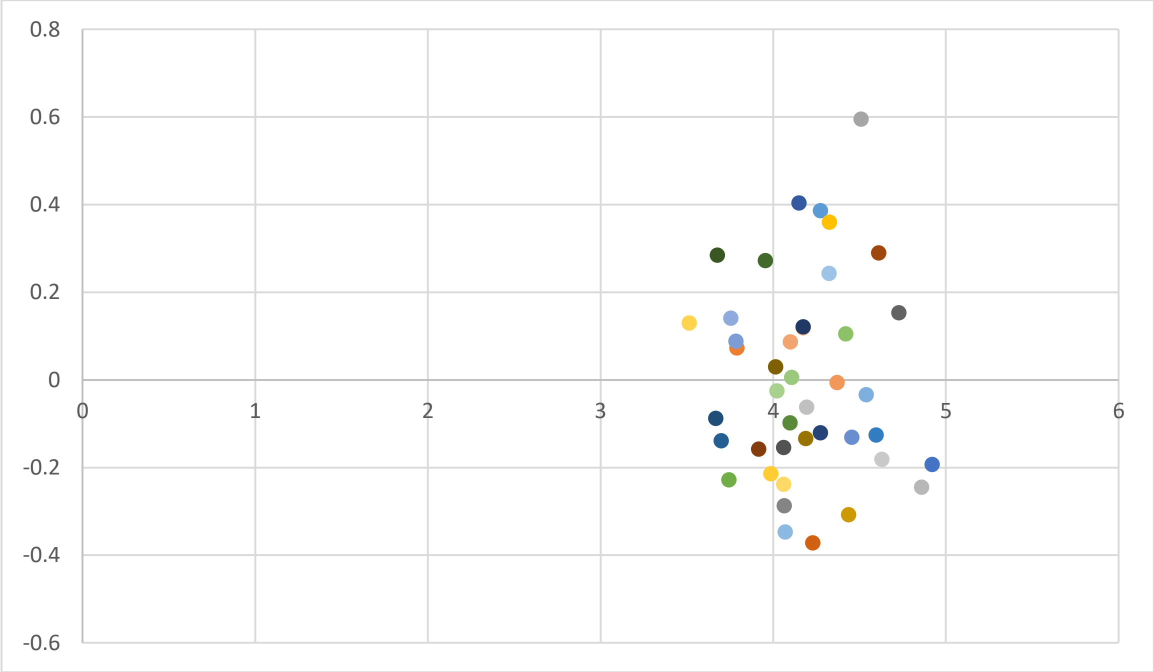
2.161	2.027	4.188	-0.134	Rapid recovery from crisis
2.197	2.076	4.273	-0.121	Security of business innovation and systems
1.840	2.112	3.953	0.272	Compatibility with modern technologies
2.286	2.252	4.538	-0.034	Continuity of digital business innovation operations
2.187	2.181	4.369	-0.006	Strengthening the culture of business innovation acceptance

Figure 3 below also presents the pattern of significant relationships. This pattern is presented in the form of a diagram in which the longitudinal axis represents the values of $D + R$, and the transverse axis is based on $D - R$. The position and relationships of each factor are determined by a point with the coordinates $(D + R, D - R)$in the coordinate system.

Figure 3

Pattern of Relationships



Discussion and Conclusion

The present study aimed to identify and prioritize the factors influencing business innovation based on artificial intelligence (AI) and blockchain technology in Golgohar Sirjan Iron Ore Company. The findings of the structural model demonstrated that all proposed relationships within the conceptual framework were positive and statistically significant. Specifically, causal conditions significantly affected the core phenomenon, the core phenomenon significantly influenced strategic actions, and strategies significantly affected organizational outcomes. Furthermore, both contextual and intervening conditions exhibited significant positive effects on the strategic dimension. In addition, the fuzzy DEMATEL analysis revealed that factors such as the diversity of business innovation resources, legal adaptability, risk assessment capabilities, managerial dashboard intelligence, and legal protection mechanisms were among the most influential determinants of AI- and blockchain-based business innovation. These findings indicate that successful technological innovation in industrial organizations is not merely a function of technological infrastructure but rather the outcome of interactions among technological, managerial, legal, organizational, and environmental factors.

The significant effect of causal conditions on the core phenomenon suggests that organizational readiness, technological capabilities, innovation resources, analytical competencies, and investment in advanced technologies play a fundamental role in shaping AI- and blockchain-driven business innovation. This finding is consistent with the argument that digital transformation initiatives require strong technological foundations and strategic alignment before they can generate meaningful innovation outcomes. Kitsios and Kamariotou emphasized that artificial intelligence becomes strategically valuable when organizations possess the necessary capabilities to integrate data, technology, and business objectives into a coherent innovation framework [1]. Similarly, Trad argued that business transformation requires the interaction of enterprise architecture, managerial systems, and technological resources, suggesting that innovation emerges through systemic integration rather than isolated technological adoption [3]. The significance of causal conditions in the present study therefore confirms that AI and blockchain technologies cannot independently create innovation unless they are supported by appropriate organizational and technological prerequisites.

Another important finding was the significant influence of the core phenomenon on strategic actions. This result indicates that once organizations establish a central innovation capability based on AI and blockchain technologies, they become more capable of formulating and implementing effective strategies. Such strategies may include process automation, intelligent decision-making, risk management systems, customer-oriented innovation, digital collaboration, and knowledge-sharing initiatives. This finding aligns with studies emphasizing that intelligent technologies enhance organizational strategic flexibility and improve managerial responsiveness. Research on intelligent online shopping behavior demonstrated that AI-driven systems can support more effective business decisions by transforming large volumes of data into actionable intelligence [4]. Likewise, studies on sentiment analysis and customer satisfaction have shown that intelligent systems provide valuable strategic insights that can guide organizational decision-making and service innovation [5]. Therefore, the significant relationship between the core phenomenon and strategic actions suggests that AI- and blockchain-based innovation capabilities serve as strategic enablers that facilitate organizational adaptation and competitiveness.

The results also revealed that strategic actions had a significant positive impact on organizational outcomes. This finding is particularly important because it demonstrates that technological innovation ultimately generates value through the implementation of effective strategies. The outcomes identified in the present study included improved decision-making, organizational agility, productivity enhancement, customer responsiveness, risk management, and competitive advantage. This finding is supported by previous research indicating that digital innovation initiatives contribute to organizational performance when they are translated into practical business processes and strategic mechanisms. Morkunas et al. emphasized that blockchain technologies can transform business models by improving value creation, value delivery, and value capture processes [2]. Similarly, Kumar et al. found that blockchain-enabled transparency and decentralization can improve operational efficiency and stakeholder trust within commercial ecosystems [6]. Consequently, the positive effect of strategies on outcomes suggests that technological innovation becomes valuable when it is embedded within organizational routines and strategic decision-making processes.

The significant influence of contextual conditions on strategies highlights the importance of environmental and organizational circumstances in shaping innovation success. Contextual conditions identified in the study included technological infrastructure, digital readiness, organizational culture, regulatory environments, access to resources, and institutional support. This finding supports the view that innovation does not occur in isolation but rather within broader organizational ecosystems. Stratan et al. argued that innovation activities are highly dependent on cooperation, institutional support, and knowledge-sharing environments, particularly in complex organizational contexts [12]. Likewise, research on IoT-based business models has demonstrated that technological innovation requires supportive infrastructures and favorable operational environments to achieve sustainable implementation [13]. In the context of Golgohar Sirjan Iron Ore Company, the significance of contextual conditions indicates that technological investments alone are insufficient unless accompanied by supportive organizational structures, digital infrastructures, and innovation-oriented cultures.

The positive and significant effect of intervening conditions on strategies also provides valuable insights. Intervening conditions include variables such as legal requirements, regulatory constraints, cybersecurity concerns, human resource capabilities, organizational resistance, and risk-related factors. These variables can either facilitate or hinder the implementation of innovation strategies. The importance of intervening conditions identified in the present study is consistent with previous research emphasizing the critical role of governance, security, and regulatory mechanisms in emerging technologies. Feng et al. highlighted that privacy protection and governance mechanisms are essential for the successful implementation of blockchain systems [7]. Similarly, Jan et al. emphasized that security challenges and governance frameworks significantly influence the effectiveness of blockchain-based digital ecosystems [8]. Therefore, the significant role of intervening conditions in the current study suggests that organizations must proactively manage legal, technological, and organizational barriers to maximize the benefits of AI and blockchain innovation.

One of the most notable findings from the fuzzy DEMATEL analysis was the prioritization of the diversity of business innovation resources as one of the most influential factors. This result suggests that organizations capable of accessing and integrating diverse sources of knowledge, technology, expertise, and innovation resources are better positioned to develop advanced business innovation systems. This finding aligns with the innovation literature, which emphasizes the value of knowledge diversity and collaborative networks in promoting innovation performance. Stratan et al. highlighted that cooperation and resource-sharing arrangements significantly enhance innovation capacity by facilitating access to complementary competencies and expertise [12]. In the context of AI and blockchain implementation, resource diversity may include technological partnerships, research collaborations, digital platforms, and interdisciplinary expertise, all of which contribute to innovation success.

Another highly influential factor identified in the study was legal adaptability. This finding reflects the growing importance of regulatory flexibility and legal readiness in technologically advanced environments. AI and blockchain technologies often challenge existing regulatory frameworks because they introduce new forms of data governance, automation, digital transactions, and decentralized decision-making. Consequently, organizations must possess the capability to adapt rapidly to evolving legal requirements. Previous studies have emphasized the importance of regulatory and governance mechanisms in blockchain ecosystems. Research on blockchain security and privacy consistently demonstrates that legal frameworks significantly influence technology adoption and organizational trust [7, 8, 16]. Therefore, the prioritization of legal adaptability in the present study suggests that organizations operating in heavily regulated industries such as mining must continuously align innovation initiatives with regulatory developments.

The prioritization of risk assessment and risk management capabilities further highlights the strategic importance of proactive governance. Emerging technologies generate substantial opportunities but also introduce new forms of uncertainty related to cybersecurity, operational reliability, technological obsolescence, and organizational transformation. Studies investigating blockchain-assisted secure data sharing and blockchain-based security architectures have emphasized the importance of risk identification, security management, and governance mechanisms in ensuring sustainable technological adoption [9, 10]. The current findings extend this perspective by demonstrating that risk assessment is not merely a protective function but also a critical enabler of business innovation. Organizations that effectively identify and manage technological risks are more likely to adopt innovative solutions with confidence and achieve sustainable performance improvements.

Managerial dashboard intelligence emerged as another highly influential factor in the prioritization results. Intelligent dashboards enable managers to visualize complex information, monitor performance indicators, evaluate risks, and make evidence-based decisions in real time. This finding supports the growing recognition that AI-based analytics contribute significantly to managerial effectiveness. Research on intelligent decision-making systems has shown that advanced analytics can enhance strategic planning, customer analysis, and operational optimization by providing accurate and timely information [4, 5]. In industrial environments characterized by large-scale operations and dynamic conditions, intelligent dashboards may serve as critical tools for translating data into actionable managerial knowledge.

The findings also underscore the interconnected nature of AI and blockchain technologies. Rather than functioning as separate technological domains, these technologies appear to create synergistic effects when integrated into organizational innovation systems. Artificial intelligence contributes predictive capabilities, automation, learning, and decision support, whereas blockchain enhances transparency, security, trust, and traceability. Previous research has repeatedly emphasized the strategic potential of combining intelligent technologies with secure digital infrastructures. Studies examining blockchain-assisted industrial systems, decentralized communication environments, and secure information-sharing mechanisms have shown that integrating advanced technologies can significantly improve organizational resilience, efficiency, and innovation capability [8-10]. The current findings support this perspective by demonstrating that both technological and governance-related factors jointly contribute to business innovation outcomes.

Moreover, the significance of customer-oriented factors, decision-making capabilities, and innovation outcomes identified in the prioritization analysis is consistent with research emphasizing stakeholder value creation. Customer satisfaction, trust, relationship quality, and service responsiveness have been recognized as critical determinants of organizational success in increasingly digital environments [17]. Although Golgohar operates in the mining sector rather than consumer services, the broader principle remains relevant: successful technological innovation ultimately creates value through improved stakeholder relationships, operational excellence, and strategic responsiveness. AI- and blockchain-based innovations therefore contribute not only to efficiency and security but also to long-term organizational sustainability and competitiveness.

Overall, the findings suggest that AI- and blockchain-based business innovation in Golgohar Sirjan Iron Ore Company is a multidimensional phenomenon shaped by the interaction of technological capabilities, legal and regulatory readiness, organizational resources, strategic management, intelligent decision systems, and risk governance mechanisms. The results reinforce the notion that digital transformation should be approached as an integrated organizational process rather than a purely technological initiative. By simultaneously addressing causal, contextual, intervening, strategic, and consequential dimensions, organizations can maximize the value generated by emerging technologies and strengthen their capacity for sustainable innovation.

This study has several limitations that should be considered when interpreting the findings. First, the research was conducted within a single organization, namely Golgohar Sirjan Iron Ore Company, which may limit the generalizability of the findings to other industries or organizational contexts. Second, the quantitative data were collected through self-reported questionnaires, making the results susceptible to respondent bias and subjective perceptions. Third, the rapidly evolving nature of artificial intelligence and blockchain technologies means that some identified factors may change over time as technological capabilities and regulatory frameworks continue to develop. Finally, the study focused primarily on identifying and prioritizing influencing factors rather than evaluating the long-term performance outcomes of technology implementation.

Future studies may expand this line of inquiry by examining AI- and blockchain-based business innovation across multiple organizations and industries to improve the generalizability of findings. Comparative studies between industrial sectors could provide valuable insights into sector-specific innovation drivers and barriers. Researchers may also investigate longitudinal effects of AI and blockchain adoption to understand how influencing factors evolve over time. Furthermore, future research could incorporate additional variables such as organizational resilience, digital leadership, innovation culture, sustainability performance, and technological readiness. The application of alternative multi-criteria decision-making methods and advanced modeling techniques may also provide deeper insights into the causal relationships among innovation factors.

Managers should adopt an integrated approach toward AI- and blockchain-based innovation by simultaneously addressing technological, organizational, legal, and strategic dimensions. Investment in intelligent decision-support systems, advanced analytics, and secure digital infrastructures should be accompanied by workforce development programs and organizational learning initiatives. Organizations should strengthen legal compliance capabilities and continuously monitor regulatory developments related to emerging technologies. Establishing risk management systems and innovation governance mechanisms can reduce uncertainty and facilitate technology adoption. Furthermore, managers should encourage collaboration with research institutions, technology providers, and innovation networks to access diverse knowledge resources and enhance innovation capabilities. Finally, organizations should prioritize the development of intelligent managerial dashboards and data-driven decision-making processes to improve agility, productivity, and competitive advantage in rapidly changing business environments.

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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

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants. Written consent was obtained from all participants in the study.

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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