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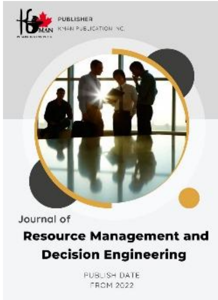

Designing a Knowledge-Based Business Model in a VUCA environment Using Artificial Intelligence and the Grounded Theory Approach

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A B S T R A C T

This study aimed to develop a conceptual model for designing knowledge-based business models in VUCA environments through the integration of artificial intelligence, using a grounded theory methodology. This qualitative study employed the grounded theory approach to construct a model for knowledge-based business operations in VUCA environments. Data were collected through in-depth interviews with 25 experts (18 male and 7 female), including both academic and industry specialists. Participants ranged from under 35 to over 45 years old, and possessed master's (n = 11) or doctoral degrees (n = 14) with 10–20 years (n = 13) or over 20 years (n = 12) of work experience. Data analysis followed the systematic coding framework of Anselm Strauss and Juliet Corbin (1998) using ATLAS.ti software, progressing through open, axial, and selective coding stages. The results revealed six main categories: causal conditions (advanced data analytics, rapid competitive innovation, AI growth, advanced knowledge management, short technology lifecycles, customization demand); contextual conditions (technological, legal–ethical, risk-taking, cybersecurity, collaborative innovation infrastructures); intervening conditions (unstable economy, shortage of skilled workforce, weak digital maturity, lack of policymaker support, absence of a learning organization, lack of an innovative culture); strategies (AI effectiveness, knowledge dynamism, customer-centric innovation, continuous organizational learning, decision-making optimization); and consequences (sustainable competitive advantage, intelligent organizational agility, knowledge-based value creation, decision-making risk management, effective customer management, digital organizational resilience). These components were structured into a theoretical model that illustrates the process of embedding AI into knowledge-based business design for turbulent environments. Integrating AI into knowledge-based business models enables organizations to enhance strategic agility, operational efficiency, and resilience in VUCA contexts. The grounded theory model offers a comprehensive framework for aligning causal drivers, contextual enablers, and strategic mechanisms to achieve sustainable competitive outcomes.

Keywords: *Artificial Intelligence, Knowledge-Based Business, Technological Infrastructure, Innovative Culture, Decision-Making Risk Management*

1. Introduction

In the rapidly evolving business landscape, organizations face unprecedented levels of complexity and uncertainty driven by globalization, technological disruption, and market volatility. These dynamics have given rise to what is commonly referred to as a VUCA environment—an acronym denoting volatility, uncertainty, complexity, and ambiguity—which challenges conventional business models and demands innovative strategies for organizational survival and growth (Rezaei et al., 2024). Knowledge-based businesses, in particular, which rely on intellectual capital, data-driven decision-making, and the conversion of knowledge into competitive advantage, must adopt approaches that combine agility with analytical rigor (Kazemi et al., 2022).

Artificial Intelligence (AI) has emerged as one of the most transformative technologies capable of reshaping how organizations operate, make decisions, and create value (Ardabili & Nabovati, 2024). The integration of AI into business models is no longer optional but a strategic imperative for organizations seeking to maintain resilience, adaptability, and competitive advantage in turbulent conditions (Adama et al., 2024). AI applications in business include predictive analytics, process automation, intelligent decision support, and personalized customer engagement—all of which contribute to improved efficiency and responsiveness (Joel et al., 2024). Furthermore, the synergy between AI and knowledge management creates an ecosystem where organizational learning and innovation are continuous, enabling companies to close the gap between academic research and market applications (Andeyesh & Kianrad, 2024).

The literature highlights the importance of aligning AI-driven capabilities with business strategies to ensure that technological adoption translates into measurable outcomes such as cost reduction, innovation acceleration, and customer satisfaction (Shil et al., 2024). For example, supply chain optimization using AI has been shown to minimize disruptions, reduce operational costs, and improve efficiency across global networks (Nzeako et al., 2024; Odimarha et al., 2024). Predictive analytics powered by AI enables real-time risk detection, allowing firms to anticipate and mitigate supply chain bottlenecks before they escalate (Kashem et al., 2023). This capability is particularly crucial in sectors such as energy and manufacturing, where disruptions can lead to significant financial losses and reputational damage (Gorji, 2023; Riera et al., 2023).

In the context of knowledge-based businesses, AI serves as both a catalyst and an enabler for strategic flexibility. As Rezaei et al. (2024) emphasize, organizations that integrate AI into their decision-making frameworks exhibit greater adaptability and are better positioned to navigate VUCA conditions (Rezaei et al., 2024). Mohammadi and Rostami (2023) argue that the design of strategic frameworks based on AI can help firms enhance foresight, align resources with dynamic market demands, and sustain competitive advantage over time (Mohammadi & Rostami, 2023). These insights are supported by Jafari and Mousavi (2024), who analyze the challenges and opportunities of implementing knowledge-based business models with AI and stress the need for industry-specific customization of AI tools (Jafari & Mousavi, 2024).

Another critical dimension is the role of AI in enhancing knowledge sharing and organizational learning. Effective knowledge management systems powered by AI facilitate the capture, organization, and dissemination of both tacit and explicit knowledge within an enterprise (Hosseini & Sadeghi, 2023; Hosseini, 2024). This creates a virtuous cycle where data from operations inform strategic planning, which in turn drives process improvements and innovation (Moqaddasi & Araqi, 2024). Keshavarz and Abedinpour (2024) further point out that AI-driven business management systems offer real-time analytics and automated decision support, freeing managerial resources for higher-order strategic tasks (Keshavarz & Abedinpour, 2024).

The application of AI in supply chain and logistics optimization has been particularly well-documented. Odimarha et al. (2024) present a comprehensive analysis of machine learning's influence on the oil and gas sector, demonstrating that AI can optimize routing, inventory management, and predictive maintenance (Odimarha et al., 2024). Similarly, Edunjobi (2024) introduces the integrated banking-supply chain (IBSC) model for fast-moving consumer goods (FMCG) markets, highlighting the intersection between financial flows and logistics optimization (Edunjobi, 2024). These innovations not only enhance efficiency but also build resilience, a key requirement for operating under uncertainty (Abaku et al., 2024).

Despite these advantages, the adoption of AI is not without challenges. Ethical concerns, data privacy issues, and the potential for algorithmic bias necessitate a robust governance framework (Ijiga et al., 2024). There is also the risk of over-reliance on automated systems, which can undermine human judgment if not carefully integrated with managerial oversight (Nzeako et al., 2024). Alizade et al. (2021) highlight that for AI adoption to succeed, there must be a balance between technological innovation and human-centered design principles, ensuring that business models remain customer-oriented and value-driven (Alizade et al., 2021).

Another consideration is the scalability and sustainability of AI-driven initiatives. Kolasani (2023) points to blockchain and distributed ledger technologies as complementary innovations that, when integrated with AI, enhance transparency and trust in supply chains (Kolasani, 2023). This convergence of technologies underpins the emergence of smart, decentralized ecosystems that are more resilient to systemic shocks (Kashem et al., 2023). Furthermore, research by Adama et al. (2024) suggests that the economic impact of digital transformation is contingent upon the readiness of organizational infrastructure and human capital development (Adama et al., 2024).

The competitive landscape also plays a significant role in shaping AI adoption strategies. Organizations must account for market volatility, evolving customer preferences, and regulatory pressures while designing AI-enabled business models (Kazemi et al., 2022). In this regard, Moqaddasi and Araqi (2024) argue that AI-based business innovation requires a dual focus on technological readiness and strategic alignment to ensure that AI deployments deliver sustainable value rather than short-term gains (Moqaddasi & Araqi, 2024).

From a theoretical standpoint, the grounded theory approach provides a rigorous methodology for exploring how AI can be embedded into knowledge-based business models (Alizade et al., 2021). By iteratively coding and categorizing data from expert interviews, researchers can derive a process-oriented model that captures causal conditions, intervening variables, strategies, and outcomes in a structured manner (Kazemi et al., 2022). This methodology enables the development of a conceptual framework that is both empirically grounded and practically relevant, offering managers actionable insights for decision-making under uncertainty.

Ultimately, the integration of AI into knowledge-based business models represents a paradigm shift in how organizations generate, apply, and commercialize knowledge (Andeyesh & Kianrad, 2024). It creates opportunities for real-time adaptability, enhances strategic foresight, and fosters innovation-driven growth (Ardabili & Nabovati, 2024). However, its successful implementation depends on aligning technological capabilities with organizational culture, developing ethical guidelines for AI governance, and ensuring that human expertise remains at the core of decision-making processes (Hosseini & Sadeghi, 2023; Ijiga et al., 2024). As such, this study aims to design a comprehensive model that integrates AI with knowledge-based business strategies to enable organizations to thrive in VUCA environments, bridging the gap between theoretical constructs and real-world applications.

2. Methods and Materials

In this study, the Grounded Theory method was used to design the model. The statistical sample consisted of 25 experts, including both practical and theoretical specialists. The qualitative part of this study was conducted based on the opinions of 25 experts in the field under investigation. Regarding gender, 18 participants were male and 7 were female. In terms of age, 3 participants were under 35 years old, 10 participants were between 35 and 45 years old, and 12 participants were over 45 years old. Regarding educational level, 11 participants held master's degrees and 14 participants held doctoral degrees. Finally, 13 participants had between 10 and 20 years of work experience, and 12 participants had over 20 years of work experience.

Table 1

Demographic Characteristics of the Experts

Demographic Characteristics	Frequency	Percentage
Gender		
Male	18	72%
Female	7	28%
Age		
Under 35 years	3	12%
35–45 years	10	40%
45 years and above	12	48%
Education		

Master's	11	44%
Doctorate	14	56%
Work Experience		
10–20 years	13	52%
Over 20 years	12	48%

The research data were analyzed using the coding process based on the systematic design of grounded theory by Anselm Strauss and Juliet Corbin (1998). Coding is an analytical process through which data are conceptualized and linked together to form theory. In this process, data analysis is not performed separately from data collection and sampling. The ATLAS.ti software was used in this study.

3. Findings and Results

In the open coding stage, the data obtained from the interviews were carefully studied, reviewed, and analyzed. Then, concepts were extracted from these data, and appropriate labels were assigned to data that were conceptually similar. For open coding, all data were entered into ATLAS.ti software. After the necessary reviews, the desired codes were extracted and labeled. This labeling was based on the interviews, and the researcher made efforts to remain as faithful as possible to the participants' perspectives on their responses to avoid any potential bias. The researcher adhered to theoretical sensitivity, which is one of the principles of grounded theory research, to enrich the study. A sample of the coding results is presented in the table. The items identified in the interviews represent the initial codes extracted through the software.

Table 2

Coded Interviews

Initial Categories	Interview Description
Level of use of machine learning algorithms	The extent to which the organization employs intelligent algorithms to analyze data and extract hidden patterns.
Accuracy of predictive analytical models	The level of error or accuracy in predictive models used in market, customer, or operational analysis.
Diversity of data sources used	The number and types of data sources (structured, semi-structured, and unstructured) used in analyses.
Response time of analytical systems	The time required to obtain analysis results from input to output.
Intelligence level of management dashboards	The degree of interactivity, customizability, and automated analysis in organizational decision-support dashboards.
Number of commercialized innovations per year	The number of innovative products or services launched in the market annually.
Average time from development to product launch	The time span from the beginning of designing an innovation to its introduction to the market.
R&D investment ratio	The ratio of R&D budget to the organization's total revenue or costs.
Product adaptability index to market changes	The ability of the product to quickly adapt to new customer needs or market conditions.
Number of AI-based projects in progress	The total number of projects using Artificial Intelligence tools or algorithms.
Percentage of processes automated using AI	The proportion of operational processes automated through artificial intelligence.
Organizational maturity level in AI usage	The organization's position on the path of implementing and institutionalizing artificial intelligence in its processes.
Cost savings from AI application	The reduction in direct or indirect costs due to the use of artificial intelligence.
Percentage of key decisions based on AI	The proportion of strategic or operational decisions made using AI-based analyses and recommendations.
Level of organizational knowledge documentation	The percentage of explicit and tacit knowledge recorded in the organization's knowledge bases.
Number of interactions on knowledge-sharing platforms	The extent to which employees use platforms and knowledge communities to share experiences.
Knowledge retrieval rate during decision-making	The ease and speed of accessing relevant information for decision-making.
Number of knowledge-based trainings from internal experiences	The number of training courses based on employees' real knowledge and experiences.
Average obsolescence time of technologies used	The average time from the adoption of a technology to its replacement within the organization.
Number of technology updates per year	The number of times software, systems, or technological equipment are upgraded or replaced.
Emerging technology adaptation index	The organization's speed and capability in adapting to new and disruptive technologies.
Dependence rate on obsolete technologies	The extent of reliance on technologies that are obsolete or becoming obsolete.
Costs of adapting to new technologies	The financial or human resources needed to replace obsolete technologies.
Percentage of customized products/services	The ratio of produced items or delivered services designed to meet specific customer needs.
Ability to adapt products to individual customer needs	The flexibility of design or production to respond to individual differences.

Percentage of customer satisfaction with customized services	The degree of customer satisfaction with the experience of receiving customized products or services.
Percentage of modular design-based processes	The share of systems designed modularly for combinability and customization.
Product differentiation	The ability to create products or services that are unique compared to competitors.
Innovation protection	Safeguarding intellectual property rights and preventing rapid imitation by competitors.
Increasing customer loyalty	Building continuous relationships and trust among customers toward the brand.
Higher productivity	Optimal resource utilization to reduce costs and improve quality.
Rapid market response	The ability to quickly respond to environmental changes and customer needs.
Rapid structural adaptability	The organization’s capability to rapidly change its internal structures.
Process flexibility	The ability to adjust and modify processes according to new conditions.
Real-time decision-making	Using artificial intelligence to make quick and accurate decisions.
Cross-departmental collaboration	Effective communication and coordination between different organizational units.
Rapid learning from the environment	The speed of organizational learning and adaptation to environmental changes.
Creation of new knowledge	Developing new knowledge through research and innovation.
Knowledge commercialization	Turning knowledge into revenue-generating products or services.
Continuous process improvement	Enhancing efficiency and quality through knowledge utilization.
Effective knowledge transfer	The ability to share and transfer knowledge within the organization and among partners.
Business model innovation	Creating new models based on knowledge and emerging technologies.
Identification of emerging risks	Detecting and analyzing hidden and new risks.
Assessment of risk probability and impact	Measuring the likelihood and consequences of risks.
Designing risk mitigation strategies	Developing solutions to address potential threats.
Continuous risk monitoring	Ongoing tracking and updating of risk information.
Informed decision-making	Making decisions based on complete and accurate risk information.
Increasing customer satisfaction	Improving customer experience and satisfaction.
Retaining key customers	Keeping high-value customers through special programs.
Customer behavior analysis	Understanding customers’ needs and preferences in depth.
Service personalization	Tailoring products and services to individual customer characteristics.
Rapid response to requests	The speed and quality of responding to customer needs and complaints.
Rapid recovery from crises	The ability to return to normal after disruptions.
Data and system security	Effective protection of the organization’s digital assets.
Adaptation to new technologies	Rapid adaptation to new technologies and digital changes.
Continuity of digital operations	Maintaining uninterrupted functioning of digital systems and services.
Strengthening a culture of flexibility	Fostering a positive attitude toward change and learning among employees.

The main objective of the axial coding stage is to establish relationships between the concepts generated during the open coding stage so that this coding can be introduced as a central axis entitled “Designing a Knowledge-Based Business Model in a VUCA environment Using Artificial Intelligence”. This topic is selected as the core and placed at the center of the model because its effects are clearly visible in the data and the interviewees’ quotations. Therefore, this concept serves as a reference point for organizing other data related to it.

In this study, the Anselm Strauss and Juliet Corbin paradigm model was used for axial coding, which helps the theorist gain a comprehensive understanding of the theoretical process governing the research. The main components of this model include the core phenomenon, causal conditions, contextual conditions, intervening conditions, strategies, and consequences.

After extracting the initial codes, categorization and conceptualization were conducted after each interview, and the concepts were continuously reviewed and revised through constant comparison until final concepts and categories were formed. For example, from the codes such as company–industry alignment, identification of partial and overall company processes, company alignment with goals and strategies, and alignment of actions with planning, the concept of “fundamental characteristics” was derived. A full explanation of how the concepts and categories were formed is presented in Table 3.

Table 3

Secondary Coding

Axial Categories	Initial Categories
Advanced data analytics	Level of use of machine learning algorithms; Accuracy of predictive analytical models; Diversity of data sources used; Response time of analytical systems; Intelligence level of management dashboards
Rapid competitive innovation	Number of commercialized innovations per year; Average time from development to product launch; R&D investment ratio; Product adaptability index to market changes
Artificial intelligence growth	Number of Artificial Intelligence-based projects in progress; Percentage of processes automated using AI; Organizational maturity level in AI usage; Cost savings from AI application; Percentage of key decisions based on AI
Advanced knowledge management	Level of organizational knowledge documentation; Number of interactions on knowledge-sharing platforms; Knowledge retrieval rate during decision-making; Number of knowledge-based trainings from internal experiences
Short technology lifecycle	Average obsolescence time of technologies used; Number of technology updates per year; Emerging technology adaptation index; Dependence rate on obsolete technologies; Costs of adapting to new technologies
Customization demand	Percentage of customized products/services; Ability to adapt products to individual customer needs; Percentage of customer satisfaction with customized services; Percentage of modular design-based processes
Unstable economy	Currency exchange rate fluctuations; Annual inflation in goods and services; Stock market and investment index fluctuations; Organizational credit and financial risk; Unemployment rate among skilled labor
Shortage of skilled workforce	Lack of specialized training; Skilled labor migration; Academia–industry gap; Weakness in soft skills; Limitations in talent acquisition
Weak digital maturity	Lack of digital infrastructure; Absence of a digital roadmap; Limited use of technology; Resistance to digital change; Traditional technology management
Lack of policymaker support	Lack of financial incentives; Ambiguous regulations; Weak innovation policies; Lack of support for start-ups; Political instability
Absence of learning organization	Bureaucratic structure; Lack of continuous updates; Lack of motivation for learning; Lack of knowledge management; Absence of team learning
Lack of innovative culture	Fear of failure; No rewards for innovation; Conservative decision-making; Lack of employee participation; Sole focus on productivity
Technological infrastructure	Access to high-speed internet; Data centers and cloud computing; Smart organizational equipment; AI-based platforms; Technology compatibility
Legal-ethical infrastructure	Data protection laws; Ethical framework for artificial intelligence; Legal adaptability; Transparency of intellectual property rights; Legal regulatory structure
Risk-taking infrastructure	Availability of venture capital; Tolerance for failure in organizational culture; Entrepreneurship support policies; Risk management training; Risk prediction systems
Cybersecurity infrastructure	Data encryption systems; Digital security training; Intrusion detection tools; Information security policies; Continuous backup systems
Collaborative innovation infrastructure	Open innovation networks; Culture of collaboration and teamwork; Policies supporting joint innovation; Accelerators and innovation centers
AI effectiveness	Model prediction accuracy; Process automation; Adaptive algorithm learning; Reduction of human error; Increased data analysis speed
Knowledge dynamism	Rapid knowledge circulation; Continuous information updates; Digital knowledge sharing; Learning from mistakes; Knowledge agility
Customer-centric innovation	User experience-based design; Use of customer feedback; Customized development; Customer sentiment analysis; Open innovation with customers
Continuous organizational learning	E-learning systems; Culture of continuous learning; Constructive internal feedback; Knowledge documentation; Adaptive environmental learning
Decision-making optimization	Data-driven decision-making; Decision-support algorithms; Scenario analysis; Decision knowledge management
Sustainable competitive advantage	Product differentiation; Innovation protection; Increasing customer loyalty; Higher productivity; Rapid market response
Intelligent organizational agility	Rapid structural adaptability; Process flexibility; Real-time decision-making; Cross-departmental collaboration; Rapid learning from the environment
Knowledge-based value creation	Creation of new knowledge; Knowledge commercialization; Continuous process improvement; Effective knowledge transfer; Business model innovation
Decision-making risk management	Identification of emerging risks; Assessment of risk probability and impact; Continuous risk monitoring
Effective customer management	Increasing customer satisfaction; Retaining key customers; Rapid response to requests; Customer-centricity; Customer behavior analysis
Digital organizational resilience	Rapid recovery from crises; Data and system security; Adaptation to new technologies; Continuity of digital operations; Strengthening a culture of flexibility

This central concept is chosen for the research and represents the main problem or topic being investigated. In the context of evaluating internal controls by auditors, the core phenomenon could involve the internal control evaluation process, such as identifying weaknesses or providing improvement recommendations.

During axial coding, the categories extracted from open coding and secondary coding were classified into six groups: the core phenomenon, causal conditions, intervening conditions, contextual conditions, strategies, and consequences. According to the aim of this study, the core phenomenon is identified as the design and presentation of a knowledge-based business model in a VUCA environment using an artificial intelligence approach. The process of forming the causal, intervening, contextual conditions, strategies, and consequences is presented in the subsequent table and diagram.

The main stage of grounded data analysis is selective coding, in which the researcher develops the theory based on the results of open and axial coding. In this section, the root causes and reasons for the formation of these conditions are presented under the title of a theoretical memo, which contains the analyst's reflections and ideas regarding the research conditions.

Table 4

Theoretical Memo: Root Causes of the Study's Conditions (Causal, Intervening, and Contextual)

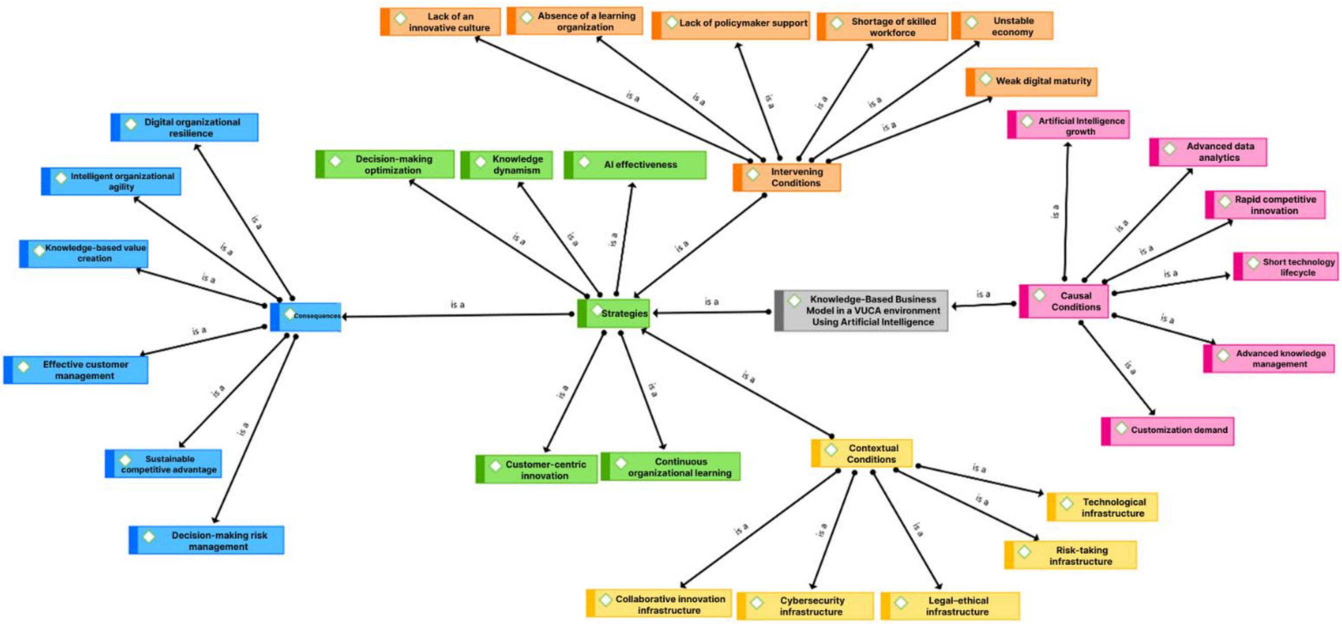
Selective Categories	Axial Categories	Initial Categories
Causal Conditions	Advanced data analytics	Level of use of machine learning algorithms; Accuracy of predictive analytical models; Diversity of data sources used; Response time of analytical systems; Intelligence level of management dashboards
	Rapid competitive innovation	Number of commercialized innovations per year; Average time from development to product launch; R&D investment ratio; Product adaptability index to market changes
	Artificial intelligence growth	Number of AI-based projects in progress; Percentage of processes automated using AI; Organizational maturity level in the use of artificial intelligence; Cost savings from AI application; Percentage of key decisions based on AI
	Advanced knowledge management	Level of organizational knowledge documentation; Number of interactions on knowledge-sharing platforms; Knowledge retrieval rate during decision-making; Number of knowledge-based trainings derived from internal experiences
	Short technology lifecycle	Average obsolescence time of technologies used; Number of technology updates per year; Emerging technology adaptation index; Dependence rate on obsolete technologies; Costs of adapting to new technologies
	Customization demand	Percentage of customized products/services relative to total production; Ability to adapt products to individual customer needs; Percentage of customer satisfaction with customized services; Percentage of modular design–based processes
Intervening Conditions	Unstable economy	Currency exchange rate fluctuations; Annual inflation in goods and services; Stock market and investment index fluctuations; Organizational credit and financial risk; Unemployment rate among skilled labor
	Shortage of skilled workforce	Lack of specialized training; Skilled labor migration; Academia–industry gap; Weakness in soft skills; Limitations in talent acquisition
	Weak digital maturity	Lack of digital infrastructure; Absence of a digital roadmap; Limited use of technology; Resistance to digital change; Traditional technology management
	Lack of policymaker support	Lack of financial incentives; Ambiguous regulations; Weak innovation policies; Lack of support for start-ups; Political instability
	Absence of a learning organization	Bureaucratic structure; Lack of continuous updating; Lack of motivation for learning; Lack of knowledge management; Absence of team learning
	Lack of an innovative culture	Fear of failure; No rewards for innovation; Conservative decision-making; Lack of employee participation; Exclusive focus on productivity
Contextual Conditions	Technological infrastructure	Access to high-speed internet; Data centers and cloud computing; Smart organizational equipment; AI-based platforms; Technology compatibility
	Legal–ethical infrastructure	Data protection laws; Ethical framework for artificial intelligence; Legal adaptability; Transparency of intellectual property rights; Legal regulatory structure
	Risk-taking infrastructure	Availability of venture capital; Tolerance for failure in organizational culture; Entrepreneurship support policies; Risk management training; Risk prediction systems
	Cybersecurity infrastructure	Data encryption systems; Digital security training; Intrusion detection tools; Information security policies; Continuous backup systems
	Collaborative innovation infrastructure	Open innovation networks; Culture of participation and team orientation; Policies supporting joint innovation; Accelerators and innovation centers
Strategies	AI effectiveness	Model prediction accuracy; Process automation; Adaptive algorithm learning; Reduction of human error; Increased speed of data analysis
	Knowledge dynamism	Rapid circulation of knowledge; Continuous information updating; Digital knowledge sharing; Learning from errors; Knowledge agility
	Customer-centric innovation	User experience–based design; Use of customer feedback; Customized development; Customer sentiment analysis; Open innovation with customers
	Continuous organizational learning	E-learning systems; Culture of continuous learning; Constructive internal feedback; Knowledge documentation; Adaptive environmental learning

	Decision-making optimization	Data-driven decision-making; Decision-support algorithms; Analysis of alternative scenarios; Decision knowledge management
Consequences	Sustainable competitive advantage	Product differentiation; Innovation protection; Increasing customer loyalty; Higher productivity; Rapid market response
	Intelligent organizational agility	Rapid structural adaptability; Process flexibility; Real-time decision-making; Cross-departmental collaboration; Rapid learning from the environment
	Knowledge-based value creation	Creation of new knowledge; Knowledge commercialization; Continuous process improvement; Effective knowledge transfer; Business model innovation
	Decision-making risk management	Identification of emerging risks; Assessment of probability and impact; Continuous risk monitoring
	Effective customer management	Increasing customer satisfaction; Retaining key customers; Rapid response to requests; Customer taste–orientation; Customer behavior analysis
	Digital organizational resilience	Rapid recovery from crises; Data and system security; Adaptation to new technologies; Continuity of digital operations; Strengthening a culture of flexibility

Based on the identified factors, axial coding was performed, and according to it, a linear relationship among the research categories—including causal conditions, core categories, contextual conditions, intervening conditions, strategies, and consequences—was determined. The figure below presents the axial coding paradigm, or in other words, the qualitative process model of the research.

Figure 1

Final Model



According to the figure above, the Anselm Strauss and Juliet Corbin model can be considered one of the most credible models for designing a knowledge-based business model in a VUCA environment using Artificial Intelligence. This model is based on a qualitative and theory-building approach, enabling managers to conduct research and evaluation processes using a systematic and logical method. The model consists of several fundamental elements, including the core phenomenon, causal conditions, contextual conditions, intervening conditions, strategies, and consequences. By using this model, independent auditors can not only formulate and investigate meaningful research questions but also evaluate the quality and efficiency of artificial intelligence processes within organizations.

The Strauss and Corbin model plays a particularly important role in designing a knowledge-based business model in a VUCA environment using an artificial intelligence approach, especially regarding efficiency. This model allows managers to comprehensively and systematically examine the relationships and interactions between various variables.

A third advantage of this model is its generalizability and applicability in different contexts. As a theory-building model, the Strauss and Corbin framework provides significant flexibility in presenting patterns and strategies for model evaluation. This enables organizations to customize the patterns according to their specific needs and conditions and to use them to improve their organizational sustainability and performance.

4. Discussion and Conclusion

The purpose of this study was to design a comprehensive model for knowledge-based business operations in a VUCA environment using an artificial intelligence (AI) approach, employing a grounded theory methodology. The results revealed a process model structured around six major components: causal conditions (advanced data analytics, rapid competitive innovation, AI growth, advanced knowledge management, short technology lifecycle, customization demand), intervening conditions (unstable economy, shortage of skilled workforce, weak digital maturity, lack of policymaker support, absence of learning organizations, lack of innovative culture), contextual conditions (technological, legal-ethical, risk-taking, cybersecurity, and collaborative innovation infrastructures), strategies (AI effectiveness, knowledge dynamism, customer-centric innovation, continuous organizational learning, decision-making optimization), and consequences (sustainable competitive advantage, intelligent organizational agility, knowledge-based value creation, decision-making risk management, effective customer management, digital organizational resilience). This model contributes to the literature by integrating AI-driven mechanisms into knowledge-based business models tailored for VUCA environments.

One of the key findings was that advanced data analytics serves as a cornerstone for building resilient and adaptive knowledge-based businesses. The integration of AI-driven predictive analytics, machine learning algorithms, and real-time dashboards enables organizations to extract hidden patterns, enhance forecasting accuracy, and improve decision-making speed (Joel et al., 2024; Nzeako et al., 2024). This aligns with the findings of Shil et al. (2024), who demonstrated that AI-based optimization of U.S. supply chains significantly reduced operational costs and increased responsiveness, suggesting that data analytics is critical to competitiveness in volatile markets (Shil et al., 2024). Moreover, studies by Odimarha et al. (2024) and Abaku et al. (2024) reinforce that machine learning can substantially improve efficiency in logistics and supply chain operations, which is a vital component for knowledge-based companies seeking to scale in dynamic environments (Abaku et al., 2024; Odimarha et al., 2024).

Rapid competitive innovation also emerged as a pivotal causal condition, with respondents highlighting that accelerating the commercialization of innovations, reducing time-to-market, and maintaining high R&D investment ratios are essential to thriving in turbulent markets. This observation resonates with Kazemi et al. (2022), who argued that knowledge-based businesses must adopt open innovation frameworks and AI-driven technologies to remain competitive under rapidly shifting conditions (Kazemi et al., 2022). Moqaddasi and Araqi (2024) similarly emphasized that AI-based business innovation facilitates the rapid prototyping and deployment of new offerings, enhancing firms' adaptability in the face of uncertainty (Moqaddasi & Araqi, 2024).

AI growth was identified as another causal driver, encapsulating the number of ongoing AI projects, automation rates, organizational AI maturity, and cost savings from AI deployment. Rezaei et al. (2024) found that organizations leveraging AI in strategic processes exhibit higher levels of strategic flexibility, allowing them to realign resources swiftly in response to market fluctuations (Rezaei et al., 2024). This supports the argument by Hosseini and Sadeghi (2023) that AI enhances strategic decision-making capacities in knowledge-based companies operating in unstable environments (Hosseini & Sadeghi, 2023). These findings collectively underscore the importance of systematically embedding AI into the organizational architecture of knowledge-based firms.

Advanced knowledge management and short technology lifecycles also played crucial roles as causal conditions. The respondents noted that capturing and codifying tacit knowledge, ensuring its rapid circulation, and updating technological assets are vital for sustaining innovation. This mirrors the perspective of Hosseini (2024), who emphasized that AI-enabled knowledge management systems accelerate the acquisition, sharing, and application of knowledge within organizations (Hosseini, 2024). Similarly, Jafari and Mousavi (2024) highlighted the necessity of robust knowledge management practices in creative industries adopting AI, as these practices help reduce knowledge silos and enable faster adaptation to market demands (Jafari & Mousavi, 2024).

Finally, customization demand emerged as a causal factor, reflecting the need to deliver personalized products and services. This finding is in line with Alizade et al. (2021), who demonstrated that customer-centric customization based on grounded theory principles strengthens brand-consumer relationships, a critical element of competitive advantage in volatile markets (Alizade et al., 2021).

While causal conditions drive capability development, several intervening conditions were found to influence the implementation of AI-driven knowledge-based models. Economic instability, for instance, creates volatility in exchange rates, inflation, and capital markets, which can undermine investment confidence. Adama et al. (2024) showed that the economic impact of digital transformation depends heavily on macroeconomic stability and institutional readiness, supporting the notion that economic turbulence can constrain AI adoption (Adama et al., 2024).

A shortage of skilled workforce also surfaced as a critical barrier, consistent with the arguments by Andeyesh and Kianrad (2024) that effective knowledge sharing and AI deployment require advanced human capital and a culture that values intellectual assets (Andeyesh & Kianrad, 2024). Weak digital maturity further exacerbates these challenges, as organizations lacking robust digital infrastructures and transformation roadmaps are less capable of integrating AI into their core operations (Keshavarz & Abedinpour, 2024).

Institutional voids, such as lack of policymaker support and absence of learning organizations, were also highlighted. This reflects the findings of Edunjobi (2024), who argued that the success of AI-driven supply chain integration in emerging markets hinges on supportive regulatory environments and continuous organizational learning (Edunjobi, 2024). Likewise, Ijiga et al. (2024) warned that ethical and governance gaps can impede the responsible adoption of generative AI in complex ecosystems such as healthcare supply chains (Ijiga et al., 2024). The absence of an innovative culture—marked by fear of failure, conservative decision-making, and limited employee participation—further restricts experimentation and learning, both of which are indispensable in volatile environments (Hosseini & Sadeghi, 2023).

The study also revealed that successful implementation of AI-driven knowledge-based models is contingent upon supportive contextual infrastructures. Technological infrastructure, including access to high-speed internet, cloud computing, and AI platforms, is foundational for operationalizing advanced analytics (Joel et al., 2024). Legal-ethical infrastructure, such as clear data protection laws and intellectual property rights, enhances trust and reduces compliance risks. Ijiga et al. (2024) emphasized that ethical considerations and regulatory clarity are vital for cross-border AI deployment, reinforcing the importance of legal frameworks (Ijiga et al., 2024).

Risk-taking and cybersecurity infrastructures were also deemed crucial. Gorji (2023) noted that emerging technologies such as green hydrogen supply chains depend on risk-sharing mechanisms and cyber-resilient architectures to withstand disruptions (Gorji, 2023). This complements the argument by Kolasani (2023) that blockchain integration can enhance transparency, traceability, and trust in AI-driven ecosystems (Kolasani, 2023). Collaborative innovation infrastructure, including open innovation networks and accelerators, further supports experimentation and rapid scaling (Kashem et al., 2023; Riera et al., 2023). These findings collectively highlight that contextual conditions form the enabling environment within which AI strategies can succeed.

Building on these enabling and constraining factors, the model identifies several strategies for achieving desired outcomes. AI effectiveness, encompassing prediction accuracy, process automation, and adaptive learning algorithms, enhances operational efficiency and reduces human error (Shil et al., 2024). Knowledge dynamism promotes rapid knowledge circulation and continuous updates, which accelerate innovation cycles (Hosseini, 2024). Customer-centric innovation—leveraging user experience design, feedback systems, and sentiment analysis—fosters stronger customer relationships and brand loyalty (Alizade et al., 2021; Jafari & Mousavi, 2024). Continuous organizational learning builds adaptive capacity, while decision-making optimization through AI-driven decision support systems enables real-time responses to market changes (Rezaei et al., 2024).

The outcomes of these strategies were found to be substantial. Organizations implementing the model achieved sustainable competitive advantage, intelligent organizational agility, and knowledge-based value creation. These outcomes align with findings by Mohammadi and Rostami (2023), who demonstrated that AI-based strategic frameworks enhance both competitiveness and adaptability in VUCA environments (Mohammadi & Rostami, 2023). They also achieved improved decision-making risk management, effective customer management, and enhanced digital resilience—echoing the observations of Ardabili and Nabovati (2024), who highlighted AI's potential to strengthen business continuity under uncertainty (Ardabili & Nabovati, 2024).

Collectively, these results demonstrate that embedding AI within knowledge-based business models enables firms to thrive in environments characterized by volatility, uncertainty, complexity, and ambiguity. The grounded theory approach used here revealed a systematic framework showing how causal, intervening, and contextual conditions interact to shape strategic choices and organizational outcomes. This model contributes to the growing body of literature advocating for AI as a strategic capability rather than a mere technological tool (Adama et al., 2024; Joel et al., 2024; Moqaddasi & Araqi, 2024).

This study is not without limitations. First, the sample size of 25 experts, although appropriate for qualitative grounded theory research, may limit the generalizability of the findings across all knowledge-based industries. The perspectives captured reflect particular contextual, cultural, and sectoral dynamics that might differ in other environments. Second, the study relied solely on interview data, which may be subject to personal biases, selective recall, and social desirability effects from participants. Incorporating triangulated data sources such as organizational documents, performance metrics, and observational data could strengthen the robustness of future models. Third, the study focused primarily on the design phase of the business model, rather than its longitudinal performance outcomes; therefore, causal claims about long-term impacts of AI integration should be interpreted cautiously. Finally, technological and regulatory conditions are rapidly evolving, which means that some findings may lose relevance as new AI capabilities and legal frameworks emerge.

Future research could build upon this study in several ways. A larger mixed-method study could be conducted to validate the conceptual model across multiple industries and national contexts, enhancing its external validity. Longitudinal studies could track the implementation of AI-driven knowledge-based business models over time to evaluate their sustained impact on competitiveness, resilience, and innovation performance. Future work could also integrate quantitative performance metrics—such as ROI on AI initiatives, time-to-market, and knowledge sharing indices—to complement qualitative insights. Another promising direction is to examine the moderating role of organizational culture and leadership styles in shaping the success of AI-driven transformations. Comparative studies between firms operating in high-VUCA and low-VUCA environments could also clarify contextual contingencies influencing the model's applicability. Finally, exploring ethical, social, and workforce implications of AI deployment in knowledge-intensive organizations would enrich understanding of the human-AI interface in future business ecosystems.

Managers and policymakers can draw several practical implications from this study. Knowledge-based firms should invest in building strong digital infrastructures, ethical AI governance frameworks, and collaborative innovation networks as foundational enablers for AI adoption. Leaders should foster an innovative organizational culture that encourages experimentation, tolerates failure, and rewards creativity to overcome resistance to digital transformation. Workforce development strategies must focus on upskilling employees in data analytics, AI tools, and knowledge management to ensure human-AI complementarity. Furthermore, firms should adopt a strategic approach to AI deployment by aligning AI projects with long-term business objectives, customer needs, and market dynamics. Finally, policymakers can facilitate the success of such models by offering supportive regulations, funding mechanisms, and cross-sector partnerships that reduce risk and encourage responsible AI adoption in knowledge-based sectors.

Authors' Contributions

Authors contributed equally to this article.

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Transparency Statement

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References

Abaku, E. A., Edunjobi, T. E., & Odimarha, A. C. (2024). Theoretical approaches to AI in supply chain optimization: Pathways to efficiency and resilience. *International Journal of Science and Technology Research Archive*, *6*(1), 092-107. https://doi.org/10.53771/ijstra.2024.6.1.0033

Adama, H. E., Popoola, O. A., Okeke, C. D., & Akinoso, A. E. (2024). Economic theory and practical impacts of digital transformation in supply chain optimization. *International Journal of Advanced Economics*, *6*(4), 95-107. https://doi.org/10.51594/ijae.v6i4.1072

Alizade, H., Kheiri, B., & Heydari, S. A. (2021). Model presentation for developing brand-consumer relationships in the hotel industry based on Grounded Theory. *Business Management Quarterly*, *13*(49), 283-303. https://www.magiran.com/paper/2261607/model-presentation-for-developing-brand-consumer-relationships-in-the-hotel-industry-based-on-grounded-theory?lang=en

Andeyesh, S., & Kianrad, Z. (2024). The Role of Artificial Intelligence in Valuing Knowledge Sharing in Knowledge-Based Organizations. 1st National Conference on Intellectual Property and Intangible Assets,

Ardabili, S., & Nabovati, M. (2024). Investigating the Impact of Artificial Intelligence in Business. 23rd National Conference on Computer Science and Information Technology,

Edunjobi, T. E. (2024). The integrated banking-supply chain (IBSC) model for FMCG in emerging markets. *Finance & Accounting Research Journal*, *6*(4), 531-545. https://doi.org/10.51594/farj.v6i4.992

Gorji, S. A. (2023). Challenges and opportunities in green hydrogen supply chain through metaheuristic optimization. *Journal of Computational Design and Engineering*, *10*(3), 1143-1157. https://doi.org/10.1093/jcde/qwad043

Hosseini, N., & Sadeghi, Z. (2023). The Role of Artificial Intelligence in Enhancing Strategic Decision-Making in Knowledge-Based Companies in Unstable Environments. *Quarterly Journal of Technology and Innovation Management*, *15*(2), 101-123.

Hosseini, S. (2024). Application of Artificial Intelligence in Knowledge Management. 8th National Conference on Management and the Tourism Industry,

Ijiga, A. C., Peace, A. E., Idoko, I. P., Agbo, D. O., Harry, K. D., Ezebuka, C. I., & Umama, E. E. (2024). Ethical considerations in implementing generative AI for healthcare supply chain optimization: A cross-country analysis across India, the United Kingdom, and the United States of America. *International Journal of Biological and Pharmaceutical Sciences Archive*, *7*(01), 048-063. https://doi.org/10.53771/ijbpsa.2024.7.1.0015

Jafari, A., & Mousavi, S. (2024). Analysis of Challenges and Opportunities in Implementing Knowledge-Based Business Models with a Focus on Artificial Intelligence in Creative Industries. *Journal of Innovative Business Management*, *4*(1), 33-57.

Joel, O. S., Oyewole, A. T., Odunaiya, O. G., & Soyombo, O. T. (2024). Leveraging artificial intelligence for enhanced supply chain optimization: a comprehensive review of current practices and future potentials. *International Journal of Management & Entrepreneurship Research*, *6*(3), 707-721. https://doi.org/10.51594/ijmer.v6i3.882

Kashem, M. A., Shamsuddoha, M., Nasir, T., & Chowdhury, A. A. (2023). Supply chain disruption versus optimization: a review on artificial intelligence and blockchain. *Knowledge*, *3*(1), 80-96. https://doi.org/10.3390/knowledge3010007

Kazemi, M., Rezaei, S., & Ahmadi, A. (2022). Designing a Knowledge-Based Business Model with an Open Innovation Approach and Artificial Intelligence Technologies in Dynamic Environments. *Journal of Technology and Innovation Research in Iran*, *12*(3), 45-68. https://doi.org/10.1201/9781003339755-5

Keshavarz, S., & Abedinpour, A. (2024). Application of Artificial Intelligence in Business Management. 2nd National Conference on New Business in Electrical Engineering and Computer,

Kolasani, S. (2023). Blockchain-driven supply chain innovations and advancement in manufacturing and retail industries. *Transactions on Latest Trends in IoT*, *6*(6), 1-26. https://www.google.com/url?sa=t&source=web&rct=j&opi=89978449&url=https://ijsdcs.com/index.php/TLIoT/article/download/477/197&ved=2ahUKEwjqqsDB9NOPAxVvh_0HHRxrOucQFnoECCEQAw&usg=AOvVaw0hDd2zg1A9OqBUCs0aG_Qo

Mohammadi, A., & Rostami, N. (2023). Designing a Strategic Framework Based on Artificial Intelligence for Knowledge-Based Businesses in VUCA Environments. *Journal of Technology and Knowledge-Based Economy*, *10*(4), 79-98.

Moqaddasi, A., & Araqi, S. (2024). AI-Based Business Innovation. 10th International Conference on Management and Accounting in Iran,

Nzeako, G., Akinsanya, M. O., Popoola, O. A., Chukwurah, E. G., & Okeke, C. D. (2024). The role of AI-Driven predictive analytics in optimizing IT industry supply chains. *International Journal of Management & Entrepreneurship Research*, *6*(5), 1489-1497. https://doi.org/10.51594/ijmer.v6i5.1096

Odimarha, A. C., Ayodeji, S. A., & Abaku, E. A. (2024). Machine learning's influence on supply chain and logistics optimization in the oil and gas sector: a comprehensive analysis. *Computer Science & It Research Journal*, *5*(3), 725-740. https://doi.org/10.51594/csitrj.v5i3.976

Rezaei, M., Ghasemi, N., & Mansouri, A. (2024). Investigating the Impact of Artificial Intelligence on the Strategic Flexibility of Knowledge-Based Companies in VUCA Conditions. *Quarterly Journal of Modern Management Research*, *9*(3), 55-75.

Riera, J. A., Lima, R. M., & Knio, O. M. (2023). A review of hydrogen production and supply chain modeling and optimization. *International Journal of Hydrogen Energy*, *48*(37), 13731-13755. https://doi.org/10.1016/j.ijhydene.2022.12.242

Shil, S. K., Islam, M. R., & Pant, L. (2024). Optimizing US supply chains with AI: reducing costs and improving efficiency. *International Journal of Advanced Engineering Technologies and Innovations*, *2*(1), 223-247. https://www.researchgate.net/publication/387222202_Optimizing_US_Supply_Chains_with_AI_Reducing_Costs_and_Improving_Efficiency