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Application of the Sandelowski and Barroso Technique in Identifying the Components of a Knowledge-Based Business Model in a VUCA Environment with an Artificial Intelligence Approach

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ABSTRACT

In a VUCA environment, unpredictable changes occur, and businesses must respond rapidly and make appropriate decisions. Artificial intelligence, through the analysis of big data and the use of intelligent algorithms, enables businesses to predict future events and trends and assists them in making strategic and operational decisions (Borges et al., 2023). The present article aims to apply the meta-synthesis technique to identify the components of a knowledge-based business model in a VUCA environment using an artificial intelligence approach. In this study, by employing a systematic review and meta-synthesis approach, the results and findings of previous researchers were analyzed. By implementing the seven-step method proposed by Sandelowski and Barroso (2007), the influential factors were identified. Out of 198 articles, 35 were selected based on the Critical Appraisal Skills Programme (CASP) method, and the validity of the analysis was confirmed with a Cohen's kappa coefficient of 0.810. In this regard, to assess reliability and control quality, the transcript method was used, which showed an excellent level of agreement for the identified indicators. The analysis of the collected data was performed using MAXQDA. Finally, from the indicators extracted from the texts of the related articles, after eliminating synonymous and repetitive indicators, and categorizing the final indicators, eight categories and seventy-one codes were obtained. The codes resulting from the meta-synthesis method include: interaction and customer relationship management, data prediction and analysis, risk management strategies, intelligent leadership and decision-making, agility and flexibility, knowledge management, resource and process optimization, and continuous innovation and improvement. These were identified as key and influential components of the model.

Keywords: Sandelowski and Barroso technique; knowledge-based business model; VUCA environment; Artificial Intelligence; meta-synthesis method

Introduction

In the rapidly evolving landscape of contemporary business, the emergence of the VUCA (Volatility, Uncertainty, Complexity, and Ambiguity) environment has fundamentally transformed the dynamics of organizational survival and growth. The VUCA paradigm reflects a world characterized by unpredictable changes, ambiguous market signals, and complex interdependencies among global actors, where organizations are constantly compelled to adapt and innovate to remain competitive [1]. This environment challenges traditional business models by disrupting stable value chains and reshaping competitive advantages, demanding new strategic approaches grounded in agility, adaptability, and technological integration [2].

In such unstable contexts, knowledge-based organizations have emerged as pivotal actors in driving innovation and maintaining strategic flexibility. These organizations leverage intangible assets—such as intellectual capital, specialized expertise, and technological infrastructure—to generate value and sustain competitiveness [3]. However, sustaining a knowledge-based business model in a VUCA setting requires continuous adaptation and reconfiguration of organizational structures, decision-making processes, and knowledge management mechanisms to meet shifting demands [4]. The capacity to redesign business models dynamically, while preserving organizational resilience and innovation capabilities, has therefore become a critical success factor [5].

A key enabler of this adaptive capacity is Artificial Intelligence (AI), which has become an integral component of strategic decision-making, operational optimization, and knowledge management in knowledge-based organizations [6]. AI technologies offer unprecedented capabilities to analyze big data, detect hidden patterns, and provide predictive insights that support timely and informed decisions in highly turbulent environments [7]. Through machine learning algorithms, natural language processing, and predictive analytics, AI systems can anticipate market changes, identify emerging risks, and automate complex operational tasks, thereby improving organizational responsiveness and strategic foresight [8].

Moreover, the strategic integration of AI has shown to significantly enhance the resilience of knowledge-based firms by reducing decision-making uncertainty and enabling proactive responses to environmental disruptions [9]. AI-driven decision support systems and real-time analytics platforms empower managers to evaluate multiple scenarios rapidly and allocate resources efficiently under conditions of uncertainty, which is vital for maintaining operational continuity and competitive positioning [10]. This is particularly critical in small and medium-sized enterprises (SMEs), which often lack the structural buffers of larger firms and must rely on agility and technological adoption to survive in volatile markets [5, 10].

The incorporation of AI into knowledge management practices further enhances organizational adaptability by streamlining the processes of knowledge creation, storage, retrieval, and dissemination [8]. AI-powered knowledge management systems can automatically extract and classify knowledge from unstructured data, support collaborative platforms, and ensure the timely delivery of relevant information to decision-makers [3]. This reduces knowledge silos, accelerates organizational learning, and fosters innovation ecosystems within firms. Consequently, the synergy between AI and knowledge management represents a strategic foundation for sustaining competitive advantage in knowledge-based business models [6].

Nevertheless, the implementation of AI technologies in organizational settings also poses challenges, particularly in terms of employee anxiety, cultural resistance, and ethical considerations. High levels of technological anxiety can hinder employees' willingness to adopt AI systems, negatively affecting digital transformation efforts and overall performance [11]. Building a culture of trust and providing continuous training are therefore essential to mitigate resistance and enhance the human-AI collaboration required for achieving organizational goals [9]. This underscores the importance of leadership approaches that foster psychological safety, encourage experimentation, and align AI initiatives with organizational values and human capital strategies [12].

Leadership styles in the VUCA context must evolve from hierarchical command-and-control models to more flexible, participatory, and adaptive forms of governance [12]. Effective leaders in knowledge-based organizations need to cultivate strategic foresight, embrace risk-taking, and orchestrate sociotechnical systems that integrate human and digital resources harmoniously [13]. Such sociotechnical self-orchestration enables organizations to rapidly reconfigure teams, processes, and technologies in response to environmental shocks, thereby sustaining innovation and competitive relevance [13]. Additionally, fostering entrepreneurial thinking and supporting cross-functional collaboration are vital for accelerating the implementation of AI-driven initiatives in knowledge-based settings [14].

The competitive dynamics of knowledge-based enterprises operating in VUCA environments demand a multidimensional strategic approach that integrates market orientation, technological innovation, and operational agility [4, 15]. These firms must not only leverage AI for predictive analytics and risk management but also redesign their business models to capture emerging opportunities in circular value chains and sustainable markets [15]. Sustainable innovation, facilitated by AI, can support firms in developing new value propositions and adaptive capabilities that align with both environmental pressures and stakeholder expectations [4].

Furthermore, research emphasizes that digital transformation driven by AI contributes to enhancing organizational agility—the ability to sense, seize, and respond to changes rapidly—which is a critical success factor for SMEs and knowledge-based firms navigating the uncertainties of the VUCA world [1, 10]. Agile organizations can continuously reconfigure their resources, processes, and strategic orientations, which enables them to maintain resilience and competitiveness even under extreme turbulence [2]. The strategic positioning of such organizations, often informed by models like the VRIO framework, further strengthens their ability to develop rare, valuable, inimitable, and organizationally embedded resources that are essential for sustaining long-term advantage [14].

Given the increasing complexity and uncertainty of global markets, the integration of AI into knowledge-based business models is no longer optional but a strategic necessity. Organizations that effectively combine AI-driven analytics, agile decision-making, and robust knowledge management systems are better positioned to achieve sustainable growth and competitive resilience in volatile environments [3, 6, 7]. To address these challenges and opportunities, this study aims to identify and analyze the core components of knowledge-based business models in a VUCA environment with an artificial intelligence approach.

Methodology

The present study, aiming to identify the components of a knowledge-based business model in a VUCA environment with an Artificial Intelligence approach based on a meta-synthesis method, is a qualitative study in terms of overall approach and was conducted using library research and the meta-synthesis technique in the field of business. Meta-synthesis is a type of method under the umbrella of meta-study, which, through the systematic review of sources, extracts, evaluates, synthesizes, and, if necessary, statistically summarizes research that has previously been conducted on a specific thematic domain (Sandelowski & Barroso, 2007). In fact, in meta-synthesis, the information and findings extracted from other related and similar studies are reviewed and analyzed. The data collected from these studies are qualitative rather than quantitative. Therefore, the sample considered for meta-synthesis is purposeful and formed based on their relevance to the research question. Meta-synthesis is not merely an integrated review of qualitative principles or the analysis of secondary and primary data from selected studies, but rather an analysis of the findings of these studies. In other words, meta-synthesis involves synthesizing the interpretations of the primary data of the selected studies. ATLAS.ti software was used for the analysis. The main stages of meta-synthesis according to Sandelowski and Barroso are presented in the next secion.

Findings and Results

As mentioned, meta-synthesis analysis comprises seven steps. In this section, the results related to each step of this analysis are presented separately.

Step One: Formulating the Research Questions

The first step in the meta-synthesis method is formulating the research questions. These questions are generally structured based on the four parameters of what, who, when, and how. In this study, the dimensions of developing knowledge-based business in a VUCA environment with an artificial intelligence approach were questioned.

Table 1.

Research Questions

Parameter	Research Question
What	Identifying the components of knowledge-based business in a VUCA environment with an artificial intelligence approach
Who	Various works including books, articles, and reports on knowledge-based business in a VUCA environment with an artificial intelligence approach
When	Covering all works from 2000 to 2025
How	Thematic review, identification and note-taking, key points, concept analysis

Step Two: Systematic Review of the Literature

The following table presents the keywords considered for this study.

Table 2.

Appropriate Keywords for Step Two of the Meta-synthesis Method

Persian Equivalent of Key Concepts	English Keywords Used in Search
کسب و کار دانش محور با رویکرد هوش مصنوعی	Knowledge-based business with an artificial intelligence approach
با رویکرد هوش مصنوعی VUCA کسب و کار دانش محور در محیط	Knowledge-based business in the VUCA environment with an artificial intelligence approach
VUCA کسب و کار دانش محور در محیط	Knowledge-based business in the VUCA environment

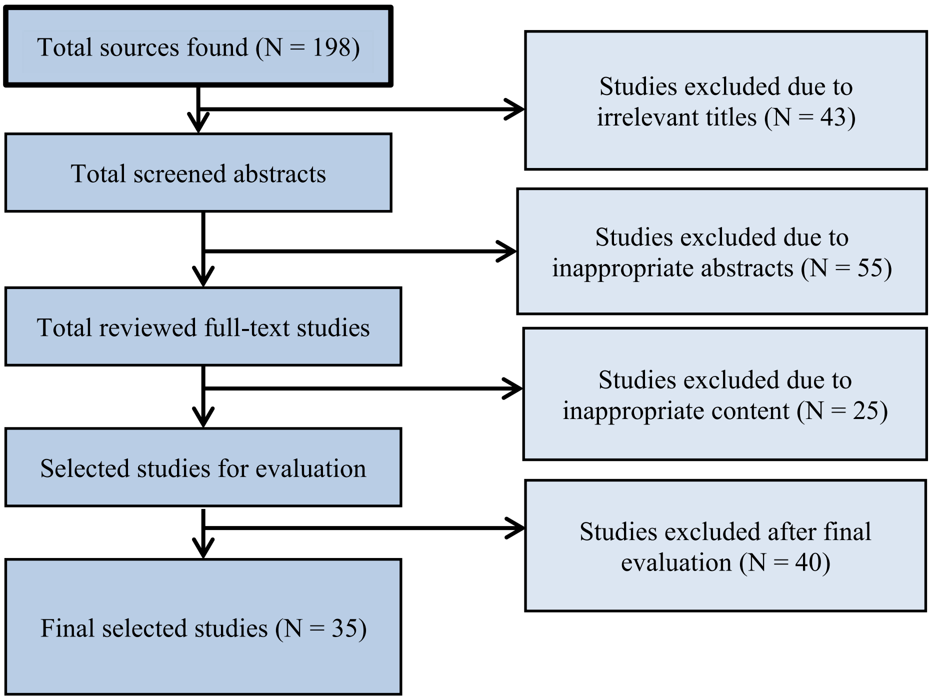
In this section, various keywords used in the research and information collection process were presented, and the various sources for collecting the required data were also introduced. In this research, only data and information available in the mentioned sources and databases were used. Additionally, for international research, databases such as Google Scholar and ScienceDirect were used. Accordingly, through the review and identification of studies using the National Library of Iran search system and other libraries, research centers, and websites such as Jahad Daneshgahi, Noormags (specialized journals database), national conference scientific articles databases, national journals databases, IranDoc, IEEE, and ScienceDirect, using keywords related to knowledge-based business in a VUCA environment with an artificial intelligence approach in the title field, a total of 198 studies were found.

Step Three: Searching and Selecting Relevant Studies

Table 3 presents the steps taken to screen the extracted articles. According to this table, four stages were completed to refine the extracted articles, with the final stage based on the opinions of five expert reviewers in this research. These experts, in order to assess the final quality of the articles, evaluated each of the finally shortlisted articles based on the approach introduced below. Articles that scored lower than the minimum threshold were excluded from the process.

Figure 1.

Screening and Selection Process



In this step, the 198 studies found in the previous step were carefully reviewed through several stages to exclude studies that were not aligned with the research questions and to finally identify the most relevant studies for answering the questions. The screening process included reviewing the title, abstract, and content of the studies, along with their research methodology. The stages of the screening process in this study were as follows:

1. At this stage, the titles of the studies were reviewed, and those unrelated to the research questions were excluded. After reviewing the titles, 43 studies were excluded due to lack of relevance to the research questions.
2. At this stage, the abstracts of the studies were reviewed, and those unrelated to the research questions were excluded. After reviewing the abstracts, 55 studies were excluded due to lack of relevance to the research questions.
3. At this stage, the full content of the studies was reviewed, meaning the entire research was read, and studies unrelated to the research questions were excluded. After reviewing the content, 25 studies were excluded for irrelevance to the research questions.
4. Since this research aims to extract a research framework by synthesizing previous studies, and according to meta-synthesis experts, studies with both qualitative and quantitative methodologies can be included, no study was excluded at this stage due to its methodology.

After removing the studies that were inconsistent with the research objectives and questions, the researcher had to evaluate the methodological quality of the studies. The aim of this step was to eliminate studies whose findings could not be trusted. The tool commonly used to assess the quality of primary qualitative research studies is the Critical Appraisal Skills Programme (CASP), which uses ten questions to help determine the rigor, credibility, and relevance of qualitative studies. These questions focus on: (1) research aims, (2) rationale for methodology, (3) research design, (4) sampling strategy, (5) data collection, (6) reflexivity (the relationship between the researcher and participants), (7) ethical considerations, (8) rigor of data analysis, (9) clear and explicit presentation of findings, and (10) value of the research.

Table 3.

Selected Articles

Article Code	Title
S01	The Straits of Success in a VUCA World
S02	Strategies to Respond to a VUCA World
S03	Business Models in a VUCA Environment
S04	Career Beliefs, Self-Efficacy and VUCA Skills: A Study Among Generation Z Female Students of Tourism and Hospitality
S05	The Impact of the VUCA Environment on the Digital Competences of Managers in the Power Industry
S06	The Importance of Technological Anxiety for the Digital Transformation of Industrial Processing Companies in
S07	Applying Organizational Ambidexterity Skills in Strategic Management Under VUCA Conditions
S08	Analysis of Strength and Weakness Using the Concept of with the Framework in Sharia Cooperatives
S09	Managing in a VUCA World: Possibilities and Pitfalls
S10	Designing a Model of the Experienced Online Shopping of Customers Under VUCA Conditions
S11	The Role of Agility in the Digital Transformation Era
S12	How Can SMEs Successfully Navigate the VUCA Environment
S13	AI-Enabled Recruiting: What Is It and How Should a Manager Use It?
S14	Understanding the Future of Through the VUCA Lens
S15	Clarifying the Conceptual Map of VUCA: A Systematic Review
S16	Strategies for Managing Sustainability Risk in a VUCA World
S17	Industrial Excellence Meets Travelling Organization: Keeping Promises in the VUCA World
S18	Adapting to a VUCA World
S19	Trend Analysis and Mapping of Management-Related Topics in the VUCA Environment Using Citation Analysis
S20	-Supported Reduction of Employees' Workload to Increase the Company's Performance in Today's VUCA Environment
S21	Identifying Key Leadership Competencies for Digital Transformation: Evidence from a Cross-Sectoral Study of Global Managers
S22	The VUCA Approach as a Solution Concept to Corporate Foresight Challenges and Global Technological Disruption
S23	The Drill Model: A Renewed Perspective Adapted to the Volatile, Uncertain, Complex and Agile (VUCA) World to Improve Situation Analysis and Support Decision-Making
S24	The Dark Side of Expatriation: Dysfunctional Relationships, Expatriate Crises, Prejudice and a VUCA World
S25	: Practices for Open Organizing Across VUCA Contexts
S26	Leadership Styles in the VUCA World, Through the Eyes of Gen-Z. In: Dhir, S., Sushil (Eds.) Flexible Strategies in VUCA Markets
S27	Ambiguity and the Value of Diversification
S28	Managing VUCA: The Human Dynamics of Agility
S29	Orchestrating Open Innovation Through Punctuated Openness: A Process Model of Open Organizing for Tackling Wicked Multi-Stakeholder Problems
S30	What a Difference a Word Makes: Understanding Threats to Performance in a VUCA World
S31	Typology of Strategic Positioning in High-Tech Organizations with Focus on VRIO's Impact in the VUCA Environment
S32	Applying Organizational Ambidexterity in Strategic Management Under a "VUCA" Environment: Evidence from High-Tech Companies in
S33	Why Systems Must Explore the Unknown to Survive in VUCA Environments
S34	Developing Organizational Resilience Through Decreasing Anxiety in the VUCA World
S35	AI Customer Service: Task Complexity, Problem-Solving Ability, and Usage Intention

To improve the quality of the research results, at this stage the remaining articles were reviewed for methodological quality to eliminate those with low methodological quality. For this purpose, the quality control tool Critical Appraisal Skills Programme (CASP) was used based on ten quality assessment criteria (clarity of objectives and research significance, suitability and alignment of the research method, suitability and alignment of the research design, appropriateness of the participant selection method, appropriateness of the data collection method, relationship between the researcher and participants, ethical considerations, rigor of data analysis, clear presentation of findings, and value of the research) (Reeder & Lunsault, 2018).

Based on this, 101 articles were included in the evaluation and assessed according to the ten criteria. The result of the structural and content analysis of the articles confirmed 22 of them. Eventually, after four stages of screening, out of 198 studies, 163 were excluded, and 35 studies were selected for data analysis.

The coding status of the first and second coders is shown in the table below, along with the results of the analyses obtained from SPSS. As observed, the significance level obtained for the Cohen's kappa coefficient is less than 0.05, therefore the assumption of independence of the extracted codes is rejected, and the interdependence of the extracted codes is confirmed. Thus, it can be claimed that the tool used for code extraction had sufficient reliability.

Table 4.

Cross-tabulation of First and Second Coders

	Second Coder: No	Second Coder: Yes	Total
First Coder: Yes	3	30	33
First Coder: No	0	2	2
Total	3	32	35

Table 5.

Agreement Measurement Values

Item	Value	Significance
Cohen’s Kappa Agreement Value	0.810	0.001
Number of Cases	35	—

Step Four: Extracting Information from Selected Articles

In this study, the information from the selected research articles was categorized in a table. This table includes the following data:

Table 6.

Sample of Extracted Codes from Selected Articles

Indicator	Concept
Data quality	Includes the accuracy, completeness, validity, and timeliness of input data required for accurate predictions. High-quality data provide a more reliable basis for predictions.
Data coverage	Examines the breadth and diversity of collected data, which should represent various market conditions and customer behaviors.
Forecast accuracy	Comparing forecasts with actual results to assess the accuracy and reliability of predictive algorithms. This indicator shows the algorithm’s ability to accurately predict future trends and behaviors.
Data analysis speed	The time required to collect, process, and analyze data. This indicator shows how quickly the organization can turn data into actionable insights.
Real-time forecasting	The ability of the system to provide immediate and up-to-date forecasts under rapidly changing conditions. This is crucial for reactive decision-making in complex and unstable environments.
Analysis coverage	Examines the level of detail and depth of data analyses, including descriptive, prescriptive, and predictive analyses. This indicates the model’s ability to provide diverse and comprehensive analyses.
Model flexibility	The ability of data analysis models to adapt to new conditions and data changes. In VUCA environments, models must be flexible to be continuously optimized.
Accuracy of Artificial Intelligence algorithms	The quality and accuracy of algorithms used in data analysis and predictions, such as neural networks, Support Vector Machines (SVM), and Random Forests.
Demand forecasting	The model’s ability to predict demand fluctuations using environmental, behavioral, and social indicators. This is especially important in consumer and manufacturing industries.
Data correlation level	Measuring the relationships between data to improve the accuracy of analysis and predictions. This helps identify and account for inter-variable effects.
Interpretability of results	The ability to interpret and explain prediction results in a way that is understandable and actionable for decision-makers. This is a crucial indicator for using analytical results to develop strategies and actions.
Responsiveness to changes	The speed of decision-making and action in response to market or environmental changes, showing the organization’s agility in seizing opportunities and reducing risks.
Operational flexibility	The ability to quickly and optimally modify processes, production, or services in response to demand fluctuations and new conditions. This is especially important for reducing costs and improving operational performance.
Human resource adaptability	The readiness and ability of personnel to quickly learn, change roles and tasks, and adapt to new technologies. Continuous training and organizational culture play an important role in this indicator.
Volatility predictability and management	The ability to predict changes and fluctuations and adjust structures and processes accordingly.
Decision-making cycle time	The time the organization spends collecting data, analyzing, and making decisions in uncertain conditions. This indicates improvements in decision-making processes.
Rapid technology development and deployment	The organization’s ability to evaluate and implement new technologies, especially artificial intelligence, to enhance agility in processes and decision-making.

Structural adaptability	The flexibility of the organizational structure to facilitate rapid changes, including adapting to hybrid models or temporary teams to better respond to challenges.
Continuous skill development	The organization’s ability to continuously enhance employees’ skills through training and development, especially in new technologies such as AI and data mining.
New product development speed	The time required to turn an idea into a new product or service and launch it to the market. This shows the organization’s ability to respond to changing customer and competitor needs.
Percentage of revenue from innovative products	The share of revenue from new products or services in total organizational revenue, indicating success in value-creating innovations.
Frequency of process improvements	The number and extent of process improvements implemented over specific periods, showing the organization’s commitment to continuous improvement.
Success rate of innovative projects	The percentage of innovative projects that achieved successful outcomes, reflecting the efficiency of innovation teams and project management processes.
Speed of adopting new technologies	The time required to evaluate, implement, and use new technologies such as AI tools and automation.
Creating an innovation culture	The level of employee participation and support for innovation and ideation processes. This culture encourages employees to propose new and creative ideas.
Return on investment from innovation	The profitability and added value from innovative projects compared to the costs incurred, showing the effectiveness of investments in innovation.
Knowledge updating and transfer rate	The speed and quality of updating and transferring knowledge to employees, teams, and departments, especially under rapid environmental changes.
Employee access to knowledge	Easy access of employees to required resources and expertise, facilitating and improving decision-making and performance.
Knowledge retention and documentation	Effective processes for storing and documenting knowledge to ensure future usability and reduce dependence on specific individuals.
Knowledge base quality	The quality, comprehensiveness, and timeliness of knowledge bases, including organizational information, documents, and reports.
Knowledge sharing index	The extent of knowledge sharing among employees, teams, and departments through collaboration networks, regular meetings, and digital tools.
Knowledge extraction from data	The organization’s ability to extract knowledge from large and complex data using AI and data mining techniques.
Tacit knowledge retention	The organization’s ability to identify and retain tacit knowledge embedded in employees’ minds and experiences and use it for decision-making and innovation.
Use of collaboration and knowledge management platforms	Using digital platforms and technologies that enable collaboration and knowledge management for employees and teams.
Monitoring and evaluating knowledge value	Systems and processes to assess and measure the value of existing knowledge and its impact on organizational performance and profitability.
Flexibility of knowledge systems to change	The ability of knowledge management systems to adapt to rapid changes and environmental fluctuations, including adding new data and removing outdated data.
Environmental forecasting and analysis capability	Leaders’ ability to forecast environmental changes and analyze existing data using AI tools to better understand complex and unstable conditions.
Intelligence level of decision support systems	The advancement level of decision support systems designed based on AI and data mining to help leaders make quick and intelligent decisions.
Data-driven insight quality	Leaders’ ability to extract valuable insights from data to provide strategic decisions with the help of AI algorithms.
Use of predictive analytics	The extent to which predictive analytics is used in decision-making to forecast the outcomes of decisions and identify risks and opportunities.
Strategic thinking skills	Leadership skills in strategic thinking and the ability to formulate and implement data-driven and AI-based strategies.
Reliance on intelligent algorithms and models	The extent of using advanced AI algorithms and models in data analysis and supporting strategic decisions.
Scenario planning ability	The use of different scenarios in strategic planning to help leaders prepare for various decision outcomes.
Customer experience personalization	The ability to create personalized customer experiences using data and AI analytics, leading to increased satisfaction and engagement.
Fast and automated response systems	The use of chatbots, intelligent response systems, and AI-based tools to quickly and accurately respond to customer questions and requests.
Customer satisfaction index	Measuring customer satisfaction with services and products regularly and analyzing feedback data for continuous improvement.
Predicting customer behavior and needs	Using AI algorithms to predict future customer needs and behaviors based on purchase and interaction data.
Customer feedback data analysis	Collecting and analyzing customer feedback from surveys, social media, and other channels to improve services and products.
Omnichannel interaction	Creating coordination and integration in customer interactions across various channels such as websites, social media, mobile apps, and email.
Intelligent and relevant recommendations	Providing customers with relevant and intelligent recommendations based on behavioral and needs analysis to increase repurchase likelihood.
Customer sentiment analysis	Using sentiment analysis tools to evaluate customer reactions and feelings toward the brand, products, and services and make appropriate decisions.
Increasing customer lifetime value	Implementing strategies to increase customer lifetime value through personalized offers, product/service upgrades, and loyalty programs.

Risk identification and prediction	Using AI algorithms and data analysis to identify and predict various risks early, including operational, financial, and environmental risks.
Data-driven risk assessment	Analyzing and evaluating risks based on historical, market, and current data to allocate resources more accurately and improve risk management precision.
Scenario-based modeling	Creating and evaluating different scenarios to analyze and understand the potential outcomes of decisions and strategies, helping the organization prepare for adverse conditions.
Cyber risk management	Identifying and mitigating cybersecurity risks using AI tools to detect threats and attacks before they occur.
Financial and market risk analysis	Using financial models and machine learning algorithms to predict market fluctuations and assess financial risks.
Real-time risk monitoring	Using AI tools to track and monitor risks in real time and quickly adapt to changing conditions.
Early warning systems	Implementing AI-based alert systems that notify management and teams when risk indicators are detected.
Resource optimization in risk management	Using AI to optimally allocate resources in risk management and increase efficiency in dealing with threats.
Risk mitigation strategies	Designing and implementing risk mitigation strategies such as exposure reduction, risk transfer, and preventive solutions.
Machine learning-based risk management	Using machine learning algorithms to improve risk management processes and identify hidden patterns and relationships in data.
Crisis impact reduction index	Evaluating the effectiveness of crisis impact reduction strategies and the organization's success in reducing the negative effects of unexpected events.
Use of predictive analytics	Applying predictive analytics to identify and prepare for potential risks and develop preventive plans.
Resource consumption analysis and optimization	Analyzing resource consumption data (energy, raw materials, workforce) and optimizing them to reduce waste and improve efficiency.
Process automation	Using robots and AI algorithms to automate repetitive processes and reduce the need for human intervention, thereby increasing the speed and accuracy of tasks.
Optimal resource scheduling and allocation	Using optimization algorithms to allocate resources appropriately to projects and processes to increase efficiency and reduce conflicts.
Cost-benefit analysis	Continuously assessing the costs and benefits of decisions and processes to optimize cost structures and increase profitability.
Automated quality control	Implementing automated, data-driven quality control systems to ensure production standards and reduce errors.
Inventory optimization	Using AI-based demand forecasting to optimize inventory levels and reduce storage and holding costs.
Maintenance scheduling optimization	Using sensor data and predictive analytics to determine optimal maintenance timing and reduce sudden breakdowns.

Step Six: Quality Control of the Analysis

Internal Validity

In this section, we aim to determine whether the results align with the objectives of the study; this assessment is referred to as internal validity. Our goal is to ensure that we do not deviate from the main focus of the study, which is knowledge management, and that no data collection errors occur regarding the relevant objectives.

This is assessed by experts who are external to the study and are able to evaluate the collected and reviewed research on knowledge-based business in a VUCA environment with an Artificial Intelligence approach.

In this study, the procedures and methodology were discussed with supervising and advisory professors, as well as with professional colleagues who specialize in knowledge-based business in a VUCA environment with an artificial intelligence approach or, more broadly, in knowledge management. The entire system and procedure were explained to them in a completely clear and transparent manner, and they were fully informed about the implementation stages.

After confirming the validity, the next step is to confirm and evaluate the reliability of the research implementation process.

Internal Reliability

To allow the researcher to use qualitative findings in analyses, they must be coded. However, this process is susceptible to human and structural errors. These errors can be studied, but when more complex and judgment-based coding is involved, coding errors can severely harm the quality of results.

The term reliability refers to the degree of consistency between coders in their coding results. Inter-coder reliability is a commonly used term referring to the degree of agreement among independent coders when evaluating the characteristics of a message or text. The specific term used for consistency in content analysis is agreement between coders.

Establishing validity and reliability is a critical stage in qualitative data analysis. Reliability refers to the consistency of results from qualitative findings in measuring the intended objectives, while validity refers to the extent to which a method measures the intended purpose of the study. In qualitative studies, validity refers to the extent to which the researcher has accurately reflected the phenomenon under study or its related variables.

In all qualitative methods—especially the Meta-synthesis method—reliability is assessed only internally, as external reliability is neither applicable nor assessed in such methods. Ultimately, in qualitative methods (especially meta-synthesis), the purpose of internal evaluation is to have experts assess whether the implementation method was accurate and appropriate, and whether the results and findings were coded correctly.

In this context, a coefficient called Cohen's kappa is used. This is a statistical formula for measuring agreement in the reliability section of the meta-synthesis method.

To assess the internal reliability of a qualitative research process, two experts were selected to evaluate this procedure. These experts, based on the execution process, the established framework, and the operational procedures, attempted to assess the method of conducting the study. Each expert provided their opinion on how the coding was performed and whether it was done correctly. Their final opinions were then compared; the closer these results and opinions were to each other, the higher the obtained kappa coefficient (or alignment coefficient), which confirms the reliability of the research.

The kappa method is a statistical decision-making tool used to examine the degree of agreement between two evaluators (or decision-making sources) who have each independently measured the same phenomenon.

The kappa coefficient is a numerical value between +1 and −1, where values closer to +1 indicate strong direct agreement, values closer to −1 indicate inverse agreement, and values near 0 indicate no agreement.

To evaluate the reliability of the meta-synthesis, a selected document was given to one expert for assessment. After evaluation, a kappa coefficient of 0.711 was calculated. A kappa value above 0.60 is considered acceptable. Therefore, this value confirms the reliability of the research results.

In this study, the following methods were also considered to maintain the quality of the research:

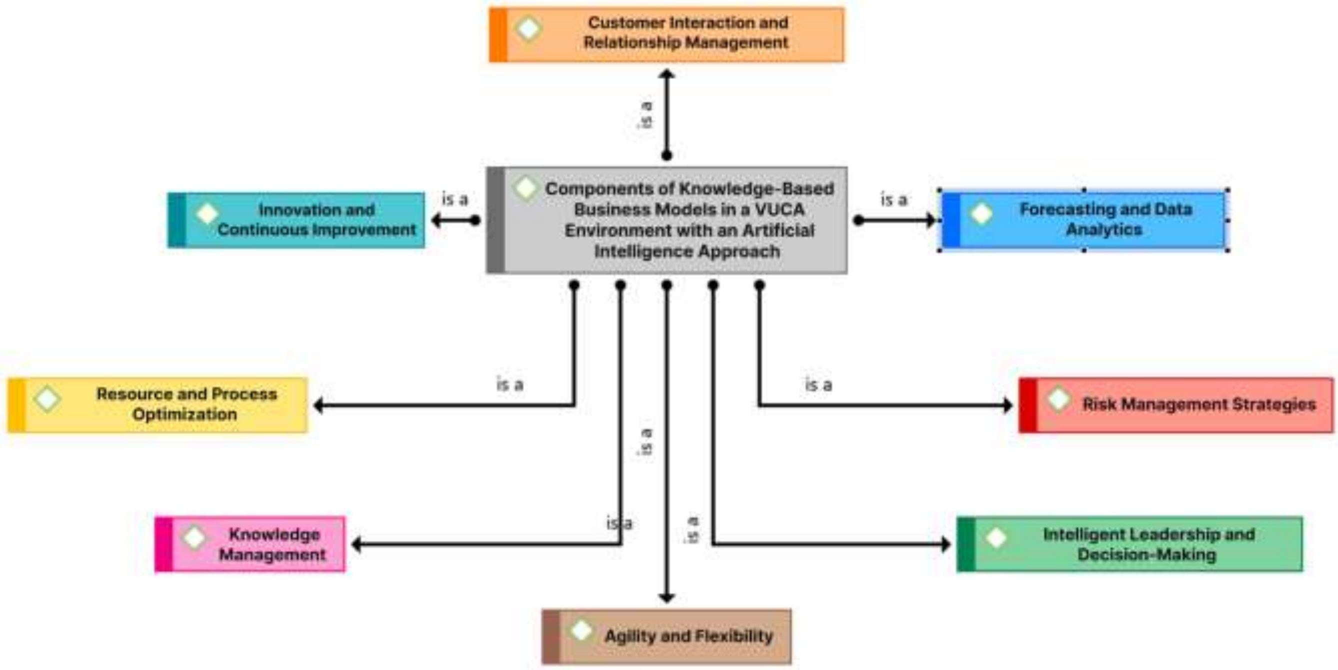
- Throughout the study, clear and transparent explanations were provided for all research options.
- Both electronic and manual search strategies were used to retrieve studies.

Step Seven: Reporting the Research Findings

In this stage of the meta-synthesis method, the findings from the previous stages are presented. The research indicators are then identified. From the indicators extracted from the texts of related articles, after removing synonymous and repetitive indicators and categorizing the final indicators, eight categories and seventy-one codes were obtained. In this stage of coding, the main and subcategories of the research were determined as shown below.

Figure 2.

Components Derived from the Meta-synthesis Technique



Discussion and Conclusion

The present study sought to identify and categorize the core components of knowledge-based business models in a VUCA environment using an Artificial Intelligence (AI) approach. By conducting a systematic meta-synthesis of 35 selected articles, eight main categories and seventy-one associated indicators were extracted, encompassing: (1) forecasting and data analytics, (2) agility and flexibility, (3) innovation and continuous improvement, (4) knowledge management, (5) intelligent leadership and decision-making, (6) customer interaction and relationship management, (7) risk management strategies, and (8) resource and process optimization. These categories represent the strategic, operational, and technological pillars required for sustaining knowledge-based organizations in conditions characterized by volatility, uncertainty, complexity, and ambiguity. The results offer a holistic framework that integrates technological capability—particularly AI—with organizational adaptability and knowledge-based assets.

The findings highlight forecasting and data analytics as a foundational pillar for knowledge-based business models in VUCA environments. This aligns with the view that organizations must leverage big data and predictive analytics to navigate uncertainty and anticipate future market dynamics [7]. AI-driven predictive models enable firms to detect emerging trends, evaluate risk scenarios, and optimize decision-making in real time, thus enhancing strategic foresight [6]. The ability to transform raw data into actionable insights is particularly vital where rapid environmental shifts can render traditional planning obsolete [8]. Similar findings by [1] emphasize that predictive analytics reduces ambiguity by transforming uncertain signals into interpretable knowledge, thereby enhancing managers' confidence in strategic choices. This suggests that forecasting and analytics capabilities function as the cognitive infrastructure of knowledge-based organizations, enabling informed, adaptive responses to environmental turbulence.

Agility and flexibility emerged as another critical component, encompassing operational flexibility, structural adaptability, and rapid technology deployment. The results resonate with research asserting that agility is a key survival trait in VUCA contexts, allowing organizations to reconfigure processes, resources, and roles swiftly [10]. By embracing iterative processes and dynamic resource allocation, knowledge-based firms can shorten decision-making cycles and maintain competitiveness despite volatile market conditions. [2] argues that organizational systems must explore unknown possibilities and continually reinvent themselves to survive, a process that is inherently rooted in agility. Moreover, structural adaptability—such as forming temporary cross-functional teams or hybrid structures—supports rapid response to emerging challenges, which has been identified as essential in digital transformation contexts [14]. This finding underscores the necessity of designing business models with inherent elasticity to withstand shocks and capitalize on fleeting opportunities.

The analysis also identified innovation and continuous improvement as a central pillar, emphasizing rapid product development, fostering an innovation culture, and increasing the success rate of innovation projects. This is consistent with evidence that innovation-driven organizations are more resilient to disruptions and better able to create new value under uncertainty [4]. Continuous improvement mechanisms, such as regular process redesign and iterative learning cycles, sustain competitiveness in turbulent contexts by fostering organizational renewal. Furthermore, [13] stresses the need for sociotechnical self-orchestration, where firms combine human creativity and digital technologies to orchestrate innovation dynamically. This aligns with the current study's observation that innovation must be embedded as an ongoing organizational capability rather than an ad-hoc initiative, particularly when rapid environmental changes threaten the viability of existing business models.

Knowledge management was also identified as a cornerstone of knowledge-based business models in the VUCA environment. AI-enhanced knowledge systems support the creation, storage, sharing, and utilization of organizational knowledge, reducing silos and accelerating organizational learning [8]. The ability to update and transfer knowledge efficiently was shown to directly affect firms' adaptability and innovation capacity [3]. These results echo [7], who found that AI applications enhance knowledge flows and marketing capabilities, which in turn mediate organizational performance. Furthermore, knowledge retention mechanisms and collaboration platforms enable organizations to safeguard tacit knowledge while facilitating real-time access to explicit knowledge, thereby supporting fast and informed decision-making. This confirms that robust knowledge management systems serve as the backbone of adaptive capacity in knowledge-based enterprises operating in unpredictable environments.

Intelligent leadership and decision-making emerged as another indispensable element, encompassing data-driven insights, strategic thinking skills, and reliance on AI-driven decision-support systems. This finding aligns with [12], who emphasized the need for transformational leadership styles that empower employees, encourage experimentation, and build psychological safety in VUCA settings. Such leadership facilitates faster, more accurate decision-making by orchestrating human and technological resources in a coordinated manner [13]. Furthermore, the integration of predictive analytics into decision processes was found to enhance the quality and speed of strategic responses, a result consistent with [6], who demonstrated that AI technologies improve strategic decision-making through their influence on organizational innovation. In sum, the findings suggest that leadership in knowledge-based organizations must evolve from traditional hierarchical structures toward adaptive, data-empowered, and collaborative models.

The results also confirmed customer interaction and relationship management as a core component, highlighting customer experience personalization, omnichannel engagement, and customer sentiment analysis as critical practices. This supports [16], who found that strong consumer-brand relationships contribute significantly to organizational performance in competitive service markets. AI-based tools can personalize customer experiences, predict customer needs, and provide instant responses, thereby fostering customer loyalty even during market instability [11]. The integration of customer data analytics enables firms to anticipate demand fluctuations and design proactive engagement strategies, which is crucial when consumer preferences are volatile and fragmented. These findings illustrate that resilient knowledge-based organizations must maintain close, data-informed relationships with their customers to ensure sustained market relevance.

Risk management strategies were also identified as essential, including data-driven risk assessment, scenario modeling, and real-time risk monitoring. This corresponds to [15], who highlighted the necessity of proactive risk management to ensure sustainability in VUCA contexts. AI-powered risk analysis tools allow firms to identify emerging threats, assess market and financial risks, and implement mitigation strategies before disruptions escalate. Such predictive risk analytics also support resource optimization by allocating capital and human resources more effectively under uncertainty [4]. [14] further emphasizes that strategic positioning informed by risk assessments is crucial for building rare and inimitable capabilities that ensure long-term survival. These findings reinforce the notion that risk management in VUCA environments must evolve from reactive to anticipatory, leveraging AI to navigate uncertainty.

Finally, the study revealed resource and process optimization as a critical enabler of resilience, involving process automation, cost-benefit analysis, and predictive maintenance. This supports [7], who found that AI facilitates operational efficiency and cost reduction by automating repetitive tasks and streamlining workflows. Similarly, [6] highlighted that AI improves strategic decision-making by enabling real-time monitoring and optimization of resources. Resource efficiency becomes particularly vital under volatile conditions, where waste or delays can threaten organizational survival [1]. This indicates that knowledge-based firms must develop dynamic optimization capabilities to sustain profitability while maintaining strategic flexibility.

Collectively, these findings provide strong evidence that sustainable knowledge-based business models in VUCA environments depend on the integration of AI across strategic, operational, and knowledge-centric domains. They also highlight the interdependence of these components: forecasting analytics enhance risk management; knowledge systems support innovation; agile structures enable rapid decision-making; and customer intelligence drives market adaptability. This systemic perspective supports [13], who argues that sociotechnical orchestration is essential for digital-era organizations to self-reconfigure under disruption. It also aligns with [10], who demonstrated that organizational agility mediates the relationship between digital transformation and performance. In essence, this study confirms that AI-driven integration of agility, innovation, knowledge management, and risk-resilience capabilities forms the strategic foundation for thriving in turbulent environments.

Despite its contributions, this study is not without limitations. First, as a meta-synthesis, it relies on secondary data from published studies, which may contain inherent biases, methodological inconsistencies, or contextual constraints beyond the researchers’ control. Second, the selection criteria focused exclusively on peer-reviewed publications, potentially excluding relevant insights from industry reports, grey literature, or unpublished case studies. Third, while the study identified eight core components and their indicators, it did not empirically test the causal relationships among these constructs, limiting the ability to infer directionality or strength of effects. Additionally, cultural and sectoral variations were not examined in depth, which may affect the generalizability of the findings across different national or industry contexts.

Future research could empirically validate the conceptual framework developed here through quantitative studies using structural equation modeling or multi-level analysis to test the interrelationships among the eight components. Longitudinal studies are recommended to capture the dynamic evolution of AI-enabled knowledge-based business models in response to changing VUCA conditions. Comparative cross-country or cross-industry studies could also uncover contextual moderators—such as cultural attitudes toward AI or sectoral regulatory pressures—that shape the adoption and effectiveness of these components. Furthermore, future research could integrate perspectives from behavioral and organizational psychology to examine how leadership styles, employee attitudes, and organizational culture influence the success of AI implementation in knowledge-based models.

Managers of knowledge-based organizations operating in VUCA environments should prioritize building integrated capabilities across the eight identified components. They should invest in AI-driven analytics and knowledge systems to enhance predictive foresight, while simultaneously fostering organizational agility through flexible structures and dynamic processes. Leaders should cultivate a culture of continuous innovation, support employee upskilling, and establish robust mechanisms for knowledge sharing and retention. Moreover, firms must embed proactive risk management practices and customer-centric strategies into their core business models to maintain resilience and relevance in turbulent markets. By orchestrating these components holistically, organizations can strengthen their capacity to adapt, innovate, and thrive amidst volatility, uncertainty, complexity, and ambiguity.

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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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