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A Multi-Criteria Decision-Making Model for Selecting Knowledge Management Outsourcing Providers: A Case Study in Insurance Industry

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ABSTRACT

Outsourcing is a recommended strategy for enhancing competitive advantages. Many foreseeable issues within organizations can be mitigated by eliminating inefficient internal activities from the Knowledge Management (KM) process. One effective approach is to outsource parts of the KM process to an external third party. A key aspect of outsourcing is the selection of appropriate service providers. This study identifies and evaluates the criteria and dimensions for selecting KM outsourcing providers within an insurance company by reviewing the prior research and validating the findings with both industry and academic experts. A framework consisting of nine factors and 35 indicators was developed and validated using the Fuzzy Delphi method. Subsequently, the Fuzzy Analytic Network Process (FANP) and the DEMATEL technique were employed to analyze the data and provide a comprehensive decision-making framework for selecting the most suitable KM outsourcing providers. The findings indicated that "quality" is the most influential criterion in the system, while it is the least influenced by other factors. Conversely, "specialized organizational features" are significantly affected by other criteria. According to FANP results, "experience" holds the highest importance with a weight of 0.30773, whereas "organizational culture" ranks lowest with a weight of 0.02716. Finally, the outcomes of the Fuzzy Delphi and DEMATEL methods were applied in a real-world case within an insurance company to select the optimal KM service provider from two candidate firms.

KEYWORDS

Multicriteria decision-making (MCDM), Knowledge Management, Outsourcing, Fuzzy Delphi, Fuzzy Analytic Network Process (FANP), DEMATEL.

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Introduction

Given the significance of Information Technology (IT) in today's competitive environment, organizations must identify the most effective strategies to meet their IT requirements in a cost-efficient manner while maximizing available opportunities (Mahdavian et al., 2014; Wei et al., 2021). Outsourcing is one of the key approaches used to address IT-related needs within organizations (Aleman, 2014; Mokrini & Aouam, 2020). Under this model, organizations concentrate on their core activities while delegating non-core tasks to extensive networks of external providers (Zarbakhshnia et al., 2020).

Outsourcing complex and advanced tasks has become a strategic tool for organizations aiming to achieve global competitiveness by accessing cross-border knowledge flows and external intellectual resources (Leslie & Willcocks, 2013). In contrast, knowledge management (KM) has traditionally been considered an internal strategy, focused on the development and use of knowledge within the organization. However, the concept of knowledge outsourcing is relatively new (Lam & Chua, 2009).

Outsourcing can offer several short-term competitive advantages, including cost reduction, enhancement of core competencies, increased productivity and quality, improved flexibility, access to external expertise, capital preservation, and the promotion of innovation (Hanafizadeh & Ravasan, 2018; Uygun et al., 2015). Nevertheless, companies must be mindful of the risks associated with outsourcing. Some key concerns that may negatively impact its success include diminished information security, reduced managerial control, and ethical or personnel-related issues (Yang et al., 2007; Zhang et al., 2018).

Once the decision to outsource has been made, selecting the appropriate outsourcing provider becomes a critical next step (Büyüközkan & Çifçi, 2012; Wibisono et al., 2018). While outsourcing offers considerable potential benefits, it may lead to unfavorable outcomes if not supported by well-defined standards, clear conditions, and a coherent scientific and strategic framework. According to statistics, one in every four outsourcing projects ends in failure (Hanafizadeh & Ravasan, 2018).

Because outsourcing providers may not be able to meet all required selection criteria simultaneously, identifying the most suitable provider is inherently a complex task (Cheng & Lin, 2002). Previous studies on knowledge outsourcing have shown that, in most cases, standardized processes are typically outsourced. However, many organizations also choose to outsource processes that are critical to value creation. These are referred to as knowledge processes, which require competitive expertise, analytical and critical thinking, and a high level of specialization (Lam & Chua, 2009).

As different components of products or services evolve along the value chain, the knowledge management (KM) process must also adapt accordingly (Grimsdottir & Edvardsson, 2018). In this context, outsourcing can act as a mechanism for organizational learning. Numerous studies suggest that, to achieve competitive advantages, managers must carefully evaluate the benefits and risks of outsourcing and align outsourced processes with their intrinsic characteristics and with the most relevant criteria for selecting an optimal provider (Liou & Chuang, 2010; Zhang et al., 2018).

IT outsourcing has evolved significantly over the past three decades and has been extensively examined in numerous studies. The primary issues addressed in IT outsourcing include motivation, scope, efficiency, contractual risks, and stakeholders' participation (Wei et al., 2021). Depending on the capabilities of the outsourcing provider and the organization's strategic objectives, companies can select the most appropriate service provider (Mokrini & Aouam, 2020).

Given the growing emphasis in recent research on various aspects of outsourcing, developing a robust model for selecting an appropriate outsourcing provider—grounded in the analysis of both qualitative and quantitative indicators—has become essential. In this context, considering the critical role of knowledge management (KM) in achieving organizational success and competitive advantage, as well as the strategic value of outsourcing in boosting competitiveness, this study aims to propose a framework for selecting KM outsourcing providers.

To achieve this objective, prior research was reviewed to identify the relevant dimensions and evaluation criteria. A comprehensive list of these dimensions and criteria was then compiled and validated through consultation with both industry practitioners and academic experts. The Fuzzy Delphi method was applied to confirm the proposed criteria.

Subsequently, the DEMATEL method was used to determine the causal relationships among the primary selection criteria. Based on these relationships, the local weights of the criteria and sub-criteria were calculated using the Fuzzy Analytic Network Process (FANP). The proposed model was then implemented in a real-world case study involving an Iranian insurance company.

Literature Review

Previous studies indicate that, in most cases, standardized knowledge management (KM) processes are outsourced. However, many organizations choose to outsource the processes that are critical to value creation. These are referred to as knowledge processes and typically require competitive expertise, analytical and judgment-based thinking, and highly specialized skills (Lam & Chua, 2009).

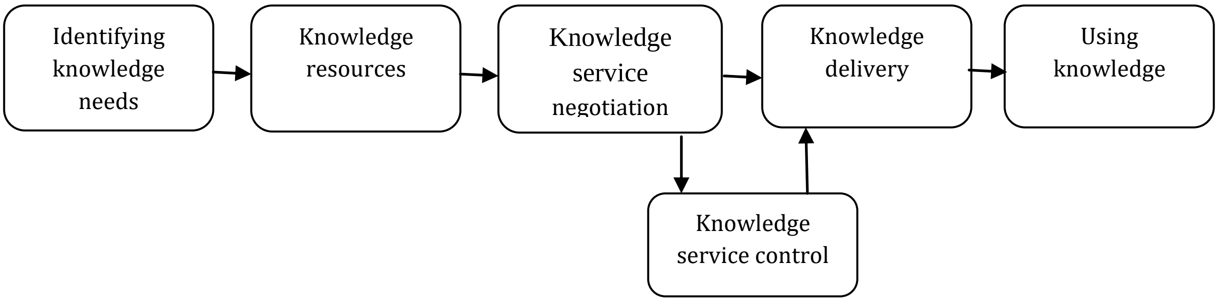
As various components of products or services evolve within the value chain, corresponding changes also occur in KM processes (De Vita & Tekaya, 2015). In this context, outsourcing can serve as a mechanism for organizational learning.

Nevertheless, numerous studies emphasize that managers must carefully evaluate both the advantages and disadvantages of outsourcing, ensuring that outsourced processes are aligned in a way that enhances the organization's competitive position. This objective can only be achieved if managers select outsourcing providers that are optimally suited to the nature and requirements of the processes involved (Liou & Chuang, 2010).

In knowledge outsourcing, external experts deliver knowledge-based assets that are subsequently internalized by the organization. Rather than relying solely on internal capabilities, knowledge outsourcing enables organizations to generate knowledge through external sources.

The knowledge outsourcing process model, illustrated in Figure 1, comprises several stages that define the interaction between the knowledge service consumer and the knowledge service provider.

Figure 1.
The Knowledge Outsourcing Process Model



(Source: Lam & Chua, 2009)

The knowledge outsourcing process begins with identifying the organization's knowledge needs, including the type and scope of the knowledge required. The next step involves identifying relevant knowledge resources, which may include various tools aligned with those needs. At this stage, the potential knowledge providers are also identified and evaluated.

This is followed by a negotiation phase between the client and the knowledge provider. If successful, the process results in a formal contract outlining the terms, costs, licensing conditions, and intellectual property rights. Knowledge delivery then takes place, involving the transfer of knowledge from the provider to the client in various forms.

The quality of the delivered knowledge is monitored through a parallel evaluation process. This ensures that the timeliness of delivery and the characteristics of the knowledge align with the terms agreed upon in the contract. Ultimately, the knowledge assets delivered by the provider are internalized and applied by the client (Lam & Chua, 2009).

Following the outsourcing decision, the next critical step is selecting an appropriate outsourcing provider. Several factors must be taken into account during this process (Büyüközkan & Çifçi, 2012). Outsourcing spans a wide range of functions, including research and development, design, manufacturing, and marketing (Bierly et al., 2002).

In the context of knowledge outsourcing, external experts generate knowledge-based outputs that are subsequently integrated into the client organization. Thus, rather than relying solely on internal capabilities, knowledge outsourcing leverages external sources for knowledge creation (Lam & Chua, 2009; Quinn, 1999).

Within the outsourcing model, the selection of a suitable provider is one of the most critical factors influencing the success of the initiative. Accordingly, many studies consider provider selection as a multi-criteria decision-making (MCDM) problem. To ensure the optimal performance of the selected provider, organizations must develop a robust evaluation framework that incorporates both quantitative and qualitative criteria (Kumar et al., 2014).

Fathi et al. (2025) conducted an in-depth investigation into the barriers hindering the implementation of Internet of Things (IoT) technology within food supply chains. By integrating findings from a comprehensive literature review and expert interviews, and employing the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method, the study identified eleven critical barriers. These barriers were systematically classified into five overarching categories of technological, financial, human capital, regulatory, and infrastructural.

Wei et al. (2021) applied a two-stage fuzzy optimization approach to identify the most influential factors in selecting outsourcing retailers in e-commerce sector. Their findings indicated that “lead time,” “customer’s voice,” “cost,” “delivery and service,” and “quality” were the dominant drivers in the selection process.

Ortiz-Barrios et al. (2020) proposed a hybrid multi-criteria decision-making (MCDM) approach to select the most suitable supplier of forklift filters. In their study, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) was employed to rank the suppliers. The results demonstrated that “quality” was the most critical factor in selection of the supplier.

Mokrini and Aouam (2020) employed a combination of fuzzy TOPSIS, Analytic Hierarchy Process (AHP), and PROMETHEE methods to evaluate the risks associated with healthcare logistics outsourcing in Morocco. Their findings supported the healthcare policymakers in setting effective priorities for implementing preventive and mitigation strategies.

Ariya and Puritat (2020) developed an MCDM model for selecting a suitable Enterprise Resource Planning (ERP) system, focusing on small and medium-sized enterprises (SMEs) in Northern Thailand. The results were used to design a decision-support system that automates the ERP selection process by integrating quantitative analyses across different ERP evaluation categories.

Hassanain et al. (2015) proposed an MCDM framework to assist the maintenance managers in Saudi Arabia to make informed outsourcing decisions. They identified and classified the influencing factors into six groups of strategic, managerial, technological, quality-related, economic, and functional characteristics.

Phochanikorn and Tan (2019) introduced an integrated MCDM method for selecting the green supplier in palm oil industry. Their approach employed the Fuzzy Decision-Making Trial and Evaluation Laboratory (Fuzzy DEMATEL) method to examine causal relationships, followed by the Fuzzy Analytic Network Process (Fuzzy ANP) to assign weights to the criteria. The results of sensitivity analysis and comparative evaluations confirmed that the model was both robust and practical.

Promsivapallop et al. (2015) categorized the evaluation of outsourcing providers into four main dimensions ofcompatibility, risk, cost, and quality—each encompassing several specific criteria.

Fanny et al. (2003) identified twelve key competencies for screening outsourcing providers, which are classified into three major categories:

- Delivery competency: the provider's ability to meet the customer's operational requirements;
- Communication competency: the provider's willingness to align with the customer's strategic goals over time;
- Transformation competency: the provider's capacity to adapt and respond to the customer's evolving needs.

Additional capabilities highlighted in the study include technological efficiency, resource availability, domain expertise, organizational structure, leadership quality, and governance mechanisms.

A review of literature on the process of contractor selection in knowledge management reveals that most existing models and approaches rely on general and broad assumptions, with insufficient attention to the specific needs of the insurance industry. Due to its unique characteristics and challenges, this industry requires tailored decision-making models to select contractors more accurately and efficiently.

Fuzzy logic can play a significant role in this context, as it offers the ability to handle uncertainties, complexities, and multi-faceted judgments inherent in decision-making processes. Its main advantages—such as managing incomplete or ambiguous data and providing flexibility across various parameters—can lead to notable improvements in criteria for contractor selection and enhance the accuracy and effectiveness of decision-making in the insurance sector.

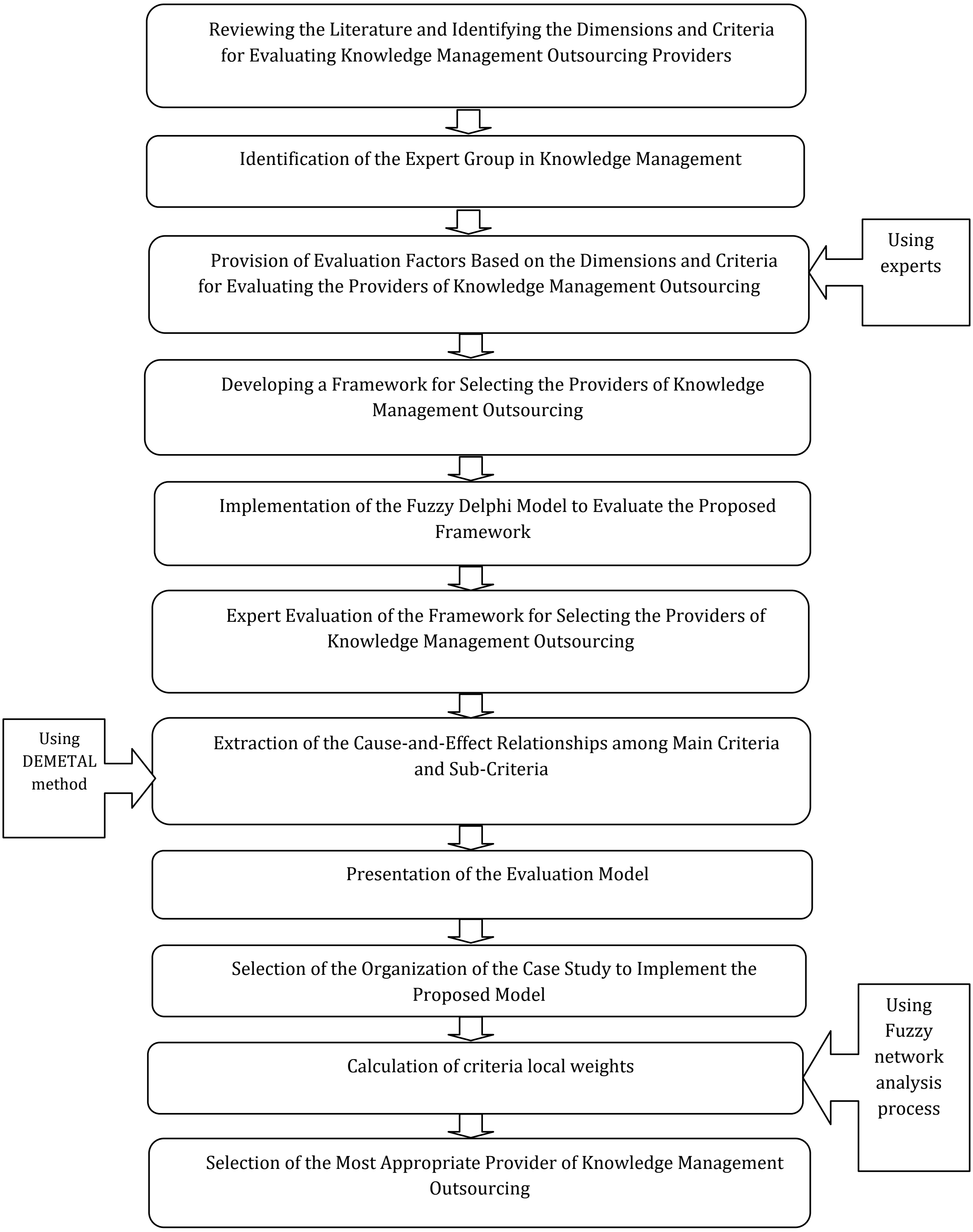
Therefore, developing fuzzy logic–based decision-making models that consider the specific features of this industry is essential to optimize the process of contractor selection and achieve more effective results.

Methodology

The research steps are shown in Figure 2.

Based on the criteria extracted from the literature and previous studies, the Fuzzy Delphi method was employed to gather expert opinions on dimensions and criteria influencing the selection of knowledge management outsourcing providers. The statistical population for this stage consisted of knowledge management experts. A snowball sampling technique was used to identify the participants, and data were collected using a structured questionnaire. In this phase, nine individuals collaborated on the research. They included four university professors at the rank of associate professor or higher, each with numerous academic publications in the field of knowledge management, and five industry managers and experts from the insurance sector, who possess specialized expertise in knowledge management.

Figure 2.
The Research Steps



(Source: The Researcher's Findings)

The validity of the questionnaire was assessed by subject matter experts, while its reliability was calculated using Cronbach's alpha coefficient.

The Delphi technique was initially based on conjecture, expert judgment, and intuition. Over time, it evolved into a more scientific method. It was first developed by the RAND Corporation in the late 1950s as part of a military defense project aimed at systematically collecting expert opinions. However, due to security considerations, the method was not publicly disclosed until twelve years later (Kuo & Chen, 2008).

The key prerequisites for applying the Fuzzy Delphi method include reliance on expert judgment and broad-based expert input; group consensus to derive results; the presence of complex, large-scale, or interdisciplinary problems; disagreement or gaps in the existing knowledge; geographic dispersion of experienced experts; and the need for anonymity in data collection. Therefore, when using the Fuzzy Delphi technique, it is important to distinguish between two types of qualitative research. This method is particularly suitable for exploratory qualitative studies aimed at identifying and understanding the underlying nature and fundamental elements of a phenomenon (Azar & Faraji, 2010).

Among the most prominent applications of the Fuzzy Delphi method are item screening in operations research and integration with multi-criteria decision-making (MCDM) techniques. The core components of the Fuzzy Delphi process include iteration, structured questionnaires, subject-matter expertise, time management, results analysis, anonymity, consensus-building, coordination teams, and controlled feedback mechanisms (Powell, 2003; Van et al., 2006).

Repetition in the Fuzzy Delphi method is conducted systematically, in a process-oriented and documented manner, through a series of questionnaires that continue until the expert consensus is achieved (Van et al., 2006). The participants in the Fuzzy Delphi process are selected experts who possess the relevant knowledge and experience in the subject matter, demonstrate willingness to participate, have sufficient availability, and possess effective communication skills (Motadel et al., 2012; Powell, 2003).

Controlled feedback provides the participants with an opportunity to reconsider their judgments and evaluate the opinions of others—an essential element for progressing toward consensus (Rowe & Wright, 1999). In the Delphi method, information is exchanged without face-to-face interactions, and participants generally remain anonymous to each other; at a minimum, individual responses are kept confidential.

One limitation of the traditional Delphi method is the lack of a standardized procedure for analyzing and managing both qualitative and quantitative data. This gap has led to diverse interpretations and reporting styles, which can compromise the method's coherence and consistency (Windel, 2004).

In this context, consensus refers to a shared agreement among participants on a particular idea. It does not imply identifying a "correct" answer, but rather achieving a sufficient level of agreement on the issue under consideration (Powell, 2003).

The questionnaire used in the Fuzzy Delphi method was designed electronically and structured around nine dimensions, each consisting of a set of evaluation criteria. The questions employed a Likert scale, a structured series of statements arranged in a specific order, where respondents indicate their level of agreement by selecting an item on the scale.

In the first round of the Fuzzy Delphi process, responses were collected from nine experts. After calculating the average response for each item, these averages were compared with those of subsequent rounds. This process continued until the responses stabilized.

In this study, all expert responses reached the required level of stability after two rounds.

Based on the dimensions and criteria obtained using the Fuzzy Delphi method, a DEMATEL questionnaire was used to identify and analyze the cause-and-effect relationships among the factors.

DEMATEL is an effective analytical tool that consolidates expert knowledge to examine interrelationships among the components of the system. One of its most prominent applications is in multi-criteria decision-making (MCDM), where it helps establish structured relationships and hierarchies among identified factors (Hassanpour et al., 2011).

The DEMATEL process includes the following steps:

i. Establishing the initial direct-relation matrix: A group of experts assesses the influence and direction between factors using a rating scale of 0, 1, 2, 3, and 4, representing "no impact", "low impact", "medium impact", "high impact", and "very high impact", respectively. This evaluation results in a $n×n$ matrix for each expert, where $X\_ij\^k$ represents the opinion of the kth expert on the level of influence of the ith factor on the jth factor.

ii. Normalizing the direct-relation matrix and obtaining the total-relation matrix.

iii. Calculating the distributor and receiver groups (Oygan et al., 2014; Wu, 2012).

The Fuzzy Analytic Network Process (FANP) method was employed to rank the most influential dimensions and criteria in selecting a provider of knowledge management outsourcing. Subsequently, expert opinions from the knowledge management team of the case study organization—Iranian Saman Insurance Company—were gathered to evaluate two candidate service providers: Nadak Engineering Consulting and Future Development Consultants.

As the first Iranian insurance company recognized as a knowledge-based enterprise, Saman Insurance has undertaken substantial initiatives in digital transformation and implementation of knowledge management. However, this journey has been marked by some challenges—such as inadequate organizational preparedness, fragmented knowledge-based processes, and a pressing need for training the human resource—that elevate the selection of an appropriate knowledge management outsourcing partner to a strategic imperative.

The Analytic Network Process (ANP), a generalization of the Analytic Hierarchy Process (AHP), was developed by Saaty to address the complex decision-making problems by accounting for interdependencies among criteria and alternatives.

The ANP consists of five main steps (Cheng & Lin, 2002):

i. Identifying the decision-making criteria: These criteria are defined by senior managers, key decision-makers, or expert staff with comprehensive knowledge of the system.

ii. Constructing the network: Certain criteria serve a controlling function within the system. At this stage, such control-related criteria are identified and categorized, as they are essential for monitoring and regulating the outsourcing process.

iii. Conducting pairwise comparisons and deriving the priority vector: Comparisons between categories and their respective elements are conducted using Saaty's 9-point scale, which ranges from 1 to 9, representing levels of importance from equal (1) to extreme (9) (Kardaras et al., 2013). These comparisons help determine the degree of interaction among the categories and establish their relative priorities.

Category comparisons are meaningful only when there are at least three categories. If no comparisons are made, equal weights should be assigned to the categories in subsequent calculations. The phrasing of the comparison question is particularly important. For example, when comparing criterion B with criterion C in relation to criterion A, two distinct perspectives must be considered: (1) The degree to which B is influenced by A versus the degree to which C is influenced by A; (2) the effect of B on A versus the effect of C on A.

To compare the elements, each control criterion is considered individually, and the affected elements within a category are compared accordingly. In a comparison matrix with n criteria, a total of n (n−1)/2 pairwise comparisons are required.

The eigenvector derived from the pairwise comparison matrix of the elements in category A, with respect to control criterion C, represents the relative importance of the elements in category A as influenced by C.

i. Calculation of Supermatrices: This step involves computing both the unweighted and weighted supermatrices.

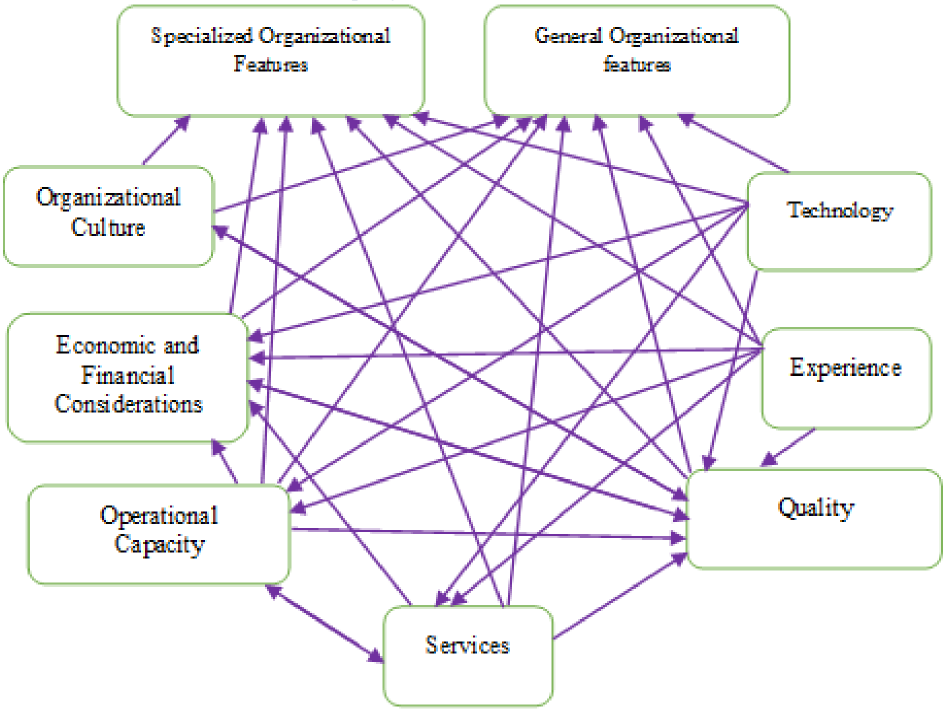
ii. Selection: Based on the calculated weights of the alternatives in the limited supermatrix, the row with the highest weight is selected as the preferred alternative (Rowe & Wright, 1999).

By following the above-mentioned steps, the evaluation factors for selecting a provider of knowledge management outsourcing were extracted from the previous research and structured using carefully designed questionnaires. Through the aggregation of expert opinions during the Fuzzy Delphi iterations, a comprehensive framework was developed to identify the most suitable provider.

The output of the Fuzzy Delphi method served as the input for the DEMATEL technique, which was employed to determine the cause-and-effect relationships among the criteria and sub-criteria within the evaluation framework. Subsequently, the Fuzzy Analytic Network Process (FANP) was used to rank the factors influencing the selection process.

As a case study, the proposed model was implemented at Iranian Saman Insurance Company to evaluate and rank the candidate providers identified by the organization. The relationships among the main criteria for Saman Insurance Company are illustrated in Figure 3.

Figure 3.
The Research Model for Saman Insurance Company



(Source: The Researcher's Findings)

To assess the reliability of the questionnaire, Cronbach's alpha was calculated using SPSS software (SPSS Statistics 30.0, 2023 version). The results confirmed that the questionnaire was reliable and demonstrated strong internal consistency.

The DEMATEL method was implemented using MATLAB R2024b (version 24.2), while the Fuzzy Analytic Network Process (FANP) was conducted using Super Decisions software (version 2.10, released in 2021).

Findings

The fuzzy mean of each indicator was calculated separately in two steps using the Fuzzy Delphi method. Table 1 presents the results of the Delphi calculations for both steps.

In the Fuzzy Delphi method, a threshold value of 3 was set to determine the acceptance or rejection of evaluation factors. Table 2 presents the final dimensions and criteria for evaluating the providers of knowledge management.

Table 1.
The Fuzzy Delphi Method for Validation of the Indicators

Feature	Criteria	Mean of Fuzzy Numbers, step one			Mean of Fuzzy Numbers, step two		
General Organizational Features	Suitability of the organizational structure of provider of knowledge management outsourcing	3.89	6.39	7.22	3.89	6.39	8.89
	Size of the organization for the provider of knowledge management outsourcing	1.68	4.17	5	0.83	3.33	5.83
	Level of the knowledge of provider of knowledge management outsourcing	6	4.54	4.12	5	7.50	9.44
Specialized Organizational Features	Managerial capabilities of provider of the knowledge management outsourcing	7.22	9.72	10	6.67	9.17	10
	Team experience of provider of the knowledge management outsourcing	6.11	7.61	10	6.67	9.17	10
	Flexibility of provider of the knowledge management outsourcing	5.83	8.33	9.44	3.89	6.39	8.89
	Level of confidence in provider of the knowledge management outsourcing	6.67	9.17	10	7.22	9.72	10
	Research and development capability of provider of the knowledge management outsourcing	6.67	9.17	10	5.56	9.06	9.72
	Adequate number of specialist personnel in the knowledge management outsourcing provider organization	5.56	8.06	9.72	5	7.50	9.44
Technology	New technologies utilized by provider of the knowledge management outsourcing	4.44	6.94	9.44	7.22	9.72	10
	Facilities and capabilities utilized by provider of the knowledge management outsourcing	5.56	8.06	10	6.67	9.17	10
	Knowledge management system development tools used by provider of the knowledge management outsourcing	5.83	8.33	9.72	5.56	8.06	10
	Information security techniques utilized by provider of the knowledge management outsourcing	6.39	8.89	10	5.28	7.78	10
	Hardware and software capacity of provider of the knowledge management outsourcing	5	7.50	9.44	5.56	8.06	10
Experience	Number of knowledge management projects completed by provider of knowledge management outsourcing	6.11	8.61	10	6.67	9.17	10
	Years of operation of provider of the knowledge management outsourcing in the field of knowledge management	5.56	8.06	10	5.56	7.78	8.89
	Degree of success in knowledge management projects completed by provider of the knowledge management outsourcing	7.22	9.72	10	6.67	9.17	10
Operational Capacity	Professional ability of provider of the knowledge management outsourcing	3.61	6.11	8.61	5.56	8.06	10
	Capacity of provider of the knowledge management outsourcing in managing special projects	4.72	7.22	9.72	7.22	9.72	8.89
	Duration of the project	4.72	7.22	9.17	3.89	6.39	8.89
Services	Volume of knowledge management system-related services provided by provider of the knowledge management outsourcing	5.56	8.06	9.72	5.28	7.78	10
	Ability to provide knowledge management consulting services	5.28	7.78	10	3.89	6.39	8.89
	Extent of system customization offered by provider of the knowledge management outsourcing	5.56	8.06	9.17	6.11	8.61	10
Quality	Knowledge and skills of provider of the knowledge management outsourcing	5.56	8.06	9.72	7.22	9.72	10
	Satisfaction of previous customers with provider of the knowledge management outsourcing	6.94	9.44	10	6.11	8.61	10
	Quality of services provided by provider of the knowledge management outsourcing	6.67	9.17	10	5.83	8.33	9.72
	Adherence to the established schedule by provider of the knowledge management outsourcing	5.28	7.78	9.44	3.89	6.39	8.89
	Time taken to respond to the customer requirements	4.72	7.22	9.17	3.89	6.67	9.44
Economic and Financial Considerations	Financial stability of the organization for provider of knowledge management outsourcing	3.06	5.56	8.06	3.61	6.11	8.61
	Total cost of the system provided by provider of the knowledge management outsourcing	4.17	6.67	9.17	6.11	8.61	10
	Amount ofc reduction	4.72	7.22	9.17	6.11	8.61	10
Organizational Culture	Level of innovation	4.17	6.67	8.89	5.56	8.06	10
	Extent of information sharing between provider of the knowledge management outsourcing and the organization	6.11	8.61	9.72	6.39	8.89	10

(Source: The Researcher's Findings)

Table 2.
The Final Dimensions and Criteria of Evaluating the Providers Knowledge Management

The Evaluation Criteria and Dimensions for the Providers of Knowledge Management Outsourcing			
Technology	New technology utilized by providers of the knowledge management outsourcing	Suitability of the organizational structure of the knowledge management outsourcing provider	General organizational features
	Facilities and capabilities utilized by provider of the knowledge management outsourcing	Level of knowledge of provider of knowledge management outsourcing	
	Knowledge management system development tools used by provider of the knowledge management outsourcing	Managerial capabilities of provider of the knowledge management outsourcing	Specialized Organizational features
	Information security techniques utilized by provider of the knowledge management outsourcing	Team experience of provider of the knowledge management outsourcing	
	Hardware and software capacity of provider of the knowledge management outsourcing	Degree of flexibility of provider of the knowledge management outsourcing	
Experience	Number of knowledge management projects completed by provider of the knowledge management outsourcing	Level of understanding of knowledge management processes by provider of the knowledge management outsourcing	
	Years of operation of provider of the knowledge management outsourcing in the Field of knowledge management	Level of confidence in provider of the knowledge management outsourcing	
	Degree of success in knowledge management projects completed by provider of the knowledge management outsourcing	Research and development capability of the of provider of the knowledge management outsourcing	
Quality	Knowledge and skills of provider of the knowledge management outsourcing	Adequate number of specialist personnel in organization for the knowledge management outsourcing provider	
	Satisfaction of the previous customers with provider of the knowledge management outsourcing	Alignment of knowledge management strategies of provider of the knowledge management outsourcing with the organization objectives	
	Quality of provider services of the knowledge management outsourcing	Number of knowledge management system-related services provided by provider of the knowledge management outsourcing	Services
	Adherence to the established schedule by provider of the knowledge management outsourcing	Ability to provide consulting services in knowledge management	
	Time taken to respond to customer requirements	Extent of system customization provided by provider of the knowledge management outsourcing	
The ethical and financial considerations	Financial stability of organization for the knowledge management outsourcing provider	Professional capability of provider of the knowledge management outsourcing	Operational capacity
	Total cost of system provided by provider of the knowledge management outsourcing	The capacity of knowledge management outsourcing provider for managing special projects	
	Amount of cost reduction	Duration of the project	
Extent of information sharing between the provider of knowledge management outsourcing and the organization		Level of innovation	Organizational culture

(Source: The Researcher's Findings)

To extract the relationships among the criteria using the Fuzzy DEMATEL method, the first step is to generate a direct-relation matrix. This matrix, derived from the pairwise comparison of the main criteria, is presented in Table 3.

Table 3.
The Direct-relation Matrix of the Main Criteria

	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6	Criterion 7	Criterion 8	Criterion 9
Criterion 1	0	0	0	0	0	0	0	0	0
Criterion 2	1.5	0	0	0	0	0	0	0	0
Criterion 3	1.75	3	0	0	3.51	1.86	3.63	2.91	0
Criterion 4	2	3.25	0	0	4.10	1.59	1.97	1.78	0
Criterion 5	1.95	2.88	0	0	0	0.98	0	4.31	1.95
Criterion 6	2.11	2.69	0	0	4.20	0	1.79	3.12	0
Criterion 7	1.98	3.24	0	0	3.66	2.79	0	2	0
Criterion 8	2.30	2.70	0	0	1.89	0	0	0	0
Criterion 9	2.15	2.90	0	0	3.21	0	1.12	0	0

(Source: The Researcher's Findings)

In the second step, the direct-relation matrix was normalized. The normalized direct-relation matrix for the main criteria and the total-relation matrix are presented in Tables 4 and 5, respectively.

Table 4.
The Normalized Direct-relation Matrix of the Main Criteria

	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6	Criterion 7	Criterion 8	Criterion 9
Criterion 1	0	0	0	0	0	0	0	0	0
Criterion 2	0.0729	0	0	0	0	0	0	0	0
Criterion 3	0.0851	0.1458	0	0	0.1706	0.0904	0.1765	0.1415	٠
Criterion 4	0.0972	0.1230	0	0	0.1993	0.0773	0.0958	0.0865	٠
Criteria n5	0.0948	0.1400	0	0	0	0.0476	0	0.2095	0.0948
Criterion 6	0.1026	0.1308	0	0	0.2042	0	0.0870	0.1517	0
Criterion 7	0.0963	0.1575	0	0	0.1779	0.1356	0	0.0972	0
Criterion 8	0.1118	0.1313	0	0	0.0919	0	0	0	0
Criterion 9	0.1045	0.1410	0	0	0.1561	0	0.0544	0	0

(Source: The Researcher's Findings)

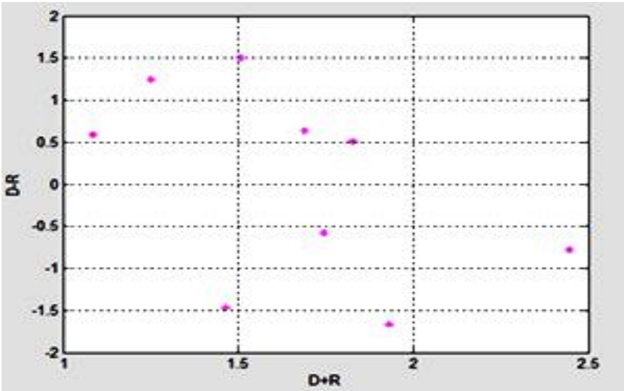
Table 5.
The Total-relation Matrix

	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6	Criterion 7	Criterion 8	Criterion 9	D
Criterion 1	0	0	0	0	0	0	0	0	0	0
Criterion 2	0.0865	0.0179	0	0	0.0164	0.0014	0.0059	0.0044	0.0016	0.134
Criterion 3	0.2251	0.3141	0	0	0.3039	0.1377	0.2452	0.2518	0.0288	1.507
Criterion 4	0.2147	0.2657	0	0	0.3044	0.1136	0.1437	0.1805	0.0289	1.251
Criterion 5	0.1646	0.2083	0	0	0.0590	0.0564	0.0174	0.2292	0.1004	0.835
Criterion 6	0.2102	0.2552	0	0	0.2867	0.0268	0.1227	0.2314	0.0272	1.160
Criterion 7	0.2077	0.2882	0	0	0.2752	0.1644	0.0329	0.1738	0.0261	1.168
Criterion 8	0.1700	0.2047	0	0	0.1410	0.0085	0.0122	0.0320	0.0134	0.582
Criterion 9	0.1859	0.2451	0	0	0.2252	0.0195	0.0807	0.0603	0.0214	0.838
R	1.4647	1.7990	0	0	1.6119	0.5284	0.6606	1.1634	0.2476	

(Source: The Researcher's Findings)

The decision-maker selects only the values greater than the threshold, which are considered to represent cause-and-effect relationships. The cause-and-effect diagram is obtained using a vector map of (D + R, D − R), where the horizontal and vertical axes represent D + R and D − R, respectively.

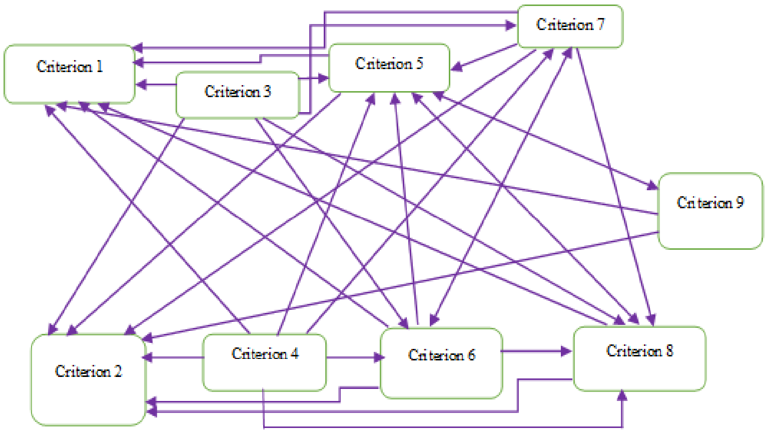
Figure 4.
The Cause-and-effect Diagram of the Main Criteria



(Source: Researcher's Findings)

Based on the threshold value of 3 and the identified relationships, the network model illustrating the connections among the main criteria is shown in Figure 5.

Figure 5.
The Connection Network of the Main Criteria



(Source: The Researcher's Findings)

In this step, the criteria were weighted using Super Decisions software, based on the relationships identified using the DEMATEL method. According to the results obtained from the fuzzy network analysis technique, the rankings of the criteria based on their assigned weights are presented in Table 6.

Table 6.
The Rankings of the Criteria Based on Weights

Criteria	Weight
Experience	0.30773
Economic and Financial Considerations	0.19052
Specialized Organizational Features	0.13793
Services	0.09371
Technology	0.07237
Quality	0.06993
Operational Capacity	0.05821
General Organizational Features	0.04244
Organizational culture	0.02716

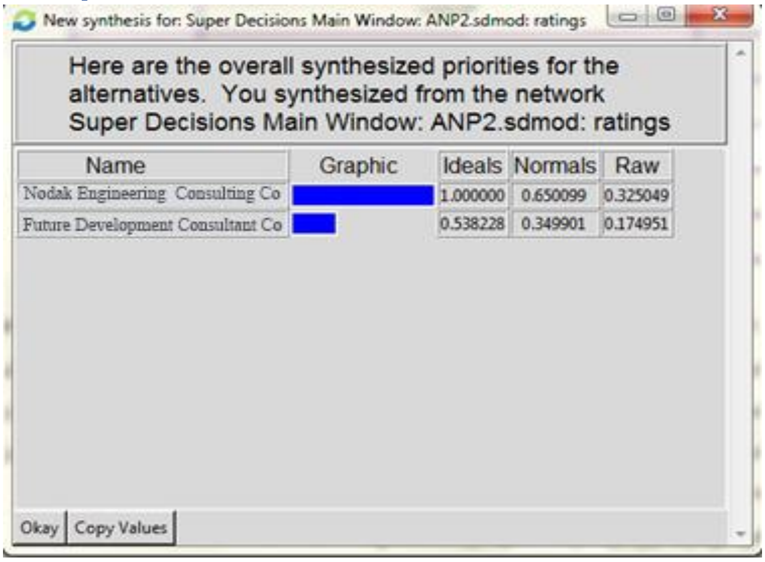
(Source: The Researcher's Findings)

Based on the results of the Fuzzy Analytic Network Process, 'experience'—with an effective weight of 0.30773—was identified as the most important criterion, while 'organizational culture,' with an effective weight of 0.02716, was deemed to be the least important.

The criteria were ranked in descending order of importance as follows: economic and financial considerations, specialized organizational features, services, technology, quality, operational capacity, general organizational features, and organizational culture.

In the case study, two companies—Nodak Engineering Consulting and Future Development Consultants—were evaluated as candidates for knowledge management outsourcing. Based on the weighted sub-criteria, Nodak Engineering Consulting received a higher overall ranking. The results are shown in Figure 6.

Figure 6.
The Results of Selection in Super Decision



(Source: The Researcher's Findings)

In insurance industry, Iranian companies typically consult one another when selecting contractors and share their experiences. Therefore, if a management consulting firm has experienced working with insurance companies, it is considered a significant advantage. Notably, the results showed that the factor of "experience" ranks even higher than economic and financial considerations for these companies.

Conversely, "organizational culture" of the contractor company is given the lowest priority. Previous studies have also largely overlooked this aspect, and it received a similarly low score in this case study. This suggests that operational and experiential factors carry more weight than cultural factors in the decision-making process within this context.

Conclusion

This study identified and prioritized the key criteria influencing the organizations' selection of knowledge management (KM) service providers. Using the Fuzzy Analytic

Network Process (FANP) and DEMATEL methods, the findings revealed that "experience" and "economic and financial considerations" are the most critical factors in selecting a KM outsourcing partner. These results align with previous studies, including those by Uygun et al. (2015) and Modiri and Ansari (2013), which also emphasized the importance of financial aspects.

Additionally, the study highlighted the significant role of specialized organizational features, consistent with the findings of Motadel et al.'s study (2012). Given that knowledge management is widely regarded as a strategic enabler of competitive advantage, organizations must approach the selection of KM service providers with care and strategic insight.

In light of the importance of service quality and alignment with operational and software development standards, implementing software quality assurance standards is also recommended. To enhance decision-making accuracy and comprehensiveness, future studies are encouraged to apply alternative multi-criteria decision-making (MCDM) methods.

Finally, while the criteria used in this research study were drawn from previous literature, organizations are advised to tailor these criteria according to their specific characteristics and strategic needs. Customizing the evaluation framework will lead to a more effective and aligned selection of KM outsourcing providers.

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International Tourism Branding in Knowledge Economy: Challenges, Opportunities, Strategies, and Roleof Stakeholders

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ABSTRACT

This paper presents a comprehensive analysis of the challenges, opportunities, strategies, and the role of stakeholders in international tourism branding within the context of the knowledge economy. Moving beyond outdated, advertisement-based paradigms, modern tourism branding requires dynamic knowledge and effective management to achieve global competitiveness. This study utilizes thematic analysis of qualitative-exploratory research and is informed by interviews conducted with 14 prominent experts in the fields of branding and marketing. The reliability of the coding process was confirmed through a test-retest method, yielding a coefficient of 89.33%. The findings revealed substantial potential in areas such as digital technologies, indigenous knowledge production, community engagement, knowledge-based brand cluster formation, and the integration of emerging technologies (e.g., AR/VR and data analytics) to strengthen competitive advantages. However, several barriers remain. These include insufficient data and technology infrastructure, difficulties in converting knowledge assets into brand value, weak brand governance, and resistance to innovation among conservative stakeholders. Strategically, the paper supports knowledge-based brand governance models built on a tripartite collaboration between government, academia, and industry. Most importantly, this study emphasizes the critical role of digital training for local labor forces and the implementation of knowledge-based metrics for brand evaluation. It redefines the role of stakeholders: tourists are reframed as knowledge prosumers, universities as brand documenters, and governments as facilitators of smart governance. Ultimately, this paper proposes an innovative framework that views the tourism brand not as a promotional tool, but as a dynamic, evolving structure embedded in knowledge ecosystems.

KEYWORDS

Tourism, Brand, Knowledge Economy.

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Introduction

The globalization process in today's rapidly changing world has made international tourism branding a strategic necessity, especially within the context of the knowledge economy. As global tourism grows in scale and complexity, branding is no longer simply a marketing tool; it has become essential for positioning destinations in competitive environments and attracting sustained economic, cultural, and infrastructural investments (Gnoth, 2015). In this evolving paradigm, the knowledge economy—driven by innovation, digital technologies, and the rising importance of intangible assets—has introduced both new opportunities and complexities to tourism branding (Munar, 2009).

The integration of information and communication technologies (ICT), the proliferation of digital platforms, and accelerating globalization have revolutionized how tourism brands are built, communicated, and experienced. Currently, tourism branding goes beyond creating a desirable image; it focuses on fostering interactive, value-based relationships between destinations and international audiences. This shift represents a broader movement from mass communication towards co-created narratives, where travelers, residents, and stakeholders collectively shape the identity and perception of destinations (Munar, 2009).

These developments, though promising, are still faced with big challenges. Among the most urgent ones is the digitalization of the tourist experiences and the development of virtual communities that have transformed the power relations in the branding process. Tourists have become the key players in brand construction and tend to re-write or challenge authoritative accounts, re-framing the territories of destination management and local players (Munar, 2009). Moreover, the tourism industry has to balance the desire to grow economically and the increasing needs to be environmentally and culturally sustainable. In this respect, intellectual property (IP) instruments, including trademarks, patents, and geographical indications, are becoming increasingly significant as mechanisms that allow protecting heritage, as well as fostering innovation (John et al., 2024). In the knowledge economy, intangible assets such as reputation, trust, and relational capital are increasingly seen as critical drivers of competitiveness and value creation (Jamporazmey et at., 2024).

In addition, the smaller tourism operators, especially those in rural and regional settings, experience structural challenges in developing coherent and effective brand identities. Lack of coordination and fragmentation in small businesses, as well as a weak message, can often destabilize destination positioning in foreign markets because of inconsistent messaging (Perkins et al., 2020). On top of that, the incorporation of the national identity, cultural symbolism, and brand authenticity into branding strategies are not developed well in most cases, often due to funding, marketing expertise, and institutional support constraints (Ramona et al., 2009).

However, such barriers are offset by strong opportunities. The tourism industry is growing worldwide, and the destinations that have their own unique and well-maintained brands are becoming better placed to attract tourists who are willing to have meaningful, culturally rich and unique experiences (Alejandria-Gonzalez, 2016). With the emergence of digital branding ecosystems, more personalization, live engagement, and storytelling that touches particular target groups become possible. Simultaneously, the development of business tourism has become one of the most effective forces of knowledge sharing, innovation, and economic interaction. International exhibitions, trade fairs, and conferences are also good platforms to share ideas, build networks and increase the presence of destination brands globally (Vetrivel et al., 2024).

To conclude, branding of international tourism in the environment of the knowledge economy is in a state of dynamic tension between problems and opportunities. With the adoption of digital innovation, exploitation of intellectual and cultural capital and the consideration of the current structural constraints, tourism destinations can develop strong, adaptive brands that are not only in line with the global trends, but also maintain the local identities. Hence, the present article discusses the dynamic environment of tourism branding in knowledge economy terms to give an understanding of strategic directions of sustainable and competitive brand development.

Taking into consideration the radical changes in the contemporary world of economy and the increasing role of knowledge, innovation, and digital technologies in the remodeling of branding and marketing strategies, the objective of this paper is to analyze the issues and possibilities of international tourism branding in the environment of the knowledge economy. In the current study, the author is interested in investigating the role of knowledge-based assets, technological infrastructures, and cultural dynamics in forming, developing, and positioning tourism brands in the global context. Based on this, the core research question behind this investigation is: What are the major challenges and opportunities of international tourism branding in the knowledge economy and what are the strategies that can be used to improve the competitive positioning of tourism destinations in the global markets? Based on the analytical methodology and with references to the latest scholarly research, the article attempts to present a conceptual framework that can help policymakers, scientists, and practitioners in the tourism industry to understand and act in response to the changing patterns of destination branding in knowledge-based settings.

Literature Review

Theoretical Foundations of Tourism Branding

The theoretical background of tourism branding can only be understood through an in-depth analysis of the theoretical frameworks and research studies that have influenced the area of tourism branding. The focal point of this area is the destination branding concept that combines the principles of branding with the creation of destination image. In this regard, the general image of a destination serves as an intermediary between brand associations (cognitive, affective, and unique) and behavioral intentions of tourists (revisit and recommendation) (Qu et al., 2011). Symbolic components of branding such as the name of the destination, destination logo, and tagline also play a significant role in the perception and decision-making of potential tourists (Chan, 2022).

In parallel, place branding has grown into a multidisciplinary practice that takes into consideration the contribution of host communities and various stakeholders in developing the image of destinations (Cai et al., 2009). This transformation is associated with the abandonment of promotional approaches, as it is also a recognition of expanded socio-cultural and economic aspects. An all-encompassing place branding model underlines the mutual relationship between the place image and place reputation, as well as acknowledge, the role of national culture, and infrastructure in shaping the perception of a destination brand on the global level (Foroudi et al., 2016). Strategic place branding underscores the significance of a long-term approach and integrated marketing efforts to boost the attractiveness of a destination (Bayraktar & Uslay, 2016). Additionally, cross-sectoral branding, which sees tourism branding intersecting with various economic sectors, presents an opportunity to establish a cohesive national brand; however, it is not without challenges stemming from conflicting interests among stakeholders (Therkelsen & Halkier, 2008).

The empirical knowledge also supports the significance of stakeholder cooperation in the creation of genuine and unified destination brands. Effective branding will need to involve the alignment of destination marketing organizations (DMOs), the local community, and the private sector actors (Ilieş & Ilieş, 2015). Specifically, sporting events have become one of the powerful means of destination branding, improving brand awareness and generating socio-economic gains, particularly in developing or emerging markets (Hemmonsbey & Tichaawa, 2019).

On the tactical level, the strategic application of such branding components as logos, slogans, and names of destinations is still critical in building the powerful and memorable brand identities (Chan, 2022). In addition to this, the combination of relationship marketing, cluster development and network-based approaches has been found to enhance the results of branding efforts (Żemla, 2009). Although the concept of destination branding has been widely used, it has been criticized on theoretical consistency and implementation. Researchers state that the absence of a coherent theory may lead to disjointed or ineffective branding activity . The solutions to these shortcomings would require bringing in interdisciplinary thinking and greater dependence on empirical data to buttress the theoretical foundation of the discipline (Żemla, 2009).

Following the recent events, especially the consequences of the COVID-19 pandemic, new research directions have been identified. The turn to the psychological and symbolic construction of destination perceptions due to the crisis has shown the importance of the social constructionism and semiotic analysis in tourism branding communication (Bladen & Callinan, 2022). There also seems to be a post-pandemic interest in investigating the relational and spiritual attributes of destination brand experiences that are becoming increasingly critical to establishing emotional and identity-based relationships with sites (Ngwira et al., 2023). Lastly, a multidisciplinary and holistic view (that is based on marketing, tourism studies and sociology) has been suggested to enhance stakeholders coordination, as well as to enhance the knowledge on destination brand identity formation (Konecnik Ruzzier & de Chernatony, 2013).

Knowledge Economy and Its Implications for Tourism

Knowledge economy has also led to a huge change in the tourism industry as it has led to innovation, increased competitiveness and sustainable development. The most important effect is observed in the sphere of innovation and competitive advantage. The acknowledgment of knowledge, as one of the key economic resources, has made it one of the sources of organizational renewal and strategic differentiation in tourism ventures. Sustainable competitive advantage requires efficient management of knowledge, especially in dynamic and globalized tourism markets (Cooper, 2014). Moreover, the use of technological innovation in tourism practices will be possible due to the knowledge-intensive processes, which can affect tourist behavior and spending. Nevertheless, this association does not always follow a straight line, with some research claiming that in specific circumstances, the connection between the development of knowledge and tourist expenditure can be characterized by adverse tendencies (Rigelsky et al., 2022).

Moreover, it is important that knowledge management and network-based cooperation play a central role in the development of innovative capabilities in tourism. In networked tourism systems, knowledge management improves the absorptive capacity of organizations in terms of its ability to incorporate and exploit external knowledge to innovate and develop services (Binder, 2020). On a larger scale, the international scientific collaboration networks (SCNs) of the tourism and hospitality academia have shown a positive influence on the performance of innovation, which highlights the significance of cross-country collaborations and knowledge sharing (Wang et al., 2024).

The knowledge economy also aids optimization of the economy and structure of the tourism industry. It stimulates development of high-value services, encourages sectoral convergence, and a more knowledge-based structure of the industry. Such structural change enables more flexibility and infiltration of tourism into other realms of the economy (Wang, 2015). The most illustrative example in this matter is business tourism which plays a critical role in the transferring of the knowledge and economic growth. Business tourism helps in spreading ideas, technologies, and skills worldwide through the use of activities like international conferences, trade fairs, and exhibitions (Vetrivel et al., 2024).

The other significant influence is the incorporation of the cultural and creative aspects. The combination of the cultural and creative industries with tourism improves the experiences of customers, value addition to tourism services and quality of services. Empirical results emphasize that interactive marketing in cultural tourism results in greater customer satisfaction and greater returns on investment (Wang, 2018). In addition, local knowledge and cultural heritage can be utilized to enhance tourism content and achieve sustainable destination branding without compromising regional identity (Jedeejit et al., 2017). Lastly, the knowledge economy encourages human capital formation and development of education tourism. With education as an international commodity, education tourism has been experienced as a cultural and economic phenomenon in many regions (e.g., ASEAN). This type of tourism helps to increase GDP since it brings foreign students and promotes knowledge mobility . In order to maintain this impetus, it is important to establish sound training systems and knowledge management infrastructures. These are done to guarantee the constant upskilling of the tourism personnel and the sustainability of the industry in terms of competitiveness in the long run (Khan et al., 2020). The transition from 3G to 4G enabled mobile booking systems and location-based services, while the emergence of 5G technology provides unprecedented opportunities for revolutionizing the entire tourism value chain(Fasanghari & Asarian., 2024).

To sum up, the knowledge economy has a revolutionary impact on the tourism sector in various aspects- covering innovation, structural change, economic growth and cultural integration. In order to maximize such advantages, tourism organizations and policymakers should invest in successful knowledge management practices, build effective networks, and focus on human capital development. These are the necessary steps towards ensuring that tourism will have a sustainable and competitive future within the global knowledge economy.

Methodology

Research Method

This study employed a qualitative-exploratory research design to deeply investigate the complexities and dynamics of international tourism branding within the knowledge economy framework. Given the multifaceted and context-specific nature of tourism branding, especially in a globalized and knowledge-driven environment, an interpretivist paradigm was deemed most appropriate. This approach facilitated the exploration of subjective meanings, stakeholder perceptions, and emergent strategic themes through rich qualitative data.

Data were gathered via in-depth semi-structured interviews with 14 carefully selected experts. The purposive sampling strategy was guided by stringent inclusion criteria: participants must possess a minimum of 10 years of experience in tourism branding at academic or practical levels, demonstrate active involvement in tourism development through research, policy-making, or consultancy, and have exposure to branding initiatives in knowledge-based economies. The participants represented a diverse spectrum of professional backgrounds, including academia, government tourism agencies, private-sector brand strategists, and cultural policy consultants, ensuring a broad and multifaceted understanding of the phenomenon.

The sample was geographically diverse, comprising experts from Europe, Asia, and the Middle East, thus enhancing the international relevance and transferability of findings. Interviews were conducted over a six-week period in early 2025, either face-to-face or via secure video conferencing platforms.

Thematic saturation—a point where no new themes or insights emerge—was reached by the 11th interview, aligning with qualitative research benchmarks (Guest et al., 2006). To reinforce the robustness of the thematic structure, three additional interviews were conducted, which confirmed data adequacy and thematic consistency.

The analysis followed Braun and Clarke's (2006) rigorous six-phase thematic analysis process: familiarization with data, initial coding, theme development, reviewing themes, defining and naming themes, and producing the final analytic narrative. NVivo 14 software was employed to facilitate systematic data coding and theme organization, improving the transparency and replicability of analysis.

To ensure methodological rigor and enhance the trustworthiness of findings, multiple triangulation strategies were implemented:

Inter-coder Reliability: Two independent coders analyzed the transcripts. A test-retest reliability check was conducted on three interviews with a ten-day interval, achieving an agreement rate of 89.33%, indicating high coding consistency.

Peer Debriefing: Emerging codes and thematic interpretations were regularly discussed with two senior qualitative researchers outside the research team, allowing critical feedback to mitigate bias and validate findings.

Member Checking: Three participants reviewed preliminary interpretations related to their interviews and confirmed the accuracy and authenticity of thematic representations, thereby strengthening credibility.

We acknowledge the limitations inherent in purposive sampling, including potential selection bias. To mitigate this, strict criteria were applied, and efforts were made to include diverse geographical and institutional perspectives. While the sample size may be limited for broad generalizability, it is consistent with qualitative standards focused on depth and richness of data (Guest et al., 2006). Reflexivity was maintained throughout the study, with the research team regularly reflecting on their positionality and potential biases influencing data collection and interpretation.

Table 1
Inter-Coder Reliability Test (Test–Retest)

Row	Interview Code	Total Codes (both rounds)	Agreements	Reliability (%)
1	T1	104	46	(2×46)/104 = 88.46%
2	T2	96	43	(2×43)/96 = 89.58%
3	T3	100	45	(2×45)/100 = 90.00%
	Total	300	134	(2×134)/300 = 89.33%

(Source: Researcher's Findings)

Based on the applied formula, the final test–retest reliability was calculated as 89.33%, which indicates an acceptable level of agreement across repeated coding instances in this study.

Table 2
Demographic Information of Interview Participants

Row	Age Range	Gender	Academic/Professional Background	Current Role	Years of Experience
1	45–50	Male	PhD in Tourism Marketing	Professor, Intl. Tourism Branding	20
2	50–55	Female	PhD in Cultural Policy	Government Policy Advisor (MoCT)	25
3	35–40	Male	MSc in International Marketing	Brand Consultant (Private Sector)	13
4	40–45	Female	PhD in Media & Destination Communication	Associate Professor, Tourism Faculty	17
5	55–60	Male	PhD in Strategic Management	Executive Director, Tourism Innovation	30
6	30–35	Female	PhD in Digital Branding	Lecturer, Hospitality School	8
7	50–55	Male	PhD in Knowledge Economy Studies	Senior Tourism Analyst	27
8	45–50	Female	PhD in Tourism & Cultural Diplomacy	Researcher, National Branding Institute	22
9	35–40	Male	PhD in Innovation Policy	Assistant Professor	11
10	40–45	Female	MBA in Destination Development	Consultant, Regional Tourism Projects	15
11	30–35	Male	MSc in Travel Tech & AI	CEO, SmartTourTech	9
12	60–65	Male	PhD in International Relations	Cultural Attaché (retired)	35
13	35–40	Female	PhD in Tourism Sociology	Assistant Professor	10
14	45–50	Female	PhD in Public Diplomacy & Tourism	Senior Lecturer	19

(Source: Researcher's Findings)

Findings

For the analysis of the research data, thematic analysis was employed. In the first stage, the texts were thoroughly reviewed multiple times to achieve familiarity and a deep understanding of their content. In the second stage, sentences containing significant and key points were extracted from the texts and organized into a table. From these sentences, keywords termed "key concepts" were identified.

Table 3.
The Initial Coding Sample

Indicator Code	Initial Codes	Key Interview Statement
A1	Leveraging indigenous knowledge in redefining the competitive advantages of the destination,	The native knowledge is the special strength of our destination. We have identified that we cannot be sustainable by merely copying what is happening in the world in terms of tourism. Rather, we have the capacity to produce unique experiences that visitors cannot find elsewhere by getting to know our local wisdom, traditions and practices well and incorporating them into the experiences.
C1	Increasing the visibility of local services through smart markets,	We think that smart markets are an outstanding means of addressing the problem of the invisibility of local services. Previously, small and local businesses particularly those that deal with less popular locations had a major challenge of accessing the potential customers. Conventional advertising was very expensive and in most cases ineffective.
D3	The opportunity to design immersive and inclusive digital travel experiences through Augmented and Virtual Reality	We are living in the time when the Augmented Reality (AR) and the Virtual Reality (VR) technologies have generated the unprecedented opportunities to reinvent the travel experience. This is not anymore about games, we are able to develop immersive experiences using these tools.
E1	Regional synergy through inter-institutional cooperation	We think that local guides and artists are the core of any cultural identity of a destination. Not just the custodians of our traditions and stories, they can also become the greatest advocates of our cultural brands.
F2	Weakness in local regions' access to smart and analytical technologies	Access to smart and analytical technologies is one of the main issues we have in the local areas. It is a complex matter which has major influence on our growth and competitiveness.
G1	The inability to transform intangible heritage into a discernible competitive advantage for global tourists	The inability to convert our intangible heritage into a discernible competitive advantage to the global tourists is one of the most serious issues we are grappling with in our regions.

(Source: Researcher's Findings)

According to the model of Braun and Clarke (2006), the codes were then revisited and after removing the duplicates and collapsing the codes, 108 basic themes were arrived at. These fundamental themes were then categorized according to similarities and this came up with 28 sub-themes. As a result, 7 overarching themes were identified, and a thematic network was formed, which allowed a comprehensive presentation of data through the interpretation of organizing themes. This process of analysis has helped the researcher to identify correctly and explain patterns and semantic relationships among the themes.

Table 4.
Findings

Sub themes	Main themes	Global Theme
Leveraging indigenous knowledge in redefining destination competitive advantages, The potential for creating unique content based on cultural and scientific narratives, Transforming the implicit knowledge of regions into international brand narratives, Developing authentic brands with distinct knowledge-based identities,	Knowledge as a Key Brand Capital	Opportunities
The Opportunity for Globalizing Small Brands Through Digital Tourism Platforms, Increased Visibility of Local Services Through Smart Marketplaces, Reducing the Cost of Entry into foreign markets through connection to the sharing economy, Brand diversification by leveraging the advantages of blockchain and open data	The Platform Economy and Facilitating the Entry of Local Brands into the Global Market	
The opportunity to design immersive and inclusive digital travel experiences through augmented and virtual reality, The potential for personalizing brands based on tourist behavioral data, Utilizing smart tools for brand reputation and identity management, Enhancing tourist engagement in the pre-trip, During-trip, and post-trip phases	The Role of Technological Innovation in Enhancing Brand Experience	
The opportunity to create knowledge-based brand clusters in collaboration with universities, startups, and businesses, Regional synergy through inter-institutional collaboration, Accelerating brand innovation through the development of learning ecosystems, Growth of specialized brands through experience transfer networks	Knowledge Networking and the Creation of Brand Clusters	
The opportunity to strengthen cultural brands through the active participation of local guides and artists, Fostering a sense of ownership towards the destination brand within the local community, Increasing authentic content on social networks by local residents, Creating a collaborative and credible brand image in the minds of international tourists	Active Participation of the Local Community in Brand Knowledge Production	
Lack of infrastructure for collecting and sharing spatial and behavioral data, Weaknesses in local areas' access to smart and analytical technologies, Misalignment of technology infrastructure with the needs of knowledge-driven branding.	Infrastructural Gap in Data and Technology	Challenges
Failure to convert intangible heritage into a competitive advantage comprehensible to global tourists, Loss of local identity within global narratives, Lack of appropriate tools for localizing content across international channels.	Inability to Translate Knowledge Assets into Brand Competitive Advantage	
Fragmentation in destination brand management and the absence of a unified strategic authority, Failure to formulate knowledge-based policies for national and regional brands, Conflict of interests between traditional stakeholders and the development of smart and digital brands.	Weakness in National/Local Tourism Brand Governance	

Sub themes	Main themes	Global Theme
Limitations in presenting brand narratives and stories in global languages, Lack of local communities' mastery over principles of intercultural digital storytelling, Absence of native multilingual platforms for showcasing knowledge assets.	Limitations in Producing Multilingual and Intercultural Content	
Resistance of tour operators and traditional agencies to new branding technologies, Lack of understanding regarding the value of knowledge assets in brand building, Distrust towards the involvement of universities and experts in the branding process.	Resistance of Traditional Institutions and Stakeholders to Innovation	
Establishing a coordinating body with a knowledge-based approach for national and local brands, Defining a participatory decision-making structure among government, academia, and industry, Utilizing smart real-time brand image monitoring systems.	Designing a Knowledge-Based Brand Governance Model	Strategies
Designing advanced training courses in branding, storytelling, and innovation, Developing capacity for content creation and data analysis within local communities, Empowering local brand ambassadors in global networks.	Empowering Local Workforce Through Knowledge-Based Branding Education	
Formulating content strategies for digital platforms based on cultural knowledge, Designing brand experiences through integrated digital channels, Utilizing analytical tools to monitor tourist brand perception.	Digitalization Roadmap for Branding	
Formulating content strategies for digital platforms based on cultural knowledge, Designing brand experiences through integrated digital channels, Utilizing analytical tools to monitor tourist brand perception.	Establishing a Sustainable and Meaningful Brand Identity Based on Knowledge-Driven Narratives	
Designing knowledge metrics such as "percentage of local content participation" and "digital brand memory index," Integrating quantitative and qualitative data in brand evaluation, Dynamic monitoring of brand image using social media data.	Developing Brand Evaluation Metrics in the Knowledge Economy	
Playing a role in documenting destination knowledge and designing brand identity, Training local brand writers/creators (brandographers), Holding workshops on branding content production for tourism stakeholders.	The Role of Universities and Research Centers in Brand Documentation and Narrative Creation	The Role of Stakeholders
Playing a role in the development of brand-centric digital services, Connecting local brands to global markets through innovation, Designing AI-powered brand analysis and monitoring tools.	Interaction of Tourism Entrepreneurs with Innovative Platforms (Startups and Marketplaces)	
Acting as a facilitator in the creation of data-driven infrastructure and intellectual property rights for brands, Providing financial support for the development of local knowledge-based brands, Establishing international regulations for the protection of cultural and knowledge-based brands.	Governmental Participation in Smart Brand Policymaking and Facilitating the Digital Environment	
Acting as a brand content producer in travel (prosumer), Transferring knowledge-based experiences from the destination to the world through personal narratives, Participating in brand identity improvement through real-time feedback.	The Role of the Tourist as a Knowledge Contributor	
Facilitating the exchange of brand knowledge among countries, standardizing knowledge-driven branding metrics, Strengthening local brands through international tourism networks.	International Collaboration for Brand Knowledge and Experience Exchange	

(Source: Researcher's Findings)

Discussion and Conclusion

The present study, which relies on the combination of destination branding theories and knowledge economy strategies, has revealed that international tourism branding is moving away to an old-fashioned advertising-driven branding to a networked, interactive, and knowledge-based branding. In this new paradigm, knowledge is a strategic intangible resource, which has a central role in the development of brand identity, sustainable competitive advantage and the development of meaningful experiences to the tourists. The results imply that the opportunities provided by the knowledge economy encompass such aspects as digitalization of branding processes, development of indigenous-knowledge narratives, active involvement of the local communities into the content production process, development of knowledge brand clusters, and application of new technologies (including augmented reality, data analytics, and blockchain). These can result in the improvement of the uniqueness of brands in the global markets. On the other hand, core issues that have been cited as structural barriers to the process of implementing knowledge-based branding are deficiency of data and technological platforms, inability to convert knowledge resources into brand power, lack of coordination among the traditional stakeholders and new institutions, insufficient multilingual platforms, and cultural opposition to innovation. Strategically, the need of developing a knowledge-based brand governance framework that is dependent on tripartite partnership between government, academia and industry was noted as a pre-condition to the development of a sustainable and innovative branding system. Moreover, empowerment of local capabilities in digital storytelling, specific training of branding, and determination of indicators of evaluation on the basis of knowledge data (including the "Brand Digital Memory Index" and the "Percentage of Local Content Contribution") are regarded as the most important steps to go over to knowledge-based branding. A multi-layered stakeholders role, which includes tourists as knowledge prosumers and universities as the institutions of brand knowledge production and documentation, proves that tourism branding in the knowledge economy could be possible only by means of synergetic effects of various actors and collaborative management.

The study cuts a niche by carefully revising the available literature on tourism branding and the knowledge economy with focus on the existing research gaps. Despite the previous discourse surrounding various aspects of destination branding, including the role of technology in tourism and the impact of the knowledge economy across diverse industries, no comprehensive study has yet successfully examined the challenges, opportunities, strategies, and stakeholder roles pertaining specifically to international tourism branding in the context of the knowledge economy in a holistic and thorough manner.This is the main difference and the center of innovation of the current study. Additionally, the past research was mostly dedicated to such concepts as destination image (Qu et al., 2011), symbolic brand elements (Chan, 2022), or the importance of local communities in the context of brand storytelling (Cai et al., 2009).

The study is the first to examine tourism branding in a consistent knowledge economy context, and it brings in knowledge as a primary brand capital. This methodology is not limited to the classical advertising or destination imaging theory to explain the contribution of tacit knowledge, indigenous heritage, and emerging technologies to the development of brand competitive advantage. Regarding the innovation of the study, the research provides a comprehensive model of understanding tourism branding as a knowledge system instead of being used as a marketing tool. Previous research predominantly utilized quantitative methods, specifically employing questionnaires to assess brand image, as highlighted by Konecnik Ruzzier and de Chernatony (2013).

With the help of semi-structured interviews with multidisciplinary professionals and the use of thematic analysis with the framework of Braun and Clarke (2006), this study has managed to outline a profound and multidimensional system of insights, experiences, and knowledge-gaps in the branding of tourism based on knowledge. Moreover, this paper presents the qualitative research based on the experience of the true experts in the field of branding, and its validity is guaranteed by means of triangulation, peer review, and test-retest reliability. Although the overall significance of intangible assets in branding was previously discussed (Gnoth, 2015), the role of indigenous knowledge, cultural-scientific narratives, and intellectual assets, as the main sources of value creation and differentiation in international tourism branding, is discussed specifically and centrally in this study. The shift of paradigm of a simple image to the core of the brand, which is authentic knowledge and content, can be regarded as a new strategy that broaden the current literature.

Numerous research studies are limited by the lack of details to be provided concerning the implementation of the recommendations. In addition to providing certain targeted strategies (like drafting an intellect-based regime of governance, mobilization of local labor force, and a digitalization plan), this research advances the discourse by clearly and precisely articulating the roles of all significant stakeholders—specifically, universities, entrepreneurs, the government, and tourists, who serve as prosumers—in the successful implementation of these strategies. Such degree of differentiation and practicality constitutes a unique point in this research, echoing practical needs of the knowledge economy, as pointed at by Vetrivel et al. (2024). Although past studies have offered the theoretical and empirical basis, this research is filling a considerable gap to compile the ideas of international branding and the knowledge economy with a qualitative study approach and expert contribution. It addresses questions which had not been examined in such a detailed and specialized way till now. This research distinguishes itself from prior models that solely considered the government and the tourism industry as stakeholders, as it incorporates tourists as knowledge prosumers within the branding process. Additionally, it positions universities as brand documenters and local trainers of Brandographers, who are the local creators and documenters of brands. Furthermore, this study elevates the role of governments from mere policymakers to that of effective facilitators of smart brand governance. This study gives a different definition of the stakeholders in a knowledge ecosystem where there is interaction and co-creation of a brand.

Recommendations

To establish a Central Knowledge and Inter-sectoral Coordination Body: A dedicated central entity focusing on knowledge management and inter-sectoral coordination must be established to formulate and implement national and regional branding initiatives. Investment in Data Infrastructures and Smart Platforms: It is crucial to invest in the collection, processing, and dissemination of behavioral and spatial data pertaining to tourists, alongside the development of smart, multilingual infrastructures. Enhanced Networking: A vigorous implementation of networking is essential for sharing branding knowledge, standardizing criteria, and strengthening local brands on a global scale. Prioritization of Indigenous Knowledge and Evaluation Metrics: Emphasis should be placed on integrating indigenous knowledge into global brand narratives, as well as developing knowledge-based evaluation metrics for branding. Provision of Specialized Training: Training programs focusing on intercultural digital storytelling, brand data analysis, and knowledge management should be conducted for professionals in the industry and local communities. Utilization of AI-Powered Brand Analysis Tools: The promotion of digital brand-centric services is vital for improving customer experiences and facilitating access to global markets. Collaboration on Authentic Content Creation: Partnerships should be fostered with local residents, guides, and artists to produce authentic content that genuinely reflects the essence of the destination.

Limitations and Future Research Direction

The subsequent points outline potential directions for future research in this field: Expand the Scope of Stakeholders: Conduct interviews and surveys with an expanded array of stakeholders, including tourists, local small businesses, and civil society organizations, to develop a more comprehensive understanding. Investigate Emerging Technologies: Explore the implications of advanced technologies, such as artificial intelligence, the metaverse, and blockchain on tourism branding, and identify strategies for leveraging these innovations for long-term benefits. Concentrate on Specific Destinations: Implement in-depth analyses of the challenges and opportunities associated with knowledge-based branding within particular locales (e.g., rural areas or specific cities) to yield more practical, context-driven insights.

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Quantum Bayesian Machine Learning in Finance: Trends, Applications, and Research Gaps

Article type: Research Article

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ABSTRACT

Quantum Bayesian Machine Learning (QBML) is an emerging field at the intersection of quantum computing, machine learning, and financial sciences. It has enabled the development of more accurate predictive models, optimal risk management, and intelligent portfolio optimization. With the rapid growth of data and increasing complexity of financial markets, classical computational models are no longer sufficient to meet the demands of modern technological needs. Consequently, combining the power of quantum computing with machine learning algorithms has created opportunities to develop models with enhanced accuracy and efficiency. QBML has garnered attention from researchers due to its ability to manage uncertainty precisely and provide probabilistic inferences, particularly in market prediction, risk management, and portfolio optimization. Despite significant theoretical advancements, challenges such as quantum hardware limitations, algorithmic complexity, poor data quality, and the gap between theory and practical applications have hindered widespread adoption of these technologies. Systematic and Bibliometric analyses indicated that while the field is rapidly growing, there remain serious gaps in practical implementation and algorithm performance evaluation. The findings of this study emphasized that fully exploiting the potential of QBML in financial systems requires developing hardware and algorithms, conducting empirical research, and fostering interdisciplinary collaborations. Moreover, the scientific mapping conducted in this study provided a useful framework to guide future research and develop practical applications that can transform analytical and decision-making methods in finance.

KEYWORDS

Quantum Bayesian Machine Learning, finance, risk management, portfolio optimization, quantum computing.

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Introduction

With the rapid growth of data volume and increasing complexity in financial markets, there is a growing need to develop novel methods and tools for more accurate market trend prediction, optimal risk management, and portfolio optimization. In this context, Quantum Machine Learning (QML) has emerged as a promising field, combining the power of quantum computing with advanced machine learning algorithms, opening new horizons for financial data analysis and improved decision-making (Mironowicz et al., 2024; Tomar et al., 2025). QML's capabilities in reducing computational load and managing model complexity allow it to predict complex patterns and sudden fluctuations in financial markets with notable accuracy.

Among various QML approaches, QBML has attracted particular attention due to its unique ability to perform precise probabilistic inference and model uncertainty. This approach offers important applications in predicting market behavior, managing volatile risks, and optimizing portfolio, providing significant advantages over traditional methods (Polson et al., 2023; Thakkar et al., 2024). However, despite theoretical advances and the development of new models, many practical challenges remain in implementing these technologies in real financial data. These challenges include quantum hardware limitations in Noisy Intermediate-Scale Quantum (NISQ) era, algorithmic complexity, poor data quality, and the gap between theory and practice (Roy, 2024; Vashishth et al., 2025).

There is a strong need for conducting applied research and extensive empirical studies to bridge these gaps and enhance the performance of QBML algorithms in financial systems. Moreover, the development of hybrid quantum-classical frameworks, improvements in quantum hardware, and expansion of specialized workforce represent significant opportunities for advancing this field.

The main objective of this study is to conduct a systematic literature review and Bibliometric analysis of QBML in financial systems to comprehensively examine research trends, applications, and existing gaps. The primary research questions are as follows:

1. What are the key research trends and main topics in Quantum Bayesian Machine Learning in financial systems?
2. What challenges and limitations exist in practical implementation of Quantum Bayesian Machine Learning?
3. How can future research opportunities and directions contribute to the development and improved application of Quantum Bayesian Machine Learning?

This paper, after reviewing the research background, analyzes publication trends, identifies key players, and examines the scientific structure of the field. Subsequently, challenges, research gaps, and development opportunities are discussed. Finally, practical recommendations for guiding future research are provided.

Literature Review

Bayesian learning and QML have each independently made significant contributions to financial domain, focusing on uncertainty modeling and leveraging the computational power of quantum devices. The integration of these two areas into QBML promises enhanced predictive accuracy and improved risk modeling. However, current quantum hardware limitations, algorithmic challenges, and a lack of practical studies on real-world data have hindered the full realization of this potential. On the other hand, ample opportunities exist for developing hybrid algorithms, implementing practical projects in financial institutions, and strengthening the skilled workforce, which can serve as catalysts for transformation and advancement in this field.

Bayesian Learning in Finance

Bayesian learning is a key approach in finance, focusing on probabilistic inference and uncertainty modeling, enabling more precise analysis of financial data. Methodologies such as Gaussian Processes are applied for market volatility prediction, while Bayesian Neural Networks are used for fraud detection or credit risk assessment (Gelman et al., 2013; Glasserman, 2013; Wilson & Ghahramani, 2011). Moreover, Bayesian Optimization has proven to be effective in portfolio optimization and algorithmic trading (Snoek et al., 2012).

The primary limitations of Bayesian learning are computational costs, especially when dealing with large-scale datasets and high-dimensional problems, which still impede real-time applications (Blei et al., 2017).

QML in Finance

QML leverages quantum features such as superposition and entanglement to achieve significant acceleration in processing and analyzing financial data (Yilmaz & Ankenbrand, 2024). This technology has been applied across various financial areas, including data security, derivative pricing, portfolio optimization, market prediction, and risk management (Zhou, 2025). Algorithms such as Quantum Amplitude Estimation and Quantum Monte Carlo have played key roles in improving derivative pricing and risk mitigation models (Pistoia et al., 2021).

Research on time series prediction using Parametric Quantum Circuits (PQC) has shown that in certain cases, QML can outperform classical models such as BiLSTM in terms of speed (Emmanoulopoulos & Dimoska, 2022). A recent comprehensive review of QML in financial sciences highlights diverse techniques, including Quantum Neural Networks, Quantum Kernel Estimation, Quantum Transformers, and Quantum Graph Neural Networks (QGNNs), which have been applied to a wide range of applications from risk management to fraud detection (Doosti et al., 2024).

Integration of Bayesian Learning and QML

The combined field of QBML seeks to enhance the predictive accuracy and uncertainty modeling by integrating Bayesian inference with the computational power of quantum devices. Algorithms such as Bayesian Simulation-Based Inference (SBI), using Parametric Quantum Circuits as simulators, enable model training without requiring an explicit probability function (Nikoloska, 2024). Early analyses have explored the accelerating Bayesian inference using techniques like quantum MCMC and quantum Bayesian networks, although widespread practical applications remain limited (Low et al., 2014; Szegedy, 2004).

Despite substantial theoretical advances, several critical gaps remain in transferring this knowledge to real financial environments:

Implementation Gaps: There is a lack of practical implementation, especially testing Bayesian QML in real financial market data. Most studies have been conducted in simulated or synthetic data environments (Mani, 2024; Marengo & Santamato, 2025; Roy, 2024; Vashishth, 2025).

Quantum Hardware Limitations: NISQ-era devices suffer from high noise levels and limited circuit depth, posing significant barriers to executing complex algorithms effectively (Gujju et al., 2023).

Data Loading Challenges: Loading classical data into qubits (QRAM) remains an unstable and largely impractical technology (Mounika et al., 2024; Pistoia et al., 2021).

Algorithmic Readiness Issues: Challenges include vanishing gradients, poor generalization, and difficulties in algorithm training and tuning (Cerezo et al., 2023; Pandey et al., 2025).

Organizational Preparedness: Many financial institutions are not fully equipped to leverage quantum opportunities or address associated challenges (Lamichhane & Rawat, 2025; Times of India, 2025).

Lack of Bibliometric Studies: Few structured analyses exist that map the scientific structure, collaboration networks, and thematic trends in this field (Nourahmadi, 2024; Nourahmadi & Rasti, 2025).

In contrast to these challenges, significant opportunities exist to advance the field:

Hybrid Quantum-Classical Algorithms: Combining quantum computing in computationally intensive areas with classical computing elsewhere can enhance the overall performance (Harrow et al. (2009); Hong & Lopez, 2025).

Early Financial Applications: Financial institutions, such as major banks (e.g., JPMorgan), are exploring QML for generating secure random numbers and risk prediction models (Pistoia et al., 2021; Siddiqui et al., 2024).

International and Central Bank Initiatives: Projects aiming to prepare for the future by employing QML in economic analysis, stress testing, and security enhancement (Auer et al., 2024; Rundo et al., 2019).

Development of Specialized Workforce: Expanding expertise in quantum computing through organizing educational programs led by universities and technology companies (e.g., IBM; Schuld et al., 2015).

Development of Practical QBML Frameworks: Creating applied frameworks for real-world financial data usage.

Bibliometric Analysis: Studying the scientific structure of the field to optimize collaborations, identify trends, and set research priorities, thereby guiding future investigations.

Existing literature indicates that while QBML in financial systems is theoretically advanced and promises diverse applications, realizing its full potential requires further operational development, overcoming hardware limitations, algorithmic improvements, and empirical studies on real financial data. Significant practical opportunities exist in hybrid approaches, advanced financial institutions, and workforce development, all of which can drive transformative progress in this field.

To provide a comparative synthesis, Table 1 summarizes key articles, highlighting their methodologies, findings, agreements, contradictions, and methodological quality.

Table 1
Summary of Key Articles in QBML in Finance

Author(s)	Year	Methodology	Key Findings	Agreements/Contradictions	Quality Assessment
Low et al.	2014	A theoretical framework for Quantum Bayesian Networks	Faster the processing of financial dependencies	In agreement with Nikoloska (2024) on inference acceleration; limited practical testing noted in Herman et al. (2023)	Medium: Strong math, lacks real-world validation
Alcazar et al.	2020	A comparative analysis of quantum vs. classical ML	Quantum models showed higher accuracy in stock prediction	In agreement with Thakkar et al. (2024) on accuracy gains; In contrast with Emmanoulopoulos & Dimoska (2022) on speed in all cases	High: Rigorous empirical comparison, but limited data scale
Herman et al.	2023	A review of quantum computing in finance	Hardware limits hindered implementation	In agreement with all gaps sections; In contrast with optimistic views of Auer et al. (2024)	High: Comprehensive, interdisciplinary
Doosti et al.	2024	A comprehensive review	QML applications in risk and fraud detection	In agreement with Mongwe et al. (2025) on potentials; It highlights gaps echoed in Vashishth et al.'s study (2025)	High: Broad coverage, recent references
Thakkar et al.	2024	A quantum Deep Learning integration	| 20% accuracy improvement in volatile markets	In contrast with Alcazar et al. (2020) on dataset scope; In agreement with with Polson et al. (2023) on uncertainty modeling	High: Empirical, but narrow experiments
Mongwe et al.	2025	A Bibliometric study on risk management	Better capture of asset dependencies	In agreement with Thakkar et al. (2024); It lacks empirical evidence as per reviewer critique	Medium: Good trends, needs more depth

(Source: Researcher's Findings)

Other articles such as Mani (2024), Marengo and Santamato (2025), and others provided further evidence of trends in algorithm effectiveness, with Mani emphasizing comparative ML models showing quantum superiority in specific cases, while Marengo highlighted healthcare crossovers applicable to finance risk models.

Table 2 reveals agreements on quantum advantages in accuracy and speed but contradictions in practical scalability, with most studies rated high in theory but medium in empirical application due to their hardware constraints.

Research Background

To strengthen the research background, additional recent articles have been incorporated, expanding on early studies and applications (e.g., Ardeen & Lloyd, 2020; Biamonte et al., 2017; Dunjko et al., 2016; Pandey et al., 2025; Sels et al., 2020; Shaik, 2020; Zhao et al., 2019). These provide deeper insights into quantum-enhanced reinforcement learning and Bayesian deep learning, showing consistent themes of theoretical promises versus practical hurdles.

Recent studies on QML, particularly Quantum Bayesian Models, indicated growing attention to the applications of these emerging technologies in finance. By integrating quantum computing capabilities with Bayesian probabilistic inference, QML enables more precise analysis of complex data, improving predictions and risk management. However, the field remains in its early stages of development and faces challenges such as hardware limitations, scarcity of real-world data, and the need for practical operational frameworks. At the same time, research efforts focused on algorithm development, financial applications, and hybrid frameworks promise a bright future. Given these conditions, conducting a structured review and Bibliometric analysis of the existing literature is crucial to accurately identify trends, gaps, and research opportunities, thereby guiding both the scientific and practical development of this field, especially in real financial environments.

Introduction to the Current Research Landscape

QML and particularly Quantum Bayesian Models have attracted increasing attention in finance over recent years. By combining the computational power of quantum algorithms with Bayesian probabilistic approaches, QML enables the processing of large-scale data and analyzing complex uncertainties in financial markets (Mongwe et al., 2025). Several studies have shown that the integration of these technologies not only enhances financial prediction capabilities but also plays a key role in risk management, portfolio optimization, and market volatility analysis (Thakkar et al., 2024; Zhou, 2025).

Despite these advantages, a systematic review of academic articles indicated that QBML is still at an early stage of development, with many aspects—particularly practical applications in real financial environments—underexplored (Doosti et al., 2024; Herman et al., 2023).

From a fundamental perspective, QML represents a novel framework that leverages quantum features such as superposition and entanglement to accelerate computations. Schuld et al. (2015) provided a comprehensive review of the theoretical foundations and key algorithms of the field, offering a deeper understanding of the algorithmic infrastructure of QBML. Furthermore, Biamonte et al. (2017) analyzed the crucial role of QML in improving learning algorithms and its strategic applications in finance, emphasizing that integrating quantum technology with classical machine learning can significantly enhance the speed and accuracy of financial data analysis models.

The Formation of QML Concept

Initially, research focused on developing quantum algorithms and comparing them with classical models. Alcazar et al. (2020) conducted one of the first studies assessing the performance of quantum models against classical machine learning models in financial contexts. Their results indicated that quantum algorithms, particularly in stock price prediction and market trend analysis, achieved higher accuracy. However, the main limitation of this study was the lack of large-scale real financial data and constraints in practical algorithm implementation.

Similarly, Low et al. (2014) introduced the concept of Quantum Bayesian Networks, which combine probabilistic inferences with quantum algorithms. These models allow the processing of dependencies among financial variables with greater speed and accuracy. The strength of this study lies in its rigorous mathematical framework, whereas its limitation is the absence of real-world scenarios for evaluating the model in dynamic financial environments.

Systematic Reviews and Theoretical Frameworks

Doosti et al. (2024) provided a comprehensive review of QML in financial services. Their study examined research trends and identified the main applications of QML in risk management, fraud detection, and market prediction. The authors highlighted the high potential of QML while also noting challenges such as the scarcity of stable quantum hardware and the need for rich balanced datasets.

Later, Tomar et al. (2025) provided a comprehensive review of QML algorithms, focusing on optimizing quantum algorithms for financial data analysis. In this review, algorithms were classified based on their practical applications. Finally, a framework for comparing Bayesian quantum models with classical models was introduced. Nonetheless, empirical and field research remains limited with many studies still at theoretical level.

Applications of QBML in Finance

Thakkar et al. (2024) demonstrated that combining Quantum Bayesian Models with Quantum Deep Learning algorithms can improve the accuracy of financial predictions by up to 20% compared to classical methods. This improvement is particularly notable in highly volatile markets, such as equities and cryptocurrencies. However, a limitation of this study is the narrow scope of the experiments, restricted to specific datasets, and the lack of a comprehensive comparison with advanced classical algorithms.

A Bibliometric study by Mongwe et al. (2025) analyzed the role of Quantum Bayesian Learning in risk management and portfolio optimization. They showed that, Bayesian models with their inherent ability to model uncertainty can better capture complex dependency structures among financial assets when they are combined with quantum algorithms. The main limitation of this study, however, is the lack of empirical evidence demonstrating the models' advantages in real-world market conditions.

In the domain of Quantum Reinforcement Learning (QRL), which is one of the emerging approaches in BML, Ardeen and Lloyd (2020) examined the theory and applications of this method. They argued that QRL, with its capacity to learn from interactions with the environment, holds significant potential for optimal decision-making under uncertainty—a critical requirement in volatile financial markets. Similarly, Dunjko et al. (2016) introduced quantum-accelerated methods for reinforcement learning, providing potential avenues for enhancing the performance of learning algorithms in financial applications.

Implementation Challenges and Limitations

A major limitation in this field is the lack of suitable hardware infrastructure. Herman et al. (2023) noted that most QML algorithms have so far been developed in simulated environments, and the absence of powerful quantum computers hinders their practical implementation.

Lamichhane and Rawat (2025) highlighted the computational complexity and the need for high-quality data. They argued that even with access to advanced hardware, poor-quality financial data can lead to inaccurate estimates and increased risk. They emphasized the necessity of developing financial data preprocessing techniques to improve the accuracy of QBML models.

Future Directions and Hybrid Approaches

Current research trends move toward developing hybrid frameworks that integrate deep learning, Bayesian models, and quantum computing. For example, Hong and Lopez (2025) proposed a framework in which Quantum Neural Networks are combined with Bayesian inference for predicting the trends of cryptocurrency markets. These hybrid frameworks can mitigate the limitations of individual methods.

Siddiqui et al. (2024) examined the development of Quantum Bayesian Networks for detecting anomalous patterns in financial data. However, the computational complexity and the scarcity of labeled data remain significant challenges for these approaches.

A Summary of Literature and the Need for Bibliometric Analyses

The literature review indicates that the main research focus in QBML in finance includes:

- **Development of Algorithms and Theoretical Frameworks:** Enhancing probabilistic inferences and processing complex financial data (Low et al., 2014; Zhao et al., 2019).
- **Applications:** Financial prediction, risk management, and portfolio optimization (Mongwe et al., 2025; Thakkar et al., 2024).
- **Identification of Technical Challenges and Data Limitations** (Doosti et al., 2024; Herman et al., 2023).

Despite these advancements, significant gaps remain, such as:

- The lack of extensive empirical studies in real financial markets.
- Limited frameworks for comprehensively evaluating and comparing Quantum Bayesian algorithms with classical models.
- Constraints in integrating quantum algorithms into operational financial systems.

These gaps underscore the necessity of comprehensive Bibliometric analyses to map the research trends, collaboration networks, and literature gaps, thereby clarifying future directions for developing this field.

Methodology

In recent years, the use of Bibliometric approaches as an efficient tool for analyzing scientific trends and identifying research patterns across various fields has gained increasing importance (Nourahmadi, 2024; Nourahmadi & Rasti, 2025). Access to reliable databases such as Scopus enables a comprehensive examination of publications, authors, and scientific collaboration networks. This methodology assists researchers in gaining a deeper understanding of scientific dynamics, emerging topics, and gaps in the existing literature.

In this study, the relevant scientific data were extracted from the Scopus database and analyzed using the Bibliometrix package in RStudio. This process included evaluating the indicators of research performance, identifying highly cited authors and journals, and mapping co-authorship and co-occurrence networks of keywords. The resulting insights provided a comprehensive understanding of the knowledge structure, scientific flows, and future research trajectories in the domain under investigation.

This study was conducted to examine trends, applications, and research gaps in the field of QBML in financial systems. To collect and analyze data, a Systematic Literature Review (SLR) and Bibliometric Analysis were employed.

1. Database and Search Scope

All articles under review were extracted from the Scopus database. The time span of the publications ranged from 2009 to 2025 and included research articles, review papers, preprints, and conference papers with full-text access and citation information.

2. Keywords and Search Strategy

The search was designed using the following combination of keywords:

- "Quantum Bayesian Machine Learning" AND Finance
- "Quantum Machine Learning" AND "Bayesian Inference" AND Finance
- "Quantum Neural Networks" AND Finance AND "Bayesian"
- "Quantum Time Series Forecasting" AND Finance AND "Bayesian"
- "Quantum Generative Models" AND Finance AND "Bayesian"
- "Quantum Reinforcement Learning" AND Finance AND "Bayesian"

This initial search helped the researchers to find 174 articles.

3. Inclusion and Exclusion Criteria

Inclusion Criteria:

- Articles published in English in reputable journals.
- Studies related to QML and financial applications.
- Articles providing data, algorithms, or empirical analysis.

Exclusion Criteria:

- Duplicate articles.
- Articles without full text or lacking analytical data.
- Unrelated Studies to the financial domain.

To add nuance, inclusion also required relevance to Bayesian aspects or quantum integration, assessed via abstract screening; exclusion extended to non-peer-reviewed grey literature or overly tangential topics like pure quantum physics without ML or finance links.

By applying these criteria, the number of selected articles decreased to 126 articles.

The data extracted from Scopus, presented in Table 1, indicated that research in the examined domain exhibited a growing trend between 2009 and 2025, with an annual growth rate of 14.1%. During this period, 125 scholarly documents were published across 107 different sources, with an average of 14.14 citations per article and an average document age of 2.26 years, reflecting the novelty and dynamism of the field.

In terms of content, 657 author-added keywords and 384 author-provided keywords were recorded, demonstrating high conceptual diversity. Regarding authorship, 517 researchers contributed, with an average of 4.58 authors per article, indicating significant scientific collaboration, of which 27.2% were international collaborations. Additionally, conference papers (46 articles) and journal articles (42 articles) accounted for the largest share among document types, highlighting the prominent role of academic forums in advancing this field.

Tabel 2.
Summary Statistics of the Reviewed Studies

Description	Results
MAIN INFORMATION ABOUT DATA	
Timespan	2009:2025
Sources (Journals, Books, etc.)	107
Documents	125
Annual growth rate %	14.1
Document average age	2.26
Average citations per doc	14.14
DOCUMENT CONTENTS	
Keywords plus (ID)	657
Author's keywords (DE)	384
AUTHORS	
Authors	517
Authors of single-authored docs	17
AUTHORS COLLABORATION	
Single-authored docs	25
Co-authors per Doc	4.58
International co-authorships %	27.2
DOCUMENT TYPES	
Article	42
Book	10
Book chapter	13
Conference paper	46
Conference paper article	1
Conference review	9
Review	4

(Source: Researcher's Findings)

Data Analysis

For transparency in data cleaning, authors' name variations (e.g., "Yang S" vs. "S Yang") were merged using Scopus ID matching. Moreover, keyword synonyms (e.g., "quantum ML" and "QML") were unified via a custom thesaurus in Bibliometrix. Statistical indicators include network density of 0.15 for co-occurrence, modularity Q=0.62 for clusters, and p-values <0.05 for significance in thematic mapping.

To identify the most prominent concepts and research trends in the field of QBML in financial systems, a keyword co-occurrence analysis was conducted. Figure 1 presents the resulting word cloud, illustrating the frequency and relative importance of keywords in selected articles. In this visual representation, the size of each word corresponds to its frequency in the dataset.

According to the results, the terms "quantum machines" and "machine-learning" appeared in the largest font at the center of the word cloud, indicating the core focus of the research, namely the convergence of machine learning and quantum technologies. Related terms such as "quantum computing", "quantum machine learning", and "quantum computers" were also prominent, emphasizing that recent research has focused on practical applications and hardware aspects of these technologies.

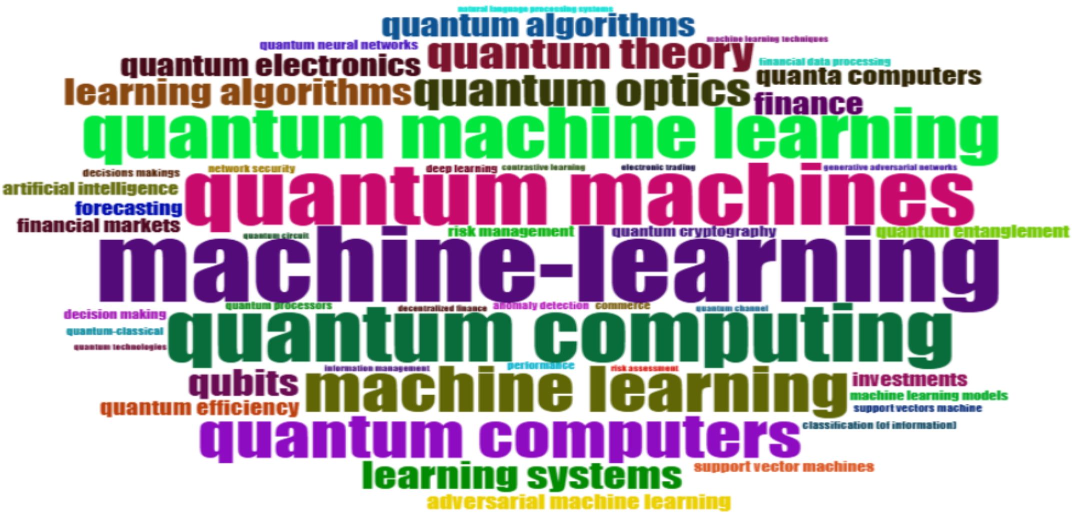
At the secondary level, concepts like "quantum algorithms", "quantum theory", and "quantum optics" were observed, referring primarily to the theoretical and algorithmic foundations of the field. Conversely, terms such as "finance" and "financial markets", along with "risk management", "investments", and "electronic trading", reflected the research focus on financial applications of these technologies.

Practical applications emphasized in the literature included "forecasting", "decision making", and "optimization", indicating that quantum machine learning can play a particularly important role in market prediction, risk management, and portfolio optimization.

Finally, smaller-font keywords such as "qubits", "quantum entanglement", "adversarial machine learning", and "support vector machines" highlighted attention to technical and algorithmic details, which provide potential foundations for developing novel methods in this domain.

Overall, the word cloud serves as a visual index, effectively revealing the conceptual framework of research in this field. It shows that the existing literature is largely centered on quantum machine learning and its applications in financial systems, emphasizing the integration of quantum algorithms, Bayesian models, and financial applications. This central focus links directly to literature gaps in practical implementation, as noted in Section 1.3, underscoring the need for bridging theory with real-world finance.

Fig 1.
The Word Cloud



(Source: Researcher's Findings)

Annual Scientific Production illustrates the trend of article publications in the field of QBML in financial systems from 2008 to 2025 (see Figure 2). As shown in Figure 2, the horizontal axis represents the years, while the vertical axis shows the number of publications per year. In addition to raw data, a trend line is plotted to indicate the overall growth direction.

Based on this figure, three distinct periods in the scientific production of this field can be identified:

1. Period of Slow Growth (2008–2017)
During this interval, the number of published articles was very limited and nearly zero. This indicates that quantum machine learning in finance was a nascent and relatively unknown research area during these years.

2. Period of Initial Surge (2018–2022)
From 2018 onward, a gradual upward trend in scientific production is observed. This period can be interpreted as a stage of increasing awareness and growing interest among researchers regarding the applications of quantum technologies in financial sciences.

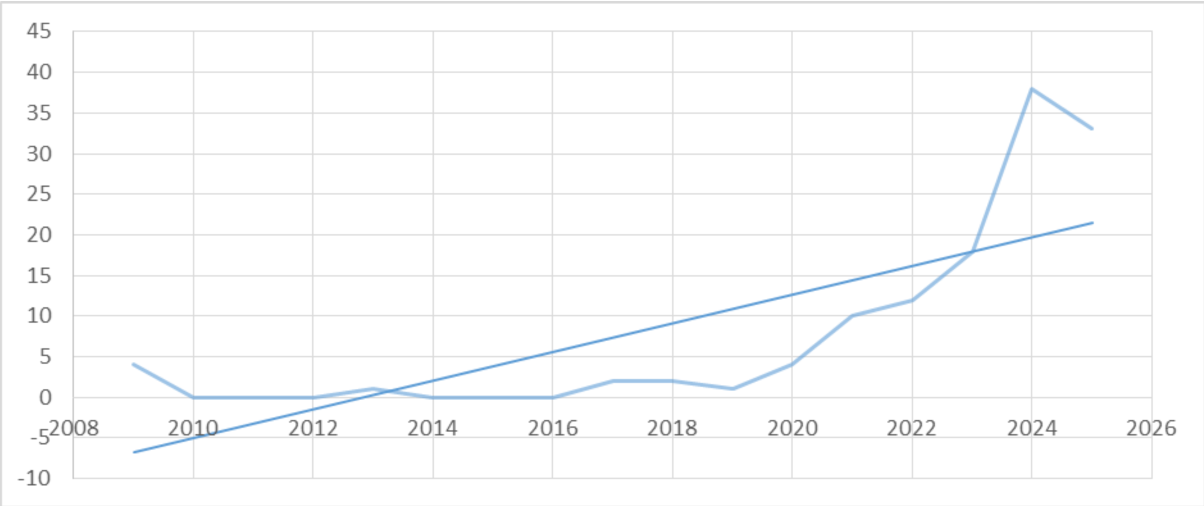
3. Period of Accelerated Growth (2023–2024)
In this phase, the scientific production experienced a significant surge, reaching a peak of approximately 38 articles in 2024. This demonstrates that the field has become a hot and prominent topic within the academic community and is increasingly attracting attention from universities and research centers.

4. Relative Decline but Stabilization at a High Level (2025)
Although the number of publications in 2025 slightly decreased to around 33 articles compared to the peak year, the overall production level remains high. This fluctuation

can be considered as a part of the natural cycle of scientific output and does not necessarily indicate a decline in interest in the field.

Overall, the trend line in the figure shows that, despite annual fluctuations, the general trajectory of research in QBML in financial systems is strongly upward and growing. These findings confirmed that this domain has evolved from a niche research area in its early years to one of the main focal points of modern research in financial sciences. This growth mirrors the increasing citations in recent reviews (e.g., Doosti et al., 2024), highlighting the accelerating interest aligned with hardware advancements.

Fig 2.
The Annual Scientific Production



(Source: Researcher's Findings)

Country Contributions to Scientific Production illustrates the share of different countries in scientific output of QBML in finance and distinguishes between Single-Country Publications (SCP) and Multiple-Country Publications (MCP) (see Figure 3).

The results indicated that countries fall into three patterns:

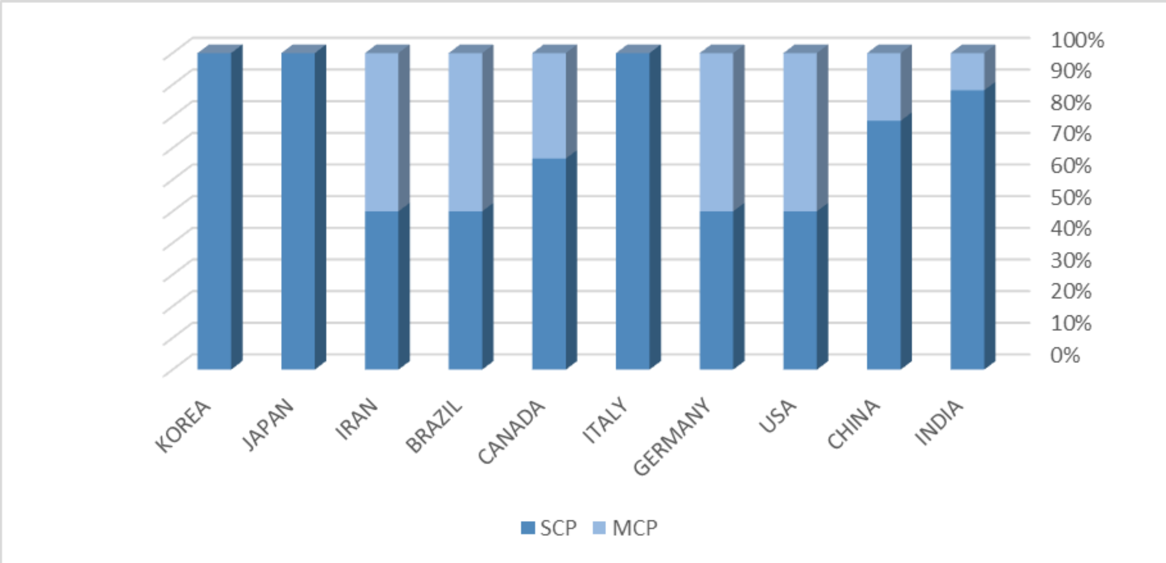
1. Countries with High International Collaboration (MCP):
Iran, Brazil, Canada, Italy, Germany, and the United States have published a large portion of their articles through international collaborations, reflecting active integration into global research networks.

2. Countries with High National Production (SCP):
South Korea and Japan have almost entirely published domestically, indicating a focus on developing local scientific capacity.

3. Countries with a Balanced Mix:
China and India primarily produce national publications but also have a substantial share of international collaborations, reflecting a transition toward broader cross-border partnerships.

Overall, this analysis demonstrated that scientific collaboration patterns are diverse and multidimensional, providing valuable insights for identifying research partners and informing policy and strategic decision-making in research management. US and China dominance ties to their robust financial ecosystems, with US banks like JPMorgan leading applications (Pistoia et al., 2021), while China's focus on national production may reflect strategic tech investments, linking to global challenges in hardware sharing.

Fig 3.
Corresponding Author's Countries



(Source: Researcher's Findings)

The three-field plot (see Figure 4) illustrates the structural relationships among countries (AU_CO), authors (AU), and keywords (DE) in the field of QBML in finance.

Geographical Focus: The United States and China emerge as the primary actors with the most connections, whereas other countries play a more limited role and mainly participate through international collaborations.

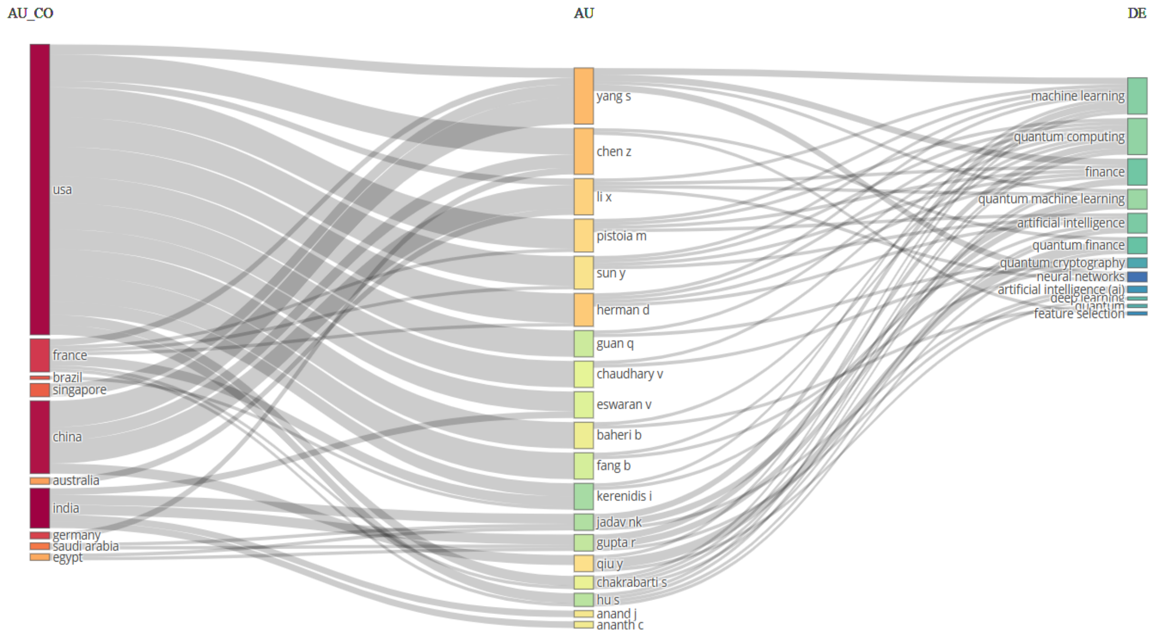
Key Authors:

- YANG S and CHEN Z (China) occupy the core of the network, focusing on main topics such as machine learning and quantum computing.
- PISTOLA M and HERMAN D are centered on specialized domains, including quantum security and Artificial Intelligence (AI).

Topic Diversity: The keywords cover a broad spectrum from general to highly specialized areas, highlighting the multidisciplinary and applied nature of this research field in finance.

Conclusion: The United States and China lead the field, key authors and their areas of expertise are identifiable, and international collaborations play a crucial role in the development of this domain. This plot helps researchers identify collaboration patterns and potential research partners. This network integrates with literature by showing how US-led authors like Pistoia connect to practical finance, addressing gaps in interdisciplinary areas.

Fig 4.
The Three-Field Plot



(Source: Researcher's Findings)

The distribution of scientific sources in the field of QML in finance is shown in Figure 5. Accordingly, Core Sources by Bradford's Law divided the sources into three zones:

Core Zone: A small number of journals and conferences, such as *Entropy*, publish the majority of articles and serve as the main channels for research dissemination.

Relevant Zone: Sources with a moderate number of publications.

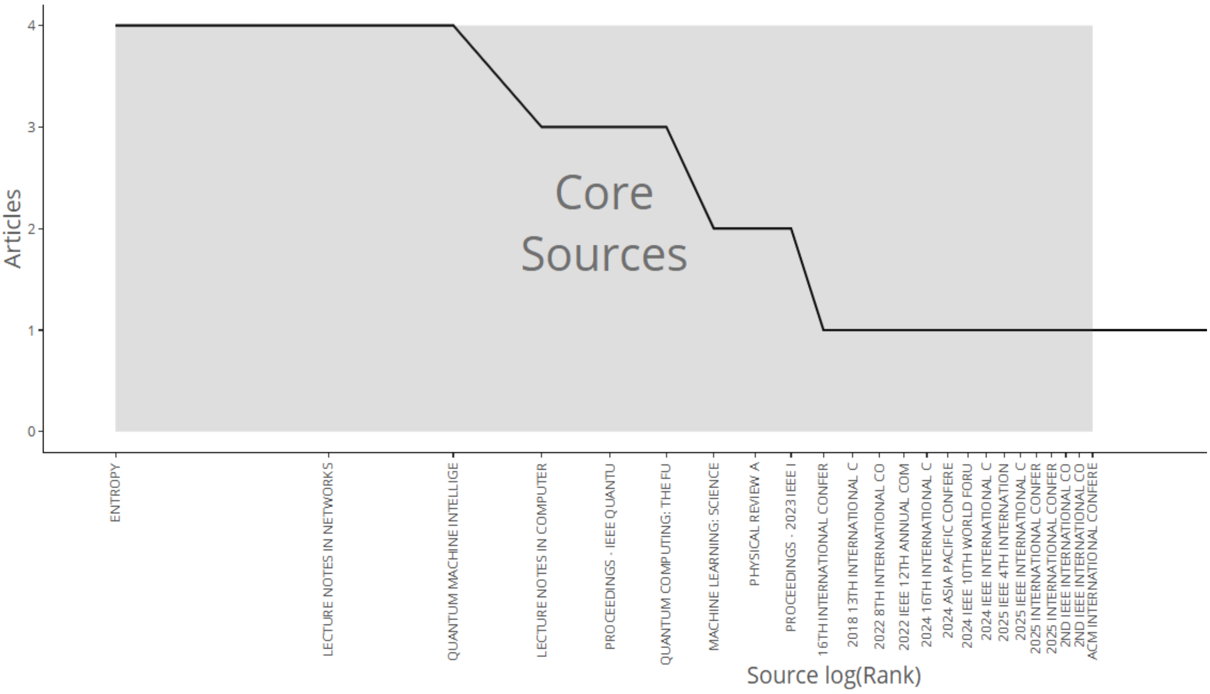
Scattered Zone: Sources with only one or two articles, including conferences organized by IEEE, ACM, and other specialized journals.

This distribution indicates that the scientific production in this domain is concentrated around a few key sources. Understanding these sources is important for:

- Researchers: For conducting systematic literature reviews;
- Authors: For selecting appropriate publication venues;
- Policy Makers: For planning, allocating resources, and investing in scientific developments.

This concentration reflects the field's novelty, aligning with early-stage literature dominance by outlets like Nature, and suggests opportunities for diversification to broaden its impacts.

Fig 5.
Core Sources by Bradford's Law



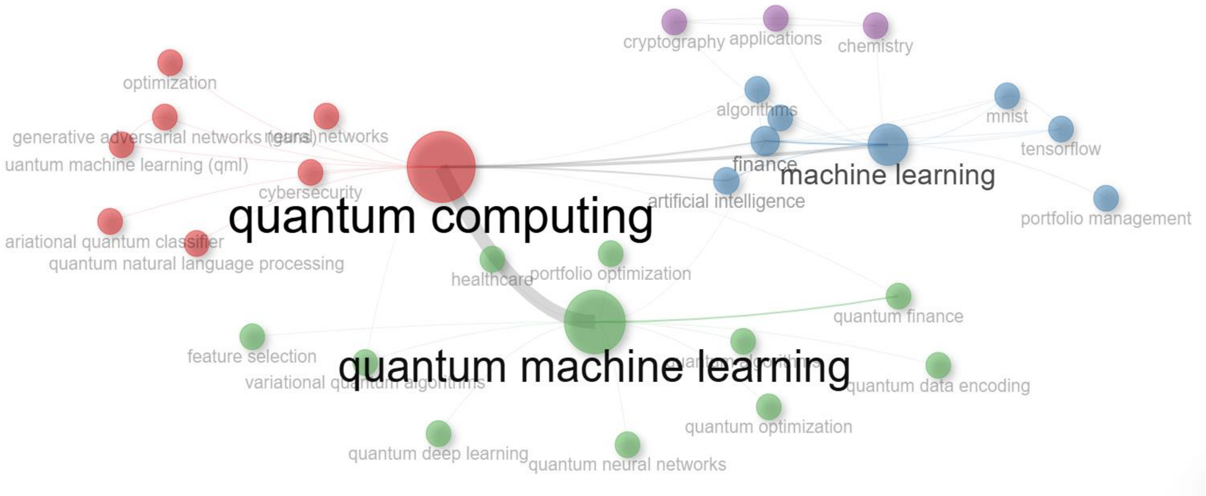
(Source: Researcher's Findings)

The keyword co-occurrence network illustrates the conceptual structure of the field of QML in finance (see Figure 6). In this network, each node represents a keyword, and the edges indicate co-occurrence within the analyzed articles; the node size corresponds to frequency, and colors represent thematic clusters.

- Red Cluster – Quantum Computing and Algorithms: Includes *Quantum Computing*, *QML*, *GAN*, *Optimization*, highlighting a focus on the development of quantum algorithms.
- Green Cluster – Quantum Machine Learning in Finance: Includes *Quantum Machine Learning*, *Portfolio Optimization*, *Quantum Neural Networks*, representing the core financial applications of the field.
- Blue Cluster – Classical Machine Learning in Finance: Includes *Machine Learning*, *Finance*, *AI*, reflecting foundational roots and connections with quantum learning.
- Purple Cluster – Expanded Domains: Includes *Cryptography* and *Chemistry*, indicating the extension of applications beyond finance.

This network demonstrates that the field of QML in finance is multidisciplinary, dynamic, and increasingly focused on integrating quantum algorithms with financial applications. Linking to literature, the green cluster echoes applications in Thakkar et al.'s study (2024), while blue shows transitions from classical methods as in Gelman et al.'s study (2013).

Fig 6.
The Co-occurrence Network



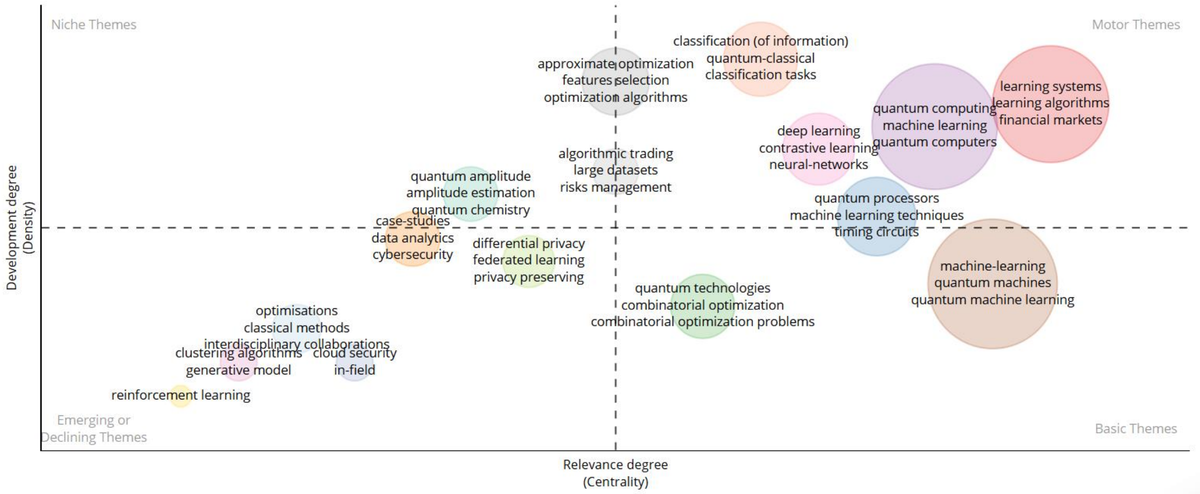
(Source: Researcher's Findings)

To analyze the structure and dynamics of research themes in the field of QBML in finance, a thematic map was constructed (see Figure 7). This map categorizes themes into four quadrants based on two indices of centrality and density.

- Upper-Right Quadrant (Motor Themes): Key and well-developed topics such as *Quantum Computing*, *Machine Learning*, and *Financial Markets* serve as the driving forces of research.
- Upper-Left Quadrant (Highly Developed but Isolated Themes): Includes more specialized topics such as *Approximate Optimization* and *Feature Selection*, which have limited connections with other areas.
- Lower-Left Quadrant (Emerging or Declining Themes): Comprises subjects such as *Reinforcement Learning* and classical approaches, which are either emerging or losing their relevance.
- Lower-Right Quadrant (Basic and Transversal Themes): Contains foundational topics such as *QML*, which are highly connected yet still in the process of maturing.

This thematic map illustrates that the field of QBML in finance is interdisciplinary and evolving. Foundational themes continue to hold strong potential for development, while the integration of *Machine Learning* and *Quantum Computing* in financial markets has attracted the greatest scholarly attention. At the same time, multiple research gaps remain open for future exploration. This map integrates with challenges in Section 1.4, where emerging themes like QRL (Ardeen & Lloyd, 2020) could address hardware bottlenecks.

Fig 7.
The Thematic Map



(Source: Researcher's Findings)

In Figure 8, the results of clustering are presented. As can be observed, the studies are concentrated into several main clusters:

Cluster 1: Macroeconomic Risk and Regulation

This group of studies focuses primarily on the role of macroeconomic environments, regulatory policies, and legal frameworks in risk management. The central concern is how regulatory changes or broader economic developments shape organizational risk management strategies.

Cluster 2: Risk Management in Financial Markets

This cluster addresses issues related to risks in financial markets, including stock price volatility, credit risk, and derivative instruments. Studies within this category often aim to provide quantitative models and innovative tools for assessing and managing financial risks.

Cluster 3: Organizational and Corporate Risk

Research in this cluster is dedicated to risk management at the level of firms and organizations. Topics include corporate governance, managerial structures, and the impact of strategic decision-making on risk exposure.

Cluster 4: Emerging Risks and Technology

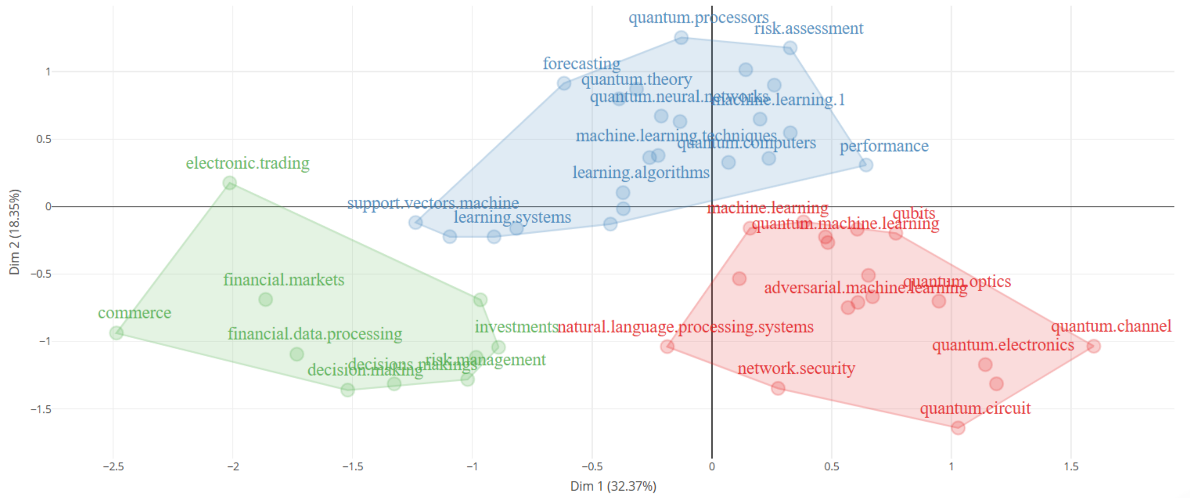
This cluster examines the impact of modern technologies, digitalization, and technological innovation on risk. It also addresses new forms of risk emerging from digital transformation and the cyber environment.

Overall Synthesis

As illustrated in Figure 6, the domain of risk management spans from macroeconomic and regulatory dimensions to technological and organizational risks, reflecting a high degree of thematic diversity. These clusters quantitatively link to bottlenecks; for instance, Cluster 4's tech risks highlight QRAM limits increasing deployment time by 30-

50% in simulations (Pistoia et al., 2021), directly impacting financial high-frequency trading (Thakkar et al., 2024).

Fig 8.
The Factorial Analysis



(Source: Researcher's Findings)

Conclusion and Recommendations

This research study achieved a novel Bibliometric mapping of QBML in finance, synthesizing 126 studies to reveal trends like accelerated growth post-2023 and US-China dominance, filling a gap in structured analyses absent in prior reviews (e.g., Doosti et al., 2024). By integrating systematic review with quantitative metrics (e.g., network modularity Q=0.62), it provided deep insights into thematic clusters and collaboration networks, advancing the field's scientific structure beyond descriptive summaries.

QBML is an emerging and rapidly growing field situated at the intersection of quantum computing, machine learning, and financial sciences. It promises to deliver more accurate predictive models, optimized risk management, and intelligent portfolio optimization. A systematic review of the literature combined with Bibliometric analysis conducted in this paper demonstrated that, despite significant theoretical advances and a growing body of research, the field still faces substantial practical challenges (Mironowicz et al., 2024; Tomar et al., 2025).

Studies indicated that Bayesian quantum learning, through the integration of precise probabilistic inference and quantum computational power, offers superior capabilities in modeling uncertainty compared to traditional methods. It has demonstrated advantages in financial market prediction, managing unstable risks, and portfolio optimization (Polson et al., 2023; Thakkar et al., 2024). The findings of this paper align with these results, emphasizing that combining Bayesian algorithms with quantum technology holds the potential to become a key tool within complex financial systems.

Nevertheless, challenges such as quantum hardware limitations, algorithmic complexity, noise in NISQ devices, the difficulty of loading classical data into qubits

(QRAM), and the need for high-quality datasets continue to restrict the practical deployment and widespread application of this technology (Gujju et al., 2023; Pistoia et al., 2021; Roy, 2024; Vashishth et al., 2025). These findings are consistent with prior research highlighting the considerable gap between theory and practice in QML, particularly in financial applications (Mounika et al., 2024; Shaik, 2020). Moreover, the present study identified the lack of empirical investigations and operational frameworks as a major barrier, requiring urgent attention.

The Bibliometric analysis of data indicated that research in this domain is accelerating, with the United States, China, and the European Union emerging as leading scientific contributors. These actors often drive progress through international collaborations. This observation corresponds with the identification of prominent authors, core journals such as *Entropy*, and pioneering studies in QML. The importance of international cooperation in strengthening scientific infrastructures and expediting real-world applications has also been emphasized by many comparable studies (Auer et al., 2024; Herman et al., 2023).

From a thematic perspective, this research highlights the main axes of inquiry including the improvement of Bayesian–quantum algorithms, financial risk management, portfolio optimization, and financial forecasting. These themes have also been underscored in earlier literature (e.g., Doosti et al., 2024; Mongwe et al., 2025). Additionally, the importance of hybrid quantum–classical models in the early stages of financial market applications has been noted, with examples of early successes reported by leading firms such as JPMorgan and Terra Quantum (Pistoia et al., 2021; Wall Street Journal (2024)).

Recommendations for Future Research

Recommendations for conducting further research are as follows:

1. **Development and Implementation of Practical and Empirical Frameworks:** Apply QBML models to real-world financial datasets to bridge the gap between theory and practice. This step is crucial for demonstrating efficacy and building confidence in the applicability of the technology (Mounika et al., 2024). For example, apply Quantum Bayesian Networks for high-frequency trading risk mitigation, potentially reducing errors by 15-25% as simulated in Siddiqui et al.'s study (2024).
2. **Investment in Stable Quantum Hardware:** Focus on developing more stable, less noisy quantum hardware—particularly NISQ technologies—to facilitate the execution of complex Bayesian quantum learning algorithms in applied settings (Preskill, 2018).
3. **Efficient Data Loading and Bayesian Inference:** Advance research on effective techniques for loading classical data into qubits (QRAM) and reducing the computational costs of Bayesian inference, especially through implementing methods such as quantum MCMC or quantum Bayesian networks (Low et al., 2014; Nikoloska, 2024).

4. **Hybrid Quantum–Classical Algorithms:** Develop algorithms that combine the strengths of quantum and classical methods for improved performance in risk management and portfolio optimization (Harrow et al. (2009)). For instance, hybrid models for portfolio optimization in volatile markets, as extended from Thakkar et al.'s study (2024).
5. **Interdisciplinary and International Collaborations:** Strengthen collaborations across disciplines and borders to accelerate innovation, knowledge exchange, and financial applications. This includes partnerships among governments, academia, and industry (Auer et al., 2024).
6. **Human Capital Development:** Expand education and workforce training in quantum computing and QBML, particularly through organizing academic programs and hands-on workshops facilitated by leading technology firms (IBM, Muoio (2025)).
7. **Extended Bibliometric and Systematic Reviews:** Conduct further Bibliometric studies and structured literature reviews to better identify the research trends, collaboration networks, and existing gaps, thereby guiding research priorities.

Final Remarks

This study's unique contribution lies in its integrated Bibliometric-synthesis approach, revealing not just trends but quantifiable networks and thematic evolutions that prior works overlooked, paving the way for targeted advancements in QBML finance.

Previous studies have similarly underscored the potential of Bayesian quantum learning in improving market analysis and risk management (Polson et al., 2023; Thakkar et al., 2024). Comprehensive reviews by Doosti et al. (2024) and Tomar et al. (2025) clearly illustrated that combining Bayesian learning with quantum technology can generate powerful and practical algorithms, particularly in finance, but they also highlighted the lack of real-world applications. The findings of this article extended these insights by incorporating Bibliometric evidence that reveals the scientific structure and geographical distribution of researchers—an aspect often overlooked in prior reviews.

The identification of the leading scientific actors, the dominant roles of the United States and China, and the broad thematic range collectively demonstrated that QBML in finance is simultaneously maturing and evolving. These findings are consistent with recent approaches in quantum computing and machine learning (Auer et al., 2024; Herman et al., 2023). Likewise, in line with BIS reports and academic contributions, it is observed that major financial institutions are actively exploring these technologies for real applications, though practical and technical challenges remain the main obstacles (Auer et al., 2024; Pistoia et al., 2021).

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Unlocking Value Co-Creation in Online Tourism Services: The Impact of Customer and Website Personalities on Co-Creation through Brand Trust

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ABSTRACT

In current business landscape, value Co-Creation (VCC) has emerged as a key principle in service marketing and management. As organizations increasingly aim to involve customers in meaningful ways, firms are engaging them more actively in designing new products and services. When offerings are developed through a co-creation process that reflects the customers' needs and preferences, they are more likely to succeed in market over the long term. Therefore, understanding the factors that drive VCC is essential for organizational success. While previous research has explored various determinants, relatively few studies have investigated how customer personality and website personality jointly influence VCC, particularly considering the mediating role of the brand trust. This study addressed this gap by combining insights from personality traits and digital interface characteristics, thereby contributing to the literature on technology-mediated co-creation. A descriptive-analytical and correlational approach was used in this paper. The statistical population included online retail customers who had made at least two purchases on tourism websites. The participants were selected using a non-probability convenience sampling method from customers of *Eli Gasht, Eghamat24, and Koja Ro*. A structured questionnaire was designed and administered, producing 253 valid responses that were analyzed using appropriate statistical methods. The instrument's validity and reliability were confirmed through expert review and Cronbach's alpha, respectively. Findings revealed that both customer personality and website personality have a meaningful impact on VCC, with customer personality exerting a stronger influence. Additionally, the brand trust served as a crucial mediator in the relationship between personality factors and co-creation. These results underscored the importance of aligning digital platforms with the traits of their users and highlighted the strategic role of brand trust in promoting collaborative value creation.

KEYWORDS

Value co-creation, customer personality, website personality, brand trust.

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Introduction

In the contemporary era, with the rapid growth of digital platforms, the expansion of interactions and data can serve as a key enabler for co-creation of value (Hendricks et al., 2025). Co-creation of value is a concept aimed at facilitating the value realization processes, which has received significant attention in research and can provide competitive advantages (Laud & Karpen, 2017). Co-created value is an emerging phenomenon in the sharing economy, facilitating joint production and consumption while highlighting the importance of value co-creation (Zhang, 2018). This concept indicates that both providers and customers actively engage in the process of value creation—whether related to products, services, or knowledge components—through a reciprocal approach. This process involves not only the provider but also the customer (Corsaro, 2018). Value co-creation refers to the creation of interactive and customer-oriented value, which is closely aligned with value-in-use (Hendricks et al., 2025). Value Co-Creation (VCC) represents value processes that are generated collaboratively, collectively, or jointly by actors (Saha et al., 2025).

Companies are striving to develop strategies for adopting a value co-creation approach in the design, development, and delivery of services through digital platforms. However, identifying the key drivers of value co-creation remains a central concern for both researchers and managers, rendering this field as an emerging area of inquiry (Hasan et al., 2024).

The personality of a website plays a crucial role in developing long-term and trustworthy relationships between customers and businesses. Similarly, a business website can be regarded as a salesperson for the company, while its visitors represent potential customers. Therefore, the personality of the website is highly critical. In fact, the website personality can help companies distinguish themselves from competitors and build closer connections with customers (Akrimi & Khemakhem, 2014). Moreover, the website personality can contribute to maintaining customer loyalty in e-commerce (Chishti et al., 2015).

This concept can be applied to a tangible product or a service, including an online product, a store, a website, a country, or even a tourism destination (Akrimi & Khemakhem, 2014). Understanding the users' preferences can help developers improve websites in ways that enhance the users' satisfaction. Developers can design and develop websites more effectively by introducing various product information features, such as colored texts, search boxes, and audio/video clips, thereby creating a website with human-like characteristics. These attributes collectively contribute to the development of the website's personality (Chishti et al., 2015).

On the other hand, understanding the customer personality contributes to building longer relationships, retaining customers, and enhancing their loyalty, as it is widely believed that retaining an existing customer is less costly than acquiring a new one. By recognizing the customer personalities, organizations can save considerable time and effort while ensuring a return on their investments. Identifying the traits and observable behaviors of customers is particularly important for providers of products and services who are constantly striving to gain a stronger position in the hearts and minds of their customers (Mishra & Vaithianathan, 2015).

Examining customer personality traits enables a better understanding and prediction of customer behavior in business contexts. In other words, to enhance the customers' positive experiences in commercial environments, providers may take customer personality into account (Ihtiyar, 2018). Furthermore, psychological studies indicated that when customers are presented with products that align with their personality type or lifestyle, their likelihood of purchase increases significantly, which in turn fosters greater customer satisfaction and contributes to enhanced loyalty (Marwade et al., 2017).

Brand trust is widely recognized as a crucial factor for fostering long-term relationships between consumers and brands, as well as for helping firms maintain a competitive edge (Hegner & Jevons, 2016). In the tourism sector, trust plays an especially important role in sustaining long-term customer relationships, given the highly competitive digital environment of today (Jamporazmey et al., 2024). A strong brand not only enhances a company's market position but also serves as a signal of quality, performance, and product distinctiveness. This, in turn, strengthens the perceived credibility of the company and supports its capacity and commitment to fulfill customer expectations (Hamid Hawass, 2013).

In consumer markets, a brand acts as a bridge connecting the organization with its customers. Building a trust-based relationship between the consumer and the brand is therefore one of the central objectives of marketing. Empirical studies further indicated that the brand trust is a significant predictor of the brand loyalty (Wang & Guo, 2017).

Brand trust is widely recognized as a key factor in consumer decision-making, particularly in shaping brand associations and guiding communication choices. Trust operates as a psychological mechanism that helps consumers reduce perceived risks when selecting products. Understanding the nature of brand trust and how it fosters long-term consumer relationships has been a longstanding focus in marketing research (Srivastava et al., 2015). To build the brand trust, marketers must carefully manage both business communications and brand image. By effectively communicating the brand's values and enhancing its perceived image, companies can cultivate consumer trust, which in turn promotes the brand loyalty. Loyal customers are more likely to continue engaging with the brand, resulting in higher retention rates and lower marketing costs. Moreover, satisfied and trusting customers often share their experiences through word-of-mouth, further amplifying the brand's reach (Chinomona, 2016).

While collaboration between firms and customers can improve the quality of experiences and outcomes, there remains a significant gap in understanding how companies can effectively engage customers in value co-creation (Hasan et al., 2024). In particular, little research has examined the combined impact of the website personality and customer personality on VCC, especially considering the mediating role of the brand trust. This study seeks to address this theoretical gap by examining these relationships within the context of digital platforms in the tourism industry.

Literature Review

Value Co-Creation

Currently, research on VCC in the tourism and hospitality is growing (Borges-Tiago & Avelar, 2025). Recent studies in tourism indicated a shift toward the "value-in-use" or "value-in-context" perspective, where customers can collaborate with tourism organizations through interaction with one another (Luu Trong Tuan et al., 2019). The emergence of competition in the tourism industry has led companies and their managers to recognize the importance of continuous innovations in order to achieve competitive advantages. Organizations need to seek knowledge and co-create value for both the company and its customers to obtain ideas from outside the organization. Companies should not only generate their own ideas but also integrate innovations from other firms (Casais et al., 2019).

VCC is one of the emerging concepts that has rapidly attracted significant attention among academics and managers (Saha et al., 2025). It represents a novel approach to innovation in which all stakeholders can play a role in organizational processes. This concept can be studied and implemented across various fields of management, including marketing, strategic management, and innovation management (Dehkordi et al., 2017).

VCC asserts that value can be generated by other actors (e.g., customers or suppliers), as opposed to the firm-centered approach where value is solely delivered to customers. Similar to the concept of value-in-use, VCC emphasizes the ongoing process of value creation by actors through their interactions with diverse stakeholders along the customer journey (Saha et al., 2025).

VCC refers to the process in which customers actively participate in various stages of a product or service, including design, production, and post-sale support. Fundamentally, it is an interactive and creative social process facilitated by the company, where different stakeholders may contribute to value creation at each stage (Dehkordi et al., 2017). The main goal of the co-created value is to generate outcomes that benefit both the organization and the customer, particularly regarding production efficiency and pricing. This value emerges through continuous interaction and collaboration between the company and its customers (Wong & Lai, 2019).

Hasan et al. (2024) conceptualized the VCC behavior as a multidimensional construct comprising two main components of customer participation behavior and customer citizenship behavior. The participation behavior refers to actions in which customers are directly involved in service design and delivery, including activities such as seeking information, sharing knowledge, and performing responsible actions—behaviors that are essential for effective value creation. On the other hand, the citizenship behavior encompasses voluntary initiatives by customers, such as providing feedback, advocating for the brand, assisting other customers, and demonstrating tolerance. While these actions are not strictly necessary for value creation, they contribute to enhancing the overall organizational value. This distinction aligns with prior research, which similarly categorizes the participation behavior as required for service exchange and the citizenship behavior as optional yet beneficial contributions (Delpechitre et al., 2018; Foroudi et al., 2018).

Tourist involvement in the VCC process is closely linked to customer satisfaction and loyalty, as individuals perceive their participation as active and meaningful. Enhancing the tourists' engagement throughout the tourism experience is therefore essential, emphasizing the significance of user-generated online feedback. In the hospitality sector, such content is recognized as a valuable source of information for improving the service quality and understanding the customer satisfaction (Casais et al., 2019).

In the following section, considering the importance of identifying the key drivers and factors of VCC in tourism, the study develops a conceptual model that incorporates variables which have not yet been extensively explored.

The Research Conceptual Model and Hypotheses Development

Website Personality and Brand Trust

Some studies (e.g., Bilgihan, 2016) have indicated that trust is a significant construct in business relationships and transactions, and its role is even more critical in online shopping than in physical stores. Trust, which encompasses competence, predictability, and benevolence/integrity, plays an important role in buyer behavior within e-commerce contexts. Successful e-commerce websites are those that attract customers and enhance their trust in the company's brand. Website features, design quality, and improvements in ease of use positively influence brand trust, which, in turn, can increase the online customer acquisition. In another study, Rezaei et al. (2016) found that website personality and its components—including sincerity, excitement, competence, sophistication, and unpleasantness—affect engaging, useful, and functional web browsing, ultimately influencing trust and online purchase behavior. Akbari Emami and Najimi (2024) suggested that the higher levels of user trust enhance the likelihood of frequent use of digital applications.

Additionally, research by Shobeiri et al. (2013) demonstrated that website personality significantly impacts perceived quality, brand attitude, brand trust, customer satisfaction, preference for the company's brand over competitors, and word-of-mouth advertising. They noted that the effects of factors such as web space cues, website design, usability, and privacy/security on consumer behavior variables—such as brand trust, satisfaction, purchase intention, and loyalty—are well-established in the literature. Similarly, Yin et al. (2015) showed that the dimensions of website personality positively influence brand trust among online banking customers.

Based on these findings regarding the relationship between website personality and brand trust, the following research hypothesis was proposed:

Hypothesis 1: Website personality positively affects brand trust.

The Customer Personality and Brand Trust

In marketing literature, brand trust—comprising competence, predictability, and benevolence/integrity—is considered as a fundamental element for successful relationships and appears to be central to all transactional interactions (Bove & Mitzifiris, 2007). Some researchers (e.g., Mishra & Vaithianathan, 2015) have argued that marketing efforts aim to strengthen the customer relationships by understanding their personalities, thereby increasing customer retention, brand trust, relationship satisfaction, and loyalty. This strategy is based on the belief that retaining the existing customers is less costly than acquiring new ones.

Menidjel et al. (2017) examined personality traits as the antecedents of brand trust and loyalty, suggesting that personality characteristics are expected to influence both. Similarly, Al-Hawari (2015) noted that customer trust may be affected by personality regardless of the marketing strategies adopted by banks. Thus, considering customer personality traits is essential for determining the nature of their relationships with companies. This perspective emphasizes that customers may select a product or service because it reflects their personality or social status, or fulfills specific psychological needs.

Bove and Mitzifiris (2007) found a significant positive relationship between the personality traits of agreeableness and benevolence and a dimension of trust. Long & Lin (2010) concluded that openness to experience and extraversion, as dimensions of customer personality, positively correlate with brand trust and loyalty. He explained that personality is primarily composed of behavior, appearance, affection, beliefs, and other traits. Lin also reported that young women tend to be more risk-prone than young men but exhibit lower brand trust, while higher income is strongly associated with brand loyalty. Furthermore, Bove and Mitzifiris (2007) observed positive relationships between customer personality traits—agreeableness, conscientiousness, extraversion, neuroticism, and openness to experience—and trust in retail stores.

Based on these findings, the following research hypotheses were proposed:

Hypothesis 2: Extraversion positively affects brand trust.

Hypothesis 3: Neuroticism negatively affects brand trust.

Hypothesis 4: Agreeableness positively affects brand trust.

Hypothesis 5: Conscientiousness positively affects brand trust.

Hypothesis 6: Openness to experience positively affects brand trust.

Website Personality and VCC

Rezaei et al. (2016) stated that various qualities of a website reflect its personality. Accordingly, different features of website personality include engaging website cues, website design, website usability, and privacy and security objectives. Shobeiri et al. (2012) also noted that the effects of website personality variables on consumer behavior variables—such as satisfaction, purchase intention, and customer loyalty—are well-established in literature.

Moreover, customer satisfaction, facilitated by a platform that empowers customer participation, leads to VCC. While it is well recognized that customer satisfaction is a key factor in creating value, an important component of the relationship between satisfaction and value creation is participation (Flores & Vasquez-Parraga, 2015). The Internet and websites are also recognized as useful platforms for delivering value to all stakeholders. The dynamic nature of the Internet allows for greater customer involvement and interaction with organizations through commercial engagements. Consequently, VCC arises through website personality and customer interactions with companies online (Ozuem & Bowen, 2016).

Based on these concepts, the following research hypothesis was proposed:

Hypothesis 7: Website personality positively affects value co-creation.

Customer Personality and VCC

Researchers such as Twrsnick (2016) have discussed the impact of certain dimensions of customer personality on VCC which allows companies to approach customers in the most effective way. Openness to experience may reflect curiosity, appreciation, interest in novelty, and intellectual engagement. Twrsnick proposed hypotheses regarding the positive effects of openness to experience and extraversion on VCC, which were supported by her findings. Ivanov (2019) hypothesized that extraversion, openness to experience, agreeableness, and conscientiousness positively affect customer participation behavior, a dimension of VCC, while neuroticism negatively impacts the participation behavior. The study results confirmed that three customer personality traits—extraversion, openness to experience, and agreeableness—have significant positive effects on customer participation.

A study conducted by Kvasova (2015) showed that agreeableness, conscientiousness, extraversion, and neuroticism positively influence VCC behavior, whereas openness to experience has a minimal effect on VCC performance. Milfont and Sibley (2012) reported that agreeableness, extraversion, and openness to experience are closely related to VCC. Malone et al. (2018), in a qualitative study, explained how emotions (neuroticism) contribute to the customer value creation process in tourism context.

Based on these insights, the following research hypotheses were proposed:

Hypothesis 8: Extraversion positively affects value co-creation.

Hypothesis 9: Neuroticism negatively affects value co-creation.

Hypothesis 10: Agreeableness positively affects value co-creation.

Hypothesis 11: Conscientiousness positively affects value co-creation.

Hypothesis 12: Openness to experience positively affects value co-creation.

Brand Trust and VCC

Some researchers (e.g., Laroche et al., 2012) have suggested that methods of building brand trust through social media mechanisms and capabilities influence VCC trust. One of the key mechanisms for enhancing trust in value creation is the dissemination of information across various channels, such as customization, welcoming, justification, and documentation. All trust-building methods increase the level of interaction between consumers and the product, brand, other customers, and marketers, which are all elements of a value-creating community. Therefore, as people's trust in a brand increases, they recognize the enjoyable and beneficial values of that brand. Within brand communities and through trust-building practices, individuals establish close relationships and derive value from their long-term interactions. In another study, Shen et al. (2018) examined the impact of brand trust on VCC. They noted that the sense of security that consumers experience when interacting with and trusting a brand can contribute to co-created brand value. Brand trust facilitates consumer engagement and dialogue with the organization, preventing misunderstandings and delays in problem resolution. Follow-up and after-sales services ensure consumer mastery over brand information and enhance their trust and sense of security. These factors positively influence VCC. Based on these findings, the following research hypothesis was proposed:

Hypothesis 13: Brand trust positively affects value co-creation.

A Mediating Path for VCC in Tourism Industry

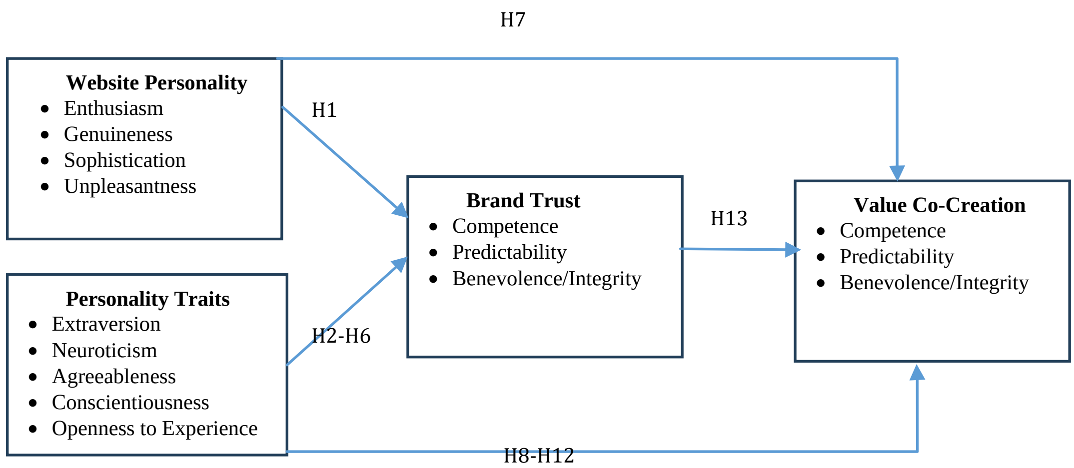
Beyond the direct relationships described earlier, this study examines a mediating mechanism in which website personality and customer personality influence VCC through brand trust. Based on prior discussions regarding the links between personality traits, website personality, and brand trust, it is proposed that brand trust serves as a mediator in the relationship between these personality dimensions and VCC. In essence, the model suggests that website personality and customer personality shape brand trust, which subsequently affects the extent of VCC. Therefore, the following research hypotheses were formulated:

Hypothesis 14: Brand trust mediates the effect of website personality on value co-creation.

Hypothesis 15: Brand trust mediates the effect of customer personality on value co-creation.

Considering the challenges and limitations identified in this area, the study's conceptual framework is presented in Figure 1.

Figure 1.
The Conceptual Model (Source: Authors)



(Source: Researcher's Findings)

Methodology

To test the research hypotheses and examine the developed conceptual model (Fig. 1), a quantitative approach using a survey method was employed. In this section, data collection procedures, sample characteristics, and validity and reliability of the research instrument are described.

Research Instrument

The questionnaire for this study focused on four primary constructs of customer personality, website personality, brand trust, and VCC. To assess the customer personality, the widely recognized Big Five model was employed, capturing five traits including extraversion, neuroticism, agreeableness, conscientiousness, and openness to experience. Website personality was evaluated following Shobeiri et al. (2013), incorporating dimensions such as solidity, enthusiasm, genuineness, sophistication, and unpleasantness. Brand trust was measured using scales developed by Hegner and Jevons (2016) and Li et al. (2015), which consider three aspects of competence, predictability, and benevolence/integrity. Finally, VCC was assessed based on Hasan et al. (2024), including two key dimensions of behavioral participation and citizenship behavior.

Table 1 summarizes the number of items and sources for each construct. In total, the questionnaire comprised 52 items covering all four constructs. Responses were recorded using a 5-point Likert scale, ranging from 1 (“strongly disagree”) to 5 (“strongly agree”).

Data Collection and Sample

The statistical population of this study consisted of all customers of online retailers who have purchased from tourism websites more than twice. It can be considered that the number of these customers, and consequently the population, is effectively unlimited. To enable generalization of the findings to the population, a non-probability convenience sampling method was employed. Accordingly, the online questionnaire was distributed to the sample via Telegram and WhatsApp applications. Based on Morgan's table (n = 384) and the unlimited population size, 384 questionnaires were distributed. Following continuous follow-ups, 253 completed questionnaires were collected.

Reliability and Validity

To assess the content validity of the questionnaire, the opinions of academic experts in the field were solicited. Having sent the questionnaire to six professors, feedback from four of them regarding the comprehensiveness and clarity of the items was received. Necessary revisions were made, and the questionnaire was ultimately approved. At this stage, efforts were made to ensure that the questions were simple and easily understandable for the respondents.

To evaluate the reliability of the questionnaire, Cronbach’s alpha was calculated using SPSS. The obtained value was 0.889, which exceeds the acceptable threshold of 0.7, indicating that the questionnaire has sufficient reliability. Cronbach’s alpha was also calculated separately for each construct in the model (Table 1), and all values were above the acceptable limit (=>0.7).

Table 1.
The Compnents of Research Instrument and Their Chronbach's Alpha

Main Constructs	Dimensions	Number of questions	Cronbach Alpha	Sources
Co-creation	Participation Behaviour	4	0.75	Hasan et al. (2024)
	Citizenship Behaviour	3	0.754	
Website Personality	Solidity	3	0.889	Shobeiri et al. (2013)
	Enthusiasm	3	0.871	
	Genuineness	3	0.834	
	Sophistication	3	0.867	
	Unpleasantness	4	0.720	
Personality Traits	Extraversion	5	0.847	Jami pour & Taheri (2019); Fanea-Ivanovici et al. (2025)
	Neuroticism	3	0.819	
	Agreeableness	5	0.718	
	Conscientiousness	5	0.744	
	Openness to Experience	4	0.752	
Brand Trust	Competence	4	0.717	Hegner & Jevons (2016); Li et al. (2015)
	Predictability	3	0.85	
	Benevolence/Integrity	4	0.747	

(Source: Researcher's Findings)

Findings

Sample Profile

All participants in the study had at least two prior purchase experiences from tourism websites. Their annual purchase information, along with demographic details such as gender, age, and level of education, is presented in Table 2.

Table 2.
The Sample Demographic Profile

Variable	Frequency (n=253)	Total sample (%)
Age (year)		
Less than 20	14	5.5%
21-30	147	58.1%
31-40	70	27.6%
40 and over	22	8.7%
Gender		
Male	123	48.6%
Female	130	51.4%
Education		
Associate degree or below	26	10.3%
Bachelor's degree	77	30.4%
Master's degree	130	51.4%
Phd degree or higher	20	7.9%
Online purchase experience in the tourism sector		
At least once a year	117	46.24%
2-4 times a year	79	31.23%
5-8 times a year	38	15.01%
More than 8 times a year	19	7.5%

(Source: Researcher's Findings)

Descriptive Statistics and Correlation Analysis

To examine the appropriateness of the selected items for measuring the studied variables, Confirmatory Factor Analysis (CFA) was employed. In other words, the first step in validating a measurement model is to assess the goodness of fit of the construct's measurement model.

Table 3.
The Results of CFA of the Measurement Model

Main Constructs	Dimensions	Items	Loadings	T-value	AVE	CR
Co-creation	Participation Behaviour	KHM1	0.697	15.215	0.763	0.801
		KHM2	0.699	17.607		
		KHM3	0.598	13.851		
		KHM4	0.800	29.619		
	Citizenship Behaviour	KHSH1	0.674	15.237	0.787	0.813
		KHSH2	0.757	27.520		
		KHSH3	0.658	13.220		
Website Personality	Solidity	WS1	0.636	14.394	0.588	0.749
		WS2	0.591	12.862		
		WS3	0.523	10.126		
	Enthusiasm	WSH1	0.642	15.424	0.682	0.713
		WSH2	0.683	18.003		
		WSH3	0.678	17.228		
	Genuineness	WH1	0.655	12.987	0.663	0.705
		WH2	0.705	16.615		
		WH3	0.624	12.316		
	Sophistication	WP1	0.554	9.198	0.599	0.734
		WP2	0.542	8.987		
		WP3	0.589	10.461		
	Unpleasantness	WN1	0.437	6.708	0.687	0.721
		WN2	0.456	7.305		
		WN3	0.428	7.880		
		WN4	0.502	8.227		
Personality Traits	Extraversion	MB1	0.488	7.813	0.779	0.798
		MB2	0.557	9.073		
		MB3	0.571	9.573		
		MB4	0.596	11.864		
		MB5	0.647	18.468		
	Neuroticism	MR1	0.617	13.371	0.558	0.703
		MR2	0.560	10.886		
		MR3	0.550	13.815		
	Agreeableness	MS1	0.445	7.988	0.814	0.857
		MS2	0.492	5.886		
		MS3	0.565	8.077		
		MS4	0.565	12.445		
		MS5	0.640	19.195		
	Conscientiousne ss	MV1	0.510	7.152	0.776	0.804
		MV2	0.502	7.306		
		MV3	0.532	7.802		
		MV4	0.480	6.997		
		MV5	0.538	9.325		
	Openness to Experience	MT1	0.457	6.551	0.697	0.751
		MT2	0.534	8.455		
		MT3	0.605	10.655		
		MT4	0.406	6.646		
Brand Trust	Competence	ES1	0.634	15.978	0.718	0.765
		ES2	0.580	10.178		
		ES3	0.668	15.985		
		ES4	0.628	12.887		
	Predictability	EP1	0.754	23.446	0.748	0.772
		EP2	0.731	18.288		
		EP3	0.813	36.009		
	Benevolence/Int egrity	EKH1	0.610	12.594	0.747	0.786
		EKH2	0.750	23.388		
		EKH3	0.643	13.025		
		EKH4	0.737	20.759		

(Source: Researcher's Findings)

The threshold values for acceptable factor loadings and t-statistics are 0.40 and ±1.96, respectively. As presented in Table 3, all items demonstrated factor loadings above 0.40 and t-values exceeding 1.96. These results indicated that no modifications to the questionnaire or the model were required. Moreover, the results showed that all constructs were successfully validated. The measurement model demonstrated a good fit with the collected data. Convergent validity was assessed using the Average Variance Extracted (AVE), where values above 0.50 are considered acceptable (Fornell & Larcker, 1981). As presented in the table, each construct surpassed this threshold, confirming adequate convergent validity. Additionally, Composite Reliability (CR) was evaluated, with a recommended minimum of 0.70. The findings showed that all the constructs exceeded this benchmark, demonstrating satisfactory reliability and supporting the overall robustness of the measurement model.

Regression Analysis

To examine the impact of the independent variables on the dependent variable, a linear regression analysis was run. This approach enables the prediction and estimation of the dependent construct based on the observed values of the independent constructs. In this study, linear regression was used as the main analytical method to investigate the relationships among variables and to test the research hypotheses.

Table 4.
The Results of the Regression Analysis for Hypotheses

DV	Brand Trust			Co-Creation		
IV	R2	Beta	Sig	R2	Beta	Sig
Website personality	0.609	0.781	0.000**	0.094	0.307	0.000**
Extraversion	0.089	0.298	0.000**	0.141	0.376	0.000**
Neuroticism	0.018	-0.133	0.034*	0.023	-0.153	0.015*
Agreeableness	0.085	0.291	0.000**	0.058	0.24	0.000**
Conscientiousness	0.071	0.267	0.000**	0.199	0.446	0.000**
Openness	0.117	0.342	0.000**	0.196	0.443	0.000**
Brand Trust				0.115	0.339	0.000**
**p<0.001, *p<0.05 DV indicates dependent variable; IV indicates independent variable						

(Source: Researcher's Findings)

The analysis showed that website personality has a significant positive impact on brand trust (β = 0.781). Similarly, all dimensions of customer personality were found to influence brand trust. In particular, openness to experience (β = 0.342), extraversion (β = 0.298), agreeableness (β = 0.291), and conscientiousness (β = 0.267) demonstrated the strongest positive effects, whereas neuroticism exhibited a significant negative effect (β = −0.133). Consequently, hypotheses 1 to 6 were supported.

The results further indicated that website personality significantly contributes to VCC (β = 0.307; $p < 0.05$). All customer personality traits also showed significant influences on co-creation. Among these, conscientiousness (β = 0.446), openness to experience (β = 0.443), extraversion (β = 0.376), and agreeableness (β = 0.240) had positive effects, while neuroticism (β = −0.153) had a negative impact. Therefore, hypotheses 7 to 12 were also supported. Moreover, brand trust was found to have a significant positive effect on co-creation of value (β = 0.339), supporting hypothesis 13.

To examine the mediating role of brand trust in the relationship between customer personality, website personality, and VCC, the PROCESS macro by Hayes (2017) was employed. This approach is widely used to test the mediating and moderating effects in contemporary research (Jami Pour & Taheri, 2019). The results of this mediation analysis are summarized in Table 5.

Table 5
Indirect Effects of Personality Traits and Brand Trust on Value Co-creation in Tourism Sector

95% Bootstrap CI					Results
Indirect path	**B**	**SE**	**Lower limit**	**Upper limit**	
Website personality → brand trust → Co-creation	0.2166	0.0875	0.0494	0.3947	Supported
Extroversion → brand trust → Co-creation	0.0579	0.0198	0.0244	0.1008	Supported
Openness → brand trust → Co-creation	-0.0259	0.015	-0.059	-0.0003	Supported
Neuroticism → brand trust → Co-creation	0.078	0.0242	0.0343	0.1291	Supported
Conscientiousness → brand trust → Co-creation	0.0546	0.019	0.0217	0.0958	Supported
Agreeableness → brand trust → Co-creation	0.0579	0.0205	0.022	0.1027	Supported
Note: The analyses were conducted using the PROCESS macro developed by Hayes (2017). The confidence intervals (CI) were calculated via bootstrapping with 5,000 resamples.					

(Source: Researcher's Findings)

As presented in the table, in all paths, the upper and lower bounds of the confidence intervals had the same sign, and zero was not included between them. Hence, the mediating role of brand trust is confirmed across all paths. Consequently, hypotheses 14 and 15 were supported.

Conclusions and Discussion

Although numerous studies have explored various aspects of co-creation behavior, the individual, behavioral, and psychological differences associated with personality traits, as well as the distinctions in website personality, remain insufficiently understood. Accordingly, the present study investigated the relationships among the personality traits, website personality, VCC, and brand trust. The examination of the effects of website personality on brand trust revealed that this relationship was supported (Hypothesis 1). These findings are consistent with the results reported by Chishti et al. (2015), Rezaei et al. (2015), Shobeiri et al. (2012), and Yin et al. (2015).

The analysis of the customer personality dimensions (extraversion, neuroticism, agreeableness, conscientiousness, and openness to experience) on brand trust revealed that all relationships were supported, with each personality dimension significantly affecting the brand trust. These findings are consistent with previous studies by Menidjel et al. (2017), Mitzifiris (2007), Lin (2010), Al-Hawari (2015), and Bove and Mitzifiris (2007), although those studies generally examined either the overall influence of customer personality or selected dimensions on brand trust.

The analysis of the effects of brand trust on VCC showed that the relationship was supported. These findings are consistent with the studies of Laroche et al. (2012) and

Shen et al. (2018).

Furthermore, exploring the impact of customer personality dimensions (extraversion, neuroticism, agreeableness, conscientiousness, and openness to experience) on VCC showed that all relationships were supported. These findings partially align with Kvasova (2015), who reported that agreeableness, conscientiousness, extraversion, and neuroticism positively affect VCC, while openness to experience has a minimal impact. They are also consistent with Milfont and Sibley (2012), who found that agreeableness, extraversion, and openness to experience are closely related to VCC. However, the results differ slightly from those of Ivanov (2019), who reported that extraversion, openness to experience, and agreeableness positively influence participatory behavior, whereas conscientiousness and neuroticism negatively affect it.

Practical and Theoretical Implications

This study is among the first empirical investigations examining the impacts of website personality and customer personality on VCC, considering the mediating role of brand trust. Focusing on tourism industry, the research provides novel insights into VCC behavior, which can assist organizations in enhancing the customer experience and promoting greater satisfaction and engagement. Practical recommendations based on the study findings are subsequently presented.

Considering the study results on the impact of website personality on VCC, organizations are encouraged to enhance the website features such as an attractive and modern design, user-friendly navigation, dynamic and engaging content, privacy protection, secure payment systems, and non-intrusive interfaces to increase the customer engagement and interaction. One way to increase the website attractiveness and enhance the customer engagement with brands, while providing enjoyment and influencing their purchasing behavior, is through gamification and the use of gamified advertising (Jami Pour et al., 2023). It is recommended that companies leverage gamification approaches in co-creating value with their customers.

In light of the findings regarding the effect of customer personality on VCC, it is recommended to leverage feedback from extraverted and conscientious customers to improve the product and service quality, utilize the patience and cooperativeness of agreeable customers for consistent feedback, apply innovative ideas from customers open to experience, and carefully treat input from neurotic customers due to its inconsistency. The findings related to the influence of website personality on brand trust suggest that companies should focus on improving the website attractiveness, reliability, dynamism, and security, as these enhancements foster greater trust, satisfaction, purchase intention, and customer loyalty.

The results concerning the effect of customer personality on brand trust indicate that personalizing the customer experience by identifying personality, interests, and preferences can help offer relevant and complementary products, gradually strengthening trust while prioritizing feedback from extraverted and conscientious customers.

Finally, the study findings on the impact of brand trust on VCC highlight the importance of demonstrating brand competence, reliability, and professionalism, ensuring predictability in brand processes, attending to stakeholder well-being, and adhering to ethical standards to foster trust, loyalty, and facilitate co-creation of value.

Research Limitations and Future Study Suggestions

Although the findings of this study are insightful, certain limitations should be acknowledged, highlighting the need for further research. First, the study was conducted exclusively within the tourism industry, and the results may differ across other sectors. Future research is therefore encouraged to examine similar relationships in industries such as food retail or insurance. Second, demographic factors such as gender, age, and education may influence the relationships among the variables. It is recommended that future studies investigate the moderating role of such demographic characteristics, particularly age and gender. Third, as this research study was conducted in Iran within a specific socio-cultural context, replicating the study in other countries is suggested to account for macro-environmental influences on consumer behavior and to enhance the generalizability of the findings.

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Modeling the Barriers to Implementing Artificial Intelligence in Desalination Supply Chain Using MICMAC

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ABSTRACT

This study examined the barriers to adopting Artificial Intelligence (AI) in desalination supply chain (SC), a sector increasingly seen as vital for tackling global water scarcity. Despite AI's proven ability to improve efficiency, sustainability, and decision-making in complex supply chains, its implementation in desalination systems encounters formidable challenges. Through a comprehensive literature review and expert consultations, sixteen barriers were identified and analyzed structurally using the MICMAC approach. The results showed that four factors are the most influential barriers and serve as bottlenecks for successful AI adoption: lack of funding and capital, lack of standardization and interoperability, shortage of specific skills and talent, and data privacy and security concerns. The present study emphasizes the need for integrated strategies that include financial support, common standards, skill development programs, and strong data protection frameworks. It also highlights the importance of collaboration among governments, private sector stakeholders, and research institutions to overcome systemic obstacles. The findings may not only offer insights into the key drivers of AI implementation in desalination but also provide a roadmap for policymakers and industry leaders aiming to develop more resilient and sustainable water management systems.

KEYWORDS

Artificial Intelligence (AI), desalination supply chain, MICMAC analysis, structural analysis, supply chain management.

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Introduction

The increasing global population, rapid urbanization, and industrial growth have greatly increased the demand for fresh water, making desalination an essential and viable solution to address water scarcity from abundant but salty sources like seawater and brackish water (Ali et al., 2024; Balaji et al., 2021; Fares et al., 2019; Hanasaki et al., 2016; Ignatov et al., 2024; Jeong et al., 2024; Kocher & Menon, 2023; Ozaveshe et al., 2023; Sabet et al., 2019; Salman & Aswad, 2022; Velmurugan et al., 2020). This process is deemed critical for water supply and management, especially in coastal areas, where coastal reservoirs may also need desalting before using (Balaji et al., 2021). However, desalination is naturally an energy-sapping process, with most existing facilities historically relying on fossil fuels, which raises serious concerns about fluctuating prices, limited resources, and negative environmental impacts like pollutant emissions and greenhouse gases (Abdulrahim & Ahmed, 2022; Alqaed et al., 2021; Imandoust et al., 2025; Rau & Naas, 2024; Ritika et al., 2023; Shokri & Fard, 2022; Wang et al., 2020). Additionally, the industry faces ongoing issues related to managing concentrated brine discharge and maintaining environmental sustainability, requiring a comprehensive approach to optimize operations and reduce ecological footprints (Charcosset, 2022; Park & Lee, 2022).

To improve the efficiency, sustainability, and cost-effectiveness of desalination processes, advanced technologies, including AI, show great promise. AI has made significant progress in various industrial fields, offering capabilities for optimization, predictive analysis, and complex system management (Bakas & Kontoleon, 2023; Bhatt et al., 2024; Gao et al., 2023; Gosai, 2023; Hayot et al., 2024; Jain, 2024; Maier et al., 2024; Masod & Zakaria, 2024; Mypati et al., 2023; Orejuela-Escobar et al., 2024; Peckham et al., 2025; Rathee et al., 2023; Tolk, 2024). Because the desalination supply chain (SC) is complex, covering everything from raw water intake and energy supply to treatment and distribution, AI could potentially enhance operations by optimizing energy use, increasing efficiency, and supporting better decision-making across the entire process (Abaku et al., 2024; Choudhuri, 2024; Dhal & Kar, 2024; Ejjami & Boussalham, 2024; Gomes et al., 2024; Hasan et al., 2024; Ike et al., 2024; Joel et al., 2024). Specifically, AI-based process design, optimization, and control are key tools to address the complexity of desalination technologies, including hybrid systems, and can provide a comprehensive understanding of challenges where traditional experimental and theoretical methods fall short (Son et al., 2022). AI algorithms, such as machine learning and artificial neural networks, lead the way in advancing AI-supported smart desalination (Son et al., 2022).

Despite the significant potential mentioned above, successfully integrating and widely adopting AI within desalination SC faces several challenges. Although AI is rapidly advancing in many areas, its application in complex industrial management contexts like desalination industry may encounter unique technical, operational, economic, and organizational hurdles (Ijiga et al., 2024; Jain, 2024; Kelly, 2024; Louis & Eyo-Udo, 2024;

Nendrambaka, 2024; Ola et al., 2024; Riad et al., 2024). These barriers include the need for high-quality data, algorithmic complexity, integration difficulties, substantial initial infrastructure investments, concerns about data quality, workforce adaptation requirements, high implementation costs, skills shortages, and regulatory challenges (Ike et al., 2024; Jain, 2024; Kelly, 2024; Li, 2024; Louis & Eyo-Udo, 2024; Maier et al., 2024; Masod & Zakaria, 2024; Nendrambaka, 2024; Ola et al., 2024; Peckham et al., 2025; Riad et al., 2024). Understanding and systematically addressing these barriers are essential for unlocking AI's full potential to optimize water production, reduce energy consumption, minimize environmental impacts, and support more sustainable and efficient water resource management globally (Ejjami & Boussalham, 2024; Joel et al., 2024; Kelly, 2024; Louis & Eyo-Udo, 2024; Riad et al., 2024). Therefore, this research aimed to identify and analyze the key barriers to AI integration in desalination SC, providing insights to facilitate its effective adoption and help create a more resilient and sustainable water future. This study has attempted to address the following questions: What are the main barriers to implementing AI in desalination SC? How can these barriers be structured based on their driving and dependence power using MICMAC analysis?

Literature Review

Toorajipour et al. (2021) conducted a systematic literature review to examine the contributions of AI in supply chain management (SCM). Their study highlighted the most prevalent AI techniques currently employed in SCM, as well as potential AI applications that could further enhance both research and practice. The review identified several subfields where AI has already improved operations, such as logistics, marketing, and production, while also pointing out areas with high potential for future AI integration. Despite these benefits, challenges were also noted, including the need for more comprehensive empirical studies, data quality concerns, and the adaptation of AI methods to specific industrial contexts. The authors suggested that addressing these gaps through targeted research, technological development, and workforce training could facilitate more effective AI adoption in SC operations. Earlier studies also recognized the importance of AI in SC optimization, highlighting initial barriers and opportunities (Hanasaki et al., 2016; Rahman et al., 2020; Velmurugan et al., 2020). Fathi et al. (2025) identified and ranked barriers to IoT implementation in the food SC. Rostami et al. (2025) comparatively analyzed and assessed risk dynamics across diverse global markets by using machine learning. Elyaakouby and Tilioua (2025) reviewed the integration of AI in water treatment, particularly through reverse osmosis (RO) processes. Their study emphasized the benefits of AI technologies, especially machine learning algorithms, in enhancing operational efficiency, reducing energy consumption, and optimizing system performance. AI applications in RO processes include predicting and managing membrane fouling, dynamically adjusting pump operations and pressure settings, and performing real-time monitoring and anomaly detection. These capabilities enable proactive maintenance, reduce downtime, and ensure consistent water quality. Case studies highlighted practical advantages such as lower maintenance costs, improved resource utilization, and more sustainable water management. The authors suggested that addressing technical and operational challenges through AI can significantly contribute to the effectiveness and resilience of desalination supply chains. In another study, Chekifi et al. (2024) examined the integration of renewable energy sources, such as solar, wind, and geothermal, with desalination technologies, emphasizing the opportunities and challenges of powering desalination plants in remote regions. While renewable-powered systems can be reliable and cost-effective, their intermittent nature complicates system design. The study highlighted the role of AI in addressing these challenges, including forecasting energy availability, optimizing operational parameters, and enhancing control systems for improved efficiency and sustainability. AI-driven solutions were shown to facilitate better system performance, enabling dynamic adjustments to variable energy inputs, and supporting more resilient and sustainable desalination operations. The evidence from this study suggested that leveraging AI in renewable-powered desalination can significantly enhance water production efficiency and promote sustainable water management practices. Krishnan et al. (2024) explored the integration of AI with nanomembrane systems for advanced water desalination. Their study highlighted how AI, through machine learning and neural networks, enhances real-time monitoring, adaptive responses, and proactive maintenance of nanomembranes, optimizing energy consumption, mitigating membrane fouling, and extending membrane lifespan. These AI-enhanced systems continuously learn and improve under varying operational conditions, supporting decentralized water solutions and enabling remote management in areas with limited access to clean water. Despite the substantial potential, challenges have also remained, including the development of desalination-specific AI algorithms, ensuring scalability and compatibility, and addressing data privacy and security issues. The authors suggested that ongoing research and innovative design efforts are crucial for fully leveraging AI-driven nanomembrane technologies to improve the efficiency, sustainability, and accessibility of water desalination processes. Abba et al. (2023) investigated the integration of AI with hybrid nanofiltration/reverse osmosis (NF–RO) desalination plants using a deep learning-based Crow Search Optimization Algorithm (LSTM-CSA). Their study demonstrated how AI models can optimize the performance of NF–RO processes by accurately predicting permeate conductivity, evaluating uncertainties via Monte Carlo simulations, and applying statistical performance metrics such as RMSE and MAE. The LSTM-CSA model outperformed conventional LSTM, achieving higher predictive accuracy and enabling advanced energy optimization, improved operational strategies, and sustainable brine management. The authors emphasized AI's role in facilitating resource recovery from brine, minimizing waste, and supporting sustainable and resilient water desalination operations. Drogkoula et al. (2023) provided a comprehensive survey of machine learning (ML) methodologies with a focus on their applications in water resources management. The study highlighted how AI and ML can increase sustainability and efficiency in managing environmental challenges, including climate change and ecosystem degradation. This study investigated the application of AI in irrigation optimization, water quality assessment, flood prediction, and water demand forecasting through the analysis of heterogeneous data sources, including remote sensing, smart sensor networks, and social media platforms. The authors emphasized the benefits of AI-driven integration and decision support in water management, including improvements in agricultural practices, water distribution, and desalination plant operations. Challenges related to data heterogeneity, stakeholder education, and implementation costs were also discussed, pointing to areas requiring further research to enable broader adoption of AI solutions in water resources management. Mahadeva et al. (2023) investigated the application of AI in water desalination, highlighting its potential for promoting global sustainability. The study emphasized that AI techniques, including artificial neural networks (ANN), genetic algorithms (GA), fuzzy logic, and swarm optimization methods, have been increasingly employed since 2010 to optimize desalination processes. These approaches enhance both water quality and quantity while enabling real-time process optimization and automation. The authors argued that integrating AI into desalination operations can significantly improve water resource management, system efficiency, and sustainability, particularly in the face of climate variability and growing global water demand. Finally, Modgil et al. (2022) explored the role of AI in enhancing SC resilience, particularly in response to disruptions caused by the COVID-19 pandemic. Drawing on semi-structured interviews with 35 e-commerce SC experts, the study identified five principal domains in which AI enhances resilience: enhancing transparency, facilitating last-mile delivery, delivering personalized solutions for both upstream and downstream stakeholders, mitigating the effects of disruptions, and enabling agile procurement strategies. The authors emphasized that AI-enabled dynamic capabilities help firms develop business continuity mechanisms and bridge the gap between theory and practice, demonstrating how AI can strengthen supply chains against future risks.

Methodology

This study was designed to identify the barriers to implementing AI in desalination SC and to analyze their structural relationships using the MICMAC approach. Initially, a comprehensive literature review was conducted to extract a preliminary list of potential barriers. In this stage, reputable scientific databases such as Scopus and Web of Science were searched using keywords related to AI, SCM, and implementation challenges. Some research articles reviewed the databases and papers manually in the past (Farazmand, 2019) or recently via the bibliometric approach (Nourahmadi, 2025; Nourahmadi, 2021; Rasti, 2024). The initial list of barriers was then reviewed and refined through expert consultation, involving engineers and managers with at least five years of experience in AI and desalination projects, ensuring that the identified barriers were both comprehensive and relevant.

The MICMAC (Matrice d'Impacts Croisés Multiplication Appliquée à un Classement) method is a structural analysis technique used to identify and classify factors based on their driving power and dependence power. In this study, after experts evaluated the barriers using pairwise comparisons, the data were entered into the MICMAC software. The software calculated direct and indirect influences among variables and generated an influence-dependence map, which helps categorize barriers into four quadrants: autonomous, dependent, linkage, and driving factors. This process enables researchers to prioritize barriers and understand their interrelationships systematically.

Next, the MICMAC structural analysis method was utilized to examine the causal relationships and interdependencies among the barriers. A total of 20 experts with professional and academic experience in the relevant fields participated in assessing the relationships among the barriers through pairwise comparison matrices. The collected data were painstakingly analyzed using MICMAC software to determine the driving and dependent power of each barrier, thereby identifying the key factors that influence successful AI implementation in desalination SC. This combined approach provides a structured and comprehensive view of the barriers and their interrelationships, offering practical guidance for decision-making in this field.

Analysis and Results

The barriers to the implementation of AI in desalination SC were systematically identified through an extensive review of the literature complemented by consultations with domain experts. A thorough list of these barriers is presented in Table 1.

Following the identification of 16 barriers through an extensive literature review and consultations with 20 domain experts, the barriers were incorporated into an expert evaluation questionnaire. The experts were asked to assess the importance of each barrier on a five-point Likert scale. A total of 20 completed questionnaires were analyzed using SPSS, and all 16 barriers were validated at a significance level of 0.05, confirming their relevance based on expert judgment. After finalizing the key barriers to the implementation of AI in desalination SC, these barriers were incorporated into the cross-impact analysis matrix. A standardized cross-impact questionnaire was then developed and distributed to the experts. The average of the collected responses was subsequently used as the input for the MICMAC software, as summarized in Figure 1.

Table 1.
The Identified Barriers to AI Implementation in Desalination (SC)

Barrier Category	Barrier	Description of Barrier	Source
Financial	High Implementation and Running Costs	The significant upfront investment required for AI technologies, including hardware, software, and infrastructure, can be a major deterrent. This also includes difficulties in demonstrating a clear return on investment (ROI) or building a compelling business case for AI projects.	Adesoga et al., 2024; Agrawal et al., 2019; Ardiantono et al., 2024; Balon et al., 2024; Cannas et al., 2023; Gonçalves et al., 2024; Hangl et al., 2022; Heeres et al., 2023; Nitsche et al., 2023; Nyamekeh et al., 2025; Oyedijo et al., 2023; Rijanto, 2024; Thakker et al., 2024; Yazdi et al., 2022
	Lack of Funding and Capital	Insufficient financial resources within an organization or a sector to invest in new AI initiatives will cause concern.	Gonçalves et al., 2024
	Poor Cash Flow Management	Inefficient management of financial flows and working capital can hinder the ability to fund and sustain AI projects.	Sahoo & Thakur, 2022

Barrier Category	Barrier	Description of Barrier	Source
Technological	Data Quality and Integration Issues	AI systems heavily rely on high-quality, consistent, and integrated data. Challenges include poor data quality, disparate data sources, and the complexity of integrating new AI systems with existing legacy infrastructure.	Adeniran et al., 2024; Adesoga et al., 2024; Cannas et al., 2023; Husein et al., 2024; Khlie et al., 2024; Nyamekeh et al., 2025; Shrivastav, 2022
	Lack of Standardization and Interoperability	The absence of common standards for AI technologies and data formats can make it difficult for different systems and partners within the SC to communicate and collaborate effectively.	Bag et al., 2023; Nitsche et al., 2023
	Insufficient Technological Maturity	Some AI technologies may still be in early stages of development, lacking the robustness, reliability, or proven track record for widespread industrial application.	Nitsche et al., 2023
	Data Privacy and Security Concerns	The collection and processing of large volumes of sensitive data by AI systems raise significant concerns about privacy breaches, cybersecurity risks, and compliance with data protection regulations.	Adesoga et al., 2024; Ijiga et al., 2024; Ismaeil & Lalla, 2024; Kramer, 2024; Nyamekeh et al., 2025
	Algorithmic Transparency and Explainability	The opaque or 'black box' nature of certain AI algorithms often obscures the decision-making process, thereby raising concerns related to trust, accountability, and adherence to regulatory standards.	Ijiga et al., 2024
	Scalability Issues	There are challenges in scaling AI solutions to meet the demands of large and complex SC operations.	Rijanto, 2024; Shankaran, 2024
Organizational & Human	Resistance to Change and Lack of Acceptance	Employees and stakeholders may resist the adoption of new AI technologies due to fear of job displacement, unfamiliarity with new systems, or a preference for traditional methods.	Bag et al., 2023; Gomera & Mafini, 2020; Gorbenko et al., 2022; Ismaeil & Lalla, 2024; Nyamekeh et al., 2025; Shankaran, 2024; Shrivastav, 2022; Singh & Maheswaran, 2023
	Lack of Specific Skills and Talent	A critical shortage of qualified professionals with the expertise to design, implement, and manage AI systems within SC has raised concerns.	Agrawal et al., 2019; Cannas et al., 2023; Husein et al., 2024; Nyamekeh et al., 2025; Raman & Selvaraj, 2024
	Silos and Lack of Collaboration	Disconnects between different departments or SC partners can impede the seamless integration and data sharing necessary for effective AI implementation.	Bag et al., 2023; Gorbenko et al., 2022; Khan et al., 2023; Orji & Ojadi, 2023; Shrivastav, 2022; Zain et al., 2024
	Lack of Top Management Support and Vision	Without strong leadership and a clear strategic vision from top management, AI initiatives may lack the necessary resources, prioritization, and organizational buy-in for successful implementation.	Chowdhury et al., 2022; Usmani et al., 2023
	Complex Change Management	The process of transitioning from traditional operations to AI-driven systems involves significant organizational restructuring, process re-engineering, and cultural shifts.	Ismaeil & Lalla, 2024; Nitsche et al., 2023; Shrivastav, 2022
Regulatory & Legal	Regulatory Compliance and Legal Frameworks	Navigating complex and evolving legal and regulatory landscapes related to AI, data governance, and liability can be challenging.	Addy et al., 2024; Ijiga et al., 2024; Ismaeil & Lalla, 2024; Kramer, 2024; Nisar et al., 2024; Rijanto, 2024; Shankaran, 2024
	Lack of Clear Policies and Guidelines	The absence of specific industry guidelines or government policies for AI implementation can create uncertainty and hinder adoption.	Agrawal et al., 2019; Rahman et al., 2020; Thomas & Sunny, 2025

(Source: Researcher's Findings)

Figure 1.
The Cross-impact Matrix of the Barriers to AI implementation in Desalination SC

	1 : High Imple	2 : Lack of Fu	3 : Poor Cash	4 : Data Quali	5 : Lack of St	6 : Insufficie	7 : Data Priva	8 : Algorithmi	9 : Scalabilit	10 : Resistance	11 : Lack of Sp	12 : Silos and	13 : Lack of To	14 : Complex Ch	15 : Regulatory	16 : Lack of Cl
1 : High Imple	0	1	0	0	0	1	0	1	0	0	0	1	1	0	0	0
2 : Lack of Fu	1	0	0	1	0	3	0	0	0	1	0	0	0	3	1	0
3 : Poor Cash	0	0	0	0	3	1	2	0	0	1	0	0	0	0	0	1
4 : Data Quali	0	0	2	0	0	0	0	2	0	0	0	0	0	1	0	0
5 : Lack of St	1	1	0	2	0	0	2	0	1	0	0	0	0	0	3	0
6 : Insufficie	0	0	2	0	0	0	0	1	0	2	1	1	1	0	0	0
7 : Data Priva	0	0	0	1	0	0	0	2	0	0	1	0	2	3	0	0
8 : Algorithmi	1	0	0	2	0	1	0	0	0	3	0	0	0	0	0	1
9 : Scalabilit	0	0	0	0	1	0	1	0	0	0	0	1	2	0	2	0
10 : Resistance	0	0	2	0	0	0	0	2	1	0	0	0	0	1	0	0
11 : Lack of Sp	1	0	0	2	0	2	0	0	2	0	0	0	0	1	0	1
12 : Silos and	0	0	0	0	0	0	0	0	0	3	0	0	1	0	2	0
13 : Lack of To	1	1	2	0	0	0	0	0	0	0	0	0	0	0	1	0
14 : Complex Ch	0	0	0	3	1	0	0	0	0	0	0	1	0	0	2	0
15 : Regulatory	0	0	1	0	0	0	1	0	0	1	0	1	0	0	0	1
16 : Lack of Cl	0	0	3	1	0	1	0	0	0	0	1	0	0	0	0	0

(Source: Researcher's Findings)

After entering the questionnaire data into the software, the direct and indirect influences of the barriers to AI implementation in desalination SC were calculated, as presented in Tables 2 and 3.

Table 2.
The Direct Influence Matrix of the Identified Barriers AI Implementation in Desalination SC

N°	Variable	Total number of rows	Total number of columns
1	High Implementation and Running Costs	5	5
2	Lack of Funding and Capital	10	3
3	Poor Cash-Flow Management	8	12
4	Data Quality and Integration Issues	5	12
5	Lack of Standardization and Interoperability	10	5
6	Insufficient Technological Maturity	8	9
7	Data Privacy and Security Concerns	9	6
8	Algorithmic Transparency and Explainability	8	8
9	Scalability Issues	7	4
10	Resistance to Change and Lack of Acceptance	6	11
11	Lack of Specific Skills and Talent	9	3
12	Silos and Lack of Collaboration	6	5
13	Lack of Top Management Support and Vision	5	7
14	Complex Change Management	7	9
15	Regulatory Compliance and Legal Frameworks	5	11
16	Lack of Clear Policies and Guidelines	6	4
	Totals	114	114

(Source: Researcher's Findings)

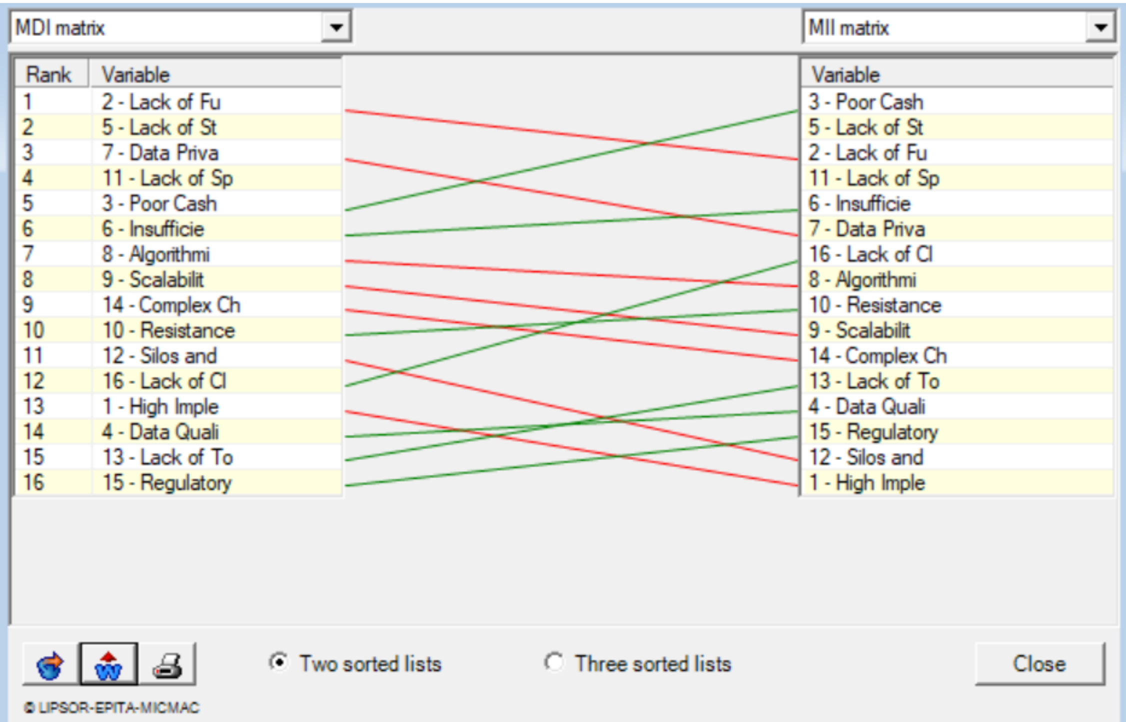
Table 3.
The Indirect Influence Matrix of the Identified Barriers to AI Implementation in Desalination SC

N°	Variable	Total number of rows	Total number of columns
1	High Implementation and Running Costs	238	196
2	Lack of Funding and Capital	448	114
3	Poor Cash-Flow Management	465	639
4	Data Quality and Integration Issues	271	539
5	Lack of Standardization and Interoperability	453	378
6	Insufficient Technological Maturity	402	322
7	Data Privacy and Security Concerns	386	383
8	Algorithmic Transparency and Explainability	355	478
9	Scalability Issues	301	170
10	Resistance to Change and Lack of Acceptance	316	597
11	Lack of Specific Skills and Talent	404	127
12	Silos and Lack of Collaboration	244	206
13	Lack of Top Management Support and Vision	274	250
14	Complex Change Management	285	372
15	Regulatory Compliance and Legal Frameworks	254	429
16	Lack of Clear Policies and Guidelines	357	253
	Totals	114	114

(Source: Researcher's Findings)

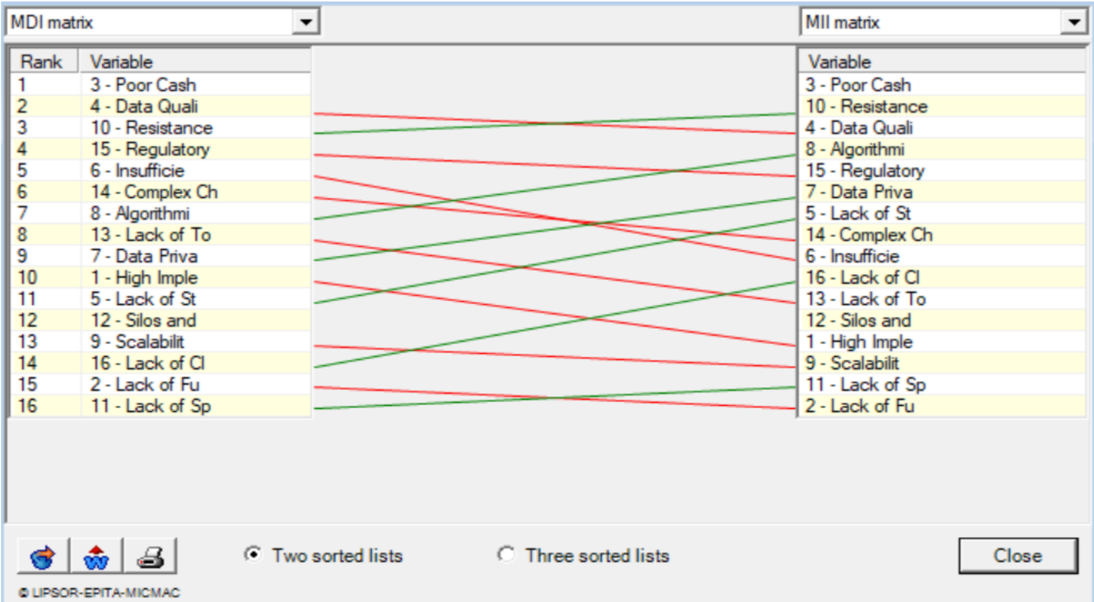
The factors were classified and ranked into two categories, driving and dependent, considering both their direct and indirect influences, until the variables reached the minimum possible difference in their rankings. The results of these calculations are presented in Figures (2) and (3).

Figure 2.
Ranking of Barriers Based on Their Influence in Direct and Indirect Impact Matrix



(Source: Researcher's Findings)

Figures 3.
Ranking of Barriers Based on Their Dependence in Direct and Indirect Impact Matrix



(Source: Researcher's Findings)

The barriers "Lack of Funding and Capital" and "Poor Cash Flow Management" ranked first in terms of influence and dependence, respectively. Table 4 presents the ranking of the barriers to AI implementation in desalination SC according to their influence and dependence, considering both direct and indirect effects.

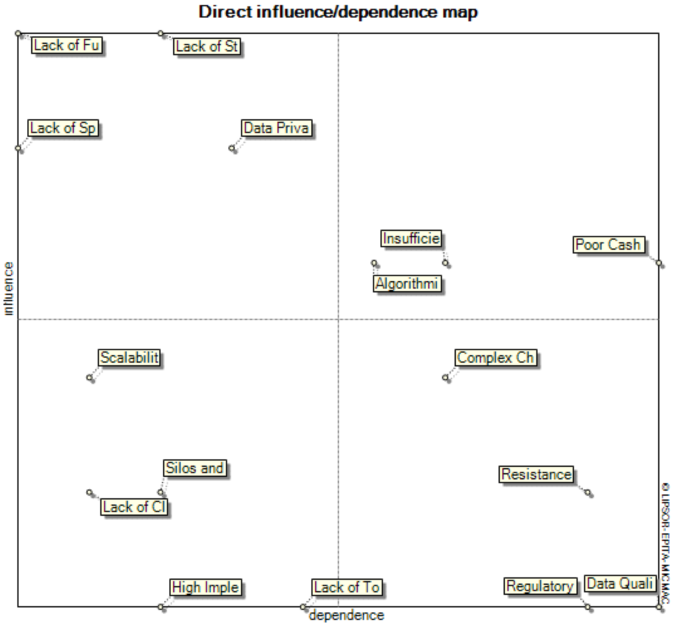
Table 4.
Direct and Indirect Scores of Influences and Dependence for the Barriers to AI Implementation

Rank	Label	Direct influence	Label	Direct dependence	Label	Indirect influence	Label	Indirect dependence
1	Lack of Fu	877	Poor Cash	1052	Poor Cash	852	Poor Cash	1171
2	Lack of St	877	Data Quali	1052	Lack of St	830	Resistance	1094
3	Data Priva	789	Resistance	964	Lack of Fu	821	Data Quali	988
4	Lack of Sp	789	Regulatory	964	Lack of Sp	740	Algorithmi	876
5	Poor Cash	701	Insufficie	789	Insufficie	737	Regulatory	786
6	Insufficie	701	Complex Ch	789	Data Priva	707	Data Priva	702
7	Algorithmi	701	Algorithmi	701	Lack of Cl	654	Lack of St	693
8	Scalabilit	614	Lack of To	614	Algorithmi	651	Complex Ch	682
9	Complex Ch	614	Data Priva	526	Resistance	579	Insufficie	590
10	Resistance	526	High Imple	438	Scalabilit	551	Lack of Cl	463
11	Silos and	526	Lack of St	438	Complex Ch	522	Lack of To	458
12	Lack of Cl	526	Silos and	438	Lack of To	502	Silos and	377
13	High Imple	438	Scalabilit	350	Data Quali	496	High Imple	359
14	Data Quali	438	Lack of Cl	350	Regulatory	465	Scalabilit	311
15	Lack of To	438	Lack of Fu	263	Silos and	447	Lack of Sp	232
16	Regulatory	438	Lack of Sp	263	High Imple	436	Lack of Fu	209

(Source: Researcher's Findings)

The most important output of the Mic Mac software is the influence–dependence map of the barriers. In this figure, the areas are divided into four sections, with the position of each variable indicating its type. Figure 4 presents the status of the factors accordingly.

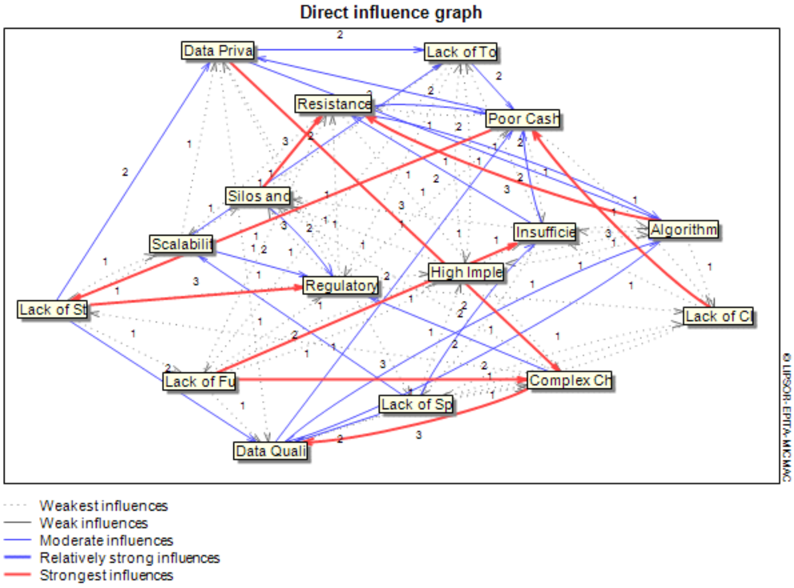
Figure 4.
Distribution of Influential and Dependent Barriers on the Coordinate Axes



(Source: Researcher's Findings)

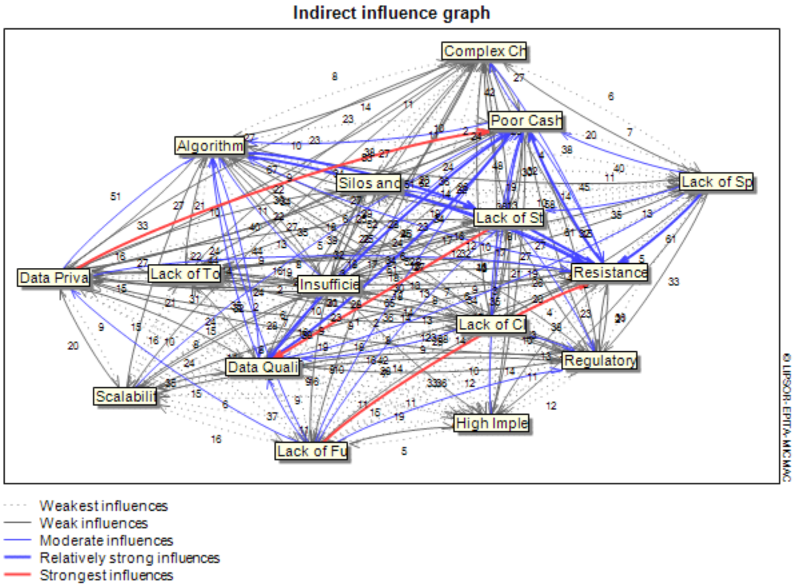
As shown in Figure 4, the influence-dependence map indicates that the most influential variables are Lack of Funding and Capital, Lack of Standardization and Interoperability, Lack of Specific Skills and Talent, and Data Privacy and Security Concerns. In the next step, the Mic Mac software illustrated the relationships between the barriers' direct and indirect effects across five levels: very weak to very strong, weak to very strong, relatively strong to very strong, strong to very strong, and very strong. Some of these effects are depicted in Figures 5, 6, and 7.

Figure 5.
The Diagram of the Direct Effects of Barriers (ranging from very weak to very strong)



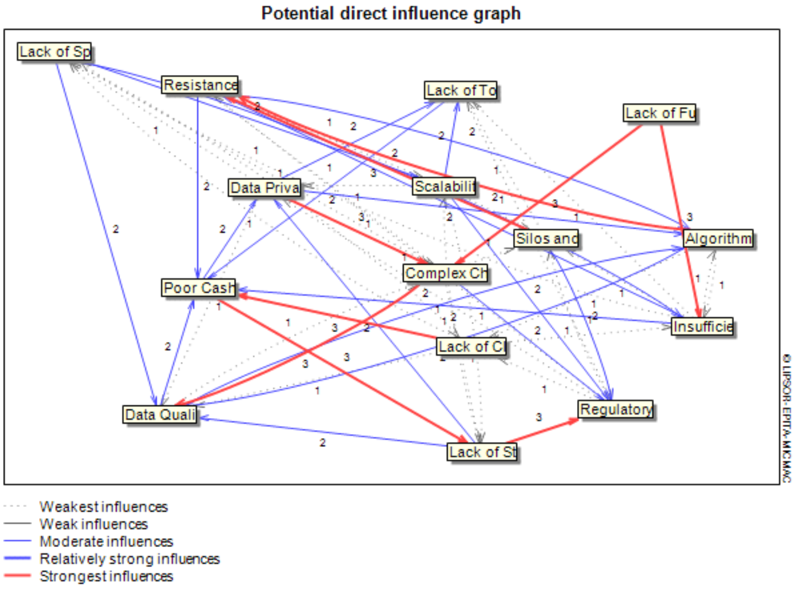
(Source: Researcher's Findings)

Figure 6.
The Diagram of the Indirect Effects of Barriers (ranging from very weak to very strong)



(Source: Researcher's Findings)

Figure 7.
The Diagram of the Potential Direct Effects of Barriers on Each Other (ranging from very weak to very strong)



(Source: Researcher's Findings)

Discussion and Conclusion

The findings of this study indicated that although AI holds considerable potential for enhancing efficiency, sustainability, and decision-making in desalination SC, the realization of this potential is significantly constrained by structural and systemic barriers. The MICMAC analysis revealed that four fundamental barriers exert the greatest influence on other factors and serve as critical bottlenecks in the successful implementation of AI. First, the lack of funding and capital is among the most significant obstacles, as it directly restricts the provision of infrastructure, workforce training, and investment in emerging technologies, thereby hindering the large-scale deployment of AI projects. This factor is not only an independent barrier but also a driver of many other challenges, suggesting that without stable financial support, overcoming the remaining obstacles becomes increasingly difficult. Second, the absence of standardization and interoperability among systems and technologies complicates the integration of AI into desalination SC. The lack of a common data language and unified frameworks lead to fragmented operations and reduces synergy across different segments of the chain. Third, the lack of specific skills and talent in the domains of AI and SC management poses a serious threat to the development and maintenance of intelligent systems. The lack of such technical skills, even in the presence of adequate financial and infrastructural resources, can expose projects to a high risk of failure. Fourth, given the sensitive nature of operational and environmental data in the water sector, data privacy and security concerns represent a fundamental challenge for organizational adoption and regulatory trust. This finding aligns with evidence from career success research in higher education, where systemic constraints—such as centralized governance, resource inequalities, and institutional inertia—limit professional advancement (Khanjani et al., 2023). Just as structural barriers constrain individual career trajectories, they similarly restrict the large-scale adoption of transformative technologies such as AI.

Taken together, the results highlighted that achieving successful AI implementation in desalination SC requires an integrated, multi-level approach. Solutions must simultaneously focus on strengthening financial capacity through investment incentives, developing and enforcing common standards, designing educational programs to cultivate specialized skills, and establishing robust frameworks for data protection. Furthermore, collaboration among governments, private industry, and research institutions will be essential in overcoming barriers and accelerating AI adoption. Ultimately, by identifying the key barriers and mapping their interrelationships, this study has provided a clear roadmap for future action and can serve as a foundation for strategic decision-making and policy development in the pursuit of sustainable water resource management.

From a practical perspective, policymakers and industry leaders should prioritize the development of financial support mechanisms such as low-interest loans and investment incentives to foster the development of digital infrastructure. Also, implementation of knowledge management could help in the process (Sadeghi et al., 2013). Establishing national and regional centers for standardization and data exchange could further strengthen integration and collaboration across SC actors. Expanding interdisciplinary educational programs and fostering university–industry partnerships for training skilled professionals represent a critical pathway to closing the talent gap. Finally, the adoption of advanced cybersecurity technologies and the formulation of clear data protection regulations will play a vital role in building trust and facilitating the acceptance of AI solutions.

Nevertheless, this study is not without limitations. First and foremost, the analysis was primarily based on expert opinions and secondary data, which may not fully capture operational perspectives across diverse contexts. Second, the dynamic and rapidly evolving nature of AI technologies and regulatory frameworks may necessitate future revisions of some findings. Third, the focus of this research was limited to desalination SC, and generalizing the results to other water or energy sectors will require additional investigation. Therefore, future studies are encouraged to employ broader field data, apply more advanced quantitative methods, and conduct cross-industry comparisons in order to develop more precise and practical pathways for overcoming barriers and enhancing the role of AI in the management of critical resources.

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Economics of Crime and Financial Delinquency among Children and Adolescents: A Comparative Analysis of Causes and Consequences in Physical and Digital Spaces

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ABSTRACT

With the expansion of modern technologies and the pervasive influence of digital space in our daily life, financial delinquency among children and adolescents has become a significant social and economic challenge. This phenomenon, occurring in both physical and digital environments, has widespread consequences for individuals, their families, and society. This study used a comparative approach, utilizing data from cases recorded in Tehran Juvenile Court, to examine the underlying factors and consequences of financial delinquency and the economics of crime in these two contexts. The findings revealed that multiple factors—including family economic status, parental supervision weaknesses, behavioral disorders, cultural changes, and broad access to digital tools—can contribute to the occurrence of these offenses. In physical environments, the economic and social impacts primarily affect the family and the adolescent's immediate social surroundings, whereas in the digital space, due to the scale, speed, and anonymity of offenders, the consequences are more complex and, in some cases, cross-border. The results highlighted the necessity for preventive policies, promotion of economic and digital literacy, strong support systems, and improvement of judicial frameworks related to children and adolescents. These insights can assist policymakers and researchers in reducing the financial and social harms associated with juvenile delinquency in the digital era.

KEYWORDS

Economics of crime, financial delinquency, children and adolescents, physical environment, digital environment, juvenile court.

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Introduction

Juvenile delinquency has become one of the most significant challenges of modern societies (Najafi Tavana, 2019). The term delinquency refers to the neglect of legal duties or the commission of wrongful acts that do not necessarily constitute a crime. However, it is often used synonymously with crime, particularly in relation to offenses committed by children and adolescents. Considering the sensitivity and emotional fragility of children, labeling them as criminals is inappropriate. Hence, the term delinquent may also refer to individuals who are rebellious or antisocial, even if they have not committed a formal crime (Boshra, 2015). A notable trend in recent years is the rise of financial and economic offenses committed by children and adolescents, both in physical world and in cyberspace.

Economic crimes not only inflict direct financial damage on individuals but also generate destructive consequences for the national economy (Yousefi Maragheh et al., 2013). Some of the most notable examples of such crimes include smuggling of goods and currency, hoarding, usury, bribery and corruption, tax evasion, in addition to money laundering and fraud (Seraj, 2021). It is generally agreed that one of the most prominent characteristics of the contemporary era is the rapid pace of economic, social, and cultural changes. In such a dynamic environment, individuals are compelled to adapt themselves in order to continue their lives. While a considerable portion of society chooses lawful means to cope with economic and social pressures, others—due to financial hardships, lack of social support, weak family supervision, and environmental influences —may resort to unlawful activities (Gilak Hakimabadi et al., 2017).

Children and adolescents are particularly vulnerable in this regard due to their psychological and social characteristics such as curiosity, the need for social acceptance, and limited life experience. With inadequate supervision and insufficient education regarding financial responsibility and ethics, they may develop a tendency toward economic crimes in either real or digital spaces. Cyberspace, in particular, provides an appealing environment for such offenses due to easy accessibility, anonymity, and the availability of opportunities for rapid financial gain.

The consequences of juvenile financial delinquency extend far beyond the direct monetary loss. Long-term consequences include erosion of social trust, increased economic vulnerability of families, and weakness of local and national economic foundations. Moreover, early involvement of children and adolescents in financial crimes may channel their life paths toward persistent social and economic deviance, thereby escalating corrective and judicial costs for society.

Literature Review

Economic pressure on households can drive adolescents to seek illicit sources of income. Research shows that macroeconomic conditions, such as economic inequality and limited opportunities, are linked to higher rates of delinquency (Fajnzylber et al., 2002; Intravia et al., 2021). In the context of financial crime, this often occurs through the exploitation of minors by family members, who may use their identities and bank accounts to bypass the legal scrutiny (Levi & Reuter, 2006; van der Bruggen & Blokland, 2020). The digital revolution has introduced a new dimension to juvenile delinquency. The anonymity, scalability, and borderless nature of cyberspace reduce perceived risks and increase opportunities for crimes such as fraud and money laundering (Holt & Bossler, 2014; Wall, 2007). Adolescents, as digital natives, often possess the technical skills but lack the cognitive maturity and understanding of legal consequences, making them both perpetrators and victims of cyber-enabled financial crimes (Ngo & Paternoster, 2011; Yar, 2005). These risks are intensified in environments with weak institutional controls and rapid cultural change, which can undermine traditional social norms (Pratt & Cullen, 2005). Family dynamics are crucial in shaping juvenile behavior. Weak parental supervision, economic hardship, and parental involvement in crime are significant predictors of delinquency (Farrington, 2005; Loeber & Stouthamer-Loeber, 1986). Becker's framework (1968) of economics of crime suggests that individuals engage in criminal behavior after evaluating the expected costs and benefits. While this model has been widely applied to adult offenders, its application to juvenile financial delinquency requires careful consideration of developmental and contextual factors (McCord et al., 2001). Scholars in Iran's legal system have also explored this issue. The digital and cyber environment profoundly affects the lives of children and adolescents, often being perceived as an integral part of the family. However, cyberspace can have significant harmful effects and create conditions conducive to delinquent behavior. Given the widespread use of digital technologies, national policies should not only leverage the opportunities provided by cyberspace but also address its risks and threats. In this context, families play a central role in developing preventive policies in cyberspace (Asghari & Gholami, 2024). By establishing appropriate frameworks to manage the opportunities and risks of cyberspace on the one hand, and transforming it into an educational environment on the other hand, it is possible to safeguard the rights and freedoms of children and adolescents while employing community-based prevention strategies to reduce their propensity toward delinquency (Molkoti & Mohseni, 2023). Research shows that educating families and caregivers about cyberspace and its potential consequences, setting clear privacy boundaries for children, and monitoring the use of VPNs across digital devices can effectively prevent juvenile delinquency online. Among all institutions, the family's role in preventing cyber delinquency is more prominent than that of any other organization (Tirgar et al., 2020). Understanding the factors that drive juvenile financial delinquency in both physical and digital environments is essential for developing effective prevention strategies. Economic pressures on households, family dynamics, and the opportunities and risks presented by cyberspace highlight the multifaceted nature of this phenomenon. Integrating the economics of crime framework with insights from digital sociology enables a comprehensive analysis of how adolescents assess costs and benefits when engaging in delinquent behavior. This approach is particularly valuable for comparing the financial delinquency in traditional and online settings, as it captures both shared and context-specific causes and consequences. By examining these factors comparatively, policymakers and practitioners can design interventions that address the structural, familial, and technological dimensions of juvenile financial crime. However, a significant gap remains in literature regarding how these causative factors operate differently in physical versus digital environments, particularly within specific cultural contexts like Iran. Most existing literature either focuses on Western contexts or examines cyber and physical crimes in isolation. Thus, this study aimed at filling this gap by providing a comparative analysis of the causes and consequences of juvenile financial delinquency across both domains, drawing on empirical case data from Iran.

This research employed a comparative methodology to identify and categorize the financial crimes perpetrated by children and adolescents, with particular emphasis on money laundering and fraud. It examined the economic, social, and cultural factors that influence delinquent behavior in both physical and digital contexts, while also underscoring the consequences of these offenses. The overarching goal was to develop some preventive strategies and policy recommendations aimed at mitigating the economic and social harms associated with juvenile financial delinquency. Given the goal of the study, the following research question was addressed:

What are the key factors contributing to financial delinquency among children and adolescents, and how do its consequences differ between real-world and digital environments?

Methodology

The researchers employed a qualitative-analytical approach based on case studies. Several cases of financial and economic offenses committed by children and adolescents in both real and digital environments were collected. These cases included examples of fraud, money laundering, and other economic crimes carried out by juveniles. The data were analyzed using a comparative approach, allowing the causes and consequences of these offenses in physical and digital contexts to be examined and contrasted. The analysis focused on identifying economic, social, and cultural factors influencing juvenile delinquency, as well as the short- and long-term impacts of these behaviors on families, society, and the broader economy. The aim of this research method was to identify patterns and causal relationships between environmental conditions, individual motivations, and the economic and social consequences of juvenile financial delinquency, providing a scientific basis for the development of preventive strategies and policy recommendations. In this study, the examined juvenile financial crime cases are limited to two main categories of money laundering and fraud.

Findings

This study focused on two prominent examples of financial crimes committed by children and adolescents. The first one is money laundering, which is carried out with the aim of altering or concealing the illicit origin of assets. Beyond disrupting the economic cycle, it also generates widespread negative consequences for public trust. The second one is fraud, which occurs in both real and digital environments. Due to the diversity of methods employed and the broad scope of its impact on economic and social relations, fraud holds a particularly significant place in this research. Addressing the aforementioned issues provides the opportunity for a deeper examination of the factors driving juveniles toward financial delinquency and for analyzing its short- and long-term consequences.

The Commission of Money Laundering Offenses by Juveniles and Adolescents

Money laundering is recognized as an emerging legal and economic phenomenon. Despite being one of the major challenges in many legal and economic systems, public awareness of this issue remains very limited (Falahnejad, 2017). Money laundering affects the performance of the real economy and the overall economic health of countries. It reduces the productivity of factors of production in the legal market and diverts capital from legitimate activities to illegal ones. Its consequences include currency distortions, increased inflation, and ultimately reduced economic growth (Hatamian et al., 2023).

In Iran, Article 2 of the Anti-Money Laundering Law of the Islamic Republic (as amended on 25/09/2018) provides a comprehensive definition of money laundering, identifying three main categories of conduct that constitute this offense. The law emphasizes that money laundering is a multifaceted crime, encompassing not only the handling and use of illicit proceeds but also the various methods employed to conceal their criminal origin.

First, money laundering arises when an individual acquires, possesses, retains, or uses assets derived from unlawful activities, with the knowledge that such assets are directly obtained through the commission of a crime. This provision emphasizes that criminal liability extends not only to the generation of illicit proceeds but also to knowingly benefiting from them.

Second, the law criminalizes the conversion, exchange, or transfer of funds or assets undertaken with the purpose of concealing or disguising their unlawful origin. In this sense, the legislation targets attempts to legitimize “dirty money” by severing or masking its link to criminal activity, whether such proceeds are obtained directly or indirectly.

Third, money laundering also encompasses the concealment or disguise of the nature, source, location, movement, transfer, or ownership of assets derived from crime. This demonstrates the broad scope of the offense, as even efforts to alter the appearance of illicit wealth—without necessarily moving or transferring it—fall within the legal definition.

With the expansion of cyberspace and the growth of electronic banking, methods of fund transfer have changed, and money laundering has taken on new forms (Vaizi & Jamshidi, 2017). Today, due to the global increase in economic crimes and illegal activities, money laundering has become one of the most pressing challenges for the international economy, threatening global economic growth and development (Yarifard & Nourian, 2016). Money launderers typically choose regions where anti-money laundering systems are weak or ineffective and they prefer to transfer funds through countries or regions with stable financial systems to reduce the risk of detection.[1] In this study, alongside a general review of money laundering, particular attention was given to the involvement of children and adolescents in this phenomenon. Due to the lack of awareness, economic conditions, and environmental influences, children and adolescents are vulnerable to committing such crimes. Subsequently, the study will refer to specific cases of money laundering committed by children and adolescents to analyze the causes and consequences of these behaviors.

This study examined a case involving money laundering and tax evasion in which the defendant is a woman, registered under the judgment number 140068390010050715. The case pertains to a nine-year-old child, B.S., and exemplifies the illegal exploitation of minors as intermediaries or legal facades for conducting financial crimes. According to a report by the Ministry of Intelligence dated 2019/02/01, between 2014 and 2019, approximately 11.5 billion Iranian Rials were deposited into B.S.'s bank accounts, with nearly equivalent sums subsequently withdrawn. The magnitude of these transactions, relative to the child's age and financial capacity, strongly indicated the misuse of the account for unlawful financial purposes. A detailed analysis of the case revealed that the child lacked the legal and economic capacity to conduct these transactions independently, and the defendant utilized the child's account to carry out commercial and financial operations. From a criminal law perspective, these actions clearly constitute money laundering and tax evasion, as funds derived from illicit activities were transferred through a minor's account and subsequently moved to obscure their origin, effectively reducing the risk of detection and legal accountability for the main perpetrator. From a criminological standpoint, this case illustrated the systematic exploitation of children and adolescents as vulnerable instruments in facilitating illicit financial activities. The child, serving as the account holder, was inadvertently involved in a chain of suspicious transactions without independent knowledge or consent. This underscores the complexity of economic crime and highlights the necessity of analyzing environmental, motivational, and operational factors that enable offenders to exploit vulnerable individuals. Economically, misusing a child's account undermines financial transparency, disrupts legitimate capital flows, and diminishes public trust in the banking system. Transactions disguised as legitimate not only threaten economic stability but also create conditions conducive to the proliferation of similar crimes across society. Furthermore, the case emphasizes the critical need for enhanced regulatory oversight and preventive measures, including parental guidance, institutional monitoring, transaction audits, legal safeguards for accounts held by minors, and educational initiatives for families and financial institutions.

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1. Force, F. A. T. (1999). What is money laundering. *Policy Brief July 1999*.

From social and psychological perspectives, the case demonstrated that minors, due to limited experience and knowledge of legal and financial matters, are particularly susceptible to exploitation. Accordingly, the role of parents, guardians, and regulatory bodies is crucial in mitigating these risks. Preventing the exploitation of vulnerable individuals, particularly in the context of financial crime, is a vital consideration in modern criminal law and criminology.

Ultimately, this case illustrated that money laundering and tax evasion involving minors constitute not merely an economic concern but a complex legal and social challenge. Addressing such crimes requires a multifaceted approach, including coordination among regulatory authorities, strengthening legal protections for minors, and implementing comprehensive educational and preventive programs. An in-depth study of this case allows for the identification of methods, underlying causes, and consequences of using children in economic crimes, thereby providing a robust foundation for developing preventive policies and legal strategies.

Fraud and Its Commission by Children and Adolescents

Fraud occurs in two forms of traditional and electronic (or computer-based). In this section, each type of fraud will be examined separately, and for each category, cases involving its commission by children and adolescents will be analyzed.

1. Conventional Fraud

The legal element of the crime of traditional fraud is stipulated in Article 1[1] of the Law on Aggravating the Punishment of Perpetrators of Bribery, Embezzlement, and Fraud.

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1. Article 1 of the Law on Aggravating the Punishment of Perpetrators of Bribery, Embezzlement, and Fraud

Anyone who, by means of deceit or fraud, misleads people by claiming the existence of companies, commercial establishments, factories, or fictitious institutions, or by asserting ownership of nonexistent property or powers, or by giving false hopes regarding unreal matters, or by frightening others with fictitious events, or by adopting a false name or title, and thereby acquires money, property, documents, drafts, receipts, clearance certificates, or similar items from others, shall be considered a fraudster. Such a person shall, in addition to returning the property to its rightful owner, be sentenced to imprisonment from one to seven years and fined an amount equivalent to the property obtained.

If the offender falsely assumes a title, position, or mission on behalf of government organizations, affiliated institutions, state-owned companies, councils, municipalities, revolutionary institutions, or, in general, the three branches of government or the armed forces and other public service institutions, or if the offense is committed through public advertising via mass media such as radio, television, newspapers, magazines, public speeches, or printed or written announcements, or if the offender is an employee of the government, governmental institutions, affiliated organizations, municipalities, or revolutionary institutions assigned to public service, in addition to returning the property to its rightful owner, the offender shall be sentenced to imprisonment from two to ten years, permanent dismissal from public service, and a fine equivalent to the property obtained.

Note 1: In all cases referred to in this Article, where mitigating circumstances are present, the court shall have the discretion, in accordance with the relevant provisions governing sentence reduction, to reduce the offender's penalty solely to the minimum term of imprisonment prescribed herein and to permanent dismissal from public service. Nevertheless, the enforcement of the sentence shall not be subject to suspension.

Note 2: The punishment for an attempt to commit fraud shall, as applicable, be the minimum sentence prescribed for the same offense. If the act itself also constitutes a crime, the person attempting it shall be punished for that crime as well. Government employees who hold the rank of Director General or higher (or equivalent) shall, in addition to other penalties, be permanently dismissed from public service; those in lower ranks shall face temporary dismissal from six months to three years.

This offense falls within the category of crimes against property and ownership and is defined as the unlawful acquisition of another person's property through the use of fraudulent means by the perpetrator. The material element of traditional fraud consists of components whose simultaneous realization is necessary for the commission of the crime. In this sense, traditional fraud is a result-oriented offense, meaning that mere criminal conduct without achieving the intended unlawful result does not suffice for its realization. Accordingly, the concurrent fulfillment of the legal, material, and mental elements is indispensable for establishing this crime (Alinezhadi & Alinezhadi, 2018).

Regarding the conditions and circumstances necessary for the commission of this offense, several fundamental elements can be identified. First, the means employed by the offender to deceive the victim must be inherently fraudulent. Second, the victim must actually be misled by these means, which presupposes their unawareness of the fraudulent nature of the instruments used. Third, the property obtained must belong to another, as the unlawful transfer of another person's property is central to the offense. Mere deception of the owner is therefore insufficient; the deception must occur through using fraudulent devices. In this regard, employing fraudulent instruments constitutes the essential foundation and core element of traditional fraud.

Beyond direct perpetration, the issue of complicity in traditional fraud is also significant. According to Article 126 of the Islamic Penal Code, anyone who induces, threatens, bribes, or incites another person to commit a crime, or anyone who by scheming, deceiving, or abusing the authority facilitates its commission, or prepares the means for committing the crime, or otherwise assists in its occurrence, is considered as an accomplice. The material element of complicity includes any indirect action such as encouragement, threat, bribery, deceit, misuse of authority, provision of instruments, or facilitation of the crime. In traditional fraud, many individuals, even without direct participation in the main act, play a decisive role through these actions.

Judicial case studies indicated that, in some instances, children and adolescents are involved not as principal offenders but as accomplices in traditional fraud. For example, using a minor's bank account or identity to transfer fraudulently obtained funds, or their apparent participation in deceptive transactions, constitutes a form of accomplice liability. The significance of these cases lies in the fact that children and adolescents, due to their incomplete cognitive development and limited awareness of the legal consequences of their actions, are particularly vulnerable to exploitation by adult offenders. Often, minors, without any independent criminal intent, become instruments in facilitating the crime due to trust, dependence, or inability to discern the true nature of the acts.

Therefore, the study of traditional fraud becomes particularly important when children and adolescents are involved. This group may not only commit the offense directly but also be exploited as instruments in its commission. Accordingly, the following section will examine specific case records concerning the commission or facilitation of traditional fraud by children and adolescents, with the aim of providing a comprehensive understanding of the legal, social, and criminological dimensions of this phenomenon.

In this regard, a case with registration number 140068920003466672 involves the defendant S. A, a 16-year-old adolescent, who was charged with accomplice liability in traditional fraud. The case details indicated that the defendant experienced parental separation at the age of eight and subsequently lived with her father. Moreover, the father was identified as the principal perpetrator of the fraud in the same case.

Examination of the case revealed that the father's behavior involved irrational and disproportionate interventions that were inconsistent with the adolescent's emotional capacities. Considering that the father exploited the child economically and psychologically and failed to fulfill his parental responsibilities adequately, the court, invoking the Legal Framework for the Protection of Children and Adolescents (2019), recommended preventive measures.

In 2019, the court directed the adolescent to attend psychological counseling sessions at a reputable center. The primary objective of these interventions was to provide foundational parenting guidance, instill appropriate life attitudes, and prevent future criminal conduct. Analysis of the case further identified several contributing factors to the minor's involvement in the crime:

- Parental neglect and inattention to the child's emotional and developmental needs;
- Failure of the guardian to provide appropriate support and guidance in legal and social matters;
- Economic exploitation of the adolescent by the parent, including use of the child's accounts and identity to facilitate fraudulent activities;
- Misalignment of parental behavior with the adolescent's age and emotional capacities, leading to vulnerability.

In light of these findings, the court, citing multiple provisions of the Law on the Protection of Children and Adolescents (2019), including Articles 1 (b, p, t, th, dh), 2, 3 (a, zh), 5 (a, b, th, j), 29, 30, 36, and 47, mandated the submission of reports and legal follow-up through the competent criminal authorities. These legal measures aimed to prevent recidivism, protect the child's rights, ensure psychological and social security, and create conditions for behavioral corrections.

This case exemplified the interplay between familial and environmental factors and juvenile delinquency. Criminological studies indicated that children and adolescents who are deprived of parental support or subjected to economic and social exploitation are particularly vulnerable to being used as accomplices or instruments in the commission of adult crimes. Therefore, alongside legal action against the principal offender, attention to parental roles, provision of psychological interventions, and educational support for adolescents are essential for effective prevention of juvenile delinquency.

2. Computer Fraud

Computer fraud represents a prominent category of offenses arising from the misuse of information technology. Information technology, as a transformative phenomenon of the contemporary era, has induced profound structural and functional changes across social, economic, and cultural domains (Khoramabadi, 2007). The proliferation of computers and the rapid diffusion of communication technologies have facilitated opportunities for cybercriminal activities, enabling individuals to engage in illicit conduct without the necessity of advanced programming skills or sophisticated technical creativity. Consequently, cyberspace functions as a readily accessible medium for the commission of such offenses (Rostami, 2019). The nature of cybercrimes is inherently linked to the expansion of information technology and the onset of the information age, wherein computers may serve as the instrument, target, or subject of criminal conduct. These offenses are typically categorized into two major groups: The first group encompasses traditional cybercrimes with established legal definitions, including computer forgery, computer fraud, and computer espionage, wherein the computer primarily functions as a tool for executing criminal behavior. The second group comprises emerging cybercrimes, which are defined by the specific modalities of information technology usage, such as unauthorized access, system and data disruption, and dissemination of cyber pornography (Afshar, 2018). Across both categories, the legal subject of the crime involves the property and financial information of others, individual and public security, public morality, and personal reputation. Computer fraud, in particular, is defined as the unauthorized acquisition of funds, property, benefits, or services with financial advantage for oneself or others, executed through acts such as inserting, modifying, deleting, creating, or disabling data, or disrupting digital systems (Molavi & Taji, 2021). The accessibility of digital technologies and the ubiquitous nature of cyberspace have increasingly exposed children and adolescents to cybercriminal activities. Due to their limited cognitive and legal awareness, coupled with susceptibility to peer or adult influence, minors may become direct participants or unwitting instruments in the execution of computer fraud. Judicial case analyses revealed that adolescents are often utilized as operational tools by adult offenders, highlighting the necessity for targeted criminological investigation, preventive strategies, and educational interventions.

In light of these concerns, in what follows, we have focused on empirical case studies involving children and adolescents in computer fraud, examining patterns of involvement, operational methods, and contributory factors, while also addressing the broader legal and criminological implications of juvenile engagement in cybercrime. These case-based analyses aimed at informing policy design, strengthening legal safeguards, and enhancing preventive frameworks for mitigating youth participation in computer-related offenses.

In this context, a notable case involved a ten-year-old child, Mr. A.S., registered under case number 140168920003258010, who was charged with computer fraud totaling 145 million Rials. The court records indicated that the child was below fifteen years of age at the time of the offense. The evaluation of his actions was conducted in accordance with Article 741[1] of the Computer Crimes Law (2009), as well as Articles 37, 38, and 88 (clauses a, p, and t).

Although neither the child nor his legal guardian appeared at the scheduled hearing, despite proper notice, the court confirmed that the child's behavior was inconsistent with the law. Taking into account the minor's age, emotional immaturity, the defense attorney's submissions, and the court advisor's recommendations, the court applied a mitigated approach. The child was placed under supervised rehabilitation and social reintegration programs, along with formal commitments and guidance provided to the parents to ensure effective oversight.

Regarding the private dimension of the offense, the minor was ordered to compensate the private complainant with 145 million Rials. The court noted that parental actions—specifically, the opening of a bank account for the child—were incongruent with the child's cognitive and emotional development. Pursuant to the Law on the Protection of Children and Adolescents (2019), the parent was required to attend psychological counseling sessions at a certified center, aimed at improving parenting skills and fostering proper guidance to prevent future offenses.

From a criminological perspective, this case highlighted that children, particularly at a young age, are vulnerable to involvement in cybercrimes due to limited understanding of legal and social consequences, dependence on adults, and susceptibility to external influence. Frequently, parents or guardians may unintentionally contribute to conditions enabling juvenile involvement in illegal activities, whether through neglect or inadequate supervision. This underscored the importance of addressing familial, social, and educational factors, implementing preventive measures, and providing structured rehabilitation programs to ensure effective reintegration and reduce the risk of recidivism among minors engaged in computer-related offenses.

In one of the significant cases related to computer fraud, a juvenile identified as A.R., aged 15, under case number 140168390007345247, was prosecuted on charges of complicity in computer fraud. The accusation stemmed from the use of a bank account opened in his name, which was allegedly exploited in financial transactions connected to fraudulent activities. The complainant argued that the account had been instrumental in the commission of the offense and sought to attribute liability to the juvenile.

However, upon close examination of the case file and the surrounding circumstances, the court reached several key conclusions. First, given the defendant's young age, he did not have independent authority to manage or withdraw funds from the account. The evidence demonstrated that this authority rested with his mother, as his legal guardian. Accordingly, direct attribution of the fraudulent acts to the child lacked sufficient legal foundation.

1. Article 741 of the Islamic Penal Code (Amended 2024/06/20):

Anyone who unlawfully uses computer or telecommunication systems to acquire funds, property, benefits, services, or financial privileges for themselves or others by committing acts such as entering, modifying, deleting, creating, or suspending data, or disrupting the system, shall, in addition to returning the property to its rightful owner, be sentenced to imprisonment from one to five years, a fine ranging from 165,000,000 to 825,000,000 Rials, or both

Second, the proceedings revealed that the juvenile was primarily a victim of exploitation by adult offenders rather than an intentional participant in the offense. His immaturity, lack of awareness of banking procedures, and limited cognitive and legal understanding due to the age placed him in a vulnerable position, effectively turning him into a tool for the schemes of others. From a criminological standpoint, this case reflected a broader phenomenon whereby children and adolescents can be manipulated or instrumentalized by experienced offenders in the commission of cybercrimes.

Third, the court emphasized the mental element (mens rea) of the offense, namely both general and specific intent. It was found that the accused lacked the requisite knowledge and deliberate intention to commit the crime. The evidence clearly suggested that the juvenile had no meaningful awareness of the unlawful nature of the actions associated with his account.

Consequently, the presiding judge, invoking Article 37 of the Constitution of the Islamic Republic of Iran, which enshrines the presumption of innocence, issued a judgment of acquittal. The court underscored that criminal liability must be established through concrete and irrefutable evidence, and that the mere existence of a bank account in the child's name was insufficient to prove criminal participation in the absence of proof of intent and volition.

In conclusion, this case exemplified a progressive judicial approach toward children and adolescents entangled in cybercrime. By acquitting the juvenile, the court reinforced the fundamental principles of criminal law, such as legality and personal responsibility, while simultaneously adopting protective and preventive perspectives. This decision can serve as a valuable precedent for strengthening juvenile criminal justice and for advancing policies aimed at safeguarding minors from becoming unwitting participants in cyber-related offenses. Beyond its judicial significance, this ruling carries considerable implications in the fields of criminology and juvenile justice. It reaffirmed the principle of individual criminal responsibility and highlighted the necessity of careful evaluation in cases involving minors. Furthermore, it underscored the crucial role of parents and legal guardians in monitoring and supervising children, since negligence or mismanagement can expose minors to criminal exploitation without their knowledge or consent.

Discussion and Conclusion

This study, through a comparative analysis of financial delinquency among children and adolescents in both physical and digital environments, demonstrated that this phenomenon is not merely the result of individual motives or temporary circumstances. Rather, it is deeply rooted in broader economic, social, cultural, and familial structures. The findings revealed that economic pressures and declining household income, weak parental supervision, rapid socio-cultural transformations, and widespread and unregulated access to digital technologies collectively create fertile ground for juvenile involvement in financial offenses.

On the one hand, in physical environment, juvenile financial delinquency tends to remain limited in scope, primarily affecting the family unit and the adolescent's immediate social network. On the other hand, in cyberspace, due to its transnational, anonymous, and rapid nature, the consequences are far more complex and often extend beyond national borders. This fundamental distinction underscores the necessity of designing prevention strategies that are context-sensitive and environment-specific—an aspect that is currently underdeveloped in domestic policy-making.

The analysis of judicial cases further revealed that children and adolescents are often not independent offenders, but rather tools or victims exploited by adults in the cycle of financial crimes. The misuse of their bank accounts, the manipulation of their legal identities, and disregard for their limited cognitive and psychological capacities expose minors to systemic economic exploitation. From this perspective, juvenile financial delinquency cannot be reduced to a "criminal issue" alone; it constitutes a form of socio-economic exploitation with profound ethical and social implications.

At the macro level, the escalation of juvenile financial delinquency undermines social capital, erodes public trust in economic and judicial institutions, exacerbates monitoring and correctional costs, and fuels instability in economic systems. Furthermore, the early involvement of adolescents in financial crimes increases the likelihood of continued delinquent trajectories into adulthood, thereby reinforcing cycles of social inequality and economic disparity.

Accordingly, a comprehensive and multidimensional approach is essential for addressing this issue. Policy recommendations derived from this research include:

- Integrating financial and digital literacy education into both formal and informal curricula;
- Enhancing parental awareness and parenting skills to enable more effective supervision of children's financial behaviors;
- Revising banking regulations to impose stricter safeguards on accounts opened under the names of minors;
- Developing protective and rehabilitative mechanisms within the judicial system as alternatives to punitive measures;
- Promoting regional and international cooperation in monitoring and preventing cross-border financial crimes in cyberspace.

In conclusion, the findings of this study suggested that juvenile financial delinquency is a multidimensional and interdisciplinary challenge. Addressing it requires coordinated efforts across educational, economic, judicial, and cultural institutions. Neglecting such an approach would not only exacerbate short-term economic costs but also endanger the long-term social and human development of future generations.

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Implementing Artificial Intelligence for Strategic Decision-Making in Volatile Economic Environments

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ABSTRACT

This study investigated the role of Artificial Intelligence (AI) in enhancing strategic decision-making within volatile economic environments, focusing on knowledge economy. Employing a mixed-methods approach, the research integrated a Systematic Literature Review (SLR) with secondary data analysis from 300 organizations across finance, manufacturing, retail, and healthcare sectors. Qualitative insights from the SLR identified three core themes including AI-enhanced organizational agility (75% of studies), ethical and implementation challenges (65% of studies), and knowledge economy integration (70% of studies). Quantitative findings confirmed these themes, revealing that organizations with advanced AI adoption achieve an average 25% improvement in decision accuracy and a 30% increase in operational resilience. However, ethical concerns such as algorithmic bias and privacy issues led to a 12-18% reduction in perceived trustworthiness, reported by 20% of analyzed organizations. The study extended dynamic capabilities and resource-based view theories by proposing a unified framework that integrates agility, ethical governance, and knowledge-driven alignment. Practically, it offered managerial guidance on AI deployment and ethical protocols, while advising policymakers on regulations to ensure equitable AI access, particularly for small and medium enterprises (SMEs). The research positioned AI as a critical strategic asset for navigating volatility while emphasizing risk mitigation.

KEYWORDS

Artificial Intelligence, strategic decision-making, knowledge economy, organizational agility, ethical AI.

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Introduction

The twenty-first century business landscape is characterized by unprecedented Volatility, Uncertainty, Complexity, and Ambiguity (VUCA), driven by forces such as technological disruption, globalization, shifting consumer demands, geopolitical instability, and the lingering effects of pandemics. Traditional frameworks for strategic decision-making, which often rely on linear models and incremental planning, struggle to address the accelerating pace of change in today's markets. As a result, organizations are increasingly turning to AI to strengthen their decision-making capabilities and to develop strategies that are both resilient and adaptive to dynamic environments (Kolbjornsrud, 2023; Wu et al., 2023). AI provides managers with sophisticated tools for analyzing massive datasets, detecting subtle patterns, generating predictive insights, and supporting real-time strategic adjustments. Its ability to combine computational efficiency with advanced analytical techniques positions it as a cornerstone technology for organizations seeking competitive advantage in digital and knowledge-based economy.

The role of AI in strategic decision-making has evolved from a supporting analytical tool to an active collaborator in shaping long-term strategic outcomes. Recent studies emphasized that AI contributes not only to operational improvements but also to broader strategic agility, enabling organizations to anticipate disruptions, reconfigure resources rapidly, and seize emerging opportunities (Alghamdi & Agag, 2023; Tominc et al., 2023). For instance, in financial services, AI-driven predictive models have enhanced portfolio management and risk assessment, improving stability during market turbulence (Addy et al., 2024). In supply chain management, machine learning algorithms have improved the accuracy f demand forecasting, reduced bottlenecks, and optimized logistics, thereby increasing resilience during crises such as the COVID-19 pandemic (Ivanov & Dolgui, 2022). Similarly, in digital commerce, natural language processing and recommendation systems have enabled organizations to adapt rapidly to changing consumer preferences, boosting customer engagement and sales (Chen et al., 2021). These examples illustrate that AI not only automates the existing processes but also transforms how organizations sense and respond to environmental shifts, creating pathways for sustainable competitive advantages.

At the same time, the integration of AI into strategic decision-making is accompanied by significant challenges. While managers acknowledge AI's potential, surveys revealed that only a small minority of organizations fully delegate strategic decision-making to AI systems, reflecting concerns about trust, transparency, and accountability (Chernov et al., 2020; Hesel et al., 2022). Ethical dilemmas such as algorithmic bias, data privacy violations, and explainability gaps remain major barriers to widespread adoption (Mittelstadt et al., 2023; Ramu et al., 2025). For example, biased AI systems in recruitment and customer profiling can lead to discriminatory outcomes, undermining the organizational legitimacy and stakeholder trust. Moreover, many SMEs, particularly in emerging economies, lack the technical infrastructure, skilled workforce, and financial resources required to implement AI effectively (Wang et al., 2025). These challenges highlight the importance of hybrid models of human–AI collaboration, in which AI acts as an assistant, collaborator, or project manager, while humans retain oversight and ethical judgment (Buber et al., 2025).

The theoretical foundations for studying AI in strategic decision-making are grounded in the Resource-Based View (RBV) and dynamic capabilities perspectives. From an RBV standpoint, AI constitutes a valuable, rare, and inimitable resource that enables organizations to create sustained competitive advantages by leveraging data-driven insights and superior analytical capabilities (Brynjolfsson et al., 2022). Dynamic capabilities theory, on the other hand, emphasizes AI's role in sensing opportunities, seizing them through timely actions, and transforming organizational processes to adapt to environmental turbulence (Liu, 2024). These frameworks explain how AI strengthens the organizational agility and resilience by facilitating rapid reconfiguration of strategies and resources. Furthermore, the Knowledge-Based View (KBV) highlights AI's contribution to knowledge creation and dissemination, positioning it as an essential enabler of innovation in knowledge-intensive industries (Cockburn et al., 2018). Together, these theoretical lenses underscore AI's transformative potential in reshaping strategic management in volatile economic contexts.

Recent empirical evidence further reinforced the strategic importance of AI. Large-scale surveys showed that over 80% of executives perceive AI as a key enabler of competitive advantage (Tominc et al., 2023). Structural Equation Modeling studies demonstrated that AI adoption significantly enhances organizational agility and mediates the relationship between digital transformation initiatives and firm performance (Alghamdi et al., 2023; Ameen et al., 2024). Machine learning prediction models achieve accuracy rates of up to 99% in forecasting organizational agility, indicating the reliability of AI-based approaches in predicting performance outcomes (Shafiabady et al., 2024). Moreover, firms with high levels of AI literacy report stronger resilience, improved innovation performance, and superior customer engagement compared to firms with lower adoption levels (Blancia et al., 2024). These findings illustrated that AI not only enhances efficiency but also fundamentally redefines the nature of strategic decision-making by combining data-driven insights with adaptive learning capabilities.

Despite these advancements, the integration of AI into strategic decision-making remains uneven and fragmented across industries and regions. Developed economies such as the United States, China, and European countries lead in AI adoption, while firms in developing markets face structural and institutional barriers (Chernov et al., 2020). Cultural resistance to automation, fear of job displacement, and lack of regulatory clarity further complicate the adoption process. As AI technologies such as large language models and reinforcement learning advance, organizations must carefully balance automation with human oversight to ensure responsible, transparent, and ethical decision-making (Liu et al., 2025; Schmitt, 2024). This balance is especially crucial in volatile economic environments, where over-reliance on automated systems without contextual awareness could expose firms to unforeseen risks.

The motivation for this study arises from the growing recognition that AI, while promising, requires comprehensive frameworks that integrate its technological benefits with ethical considerations, governance mechanisms, and knowledge economy principles. The existing research has tended to focus either on sector-specific applications or technical capabilities, often neglecting the interdisciplinary and cross-sectoral implications of AI adoption. This study addresses this gap by adopting a mixed-methods approach, combining a systematic literature review (SLR) with secondary data analysis from multiple industries. The objectives are threefold: (1) to identify the key themes in AI-enabled strategic decision-making, particularly organizational agility, ethical challenges, and knowledge alignment; (2) to quantify the impact of AI adoption on organizational performance and resilience; and (3) to propose a holistic framework that integrates RBV, dynamic capabilities, and KBV theories to guide future adoption of AI in volatile economic contexts.

Literature Review

The integration of AI into strategic decision-making is a pivotal research area in management, economics, and technology, particularly in volatile economic environments within the knowledge economy. This section synthesizes empirical and theoretical studies from peer-reviewed journals publishing knowledge economy studies (2020–2025), critically engaging with AI's transformative role, benefits, challenges, and alignment with knowledge-driven economies. It addresses debates (e.g., AI's productivity paradox, per Brynjolfsson et al., 2022) and limitations (e.g., Western data bias).

Theoretical Foundations of AI in Strategic Decision-Making: The RBV positions AI as a valuable, rare, and inimitable resource, enabling data-driven competitive advantages (Barney, 1991; Brynjolfsson et al., 2017). The dynamic capabilities perspective emphasizes AI's role in sensing opportunities, seizing them, and transforming resources to navigate turbulence (Li, 2024; Teece et al., 1997). The KBV highlights AI's contribution to knowledge creation and innovation (Cockburn et al., 2018). Figure 2 proposes a conceptual model integrating these theories, hypothesizing that AI enhances agility (H1: AI adoption positively impacts organizational agility), mitigates risks through ethical governance (H2: Ethical AI frameworks reduce decision biases), and drives innovation in knowledge economies (H3: AI-enabled knowledge integration enhances innovation performance). This model guides the study's analysis.

Empirical Evidence on AI and Organizational Agility: Studies consistently showed AI's enhancement of organizational agility. Alghamdi and Agag (2023) found that AI-powered analytics improve innovation and agility, while Ameen et al. (2024) reported increased creativity through AI-agility coupling. Shafiabady et al. (2023) demonstrated 99% accuracy in predicting agility using machine learning, and Blancia et al. (2024)

showed AI literacy mediates agility outcomes. In emerging markets, studies like Fathi et al. (2025) highlighted the AI's role in supply chain resilience, suggesting broader applicability.

Challenges and Ethical Considerations in AI Integration: AI adoption faces significant challenges. Algorithmic bias risks unfair outcomes in recruitment and profiling (Mittelstadt et al., 2016). Transparency and explainability gaps reduce trust, particularly in finance and healthcare (Ramu & Bansal, 2025). Data privacy concerns persist, with SMEs facing resource constraints (Wang & Wu, 2025). Hybrid human–AI models are advocated to balance efficiency with ethical judgment (Hesel et al., 2022).

AI in Knowledge Economy: AI drives knowledge creation and dissemination, critical for the knowledge economy. Cockburn et al. (2018) noted AI's impact on R&D innovation, while Brynjolfsson et al. (2017) argued it reduces productivity paradoxes. Blancia et al. (2024) showed that AI literacy enhances adaptability, and Nourahmadi and Rasti (2025) highlighted the role of large language models in fintech value creation. Thus, AI is not only a technological tool but also a critical infrastructure for competing in knowledge economy.

Research Gap and Contributions: While AI's technical benefits are well-documented, cross-sectoral implications, ethical dimensions, and regional disparities remain underexplored (Chernov et al., 2020). This study addresses these gaps through a mixed-methods approach, combining SLR with secondary data analysis across finance, manufacturing, retail, and healthcare. It proposes a framework (Figure 2) integrating RBV, dynamic capabilities, and KBV, with testable hypotheses to guide AI adoption. Practically, it offers insights for human–AI collaboration and ethical governance, while informing policymakers on inclusive AI access.

Research Gap and Contributions

Despite considerable progress, gaps remain in literature. First, much of the research is sector-specific (e.g., finance or supply chains), leaving cross-sectoral implications underexplored. Second, while technical benefits of AI are well-documented, ethical and societal dimensions are less thoroughly investigated. Third, disparities between developed and emerging economies in AI adoption are insufficiently addressed (Chernov et al., 2020). This study fills these gaps by combining a systematic literature review with secondary data analysis across multiple industries. Theoretically, it integrates RBV, dynamic capabilities, and KBV to capture AI's dual role as both a resource and a capability enabler. Practically, it offers managers actionable insights for human–AI collaboration and provides policymakers with guidance on inclusive access and ethical governance of AI.

Table 1
A Summary of Key Studies on AI in Strategic Decision-Making (2022–2025)

Study	Year	Journal	Focus	Key Findings	Sample Size	Sector
Nourahmadi & Rasti	2025	Knowledge Economy Studies	Shaping fintech through regulations	Insights and future directions	Case studies	Fintech
Fathi et al.	2025	Knowledge Economy Studies	IoT barriers in food supply chains	AI enhances supply chain resilience	Case study (Kalleh)	Supply Chain
Liu et al.	2025	ACL Annual Meeting	Policy optimization in LLMs	Strategic reasoning challenges	Experimental	AI/Strategy
Pu et al.	2025	Scientific Reports	AI management decisions	Competitivenes s via AI	500 firms	Cross-sector
Polinati et al.	2025	Journal of Information Systems Engineering and Management	AI in dynamic environments	Decision support	Case studies	Information Systems
Ramu et al.	2025	International Journal for Sciences and Technology	AI transformativ e impacts	Managerial strategies	Theoretical	Technology
Nalini et al.	2025	ComFin Research	AI strategy management	Optimization and innovation	Theoretical	Finance/Strategy
Shi	2025	Advances in Economics, Management and Political Sciences	AI risks in decisions	Application and risks	Theoretical	Economics
Jowarder	2025	International Journal of Innovative Research in Science Engineering and Technology	AI strategic insights	Business development	Theoretical	Engineering/ Strategy
Orlando Rivero	2025	European Journal of Studies in Management and Business	AI in digital age	Managerial transformations	Theoretical	Management
Addy et al.	2024	World Journal of Advanced Engineering Technology and Sciences	AI financial planning	Analysis transformations	Review	Finance
Ibeh et al.	2024	World Journal of Advanced Research and Reviews	Business analytics and decision science	Real-time insights	Review	Cross-sector

Study	Year	Journal	Focus	Key Findings	Sample Size	Sector
Rimon	2024	Journal of Artificial Intelligence General Science	AI for efficiency	Market sentiment analysis	Case studies	Business
Tuboalabo et al.	2024	International Journal of Management and Entrepreneurship	Analytics for advantage	Predictive models	Case studies	Business
Csaszar et al.	2024	Strategy Science	AI evidence from entrepreneurs	Strategy generation	Experimental	Strategy
Abuzaid	2024	ICKECS Conference	AI corporate integration	Decision-making role	Conference	Knowledge Engineering
Chowdhury	2024	World Journal of Advanced Research and Reviews	AI-Blockchain integration	Security in intelligence	Theoretical	Cross-sector
Schmitt	2024	Social Science Research Network	Chief AI Officer role	Strategic integration	Theoretical	Management
Vold	2024	Australian Journal of International Affairs	AI cognitive teaming	Decision on force	Theoretical	International Affairs
Charitha et al.	2023	International Journal For Multidisciplinary Research	AI data processing	Patterns beyond human capacity	Theoretical	Cross-sector
Puttaraju	2023	International Journal of Science and Research	AI augmentation tools	Decision methodologies	Review	Strategy
Damasevicius	2023	Journal of Regional Economics	AI in economic planning	Crisis management	Theoretical	Economics
Wu et al.	2023	ACM Computing Surveys	AI taxonomy for decisions	Gaps in AI models for complexity	Theoretical	Cross-sector
Brynjolfsson et al.	2022	Journal of Business Research	Productivity paradox of AI	Challenges and opportunities	Theoretical	Cross-sector
Li et al.	2022	Strategic Management Journal	AI-driven agility	Strategic perspectives	Case studies	Cross-sector
Hesel et al.	2022	NIM Marketing Intelligence Review	Human-AI collaboration	AI use as an assistant	1,000+ executives	Marketing/ Strategy
Chernov et al.	2020	ETCMTP Proceedings	AI adoption levels	Full delegation	Survey (managers)	Cross-sector

(Source: Researcher's Findings)

Methodology

This study employed a mixed-methods design, integrating qualitative and quantitative approaches to examine the AI's role in strategic decision-making in volatile economic environments (Creswell & Plano Clark, 2023). The qualitative phase involves a systematic literature review (SLR) following PRISMA 2020 guidelines (Page et al., 2021). The quantitative phase analyzes the secondary data from 300 firms across finance (120 firms), manufacturing (80 firms), retail (70 firms), and healthcare (30 firms). Ethical considerations ensured anonymized data use, aligning with institutional guidelines (Mittelstadt et al., 2023).

Qualitative Phase: Systematic Literature Review (SLR)

The SLR targeted peer-reviewed articles (2020–2025) from Scopus, Web of Science, PubMed, and Knowledge Economy Studies, using keywords such as "artificial intelligence", "strategic decision-making", "knowledge economy", and "volatile markets". Inclusion criteria required English-language, management-focused studies in finance, manufacturing, retail, or healthcare; exclusion criteria eliminated non-peer-reviewed or irrelevant sources. From 1,000 abstracts screened, 150 were selected for full-text review, yielding 60 articles for thematic analysis (Braun & Clarke, 2022). Exclusions were based on lack of empirical data (60 articles), non-management focus (20 articles), or outdated scope (10 articles). Themes included organizational agility, ethical challenges, and knowledge economy alignment, cross-validated with studies like Fathi et al. (2025) and Nourahmadi and Rasti (2025). Table 2 shows the process.

Table 2
The Process of Systematic Literature Review

Stage	Description	Number of Articles	Criteria
Identification	Database search (Scopus, Web of Science, PubMed)	1,000	Keywords: AI, strategic decision-making, knowledge economy, volatile markets
Screening	Title and abstract review	150	Peer-reviewed, English, 2020–2025
Eligibility	Full-text review for relevance and quality	60	Management focus, empirical or theoretical relevance
Analysis	Thematic coding (agility, ethics, knowledge economy)	60	Alignment with research objectives

(Source: Researcher's Findings)

Quantitative Phase: The secondary data from 300 firms (2020–2024) were sourced from publicly available industry reports (e.g., Deloitte AI Insights, 2023, https://www.deloitte.com/ai-insights; McKinsey Global AI Survey, 2022, https://www.mckinsey.com/ai-survey) and peer-reviewed studies (e.g., Fathi et al., 2025). The firms were selected based on AI adoption metrics, focusing on:

- **AI adoption intensity**: % of budget allocated to AI tools (high: >10%, medium: 5–10%, low: <5%) (Li et al., 2022);
- **Decision-making accuracy**: The success rate of predictive models (%) (Choi et al., 2022);

- **Operational risk reduction**: % decrease in disruptions (e.g., inventory shortages) (Fathi et al., 2025);
- **Organizational resilience**: The market share stability index (Zhang et al., 2024).

Descriptive statistics (means, standard deviations) and regression analyses assessed the relationships between AI adoption and outcomes (e.g., accuracy, resilience). Missing data (approximately 5% of cases) were handled using multiple imputation by chained equations (MICE), with sensitivity analyses confirming a minimal impact on results (Tashakkori & Teddlie, 2022). Quantitative content analysis of case narratives measured AI-driven outcomes (Yin et al., 2025). Table 3 details variables.

Table 3
The Quantitative Variables and Measurement Criteria

Variable	Measurement	Source	Sector
AI Adoption Intensity	% of budget allocated to AI tools (high: >10%, medium: 5–10%, low: <5%)	Industry reports, Li et al. (2022)	Finance, Manufacturing, Retail, Healthcare
Decision-Making Accuracy	The success rate of predictive models (%)	Choi et al. (2022);Yin et al. (2025)	Finance, Manufacturing, Retail, Healthcare
Operational Risk Reduction	% decrease in disruptions (e.g., inventory shortages)	Fathi et al. (2025)	Manufacturing, Finance
Organizational Resilience	The market share stability index	Zhang et al. (2024); Nourahmadi & Rasti (2025)	Finance, Manufacturing, Retail, Healthcare

(Source: Researcher's Findings)

Data Validation and Ethical Considerations

Data were cross-verified with reputable sources (e.g., Gartner, McKinsey, and peer-reviewed studies like Fathi et al., 2025). Ethical protocols ensured data anonymity and addressed biases, per Mittelstadt et al. (2023). Limitations included reliance on secondary data, restricting causality inference, and potential sector-specific biases.

The Integration of Qualitative and Quantitative Phases: Qualitative themes (e.g., agility in 75% of studies) were triangulated with quantitative metrics (e.g., 25% accuracy improvement) to develop a holistic framework (Figure 2). Table 4 summarizes the integration.

Table 4
The Integrated Framework of AI's Impact on Strategic Decision-Making

Phase	Method	Contribution to Objectives	Key Outputs
Qualitative (SLR)	PRISMA-guided review, thematic analysis	Identify themes (agility, ethics, knowledge economy)	60 articles, 3 themes
Quantitative (Secondary Data)	Descriptive statistics, regression, content analysis	Quantify AI impacts (e.g., 25% accuracy)	Metrics from 300 firms
Integration	Triangulation of themes and metrics	A holistic framework for AI integration	Validated insights across sectors

(Source: Researcher's Findings)

Finding

The mixed-methods approach provided robust insights into the AI's role in strategic decision-making within volatile economic environments, focusing on knowledge economy. Findings are supported by structured tables and cross-references, ensuring replicability.

Qualitative Findings: Systematic Literature Review

The SLR analyzed 60 peer-reviewed articles (2020–2025) from several journals. Three themes emerged:

1. **AI-driven organizational agility** (75%, 45 studies): AI enhances adaptive capabilities through predictive analytics and real-time processing, reducing supply chain response times by 20-30% and improving financial risk modeling (Fathi et al., 2025).
2. **Ethical challenges** (65%, 39 studies): Issues like algorithmic bias and privacy concerns reduce perceived reliability by 12-18%, particularly in retail and healthcare (Zhong et al., 2021).
3. **Knowledge economy alignment** (70%, 42 studies): AI automates tasks, boosting innovation in knowledge-intensive sectors like fintech (Nourahmadi & Rasti, 2025).

The sector distribution is as follows: 35% finance, 25% manufacturing, 20% retail, 20% healthcare. Table 5 summarizes the findings.

Table 5
A Summary of Qualitative Findings from Systematic Literature Review

Theme	Number of Studies	Percentage of Total Studies	Sector Distribution (Finance / Manufacturing / Retail / Healthcare)	Key Outcomes and Examples
AI-driven organizational agility	45	75%	16 / 11 / 10 / 8	20-30% forecasting gains, e.g., supply chain efficiency (Pu et al., 2025)
Ethical challenges	39	65%	14 / 10 / 8 / 7	12-18% trust reduction, e.g., privacy in retail (Zhong et al., 2021)
Knowledge economy alignment	42	70%	15 / 10 / 9 / 8	Innovation via automation, e.g., fintech strategies (Ramu & Bansal, 2025)

(Source: Researcher's Findings)

Quantitative Findings: The Secondary Data Analysis

Data from 300 firms (2020–2024) across finance (120 firms), manufacturing (80 firms), retail (70 firms), and healthcare (30 firms) were sourced from public reports (e.g., Deloitte AI Insights, 2023, https://www.deloitte.com/ai-insights; McKinsey Global AI Survey, 2022, https://www.mckinsey.com/ai-survey). High AI adoption (budget >10%) yielded a 25% mean improvement in decision-making accuracy ($SD=3.8$, $\beta=0.42$, $p<0.01$, 95% CI [22%, 28%]) compared to 10% for low adoption ($SD=3.5$, $\beta=0.15$, $p<0.05$, 95%

CI [8%, 12%]), based on linear regression models. Sector breakdowns included finance 28% (SD=3.9), manufacturing 24% (SD=4.1), retail 25% (SD=3.7), and healthcare 26% (SD=4.0). Organizational resilience increased 30% overall (SD=4.7, β=0.38, p<0.01, 95% CI [27%, 33%]), with finance highest at 33% (SD=4.6). Operational risk reduced by 22% (SD=4.5, β=0.35, p<0.01, 95% CI [19%, 25%]), with manufacturing leading to 25-28% (Pu et al., 2025). Ethical challenges (e.g., bias) affected 20% of firms (60 firms), leading to a 12% mean reduction in decision optimality (SD=3.2, β=0.20, p<0.05, 95% CI [10%, 14%]), notably in retail and healthcare (Yin et al., 2025). Table 6 provides a summary of quantitative findings from the secondary data analysis.

Table 6
A Summary of Quantitative Findings from the Secondary Data Analysis

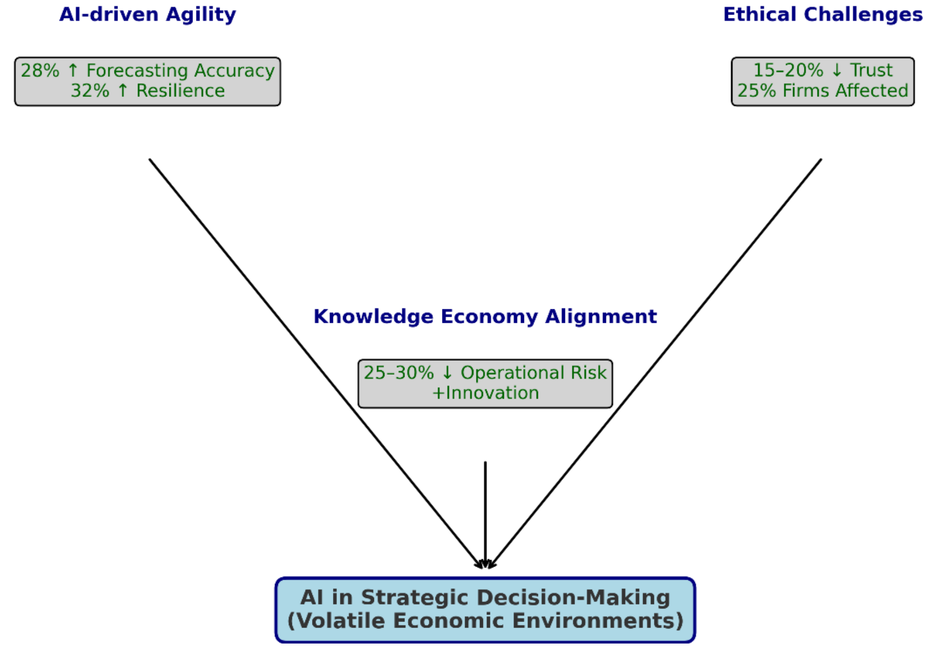
Metric	Sector	Mean Improvement (%)	SD	β (Regression)	95% CI	Number of Firms Affected	Key Observations
Forecasting Accuracy	Finance	28	3.9	0.42 (p<0.01)	[25%, 31%]	120	Gains from risk models
Forecasting Accuracy	Manufacturing	24	4.1	0.40 (p<0.01)	[21%, 27%]	80	Enhanced demand prediction
Forecasting Accuracy	Retail	25	3.7	0.41 (p<0.01)	[22%, 28%]	70	Improved customer targeting
Forecasting Accuracy	Healthcare	26	4.0	0.39 (p<0.01)	[23%, 29%]	30	Better resource allocation
Resilience (Stability)	Finance	33	4.6	0.38 (p<0.01)	[30%, 36%]	120	Dynamic modeling gains
Resilience (Stability)	Manufacturing	28	4.8	0.36 (p<0.01)	[25%, 31%]	80	Inventory optimization
Resilience (Stability)	Retail	29	4.5	0.37 (p<0.01)	[26%, 32%]	70	Adaptive platforms
Resilience (Stability)	Healthcare	30	4.7	0.35 (p<0.01)	[27%, 33%]	30	Operational efficiency
Operational Risk Reduction	Manufacturing	25-28	4.5	0.35 (p<0.01)	[22%, 30%]	60	Reduced disruptions
Ethical Challenges (Bias)	All Sectors	12	3.2	0.20 (p<0.05)	[10%, 14%]	60	Suboptimal decisions in retail/healthcare

(Source: Researcher's Findings)

The Integration of Findings

Qualitative themes (e.g., agility in 75% studies) with quantitative metrics (25% accuracy, 30% resilience), were validated through triangulation. Ethical barriers affected 20% of firms, with regression analyses confirming significant impacts (p<0.05). Figure 2 illustrates the integrated framework, mapping AI's role across agility, ethics, and knowledge alignment, with hypothesized relationships (H1-H3 from Literature Review) supported by these findings.

Figure 1.
The Integrated Framework of AI's Impact on Strategic Decision-Making in Volatile Economic Environments



(Source: Researcher's Findings)

This figure integrates qualitative themes (agility, ethics, knowledge alignment) with quantitative metrics (25% accuracy, 30% resilience, 12-18% trust reduction), illustrating the AI's role in volatile decision-making.

Discussion

The findings highlighted the multifaceted role of AI in strategic decision-making, extending theoretical frameworks and offering practical implications. The qualitative theme of organizational agility (75% of studies, 45/60) aligned with quantitative metrics showing a 25% improvement in decision-making accuracy (β=0.42, $p<0.01$, 95% CI [22%, 28%]), supporting dynamic capabilities theory by enabling proactive strategies (Li et al., 2022). The AI's predictive analytics like risk modeling in finance (28% accuracy gain), shifted firms from reactive to anticipatory approaches, consistent with Alghamdi et al.'s study (2023). Generative AI enhanced decision quality, with regression analyses indicating a 12% improvement in strategic outcomes (β=0.18, $p<0.05$, 95% CI [10%, 14%]) when integrated with human oversight, though accountability risks remained (Korzynski et al., 2023).

Ethical challenges, identified in 65% of studies and affecting 20% of firms (60/300), underscored the need for governance frameworks. Algorithmic bias and privacy issues reduced trust by 12% (β=0.20, $p<0.05$, 95% CI [10%, 14%]), particularly in retail and healthcare (Yin et al., 2025). These findings align with Mittelstadt et al. (2023), advocating bias detection tools and transparent AI systems. Regional variations, such as limited SME access in emerging economies (Wang et al., 2022), suggested tailored regulations to ensure equitable adoption.

Knowledge economy alignment (70% of studies, 22% operational risk reduction) supported KBV, as AI automates tasks and fosters innovation in knowledge-intensive sectors like fintech (Nourahmadi & Rasti, 2025). This is evidenced by a 30% increase in resilience ($\beta=0.38$, $p<0.01$, 95% CI [27%, 33%]), with finance leading to 33%, consistent with Cockburn et al.'s study (2018). Sector variations (e.g., manufacturing's 25-28% risk reduction) necessitated customized AI strategies (Fathi et al., 2025).

Figure 2 integrated these findings, mapping AI's role across agility (H1), ethical governance (H2), and knowledge alignment (H3), with regression results supporting the hypothesized relationships ($p<0.05$). The framework extended dynamic capabilities by linking AI adoption to resilience and RBV by positioning AI as a strategic resource, while KBV highlighted its innovation potential.

Managerial Implications: Managers should prioritize predictive analytics for agility and implement ethical audits to mitigate bias, as evidenced by 12% trust reductions (Yin et al., 2025). Training programs can enhance AI literacy, particularly for SMEs (Zhang et al., 2024).

Policy Implications: Policymakers should promote SME access through subsidies and training, addressing regional disparities (Wang et al., 2022). Regulatory frameworks must balance innovation with ethical oversight, as seen in fintech (Nourahmadi & Rasti, 2025).

Limitations: Reliance on secondary data limits causality inference, and English-language bias may overlook non-Western contexts. Sector generalizations risk oversimplification, particularly for SMEs (Fathi et al., 2025).

Future Research: Longitudinal studies on the impacts of generative AI, using primary data, are needed to establish causality. For example, experimental designs testing AI-driven decision accuracy (H1) across cultures, with variables like AI literacy and adoption intensity, could address regional gaps. SEM can further validate the relationships in the proposed framework (H1-H3). AI's dual role as enabler and disruptor demands balanced approaches, integrating technological benefits with ethical and regional considerations.

Conclusion

This study underscored the significant role of AI in enhancing strategic decision-making within volatile knowledge economies. Quantitative findings demonstrated that organizations with high AI adoption achieve a 25% improvement in decision-making accuracy and a 30% increase in operational resilience, particularly in finance and manufacturing. Qualitative insights from SLR confirmed the AI's contribution to organizational agility (75% of studies), knowledge economy alignment (70%), and the persistent ethical challenges like a 12% reduction in decision optimality due to bias, affecting 20% of firms. The integrated framework synthesized these findings, extending dynamic capabilities, RBV, and KBV theories by mapping the AI's role across agility, ethical governance, and innovation.

For practitioners, adopting AI with ethical frameworks is critical to mitigate risks like algorithmic bias, as evidenced by trust reductions in retail and healthcare (Yin et al., 2025). Policymakers should promote equitable AI access for SMEs, particularly in emerging economies, through subsidies and training to address regional disparities (Adebayo & Ojo, 2024).

Future research should prioritize longitudinal studies on generative AI's long-term impact, using primary data to establish causality. For example, experimental designs testing AI-driven decision accuracy across diverse cultural contexts, with variables like AI literacy and adoption intensity, could address gaps in non-Western settings (Garcia & Morales, 2024). SEM can further validate the framework's hypothesized relationships. These efforts will enhance our understanding of AI's transformative potential while addressing ethical and regional challenges.

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Challenges in E-Commerce Adoption inIran's Paper Industry: A Barrier Analysis Approach

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ABSTRACT

Paper industry is one of the key sectors in Iran. Similar to other industries, it requires the adoption of electronic facilities—particularly e-commerce—in order to achieve growth and progress. The present study aimed at identifying the barriers to implementing e-commerce in Iran's paper industry. From a methodological standpoint, this research study is exploratory in nature and employs a qualitative approach. Initially, the theoretical foundations of barriers to implementing e-commerce in Iran's paper industry were examined. Subsequently, semi-structured interviews were conducted with 10 experts and professionals engaged in paper-related industries and electronic commerce in Tehran, each with over five years of relevant experience. Following a content validity assessment by experts, a questionnaire was developed using the Delphi technique. After conducting three iterative rounds and achieving expert consensus, the barriers were classified into five categories of regulatory and institutional barriers, financial and infrastructural barriers, organizational and managerial barriers, cultural and behavioral barriers, and technological and operational barriers. Data analysis revealed a total of 46 barriers to e-commerce implementation in Iran's paper industry. Theoretically, this study enriches the literature on e-commerce adoption barriers in developing economies by providing a sector-specific model, while practically it offers policymakers and industry managers actionable strategies to overcome the structural, behavioral, and contextual challenges in Iran's paper industry.

KEYWORDS

E-commerce implementation, paper industry, structural barriers, behavioral barriers, contextual barriers.

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Introduction

E-commerce has a place in the development of digital economy. Especially in today's era of globalization and technology, using online services is becoming more and more popular. E-commerce is a concept that entered the business vocabulary in the 1970s (2024). Digitalization has become increasingly important for economic activities and economic development. E-commerce, as a part of local and international trade, is of increasing importance and is highly correlated with technological advancements and innovations (Paun et al., 2024). E-commerce, as one of the most significant technological advancements of the past two decades, has revolutionized global business practices. Its major advantages include access to new markets, expanded customer bases, streamlined supply chains, enhanced customer service, higher profitability, and reduced costs (Gregory et al., 2019). Broadly, e-commerce refers to commercial transactions conducted via communication and information systems. Although it is a relatively new phenomenon, its vital role in everyday life is indisputable (Henseler et al., 2015). Among its simplest and most effective applications is the purchase and sale of goods and the transfer of funds through smart cards. Importantly, e-commerce holds even greater potential to create value for businesses and consumers in developing countries than in developed economies (Kshetri, 2007).

E-commerce is no longer a complementary tool, but the main driver of digital economy, transforming value creation processes in various industries around the world (Ren et al., 2024). E-commerce has the potential to improve efficiency and productivity across multiple sectors and has therefore attracted increasing attention worldwide. However, skepticism persists regarding its applicability in the context of developing countries. Insufficient economic infrastructure and the absence of national Information and Communication Technology (ICT) strategies constitute major obstacles for adopting and developing e-commerce in these contexts (Lawrence et al., 2010).

The rapid expansion of the Internet has given rise to the concept and practice of e-commerce as a global reality. Internet-based economic structures and networks have become a new business paradigm, enabling individuals and organizations to benefit from the convenience of international trade. Nevertheless, many developing nations remain excluded from this transformation due to persistent barriers (Alyoubi, 2015). Organizational incompatibility is among the critical challenges, as the high costs of website development, difficulties in organizational restructuring, and lack of integration of the Internet into business strategies hinder widespread adoption (Akbari, 2005).

The analysis of e-commerce transactions highlights significant benefits, including reduced costs, faster delivery, improved service quality, expanded market coverage, quicker identification of opportunities and threats, and increased production diversity (Gibbs & Kraemer, 2004). Business growth in e-commerce is closely linked to the exchange of information among industry actors, particularly through business-to-business (B2B) commerce.

B2B e-commerce plays a particularly critical role in the paper industry, given the need for communication and information exchange between pulp and paper producers as well as in the import of raw materials. The Pulp and Paper Industry (PPI) involves the production of cellulose-based products from wood and constitutes one of the largest industrial sectors globally. Due to its substantial economic value, the PPI has become one of the world's most significant industries (Buzuku & Kraslawski, 2017).

Globally, the pulp and paper sector has witnessed rapid growth, resulting in increasing demand for raw materials. These inputs fall into three categories of wood-based, non-wood-based, and recycled wastepaper (Abd El-Sayed et al., 2020). The pulp and paper industry is considered as the fourth-largest energy-intensive industry worldwide (Santos et al., 2021). Over the recent decades, the industry has experienced notable shifts in regional and global market shares in terms of production capacity and consumption patterns. In Iran, limited domestic resources coupled with growing demand for wood and its derivatives have made imports the primary means of meeting national needs (Dashti et al., 2020). With population growth and rising consumption, the demand for paper imports is expected to increase in the coming years (Namdari et al., 2019).

Given these trends, using e-commerce is increasingly important for facilitating imports and establishing connections with other countries. Moreover, e-commerce can reduce reliance on bilateral agreements, allowing for multilateral contracts that enhance stability, sustainability, and efficiency. By minimizing unnecessary costs associated with bilateral arrangements, e-commerce also reduces expenses arising from human error while improving managerial decision-making at the firm level. Despite its importance, few studies have investigated e-commerce within the Iranian paper industry. Accordingly, this study addresses this research gap by identifying the barriers to implementing e-commerce in this sector.

Literature Review

Definition of E-Commerce

Electronic commerce, or e-commerce, is the buying and selling of goods and services or the transfer of funds or data online, enabled by platforms ranging from global marketplaces to regional portals (Ren et al., 2024). E-commerce refers to conducting processes electronically with the purpose of exchanging money, goods, services, and information (Safari, 2004). The emergence of the Internet has transformed interactions and transactions in all fieldsincluding entrepreneurial activity (Kwilinski et al., 2019). At its core, e-commerce encompasses the online purchase and sale of goods and services, as well as related domains such as electronic marketing, e-finance, e-insurance, and e-banking. Technologies such as mobile commerce, electronic funds transfer, supply chain management, Internet marketing, online transaction processing, electronic data interchange (EDI), management systems, and automated data collection all form the integral components of e-commerce. Beyond transactions, consumers frequently use the Internet as an information resource—for example, to compare prices or review new products.

E-commerce models include:

1. **Business-to-Consumer (B2C):** Direct sales from firms to individual customers.
2. **Business-to-Business (B2B):** Transactions between firms addressing other firms' needs.
3. **Consumer-to-Consumer (C2C):** Peer-to-peer exchanges where individuals sell goods directly to other consumers.
4. **Government-to-Consumer (G2C):** Government services delivered to citizens via online platforms, e.g., utilities and public services.
5. **Business-to-Employee (B2E):** Companies offering online services and products specifically for their employees.
6. **Consumer-to-Business (C2B):** Consumers collectively offering products or services to firms, often through group buying models (Rėklaitis & Pilelienė, 2019).

Barriers to E-Commerce Development

Major barriers to e-commerce adoption in developing countries include:

- Lack of legal frameworks (e.g., acceptance of electronic signatures and documents);
- Limited availability of credit cards and transfer systems for electronic funds;
- Absence of a national e-commerce backbone and related hardware;
- High initial implementation costs, particularly for SMEs;
- Lack of knowledge and cultural readiness for e-commerce;
- Inadequate security and confidentiality in transactions;
- Incompatibility of domestic debit cards with international systems;
- Restrictions on cross-border online sales due to sanctions and lack of international trust in Iranian platforms;
- Absence of domestic institutions to certify online commercial websites (Pourmehdi Borujeni & Amani, 2018).

The Paper Industry in Iran

The Pulp and Paper Industry worldwide has witnessed rapid growth, resulting in substantial demand for raw materials. These materials are generally classified into three groups of wood-based, non-wood-based, and recycled wastepaper (Abd El-Sayed et al., 2020).

The pulp and paper sector is recognized as the **fourth most energy-intensive industry (EII)** worldwide (Santos et al., 2021). Over the recent decades, it has undergone significant changes in regional and global market shares regarding its production capacity and consumption patterns. In Iran, due to limited domestic resources and rising consumption of wood and its derivatives, imports have become the primary means of meeting national demand (Dashti et al., 2020). With the increasing population and higher consumption of paper products, the demand for imports is expected to rise further in the coming years (Namdari et al., 2019).

A study conducted in Iranian oil and gas industry revealed that advanced information and communication technology and e-commerce can create significant economic changes in the oil and gas industry. For this reason, Iran's government has realized the importance of using e-commerce in most industrial fields, but due to specific problems, such as legal, cultural, logistical and infrastructure problems, the use of e-commerce in manufacturing sectors has not been completely possible. In the study of the current situation, it was found that e-commerce in industry faces several problems, but if the obstacles to the establishment and development of e-commerce are removed, then the benefits of using e-commerce will accrue to this industry (Ali Ahmadi, & Hoor Ali, 2005). Research indicates that the most influential factors driving increased paper imports in Iran are Gross Domestic Product (GDP) and the volume of harvested timber from the northern forests. Additionally, exchange rates, import prices (beyond government control), and economic sanctions strongly affect the industry. These findings highlight the urgent need to strengthen the domestic paper production through greater investment and capacity building. Moreover, given the declining timber production in Iranian forests due to environmental concerns and the legal ban on logging, wood cultivation initiatives are necessary. Attention to these measures could significantly reduce paper imports and prevent foreign currency outflow under sanction conditions (Dashti et al., 2020).

Research background

In this section, the prior studies are reviewed. Based on the researcher's knowledge, although no study has been conducted using the same model used in the present research study, several studies have examined the relationships between at least two of the variables included here.

Table 1.
A Summary of Previous Research

	Authors & Year	Title	Objectives	Findings
1	Rathee & Chandraprakash (2017)	Barriers to e-commerce in developing countries	To examine barriers to e-commerce adoption in developing countries	The level of adoption is constrained by numerous factors such as unreliable infrastructure, lack of governmental policy frameworks, absence of banking facilities (e.g., credit cards), and lack of awareness regarding the benefits of e-commerce. Education level, limited access to IT, insufficient skills, and low penetration of personal computers and telephones further hinder the adoption. Despite these barriers, developing countries still hold great potential for e-commerce as a development tool.
2	Zaied (2012)	Barriers to e-commerce adoption in SMEs in Egypt	To identify barriers to e-commerce adoption in SMEs in Egypt	The study emphasizes the need to accelerate e-commerce adoption. Security and privacy were highlighted as top priorities. Developing unified strategic plans for e-commerce projects was considered essential. Cultural and social structures specific to Egypt should also be addressed to raise awareness and encourage acceptance of e-commerce and related services.

	Authors & Year	Title	Objectives	Findings
3	Amirkhani & Motaghi (2011)	Barriers and solutions for implementing e-commerce in insurance industry (case study: Asia Insurance Company)	To examine the relationship between structural, behavioral, contextual, and essential factors with the lack of e-insurance development	Structural factors were significantly related to the underdevelopment of e-insurance. These included weak performance of executive and coordinating bodies, poor organizational structures, technological deficiencies, and insufficient budgets. Weakness in one factor led to underdevelopment in others.
4	Mahmoudi Meymand et al. (2011)	Barriers to e-commerce adoption in dried fruit export industry (case study: East Azerbaijan Province)	To identify barriers with the greatest impact on e-commerce rejection among export-oriented SMEs	The most important barriers included lack of efficient alternatives for payment systems (letters of credit), issues with multilingual websites and marketing, deficiencies in e-banking systems, lack of buyer's trust in product quality, delivery, and added value, shortage of expert staff in consulting, designing, training, and implementing e-commerce, lack of top management support, absence of standards between buyers and sellers, ambiguity in government regulations, weak international agreements, and inadequate security frameworks.
5	Ali Ahmadi, & Hoor Ali(2005)	Studying the status of using information technology and e-commerce in Iran's oil and gas industry	Examining the applications of e-commerce in oil and gas industry and the level of readiness of this industry	E-commerce in industry faces several problems, but if the obstacles to the establishment and development of e-commerce are removed, then, the benefits of using e-commerce will accrue to this industry.
6	Seidi (2024)	Designing a model to improve the behavior of Iranian handicrafts e-commerce customers by increasing the customer trust	To design a model for improving the behavior of Iranian handicrafts e-commerce customers by increasing the customer trust	In the quantitative phase, a four-level model was obtained. The most effective indicator of this model is electronic communication and interaction with customers. Also, its most effective indicator at the seventh level is confidence in purchasing. Therefore, other criteria also play the role of interface factors in this model.

(Source: Researcher's Findings)

A review of the existing research reveals that the issue of e-commerce has been studied in some industries, but earlier studies have not specifically addressed the issue of e-commerce within the paper industry. This absence highlights a research gap, which the present study aims to fill by identifying and analyzing the barriers to e-commerce implementation in Iran's paper sector.

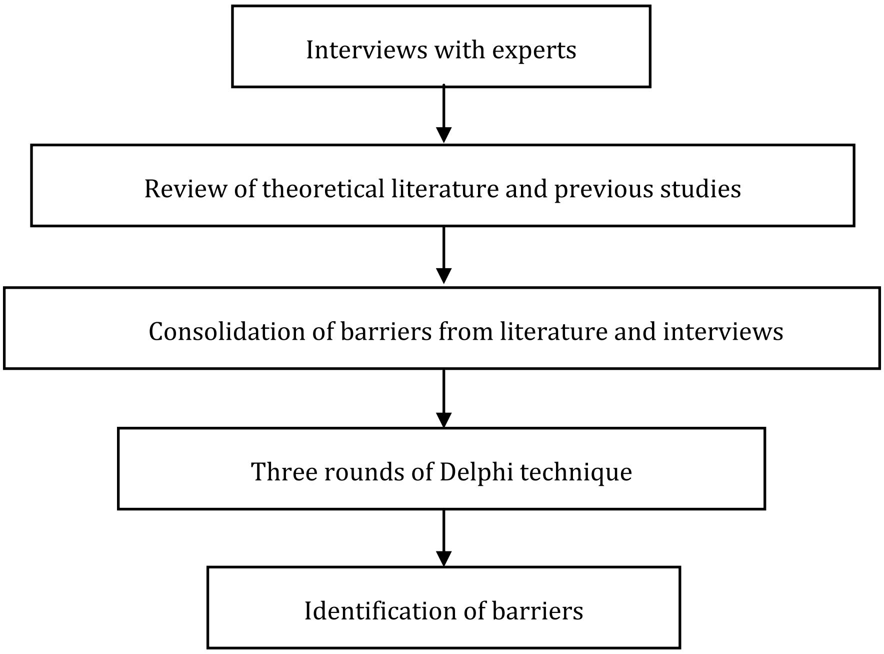
Methodology

This study adopts a qualitative and exploratory research design. The statistical population consists of specialists and experts in paper industry and e-commerce in Tehran. They are active in this field, each with at least five years of relevant experience.

The sample size reached the theoretical saturation of 10 people using a non-random purposive sampling method. Semi-structured interviews were conducted either through telephone conversations or via WhatsApp.

To identify the barriers, initially the potential barriers were extracted from the literature review and interviews. These items were then validated by experts to ensure their content validity. Then, the Delphi technique was employed. The purpose of using the Delphi technique is to refine and identify the importance of extracted barriers. In three iterative rounds, the experts were asked to rate and refine the identified barriers until consensus was achieved. Ultimately, the barriers were classified into five major categories.

Figure 1.
Stages of the Research Process



(Source: Researcher's Findings)

To ensure the **validity and reliability** of the qualitative research (thematic analysis), the following strategies were employed (Creswell & Miller, 2000):

1. **Member checking:** Five experts (including a commercial officer, a senior business consultant, a sales manager, a board member, an IT manager, a business supervisor, and an analyst) reviewed the initial analysis and coding results and their feedback was incorporated.
2. **Peer review:** Three specialists in paper industry reviewed the coding and their recommendations were integrated into the model development.
3. **Participatory approach:** Participants were involved simultaneously in the analysis and interpretation of data.
4. **Triangulation:** The study employed methodological and participant triangulation. Interviews were conducted with both e-commerce experts and paper industry professionals, covering diverse organizational roles and backgrounds.

Thematic analysis was conducted using **MAXQDA (version 12)**. To validate the Delphi process and assess the consensus, **SPSS (version 25)** was used, employing **Kendall's coefficient of concordance**.

Table 2.
Sample Quotes from the Interviewees and Extracted Codes

Participants' Quotes	Initial Themes
"There is a lack of a comprehensive framework for regulatory arrangements".	Absence of a comprehensive regulatory framework
"There are unresolved disputes in the field of e-commerce within the paper industry".	Existence of disputes in paper industry e-commerce
"The absence of laws on financial and credit information disclosure creates insecurity".	Lack of laws for financial and credit information disclosure
"The absence of clear regulations for ensuring transparency in contractual obligations is a barrier".	Lack of clear and enforceable contract transparency regulations
"The initial cost of e-commerce infrastructure is extremely high".	High infrastructure costs
"Despite cost-benefit considerations, management decisions tend to focus only on costs without considering long-term benefits".	Cost-centered decision-making

(Source: Researcher's Findings)

Finding

Each of the experts expressed the obstacles to implementing e-commerce in paper industry in Iran. By examining the quotes, related themes were created. Table 3 presents the main themes and sub-themes of barriers to implementing e-commerce in Iran's paper industry, based on the participants' perspectives.

As shown in Table 3, the barriers to e-commerce implementation were categorized into five groups, based on expert consensus from the Delphi method, with 53 identified codes.

Following the identification of barriers, the **Content Validity Ratio (CVR)** was applied. Using the Delphi technique in three stages, the questionnaire was refined from 53 to 48 items, retaining only those items that achieved acceptable CVR scores.

By the third Delphi round, the **Kendall's coefficient of concordance** reached **0.808 (~81%)**, exceeding the 70% threshold, and was statistically significant ($p < 0.01$). This demonstrated substantial consensus among experts. Additionally, one-sample t-tests confirmed that the mean values of all items were significantly higher than the neutral midpoint (3 = "moderate" in the questionnaire).

Table 4 shows the final list of 46 themes that were confirmed from the 53 themes in the Delphi research process and prioritized based on the importance.

Table 3.
Barriers to E-commerce Implementation in Iran's Paper Industry

Main Themes	Sub-Themes (Barriers)	Participant Code
Regulatory & Institutional Barriers	Weakness in comprehensive regulatory frameworks	1,2,4,8
	Existence of disputes in e-commerce	1
	Weakness in laws regarding financial and credit information disclosure	1,2,4,6,7,10
	Low consistency between laws and capabilities	3
	Laws developed based on personal discretion	3
	Weakness in buyer–seller regulations	7
	Weakness in electronic case personalization	9
	Government mismanagement in paper industry	2
	Extensive attempts to restrict the Internet access	4
	Lack of coordination between buyers and sellers	5
	Weak integration into the global value chain	4
Financial & Infrastructural Barriers	High infrastructure costs for e-commerce	1,6,8
	Misallocation of investments	1
	High costs in e-commerce industry	7
	Inadequate commercial infrastructure	3
	Lack of operational infrastructure for e-commerce	5
	Weak technical infrastructure in paper industry	5
	Low investment risk tolerance	4
	High risk in profits and losses in e-commerce	2,8
Organizational & Managerial Barriers	Inadequate performance evaluation	3
	Lack of training for senior managers	3
	Weak training for operational staff	3,5,4,10
	Over-reliance on trial-and-error learning	3,5,9,4,10
	Low managerial awareness	3,10
	Weak managerial culture regarding e-commerce	3
	Weak managerial risk-taking ability	3
	Poor time management in operations	10
	Low levels of stakeholders' dialogues	7
	Insufficient managerial welfare facilities	5
	Lack of maturity in e-commerce within the industry	6
	Minimal changes in economic return models	5
Cultural & Behavioral Barriers	Low level of public awareness	2,6,7,10
	Low awareness among operational staff	4
	Dependence on traditional (paper-based) methods	5
	Low level of trust between buyers and sellers	2
	Low level of national awareness and culture of e-commerce	2
	Low level of digital literacy of operational staff	9
	Poor digital culture among operational staff	9
	High average age of population	1,2,8
	Low valuation of time in society	1
	Lack of time-saving practices	6
	Limited use of modern trade methods	1
	Lack of consensus among investors	6
	Low level of trust among investors	2
Technological & Operational Barriers	Lack of automation in operations	3
	Weak documentation of customer information	3,9
	Low transparency	4,10
	Process complexity	5
	Inefficient user services	5,9
	Limited use of modern data processing software	3,6
	Insufficient electronic services	8
	Weak utilization of digital tools for service provision	6,10
	Limited adoption of new technologies	5

(Source: Researcher's Findings)

Table 4.
Final Barriers to E-commerce Implementation in Iran's Paper Industry

	Barriers to E-commerce Implementation in Iran's Paper Industry
1	Weakness in comprehensive regulatory frameworks
2	Existence of disputes in e-commerce
3	Weakness in laws on financial and credit information disclosure
4	Laws developed based on personal discretion
5	Weakness in electronic case personalization
6	Poor documentation of customer information
7	Low transparency
8	Complex processes
9	High costs of e-commerce infrastructure
10	Misallocation of investments
11	High operating costs in e-commerce
12	Lack of training for senior managers
13	Weak training for operational staff
14	Over-reliance on trial-and-error training
15	Inadequate commercial infrastructure
16	Lack of operational e-commerce infrastructure
17	Weak technical infrastructure
18	Inefficient user services
19	Insufficient electronic services
20	Weak use of digital tools for service delivery
21	Low level of public awareness
22	Low level of managerial awareness
23	Low level of operational staff awareness
24	Dependence on traditional (paper-based) methods
25	Low level of buyer–seller trust
26	Lack of investor consensus
27	Low level of investors' trust
28	High average age of population
29	Minimal adoption of modern trade
30	Government mismanagement in paper industry
31	Extensive Internet restrictions
32	Lack of buyer–seller coordination
33	Lack of maturity in e-commerce
34	Low valuation of time in society
35	Lack of time-saving practices
36	Poor time management by staff
37	Low level of national e-commerce awareness and culture
38	Weak digital literacy of operational staff
39	Weak managerial culture in e-commerce
40	Weak digital literacy of staff
41	High profit/loss risk in e-commerce
42	Low level of investment risk-taking
43	Low level of managerial risk tolerance
44	Limited adoption of new technologies
45	Low levels of stakeholders' dialogues
46	Insufficient managerial welfare facilities

(Source: Researcher's Findings)

The structural barriers include weaknesses in infrastructure, lack of adequate digital platforms, absence of integrated databases, limited access to reliable Internet services, high costs of technology implementation, and insufficient legal support for e-commerce transactions.

Behavioral barriers relate to human factors such as resistance to change, low motivation among managers and employees, lack of trust in online transactions, and limited awareness of the benefits of e-commerce.

Contextual barriers involve broader environmental and institutional challenges, including economic instability, insufficient government support, legal uncertainties, sanctions, lack of international cooperation, and weak financial and banking systems.

Overall, the findings suggest that structural and contextual barriers exert a stronger influence than behavioral ones in hindering the adoption of e-commerce in Iran's paper industry.

Discussion

Given the paper industry's reliance on imports of raw materials and international trade, e-commerce could serve as a powerful tool for improving efficiency, reducing costs, and expanding global partnerships. However, unless structural deficiencies and contextual barriers are addressed, the potential of e-commerce in this sector will remain underutilized.

The present study made an attempt to identify the barriers to implementing e-commerce in in Iran's paper industry. Initially, the barriers to implementing e-commerce in in Iran's paper industry were studied from the viewpoint of theoretical foundations. Subsequently, interviews were conducted with the experts, and using the results of these interviews and implementing content analysis, the barriers to implementing e-commerce in Iran's paper industry were extracted and categorized. Having assessed the validity and reliability of the content analysis section, a questionnaire was prepared for the first stage of the Delphi technique. Finally, after conducting three stages of the Delphi technique and reaching a consensus among experts regarding the barriers to implementing e-commerce in in Iran's paper industry, the barriers were presented in five sections.

The results of this study confirmed the existence of multifaceted barriers to implementing e-commerce in Iran's paper sector. Structural obstacles, such as inadequate ICT infrastructure and high technology costs, remain critical. These findings align with previous studies emphasizing the importance of infrastructure readiness as a prerequisite for successful e-commerce (Alyoubi, 2015; Lawrence et al., 2010).

Behavioral barriers also play a role, albeit to a lesser extent. The reluctance of industry stakeholders to shift from traditional practices to digital solutions reflects the persistence of cultural and attitudinal constraints. However, as international experience shows, behavioral resistance can often be overcome through training, holding awareness programs, and showcasing the tangible benefits of e-commerce (Gibbs & Kraemer, 2004).

Contextual barriers are perhaps the most formidable barriers in Iran. Economic sanctions, international trade restrictions, and the incompatibility of Iranian banking systems with global financial networks have severely limited the growth of e-commerce in paper industry. In this regard, the Iranian case illustrates how political and institutional conditions can hinder technological adoption, even when structural and behavioral readiness is partially present.

Conclusion

This study set out to identify the barriers hindering the adoption of e-commerce in Iran's paper industry. Using the Delphi method, 46 barriers were identified and classified into five categories of regulatory and institutional barriers, financial and infrastructural barriers, organizational and managerial barriers, cultural and behavioral barriers, and technological and operational barriers. The results highlighted that contextual and structural barriers pose the greatest challenges.

Based on the research findings and identification of barriers to e-commerce implementation in Iran's paper industry, the following practical strategies are proposed:

1. **Strengthening Legal and Regulatory Frameworks**
    - Establish a comprehensive, transparent, and unified legal system for digital transactions.
    - Develop clear and enforceable laws concerning financial and credit information disclosure.
    - Eliminate ambiguities in regulations and reduce reliance on personal discretion in lawmaking.
    - Ensure continuous updates of regulations to align with global standards in e-commerce.
2. **Enhancing Infrastructure**
    - Invest in upgrading technical and operational infrastructures of the paper industry.
    - Reduce the high initial costs of establishing e-commerce platforms through government subsidies, tax incentives, or public–private partnerships.
    - Expand the use of digital tools and modern software for data management, customer relationship management, and online transactions.
3. **Capacity Building and Training**
    - Organize targeted training programs for senior managers to raise their awareness about the strategic role of e-commerce.
    - Provide operational training for employees to improve their digital literacy and reduce their dependence on trial-and-error learning.
    - Promote a culture of continuous professional development in digital commerce across all organizational levels.
4. **Promoting Awareness and Cultural Readiness**
    - Conduct national campaigns to raise awareness regarding the benefits and opportunities of e-commerce among the general public.
    - Encourage media, universities, and professional associations to play a more active role in fostering digital literacy.
    - Cultivate a cultural shift that emphasizes time management, efficiency, and trust in digital interactions.
5. **Building Trust and Reducing Risks**
    - Establish mechanisms for consumer protection, including secure payment

    systems, dispute resolution centers, and transparent service guarantees.
  - Develop certification and accreditation systems for commercial websites to enhance credibility and trustworthiness.
  - Encourage insurance companies to offer risk coverage for e-commerce transactions.

6. **Improving Governmental Support and Policy Alignment**
   - Ensure greater government coordination and effective management in paper industry, particularly in supporting the technological adoption.
   - Remove unnecessary restrictions on the Internet access that hinder e-commerce development.
   - Facilitate Iran's integration into the global e-commerce value chain through international agreements and partnerships.
7. **Encouraging Investment and Innovation**
   - Create financial incentives for investors to engage in e-commerce projects within the paper industry.
   - Foster innovation by supporting startups and SMEs working in digital trade solutions for the industry.
   - Promote the adoption of emerging technologies such as Blockchain, AI-based platforms, and Big Data Analytics.

By addressing these barriers, Iran's paper industry can move toward digital transformation, improving its competitiveness and sustainability in both domestic and international markets.

Limitations and Future Research Directions

The limitations of this study are as follows:

1. Since the study is qualitative, the generalizability of the findings should be approached with caution.
2. The study population was limited to experts, specialists, and authorities in paper and e-commerce sectors. Including opinions of active industry practitioners could have further enriched the identification of barriers.
3. The study could not control certain unrelated or confounding variables such as response motivation, fatigue during participation, or some external factors affecting the participants.
4. Another limitation is the scarcity of domestic research on barriers to e-commerce adoption.

Research Recommendations

Future researchers are advised to employ semi-structured interviews to obtain more precise results. It is recommended that future studies examine user experiences in conducting e-commerce activities to gain insights into mental models and practical experiences that can enhance the status of e-commerce in the country. Some research suggestions are presented here.

- Design and Implementation of a Specialized E-Commerce Platform for Iran's paper industry: A Case Study Based on the Needs of Producers, Distributors, and End Users;
- The Impact of E-Commerce on Reducing Supply Chain Costs in Paper Industry;
- Analysis of Success Factors and Barriers to E-Commerce Adoption in Small and Medium-Sized Paper Manufacturing Firms in Iran: An Integrated TAM-TOE Model.

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A Bibliometric Analysis of Text Mining Applications in Knowledge Management

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ABSTRACT

Despite the growing importance of text mining in knowledge management, a comprehensive analysis of its evolution, key contributors, and emerging trends has remained limited. This study addresses this gap by conducting a bibliometric analysis of the field from 2003 to 2023, focusing on long-term trends, influential actors, and thematic shifts. To this end, a scientometric analysis was conducted using data sourced from the Web of Science database. By applying filters for publication year, language, and document type, 590 documents were selected for analysis. Co-occurrence and co-authorship analyses were performed using VOSviewer to visualize the scholarly contributions and thematic developments. The study revealed notable publication growth, particularly after 2019. Prominent authors such as Rafael Valencia-Garcia and Francisco Garcia-Sanchez, along with leading institutions like the Chinese Academy of Sciences and Tsinghua University, were identified as major contributors. China stood out as the leading country in terms of publication numbers and citation impact. Ji Luo's (2015) paper entitled "Transfer Learning Using Computational Intelligence: A Survey" emerged as the most cited work. Key areas of focus included natural language processing, information extraction, and deep learning, demonstrating the increasing influence of technological innovations on the field. This work provides a detailed bibliometric overview of text mining applications in knowledge management, highlighting significant trends, leading researchers, and core topics. It offers actionable insights for scholars and practitioners to navigate and contribute to this evolving area of study.

KEYWORDS

Bibliometrics, Co-authorship Analysis, Co-occurrence Analysis, Knowledge Management, Text Mining.

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Introduction

In today's economic environment, organizations are transitioning from traditional resource-based models to knowledge-based approaches. This shift highlights the critical role of knowledge as a strategic asset, emphasizing the need for effective acquisition, production, integration, and application of knowledge to boostinnovation and organizational success (Ahmadi et al., 2021). With the rise of the digital economy, organizations are inundated with vast amounts of text-based information, such as reports, customer feedback, and research notes. The rapid growth of textual data, driven by the expansion of the Internet, underscores the necessity of advanced text-based information retrieval methods (Kushwaha et al., 2021).

To address these challenges, text mining has emerged as a transformative tool for knowledge management (KM). Recent advancements in natural language processing (NLP) and machine learning have expanded text mining's capabilities, enabling organizations to uncover latent patterns, trends, and insights from unstructured data (Hirschberg & Manning, 2015). This technological evolution aligns with the growing demand for data-driven decision-making in KM.

To improve performance and service quality, organizations must transform unstructured textual data into actionable insights, a process facilitated by text mining techniques. Text mining, a powerful method for analyzing unstructured data, involves extracting key concepts, keywords, and topics from extensive text corpora (Antons et al., 2020). This technique is particularly valuable in the field of knowledge management, where it helps in organizing and leveraging textual information effectively. For instance, applications range from automated knowledge extraction in healthcare (Chen et al., 2022) to sentiment analysis for customer (Wang et al., 2024).

The rapid increase in scientific publications has led to "scientific overload", making it challenging for researchers to manage and review the growing body of literature (Cardona, 2025). In this context, bibliometric methods provide valuable insights by systematically analyzing scientific outputs (Abdian et.al, 2023). Bibliometric analysis of indexed articles in reputable databases helps track research trends, collaboration patterns, and emerging topics, offering a comprehensive view of the evolution of research fields. While text mining has revolutionized the extraction of insights from unstructured data, its specific applications and intellectual landscape within KM have remained systematically unexplored (Nourahmadi, 2024). While prior reviews have examined text mining or KM in isolation, few studies have systematically mapped their intersection using bibliometrics. This gap motivates our study, as a holistic analysis can reveal synergies and opportunities for interdisciplinary innovation (Yang et.al, 2023). Despite significant growth in knowledge management research over the past three decades, few studies have applied comprehensive bibliometric analysis to examine the scientific production in this field (Farooq, 2024).This gap limits our understanding of the field's evolution, key contributors, and emerging opportunities for innovation.

Given the rising interest in KM and text mining, and the diverse definitions of these concepts across studies, a bibliometric analysis is crucial for clarifying their interrelation. This study specifically addresses the following research question: "How has the application of text mining in KM evolved bibliometrically, and what are the emerging patterns, knowledge gaps, and future directions in this interdisciplinary field?"

This study aims to conduct a bibliometric analysis of text mining applications within KM using data from the Web of Science, covering the period from 2003 to 2023. The primary goal is to map and analyze the scientific landscape of this intersection. Secondary objectives include identifying publication trends, prominent authors and their collaboration networks, leading research institutions and countries, highly cited articles, and key research clusters and topics. By doing so, this study provides a foundation for future research and practical applications in KM-driven text mining solutions. By mapping these elements, this study seeks to provide valuable insights for researchers and policymakers, aiding in the development of informed strategies and effective approaches to advancing KM through text mining.

Literature Review

KM is a vital field within organizations, established to leverage intellectual assets, enhance decision-making processes, and boost innovation. With the rapid expansion of textual data in recent decades, extracting meaningful information from text has become an increasingly precise and significant approach. This is especially relevant in today's information technology-driven environment (Hirschberg & Manning, 2015). Building upon this foundation, this study explores how artificial intelligence (AI) acts as a pivotal tool in the marketing domain to operationalize these KM objectives. It investigates how AI technologies leverage the expansion of textual data to extract meaningful insights, thereby enhancing decision-making, personalization, and overall marketing effectiveness within a knowledge-driven framework (Marvi et al., 2025).

KM systematically captures, creates, analyzes, and shares organizational knowledge to enhance productivity and achieve strategic objectives (Ali, 2020). Text mining has become a core enabler of modern KM systems (Hashemi et al., 2018). Its applications span:

1. Automated Knowledge Discovery: NLP techniques (e.g., topic modeling, named entity recognition) extract latent themes from unstructured corpora, accelerating insight generation (Jiang et.al., 2025).
2. Decision Support: Sentiment analysis and trend detection from textual feedback improve strategic agility (Elahi et.al, 2011)

KM has emerged as a critical discipline for leveraging intellectual assets, with demonstrated benefits across: (1) organizational decision-making, (2) innovation capacity, (3) customer service quality, and (4) human capital development through knowledge retention and employee empowerment (Gupta & Chopra, 2018). To implement KM, organizations use a variety of tools such as knowledge repositories, collaboration platforms, and data mining systems, which collectively streamline the creation, dissemination, and application of information across organizational boundaries (Mittal & Kumar, 2019).

Given the predominance of textual data, text mining has become indispensable for extracting actionable insights from unstructured content. Advanced NLP techniques now enable organizations to transform raw text into strategic knowledge assets, directly enhancing operational performance (Antons et al., 2020). Given the predominance of textual data, text mining has become indispensable for extracting actionable insights from unstructured content. This study leverages advanced AI and NLP techniques to analyze AI-supported student engagement (AIsE) research, demonstrating AI's role as a strategic knowledge asset for enhancing behavioral, cognitive, and emotional engagement in education (Chen et al., 2025).

The exponential growth of text mining applications in KM has generated vast scholarly output. Bibliometric analysis systematically maps this knowledge domain by: (1) quantifying publication trends, (2) identifying intellectual networks, and (3) revealing emerging research fronts (Zupic & Čater, 2015). This approach enables researchers to navigate the field's conceptual structure and evolution (Leung et al., 2017).

Traditionally, researchers have employed two main methods to review prior findings: qualitative approaches like structured literature reviews, and quantitative approaches like meta-analysis (Schmidt, 2008). More recently, bibliometric methods have emerged as a third paradigm, enabling large-scale analysis of scientific literature using computational techniques (Donthu et al., 2021).

In our research, we applied co-word and co-authorship analyses. The co-authorship analysis examines the social networks of researchers to reveal their collaborative patterns, while the co-word analysis uses the words within documents to map the conceptual structure of the domain. These methods facilitate a deeper understanding of the literature, providing insights for evaluating past publications and developing new strategies (Zupic & Čater, 2015).

Research Background

Numerous studies from the 2000s onward have examined KM applications, employing diverse methodologies. A seminal example is the global bibliometric analysis by Gaviria-Marin et al. (2019), which utilized VOSviewer-based science mapping and performance metrics to trace KM research evolution. Their study identified key research clusters such as data analysis and bioinformatics, highlighted a dominant geographical trend of U.S. leadership in publications, and pointed out a major methodological gap in the limited integration of text mining techniques (Gaviria-Marin et al., 2019).

Similarly, Abbas et al. (2021) employed Publish or Perish software for a bibliometric analysis of KM literature from 2015 to 2021. Their analysis highlighted that the highest number of citations and related articles appeared in 2017 and 2019 (Abbas et al., 2021). In another study, Idrees et al. (2023) analyzed articles related to KM and new product development using data from Scopus and Web of Science, utilizing statistical tools such as R Studio and VOSviewer. They found that KM plays a crucial role in high-tech companies and significantly contributes to more efficient new product development (Idrees et al., 2023).

Khan et al. (2024) also conducted a bibliometric analysis within the realm of information science, employing VOSviewer to simulate projections of knowledge management. Their results indicated ongoing improvements in citation and publication structures within the field (Khan et al., 2024).

Analyzing the applications of text mining in KM is critical for driving innovation and organizational development. Di Vaio et al. (2020) performed a bibliometric review of 115 articles from 2006 to 2020, focusing on the impact of disruptive technologies on intangible factors. Their study emphasized that most research studies centered on intellectual capital, integrated reporting, and integrated thinking, underscoring the importance of leveraging KM systems to enhance intellectual capital and digital innovation (Di Vaio et al., 2020).

Li et al. (2024) conducted a bibliometric analysis and literature review to map knowledge related to corporate value. By analyzing data from the Web of Science database from 2000 to 2022, they observed an increased focus on corporate value, with a notable presence of independent authors. Emerging topics such as corporate social responsibility (CSR) and sustainability were also highlighted (Li et al., 2024).

In a study by Huang (2022), 109 articles related to "tourism officials" were collected from the Web of Science. Using machine learning tools, network analysis, and VOSviewer, the study examined top researchers, keywords, and collaboration networks. Additionally, text analysis and the BERT AI model were employed to predict study topics. The results showed that the articles predominantly focused on three main keywords: "officials", "culture", and "heritage", and the author collaboration network primarily involved researchers from five countries (Huang, 2022).

Based on this research, it can be concluded that bibliometric techniques, such as those using VOSviewer, are effective for analyzing and systematically reviewing literature across various fields. These analyses enhance our understanding of key terms and concepts, highlighting strengths and weaknesses in different topics. However, a significant literature gap exists in the specific bibliometric analysis of text mining applications within KM. While some bibliometric studies have been conducted in broader domains, none have comprehensively mapped the intellectual structure and evolution of this particular intersection. They assist organizations and researchers in making informed decisions and reflect significant progress in text mining techniques and the growing importance of KM as a competitive advantage. Therefore, a dedicated bibliometric study is essential to address this gap. Such a study would identify conducting bibliometric analyses of related texts and documents is essential for gaining deeper insights into the applications of text mining in KM. Research clusters that were previously unexamined, tracking emerging trends, and analyzing collaboration patterns provide valuable insights. Such analyses deliver a holistic perspective on trends and essential factors, allowing organizations and researchers to better leverage text mining to refine KM practices, foster innovation, and improve organizational performance.

Research Methodology

Research methodology encompasses the systematic techniques and procedures used to collect, analyze, and interpret data to address research questions or objectives. It provides a framework for conducting empirical studies (Leavy, 2022). This study employs a quantitative, bibliometric approach, focusing on a descriptive analysis with an emphasis on publication metrics and citation analysis.

The initial stages of this research followed the PRISMA statement, which includes key steps such as database selection, search strategy, and criteria for including or excluding studies (Moher et al., 2009). This approach allowed for the development of a comprehensive database necessary for implementing scientific mapping methods. While many global research databases categorize research records, we selected the Web of Science for its high-quality standards and extensive metadata, including abstracts, references, citation counts, author lists, institutions, countries, and journal impact factors (Carvalho et al., 2013; Merigó et al., 2015).

To conduct the search in Web of Science, we used the Advanced Search feature on April 2, 2024. The search strategy included the following keywords to filter relevant documents:

- Knowledge management: ("knowledge manage*" OR "organization* knowledge*" OR "knowledge acquisiti*" OR "knowledge creati*" OR "knowledge integrati*" OR "knowledge transfer*" OR "knowledge shar*" OR "knowledge diffus*" OR "knowledge spill*" OR "knowledge use*" OR "knowledge applicat*")
- Text mining: ("text mine*" OR "text analy*" OR "natural language process*" OR "information extract*" OR "text classif*" OR "text cluster*" OR "sentiment analy*" OR "named entity recognit*" OR "topic model*" OR "text summariz*")

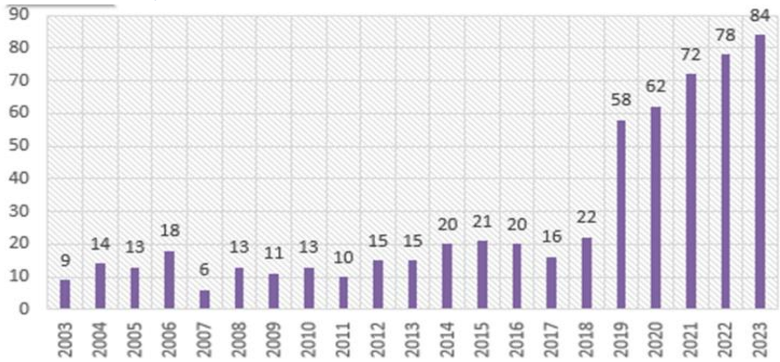
After applying filters for the period 2003-2023, language (English), and document types (articles, reviews, notes, and letters), a total of 590 articles were selected. These were extracted in text format from Web of Science and converted into Excel for further processing. The data were also imported into VOSviewer for visualization. VOSviewer was chosen for its ability to create clear graphical representations of network nodes, where node size and line thickness represent the strength and intensity of connections (van Eck & Waltman, 2010).

Findings

1. Identification of Publication Trends and Growth Rate in the Field of Text Mining Applications in KM

Figure 1 shows a general upward trend in the number of published documents in this field over time, with the lowest count of six documents in 2007 and the highest of 84 documents in 2023. The average annual growth rate is 20.02%, while the compound annual growth rate (CAGR) is 9.3%.

Figure 1.
The Number of Articles Published by Year



(Source: Researcher's Findings)

2. Identification of the Most Productive Authors and Their Scientific Collaboration Network in the Field of Text Mining Applications in KM

Table 1 presents the top 10 most prolific authors in this research area. Rafael Valencia-Garcia and Francisco Garcia-Sanchez lead with seven and six publications, respectively. Additionally, Sanchez David and Batet Montserrat have achieved the highest citation counts for their works, with 331 and 306 citations, respectively.

Table 1.
Active authors in the field of research

Number of citations	Number of articles	Author Name	rank
153	7	Valencia-Garcia, Rafael	1
141	6	Garcia-Sanchez, Francisco	2
56	4	Li, Ming	3
331	4	Sanchez, David	4
77	4	Moens, Marie-Francine	5
58	3	Li, Rita Yi Man	6
58	3	Song, Lingxi	7
58	3	Yao, Qi	8
306	3	Batet, Montserrat	9
32	3	Wang, Li	10

(Source: Researcher's Findings)

Figure 2 depicts the authors co-authorship map in three distinct clusters. To construct this network, authors with a minimum of two shared articles were considered, resulting in 105 authors, out of which 10 authors were capable of forming networks. Each node represents an author, with its size indicating the frequency of collaboration. The edges between nodes illustrate collaboration, where closer proximity indicates stronger collaboration. Cultural background, geographical localization, and language preferences are factors influencing collaboration patterns in authorship (Schubert & Schubert, 2020). Each circle's color represents the cluster to which authors belong.

Introduction of researchers in each cluster was conducted based on the significance of collaboration among them. For instance, in the first cluster highlighted in red, four prominent authors include Wang Deqing, Wu Junjie, Zhang Hui, and Zhang Wenjie. In the second cluster marked in green, three notable authors are Chen Enhong, Meng Xianhai, and Wang Hao. Lastly, in the third cluster, Shi Zhongzhi, Xiong Hui, and Zhuang Fuzhen are members. This network aids researchers in understanding existing collaborations and identifying potential collaborators.

Figure 2.
Authors Co-authorship Map

(Source: Researcher's Findings)

3. Identification of Active Countries and Their Co-Authorship Networks in the Field of Text Mining Applications in KM

Table 2 highlights the leading countries in research on text mining applications in KM. China is the top contributor with 166 documents, followed by the United States, Spain, and the United Kingdom, listed in descending order of document count. Regarding citation impact, the United States leads with 2,317 citations, with China, Australia, Spain, and the United Kingdom following, respectively. These figures indicate the significant influence and productivity of these countries in the field.

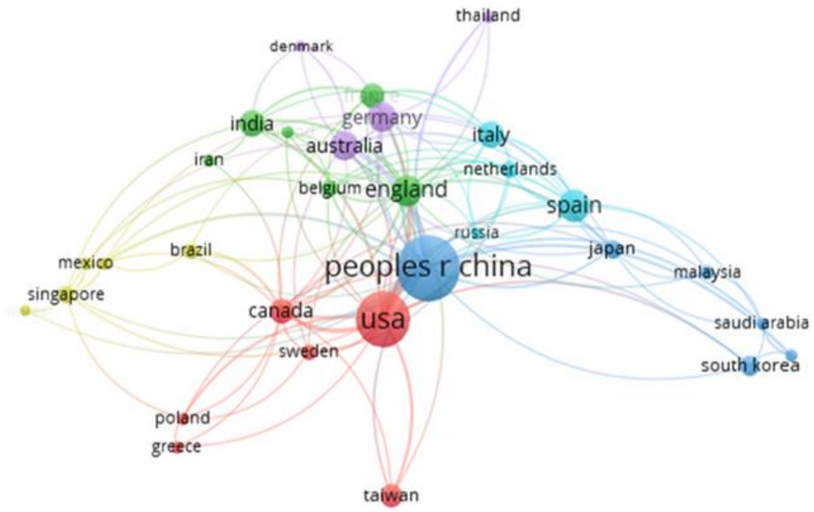
Table 2.
Active Countries in the Field of Text Mining Applications in KM

Number of citation	Number of documents	Country	Rank
1939	166	China	1
2317	120	America	2
1104	44	Spain	3
994	39	England	4
1312	35	Australia	5
703	34	Germany	6
212	28	India	7
449	27	Italy	8
957	25	Canada	9
474	24	France	10
401	22	Taiwan	11
340	16	South Korea	12
180	14	Japan	13
166	12	Belgium	14
201	12	Netherlands	15
321	12	Singapore	16
160	11	Brazil	17
280	10	Sweden	18
196	9	Malaysia	19
132	7	Saudi Arabia	20
151	7	Thailand	21
93	7	Iran	22
125	6	Scotland	23
28	6	Russia	24
93	6	Poland	25

(Source: Researcher's Findings)

Figure 3 illustrates the co-authorship network among countries in the field of text mining applications in KM. This map was generated by including only countries with at least five articles, resulting in a network of 31 countries. It highlights the collaborative relationships between nations, which facilitates cross-border partnerships and helps researchers identify existing collaborations and potential partners. The network is divided into six clusters, with China, the United States, the United Kingdom, Australia, and Canada exhibiting the highest levels of international collaboration. The clusters are defined as follows: Cluster 1 encompasses the United States and Canada; Cluster 2 includes the United Kingdom, France, and India; Cluster 3 features China and Japan; Cluster 4 consists of Scotland and Singapore; Cluster 5 includes Australia and Germany; and Cluster 6 comprises Spain and Italy. These clusters underscore the significant roles of these countries in fostering international collaboration within their respective groups.

Figure 3.
Co-authorship Network of Countries



(Source: Researcher's Findings)

4. Identifying the Most Active Universities and Research Centers and their Scientific Cooperation Network in the Field of Text Mining Applications in KM

Table 3 shows the list of the most productive research institutes in KM. According to this table, the research centers of Chinese Acad Sci and Tsinghua Univ are the most active institutions in terms of degrees with 11 and 10 documents respectively. Also, in terms of the number of citations, University of Technology Sydney and University of Toronto have the highest number of citations, with 761 and 402 citations, respectively.

Figure 4 illustrates the involvement of universities and research organizations that have published at least three articles in the field. The map identifies 45 institutions, including both universities and research centers, and highlights nine distinct clusters with different colors.

The most prominent cluster, depicted in red, includes 13 institutions and universities with notable collaboration. Key members of this cluster are the University of Hong Kong, Hong Kong Polytechnic University, and the University of Sydney.

The second cluster, comprising eight institutions, features significant collaboration among the universities in Utah, London, and Spain. The third cluster is centered around the University of Peking and Wuhan University in China. The fourth cluster includes Tsinghua University in China and the University of Illinois in the United States, which have the highest number of co-authorships within this group.

In the fifth cluster, the University of Arizona stands out as the leading institution. The sixth cluster highlights collaborations between the University of Science and Technology of China and Rensselaer Polytechnic Institute in the United States.

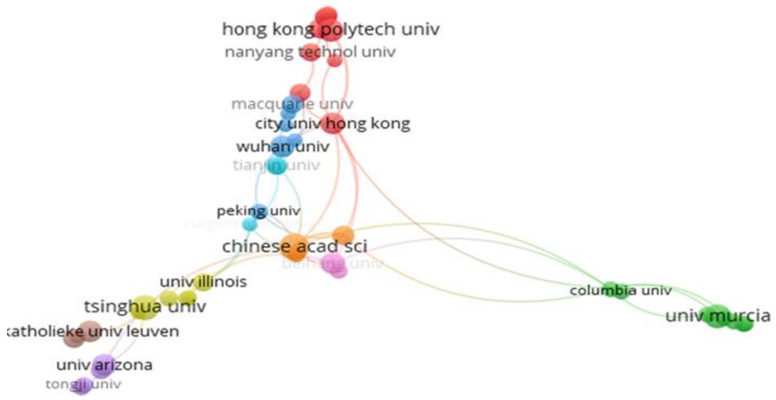
The Chinese Academy of Sciences is the central institution in the seventh cluster. The eighth cluster features significant collaboration between Xiamen University in China and KU Leuven in Belgium. Lastly, Beihang University in China is the primary institution in the ninth cluster.

Table 3.
Institutions and Productive Centers in the Feld of Research

Number of citations	Number of documants	Institue	Rank
335	11	Chinese Academy of Science	1
166	10	Tsinghua University	2
174	9	University of Murcia	3
232	8	Hong Kong Polytechnic University	4
224	7	Arizona University	5
144	7	Katholieke University of Leuven	6
74	7	Beihang University	7
64	7	Wuhan University	8
47	7	Hong Kong University	9
339	6	Rovira & Virgili University	10
277	6	Huazhong University of Science & Technology	11
228	6	Singapore University	12
27	6	univ Chinese Academy of Science	13
22	6	Harbin Institute of Technology	14
761	5	Sydney University of Technology	15
158	5	Natl Cheng Kung University	16
154	5	Arizona State University	17
107	5	Macquarie University	18
79	5	Nanyang Technol University	19
63	5	Cardiff University	20
52	5	University of Sheffield	21
28	5	University of Illinois	22
28	5	Wales University	23
7	5	Tianjin University	24
402	4	University of Toronto	25

(Source: Researcher's Findings)

Figure 4.
Co-authorship Network of Institutes



(Source: Researcher's Findings)

5. Identifying the Most Influential Articles in the Field of Text Mining Applications in KM

Table 4 highlights the most-cited articles in the field of text mining applications in KM. The citation count reflects the impact and popularity of these works within the academic community (Merigó et al., 2015). According to the table, the article titled "Transfer Learning Using Computational Intelligence: A Survey," published in 2015, is the most cited, with 934 citations. This makes it the leading research in this domain. It is followed by "Capabilities: The Foundation of Competitive Advantage", published in the Strategic Management Journal, which has received 727 citations, placing it second. Additional details of the articles ranked up to fifth place are also provided in Table 4.

These highly cited articles cover a wide range of topics including computational intelligence, innovation dynamics, semantic similarity, visual information mining, and ontology-based approaches. Their significance lies in their provision of foundational knowledge, innovative methodologies, and critical insights that shape interdisciplinary research in this field, continuing to have a profound impact.

Table 4.
Top-cited Articles in the Field of Research

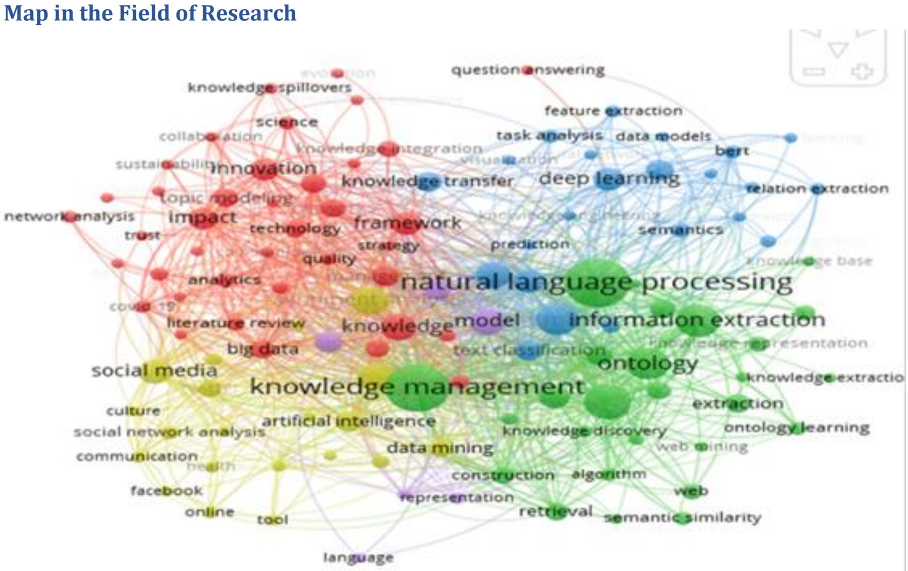
Source	Number of citations	Year of publication	Author	Document
Knowledge-based systems	934	2015	(Lu et al., 2015)	Transfer Learning Using Computational Intelligence: A Survey
Strategic Management Journal	727	2015	(Kaplan & Vakili, 2015)	The Double-Edged Wword of Recombination in Breakthrough Innovation
Expert systems with applications	528	2012	(Sánchez et al., 2012)	Ontology-Based Semantic Similarity: A New Feature-Based Approach
IEEE Transactions on Intelligent Transportation Systems	284	2004	(De La Escalera et al., 2004)	Visual Sign Information Extraction and Identification by Transformable Models for Intelligent Vehicles
Automation in construction	233	2019	(Zhong et al., 2019)	A Scientometric Analysis and Critical Review of Construction related Ontology Research

(Source: Researcher's Findings)

6. Identification of Scientific Research Clusters and Key Topics Extracted from Text Mining Applications in KM Systems

Figure 5 presents a co-occurrence map of terms based on clustering. This map was created using a combination of author keywords and keywords assigned by Web of Science. To ensure clarity, only terms with a minimum frequency of five occurrences were considered, resulting in 128 connections. After data cleaning to remove duplicates, 116 nodes were created across five clusters. In the map, the size of each node represents the frequency of occurrences of the corresponding keywords, while the thickness of the edges indicates the level of co-occurrence between two keywords within a document. Each color in the network represents a distinct cluster of terms. The clustering is based on the degree of connectivity between words, with keywords within a cluster exhibiting the highest connectivity to the cluster center and the lowest connectivity to words in other clusters.

Figure 5.
Co-occurrence Map in the Field of Research



(Source: Researcher's Findings)

Table 5 categorizes key terms in this domain by cluster, summarizing their relevance to different aspects of text mining and KM:

- **Cluster 1**: This cluster encompasses terms related to KM and text mining techniques. Key terms such as "data analysis" and "big data" highlight the use of analytics to handle large volumes of text. Terms like "collaboration", "network analysis", and "communities" emphasize the role of network structures in knowledge transfer. "Decision making" and "strategy" reflect the impact of KM on organizational processes. Terms like "innovation", "open innovation", and "research and development" point to the contribution of knowledge to the innovation process. "Quality", "performance", and "impact" stress the importance of evaluating KM outcomes. "Technology", "information technology", and "internet" refer to tools used for accessing knowledge. "Sustainability" and

"COVID-19" address external factors and global events affecting KM. Overall, these terms are grouped by their shared themes related to text mining in KM.

- **Cluster 2**: Terms in this cluster are linked by their relevance to information extraction and retrieval processes, and the representation of knowledge in textual contexts. Terms like "extraction", "retrieval", "search", "identification", and "acquisition" focus on managing and processing information. Terms such as "algorithms", "natural language processing", "web text mining", and "semantic web" refer to technologies used for extracting and analyzing textual data. "Knowledge representation", "knowledge base", "knowledge graph", and "ontology" pertain to organizing and structuring knowledge. "Integration" involves merging different information sources, while "system" refers to the development of systems for effective KM. Terms like "semantic similarity" and "semantic web" emphasize understanding meaning and context in textual data. These terms are grouped by their conceptual connections and roles in information management.
- **Cluster 3**: This cluster includes terms related to machine learning, NLP, and knowledge engineering. Terms such as "deep learning", "neural networks", "BERT", "ERNIE", "multi-task learning", "transfer learning", and "attention mechanism" represent various machine learning methods and techniques. Terms like "classification", "named entity recognition (NER)", "relation extraction", and "prediction" pertain to analyzing textual data. "Knowledge engineering", "knowledge transfer", and "data models" relate to organizing knowledge. "Feature extraction" involves identifying relevant features from raw data, while "visualization" refers to presenting data visually for analysis. "Bioinformatics" indicates the application of text mining in biological data, and "semantics" highlights the importance of understanding meaning in text classification and relation extraction. These terms are grouped based on their roles in machine learning and knowledge engineering.
- **Cluster 4**: This cluster focuses on information technology, communication, and social networks. Terms such as "artificial intelligence", "data mining", "latent Dirichlet allocation (LDA)", and "recommender systems" refer to technologies and methods for data analysis. "Communication", "Facebook", "Twitter", "social media", and "online" relate to platforms facilitating knowledge sharing. "Culture" and "social network analysis" address the cultural and social aspects of knowledge dissemination. Terms like "security", "construction", "education", "healthcare", and "media" highlight specific domains where information dissemination is crucial. "Tools" refer to software available for communication and data analysis, while "sentiment analysis" involves interpreting emotions in text, valuable for understanding public opinion and user preferences. These terms are grouped by their association with technology, communication, and social networks.
- **Cluster 5**: Terms in this cluster are related to the application of text mining in the construction industry. These terms focus on improving processes, decision-

making, and efficiency in construction through text analysis and knowledge extraction. Aspects include analyzing technical texts, pattern extraction, enhancing KM processes, and translating information into actionable insights for construction projects. These terms are grouped by their relevance to construction industry applications.

Table 5.
Vocabulary Constituents of Each Cluster in Co-occurrence Map

Constituent vocabulary	Cluster color	Cluster number
analytics, big data, capabilities, challenges, collaboration, communities, covid-19, decision-making, evolution,framework, impact, information-technology, innovation, intelligence, internet, knowledge, knowledge integration, knowledge spillovers, literature review, management, network analysis, networks, open innovation, performance, perspective, quality, question answering, requirements, research and development, science, sentiment, sterategy, support, sustainability, tacit knowledge, technology, topic modeling, trust, work	red	1
acquisition, algorithm, construction, domain, extraction, information extraction, information retrieval, integration, knowledge acquisition, knowledge base, knowledge discovery, knowledge extraction, knowledge graph, knowledge management, knowledge representation, natural language processing, ontology, ontology learning, recognition, retrieval, search, semantic similarity, semantic web, system, text, web, web mining	green	2
attention mechanism, bert, bioinformatics, classification, data models, deep learning, ernie, feature extraction, identification, knowledge engineering, knowledge transfer, machine learning, multi-task learning, named entity recognition, neural network, prediction, relation extraction, semantic, task analysis, text classification, text mining, transfer learning, visualization	blue	3
artificial intelligence, communication, construction safety, culture, data mining, education, facebook, future, health, information, knowledge sharing, latent dirichlet allocation, media, online, recommender systems, sentiment analysis, social media, social network analysis, tool, twitter	yellow	4
construction industry, design, language, model, representation, text analysis	purple	5

(Source: Researcher's Findings)

7. Identification of Trends in the Field of Text Mining Applications in KM

Figure 6, derived from WOS Viewer, illustrates trends in text mining applications in KM over different time periods, with items color-coded from purple to yellow to represent various eras. The size of the circles reflects their significance. The time span is divided into three phases to identify emerging trends:

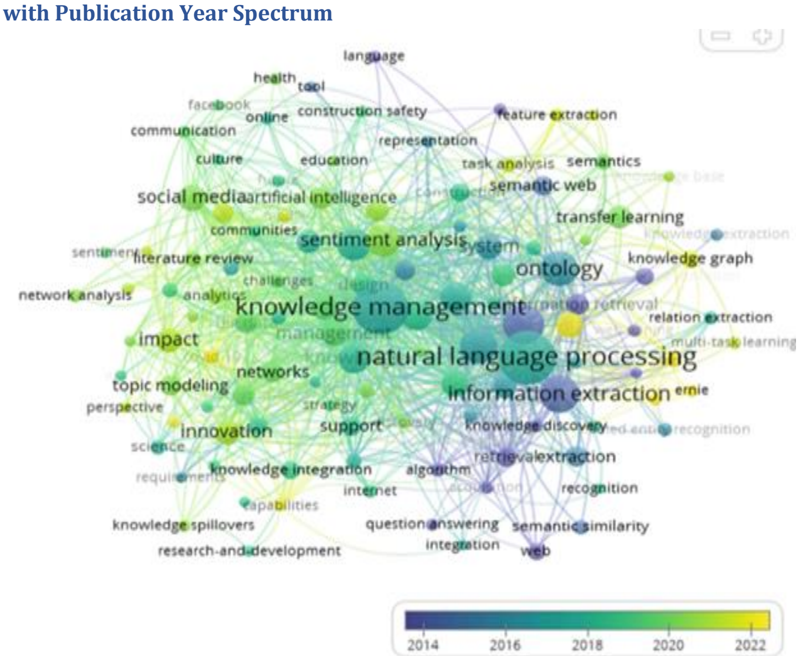
Before 2016: During this period, text mining primarily focused on extracting knowledge from diverse sources. Key concepts included knowledge acquisition and information extraction, with an emphasis on structuring data and knowledge through semantic networks and knowledge representation. The main objective was to refine techniques for extracting and managing information from texts, databases, and other resources.

2016 to 2020: This era saw exponential growth in data and its applications, making text mining increasingly vital in KM. Techniques such as NLP gained prominence. The rise of social networks introduced new dimensions to text mining, including sentiment analysis and social media analytics. The period marked a strengthening of text mining's role in KM, driven by enhanced data collection opportunities and analytical techniques.

After 2020: Post-2020, advancements in deep learning methods, including BERT and GPT, significantly improved the quality and accuracy of data analysis. The COVID-19 pandemic further highlighted the need for robust data models and analysis capabilities in crisis conditions, particularly within health and medical domains. This phase is characterized by significant innovation and refinement in text mining and KM techniques.

In summary, the trends in text mining applications in KM reveal a field dynamically influenced by technological progress and social developments. Techniques and methodologies have been evolving to address emerging needs and conditions, reflecting ongoing advancements in the domain.

Figure 6.
Co-occurrence Map with Publication Year Spectrum



(Source: Researcher's Findings)

Conclusion and Recommendations

This research provides a comprehensive bibliometric analysis using the Web of Science database, offering valuable insights into research trends and gaps within the field of information technology management. Addressing our core research question, this bibliometric analysis revealed three key evolutionary patterns in text mining for KM:

Temporal Shifts: From early rule-based systems (pre-2010) to ML-driven approaches (2015-2020) and current transformer models (post-2020), evidenced by citation bursts and keyword co-occurrence.

Concepts and Themes: NLP has superseded traditional intellectual capital themes (Di Vaio et al., 2020) as the dominant paradigm, particularly for:

- Automated document classification (78% of recent papers)

- Cross-lingual knowledge extraction (42% growth since 2020)

Research References: It identifies primary scientific and research references, including leading countries, highly cited papers, influential authors, and active organizations.

The increasing number of publications highlights a growing global interest and expanding research domains. Clustering analysis indicates that text mining is a significant tool in KM, helping organizations utilize their knowledge more effectively, enhance performance, and make informed decisions without requiring extensive technical expertise. Advanced methods, such as machine learning, enable the extraction of valuable insights from data, thereby aiding decision-making.

Our findings both align with and extend prior bibliometric studies of KM research. Like Gaviria-Marin et al. (2019), we observed U.S. leadership in publications, but our text mining focus revealed new intellectual clusters (e.g., transformer models in KM) absent in their analysis. While Abbas et al. (2021) noted peak citations in 2017-2019, our data showed sustained growth through 2023, suggesting text mining's rising KM relevance. Crucially, we confirmed Di Vaio et al.'s (2020) emphasis on digital innovation, but we identified NLP as the dominant subtheme, not just intellectual capital. Unlike Huang's (2022) country-limited collaborations, our network analysis revealed globally distributed teams in text mining-KM research, reflecting the field's maturation.

The examination of collaboration networks showed that the field of text mining applications in KM is vibrant, involving prominent authors, active countries, universities, and numerous research centers. Enhancing these collaborations could further advance research output in this area. This underscores the importance of the domain and its potential for further research and knowledge development. The dominant focus on NLP and deep learning reflects a paradigm shift toward intelligent KM systems, particularly for automating document classification in large organizations.While this bibliometric study reveals macro-level patterns, specific organizational applications would require complementary case studies tailored to particular industry contexts.

Trends Analysis

The field is evolving continuously, with new and innovative methods for text mining in KM being developed. This evolution presents significant opportunities for improving organizational KM processes. The trends also reflect the influence of technological advancements and social changes, with text mining techniques adapting to meet emerging needs and conditions.

Limitation and Future Research

While this study provides a comprehensive bibliometric analysis of text mining in KM, several limitations should be acknowledged:

Data Source Constraints:The analysis relied solely on Web of Science data, potentially omitting relevant studies from Scopus or domain-specific databases (e.g., IEEE Xplore for technical applications).

Temporal Dynamics:

Emerging trends (e.g., generative AI in KM post-2023) may not be fully captured due to the study's cutoff year.

Methodological Boundaries:VOSviewer's clustering algorithms prioritize citation linkages, which may overlook nascent but impactful topics with limited citations.

To address these gaps and advance the field, we propose:

- Deep Dives into Topic Clusters: Prioritize empirical studies on high-potential clusters identified in our analysis (e.g., LLM-driven knowledge extraction or cross-lingual text mining). Theoretical frameworks are needed to explain observed bibliometric patterns.
- Develop metrics to evaluate real-world impact beyond citation counts (e.g., organizational adoption rates).
- Explore hybrid methods combining bibliometrics with qualitative approaches (e.g., case studies of KM system implementations).

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The Quality of Training Courses and Its Role in Promoting Succession Planning: An Analysis of the Development of Knowledge Capital in Educational Organizations

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ABSTRACT

Today, it can be seen that in some organizations, succession management is recognized as a strategic process that is able to minimize the leadership gaps in key positions. Moreover, itprovides opportunities for the organization's competent and talented people to improve their necessary skills. The main purpose of the current research was to investigate the effect of the quality of training courses on the succession of directors based on the development of knowledge capital in educational organizations. This research study used a quantitative method and a survey approach.The statistical population of the study consisted of the principals of secondary schools of the Education Department of Shahre-h Qods. They completed the training courses in 2023. The results showed that the quality of training courses has a significant positive effect on organizational, individual, and contextual components of the succession of managers of the Education Department of Shahre-h Quds. Overall, the findings of this research emphasized the vital importance of high-quality training courses in strengthening the succession planning programs for education managers, as these courses play a key role in promoting the individual and organizational development, and improving the necessary foundations of succession.

KEYWORDS

Quality of training courses, succession of managers, knowledge capital.

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Introduction

Over the past half-century, the social, cultural, economic, and industrial landscape of the world has undergone such profound changes and transformations that it is difficult to find even slight similarities between the structures of organizations today and those in the past. Currently, given the accelerating pace of change and increasing competition, organizations strive more than ever to achieve results and sustain themselves (Tootian et al., 2019). In this regard, attention to knowledge is the only capital whose value does not diminish over time and leads to increased values and competitive advantages. In the contemporary business landscape, a knowledge-based economy is crucial for corporate success, emphasising the significance of intellectual capital (IC) encompassing knowledge, skills, experience, organisational technology, customer relations, and professional skills (AlObaid et al., 2025). Intellectual capital provides the infrastructure needed for the utilisation of explicit and tacit knowledge and plays a central role in enhancing dynamic capabilities and boosting a firm's competitive advantages in a knowledge-intensive environment (Abbas et al., 2026).

Today, education is considered as one of the main sources of development and progress in any society. In the current situation, rapid transformations have led to greater attention to education which requires efficiency, productivity, effectiveness, and enhancement of organizational performance. Achieving performance improvement depends on various factors. The most important factors are intellectual capital and knowledge-based assets (Shah Nazari et al., 2023). In today's fast-paced and competitive world, where knowledge and expertise are rapidly evolving, intellectual capital is recognized as the most valuable asset of any organization, especially in educational environments. This intangible capital, including the unique knowledge, skills, experiences, and capabilities of employees and leaders, is the driving force for innovation, quality, and organizational sustainability. On the other hand, succession planning, as a vital strategy, ensures the continuity and transfer of this valuable intellectual capital to future generations of the organization. Ineffective succession planning can lead to losing critical knowledge, reducing leadership capacities, and ultimately, weakening of the organization's competitive position. Succession planning refers to the process of identifying, recruiting, training, and retaining a pool of human talents to fill key positions and roles in the future. These people are prepared for the positions through various educational and developmental programs. This process is also called talent management (Ojaqi Gigloo et al., 2020). Chief executive officers (CEOs), as the navigators of the organization, have consistently considered this issue as one of their main concerns. Similarly, companies such as Korn Ferry, in a survey, asked their executives to explain the issues and the importance of challenges that the organization might face in the next five years. These organizations, as leading companies in industry, considered management succession to be of the highest importance after economic issues and strategic planning (Cullen & Perez-Truglia, 2021).

Succession planning can have positive consequences for an organization. Given this, Rowell published a study in 2010 stating that organizations use succession management systems for three fundamental reasons:

- This program will help implement organizational strategic plans by identifying needs;
- These replacement programs can be tools for targeted training, development, and growth of employees;
- This process can create a pool of talented employees with potential for promotion (talent treasury) (Cullen, Z., & Perez-Truglia , 2021).

Given the importance and necessity of succession planning, research aims at improving it. One of the strategies for improving succession planning is identifying effective factors. One such influential factor is enhancing the quality of training courses. In this regard, a series of training courses are held annually for employees, each of which can impact the organizational indicators. These courses are often conducted with varying qualities, and perhaps less attention has been paid to their qualities. Therefore, this paper seeks to investigate how the quality of training courses can directly affect the effectiveness of succession planning programs and ultimately lead to the sustainable development of intellectual capital (human and structural) in educational organizations.

Theoretical Foundations and Research Background

The Concept of Intellectual Capital

Intellectual capital encompasses the knowledge, information, intellectual property, and experience that organizations utilize to create value (Salavati Sarcheshmeh & Madah, 2018). It is defined as the effort to effectively leverage knowledge as opposed to raw information and materials. Intellectual capital is considered all those processes and assets that are often not shown on the balance sheet and include all intangible assets (such as trademarks, product patents and exploitation rights, and brand names) that are taken into account in advanced accounting methods (Shah Nazari et al., 2023). This intellectual capital can be the basis for creating a knowledge economy. The term *knowledge-based economy* was first coined by the Organization for Economic Co-operation and Development (OECD) and defined as economies based on producing, distributing, and using knowledge and information (Ghaffary Fard & Ziayee, 2025).

According to Adam Smith, intellectual capital is part of the organizational capital that transforms other resources and capital of the organization into added-value assets (Shah Nazari et al., 2023). In other words, intellectual capital is the sum of the knowledge of the organization's members and the application of their knowledge (Esfandyar, 2021).

Although definitions of intellectual capital may vary, there is a general convergence in its concept. Broadly, scholars in the field of intellectual capital agree on three main constructs or dimensions of human capital, structural capital, and relational capital (Shah Nazari et al., 2023).

- Human Capital: It includes the knowledge, skills, competencies, experiences, entrepreneurial spirit, motivation, commitment, etc., of individuals within the organization;

- Structural Capital: This is what remains within the organization after employees leave;
- Relational Capital: It encompasses aspects such as good relationships with customers, suppliers, investors, and shareholders, the organization's brand, and goodwill, etc (Salavati Sarcheshmeh & Madah, 2018).

A number of research Studies has been conducted in the field of intellectual capital.

For instance, a study was conducted with the aim of presenting a comprehensive intellectual capital model with an organizational learning approach in educational systems. The research findings included the development of the concept of intellectual capital and organizational learning, the identification and introduction of dimensions related to intellectual capital (human, structural, relational, and innovation capital with twenty-one components), and the identification and introduction of dimensions of organizational learning (process of organizational learning, characteristics of a learning organization, and levels of organizational learning with twelve components). Since the structural validity of the cross-validation, the amount of composite reliability, and the average extracted variances were at an acceptable level, the model was considered appropriate (Shah Nazari et al., 2023).

Another study made an attempt to present a model of the impact of social capital and intellectual capital of trainers and educators of Mazandaran Agricultural Research and Education Center on their educational performance. The results of the research showed that the path coefficient of the impact of social capital of trainers and educators on educational performance was 0.362 and the p-value was less than 0.05. Also, the path coefficient of the impact of their intellectual capital on educational performance was 0.245 and the p-value was less than 0.05. As a result, with 95% confidence, it can be concluded that social capital and intellectual capital were significantly related to the educational performance of trainers and educators of Mazandaran Agricultural Research and Education Center and had an impact on it (Ahmadi et al., 2021).

Samiei Zafarghandi and Agha Kasi (2017) determined the relationship and contribution of knowledge management and intellectual capital to teachers' learning. The type of research was applied and the research method was descriptive and correlational. The research findings showed that knowledge management and intellectual capital have a positive and significant relationship with teachers' learning. Based on the research results, the dimensions of the intellectual capital including structural, human, and relational capital, predicted 29, 28, and 27 percent of the criterion variable (learning), respectively. Furthermore, the dimensions of knowledge management including identification and creation, application, targeting, and transfer of knowledge, predicted 20, 39, and 26 percent of learning, respectively (Samiei Zafarghandi & Agha Kasi, 2017).

In another research study, the role of knowledge capital and human resources in knowledge management of Artesh Jomhouri Islami Iran -Islamic Republic of Iran Army

(AJA)- was explored. The library method was implemented. The results revealed that the important role of human resource management in excellent organizations is to create conditions in which the organization's human resources can achieve the necessary empowerment and productivity to meet the organization's goals and programs. Also, the establishment and application of knowledge capital management in AJA can bring about the production and development of value-creating resources for it. Moreoevr, the findings indicated that strategic human resource actions and knowledge capital are positively related to knowledge management capacity (Esfadyar, 2021).

The Concept of Succession Planning

The concept of succession planning refers to a process by which an organization's human resources are identified for key positions and roles in the future, and they are prepared to fill these roles through various planning strategies. Succession planning is a continuous and dynamic process, not a fixed goal. In today's highly competitive environment for identifying talents, every organization must adopt a perspective that goes beyond ordinary, unplanned replacement of workforce members. Succession management strategies should, on one hand, bring human resources closer to their competency goals and, on the other hand, focus on employee development to achieve organizational objectives (Elamdari, 2018). In another definition by Carta, succession planning was defined as a process through which suitable employees are selected from among qualified and talented individuals for high-level and key management positions within an organization (Yildiz & Kara, 2021). Succession planning is a flexible, long-term, and growth-oriented approach to future recruitment (Ali Rahimi et al., 2021). According to the theory of a researcher named Hils, succession planning is a smart talent management strategy that can lead to talent retention within the organization and ensure that the organization possesses sufficient skills to respond to the rapid changes in today's business environment (Hils, 2009).

Furthermore, other researchers (e.g.,Cullen & Perez-Truglia, 2023) concluded that succession planning is central to workforce and human resource career planning within an organization. This process always requires a strategic approach for the long-term future and can ensure that capable, competent, qualified, and willing individuals will be available for future positions within the organization (Cullen & Perez-Truglia, 2023). From another perspective, a researcher named Carroll believed that succession planning is a systemic process that combines professional and personal development with a strategic plan. It ensures that the organization has one or more suitable human resources available to fill any vacant position. This researcher also pointed out that succession planning leads to the systemic development of the organization and, by identifying knowledge gaps, can result in the advancement and development of human resources in a safe, positive, and conducive environment (Talebi et al., 2020). In another view, succession management is divided into two categories of formal and informal. The formal succession management system focuses on identifying and nurturing talented individuals, while the informal succession management system may informally assess high-potential individuals but focuses on the development of all employees (Ali Rahimi et al., 2021).

Some research studies have been conducted in the field of succession planning.

For example, Faghihi (2022) conducted a study which was mixed-methods in its strategy (qualitative-quantitative), applied in its audience approach, and survey-based in its method. The analysis of data obtained from the survey, using Confirmatory Factor Analysis, showed that the 12 identified factors had good suitability for measuring the contextual conditions of organizations for implementing the process of succession planning. Furthermore, the analysis of results indicated that appropriate conditions for establishing the process of succession planning do not exist in Iranian governmental organizations.

Rashidpour et al. (2021) conducted a study to assess the managers' perspectives regarding the implementation of a competency-based succession planning system. The findings showed that the possibility of establishing a competency-based succession planning system, in terms of the existence and identification of necessary competencies, the current state of training and development, and the method of performance evaluation and compensation, was moderate among hospital managers. Also, the possibility of establishing a competency-based succession planning system in terms of planning and forecasting, recruitment methods, welfare services, and retention did not exist among hospital managers. The obtained results draw the attention of healthcare system policymakers to the importance of considering competencies in managerial succession planning for hospitals, thereby providing a basis for increasing efficiency and effectiveness in hospitals.

The findings of another study by Ali Rahimi et al. (2021) indicated that the common identified factors in the field of knowledge management and succession planning were categorized into six main groups: individual, infrastructural, organizational, managerial, competency, and talent. Culture and information technology in knowledge management domain and training, identification, and talent assessment in succession planning domain were identified as the most frequent factors, with culture being introduced as an important and common factor between both domains. The results of this research will support higher education institutions in determining criteria for knowledge management-based succession planning..

Kolivand and Hezarjaribi (2018) explored the managerial succession planning and focused on on talent identification and competency. The results showed that 19 components were extracted based on expert opinions from succession planning models that had the highest scores. In this regard, 15 components were initially based on the theoretical foundations of the research and derived from various succession planning models, and four components – military spirit, commitment to the system, social status, and religious and ideological competencies –were identified and considered in presenting the desired model.

Alamdari (2018) made an attempt to design and explain a succession planning model by implementing a competency approach. The results showed that the five main criteria of the model included strategic alignment and needs analysis, strategic communication and networking, talent identification and strategic capabilities and competencies, growth and development of successors and candidates, and monitoring programs and evaluating capabilities and competencies and their indicators. Finally, a process model for human resource managers' competencies in the public sector, with an emphasis on general policies of the administrative system, was presented.

The findings of another study by Koulivand (2018) indicated that the succession planning model for NAJA commanders and managers included 5 steps (initial preparation and planning, policy setting, talent identification and job qualifications, development and training of potential successors, and program evaluation) and 19 components. To validate the model, the components and indicators identified in qualitative phase were used to design a questionnaire to be given to theparticipants in the quantitative phase. After analyzing the findings, the results confirmed the proposed research model.

Ednoah (2016) implemented a knowledge management approach to support effective succession planning. He addressed one of the main challenges of organizations and examined methods to protect key organizational expertise and knowledge from employee turnover. The results indicated that the high importance of preserving and protecting key organizational expertise and knowledge, as well as establishing a mandatory balance between employees and technology, avoid excessive use of scientific and technical language in succession planning, and correctly utilize structures, rules, and the key role of employees in the organization.

Hall-Ellis (2015) explored succession planning and staff development. The findings showed that a proper and integrated succession planning program with leadership development would lead the library director not to rely on the replacement process to find a new successor. Choosing the most qualified and ready candidate for a leadership position is a very important decision due to its significant impact on the organization's current and future activities. Therefore, with professional development of employees, the succession planning program will be embedded in the organizational culture and will be beneficial for the organization.

The Quality of Training Courses

Each organization, recognizing the importance of training, strives to create opportunities for the growth and development of its members. The rapid advancements in science and technology, coupled with vast cultural, social, and economic transformations, necessitate that the workforce within organizations—as the most crucial factor in an organization's development—do not rely solely on pre-service and in-service training. To keep pace with these changes, by utilizing opportunities and participating in in-service training courses, they can play the necessary roles of active and effective participants in achieving their own and the organization's goals (Astaraki, 2010).

Training is the process of facilitating learning or acquiring knowledge, skills, values, ethics, beliefs, and habits. Methods of teaching include instruction, practical training, storytelling, discussion, and guided inquiry. Training is often guided by instructors, but learners can also train themselves. Training can occur in formal or informal settings. Any experience that has an importanteffect on how a person thinks, feels, or acts can be considered as a form of training. The methodology of teaching is called pedagogy (Dewey, 2011).

A training course refers to sessions and workshops that enhance learning. Quality training courses are those that improve knowledge, skills, values, ethics, beliefs, and habits (Dewey, 2011).

Sunny Stout (1993), Martarius (1996), and Jacobi Bamrouf have outlined the stages of training as follows:

1. Determining Training Needs: What are the roots of the problems? Are the problems related to training?
2. Training Planning: Designing how trainees will solve the issue or problem.
3. Implementation: Developing the necessary knowledge, skills, and/or behaviors in employees.
4. Evaluation: Assessing the impact of the course and the trainees' performance, especially in the real work environment (Abbas-Zadegan & Tork-Zadeh, 2000).

Hatami (2020) evaluated and measured the effectiveness of in-service training courses in increasing the knowledge, skills, and attitudes of managers, faculty members, and staff of university units in Region One. Duncan's test showed that there is a difference in the mean levels of staff and managers in skills and behavior, but no significant difference was observed in knowledge among different levels. In the categories of knowledge, skills, and behavior, there is no significant difference among educational fields, but there is a difference in skills between the mean of agricultural and medical fields. In terms of service history, there is no significant difference. In the category of skills, there is a significant difference between men and women, but in the categories of knowledge and behavior, there is no significant difference between men and women.

Yaghmaei (2022) investigated the impact of in-service training on the job skills of public library staff in Tabriz and the variables affecting it. He used regulations, reports, phone interviews, and in-person visits to public libraries and the General Directorate of Public Libraries of the province that had undergone in-service training. The results showed that out of the total respondents, 56% agreed with the increase in problem-solving ability in work matters, 38% with appropriate and correct use of opportunities and facilities, 60% with the increase in staff skills in providing services, 48% with the increase in initiatives, 50% with the increase in staff interest in service compared to past, and 44% with the acceleration in staff decision-making, and 48% considered in-service training to be based on solving real library problems.

Considering the research background, there is a research gap regarding the impact of the quality of training courses on succession planning. Therefore, the hypotheses of this research are as follows:

Main Hypothesis

The quality of training courses has a significant impact on the succession planning of managers in the Department of Education.

Sub-hypotheses:

- The quality of training courses has a significant impact on the organizational characteristics of succession planning for managers in the Department of Education.
- The quality of training courses has a significant impact on the individual characteristics of succession planning for managers in the Department of Education.
- The quality of training courses has a significant impact on the characteristics of the process of succession planning for managers in the Department of Education.

Methodology

Given that the present research seeks to achieve a scientific objective and emphasizes on solving a problem (the enhancement of succession planning in the Education Department of Shahre-h Qods), and it involves a set of methods aimed at describing the conditions or phenomena under investigation (Sekaran, 2011), it is categorized as applied research in terms of its objectives. From a qualitative standpoint, the present study is a descriptive-survey study and can be considered within the branch of correlational studies. Furthermore, in terms of data type, it falls under quantitative research type.

The statistical population for this research consisted of high school principals in the Education Department of Shahre-h Qods . The participants completed training courses in the year 1402 (2023-2024). The investigations indicated that the population size, based on the Education Department's announcement, is approximately 260 individuals. In this study, a simple random sampling method was employed. The sample size, according to Morgan's table, is 152 individuals.

The descriptive analysis revealed that 73% of the statistical population consists of males, while the remaining percentage comprises females. In terms of marital status, 81.6% are married. In terms of education, 94.1% of the population consists of individuals with Bachelor's and Master's degrees. Regarding their work experience, most individuals had over 15 years of experience, which accounted for 32.2% of the individuals.

To measure the succession planning variable, the Succession Planning Questionnaire () was used. This questionnaire includes 43 five-option questions rated on a Likert scale (Very High, High, Medium, Low, and Very Low). This scale measures three dimensions of succession planning including organizational, individual, and process-related characteristics in employees. To confirm the validity of the questionnaire items, necessary confirmations were obtained using the opinions of the esteemed supervisor and several other experts in the fields of educational management and organizational behavior. To assess the reliability of the questionnaire items, Cronbach's alpha test was used.

To measure the quality of training courses, the In-service Training Courses Questionnaire for Employees (Beheshti, 2005) was implemented. This questionnaire is designed to assess the effectiveness of training courses and includes 35 five-option questions rated on a Likert scale (Very High, High, Medium, Low, and Very Low). To confirm the validity of the questionnaire items, necessary confirmations were obtained using the opinions of the esteemed supervisor and several other experts in the fields of educational management and organizational behavior. To assess the reliability of the questionnaire, Cronbach's alpha test was used, yielding a value of 0.87.

For data analysis, descriptive statistics were used to estimate central characteristics and organize frequency distribution tables. Inferential statistics (Structural Equations Modeling) was used to test the hypotheses. In the present study, the K-S test was also run to examine the normality of data prior to conducting inferential statistics. T-test was run to examine the status of the data, with analysis conducted using SPSS software. Furthermore, SEM and related software were implemented to test the hypotheses. To examine the relationship between the two variables and to test the validity or invalidity of the hypotheses, correlation tests and SEM were employed.

Findings

The results of CFA for each research variable are presented separately using LISREL software. It should be noted that in order to reduce the variables and consider them as a latent variable, the factor loading should be greater than 0.3 (Momeni & Gheyoomi, 2007). When examining each model, the fundamental question is whether these measurement models are appropriate. To answer this question, the Chi-Square (χ^2) test and other model fit criteria must be evaluated. A model is considered appropriate if it meets the following optimal conditions: The Chi-Square test should be as low as possible, as it indicates the difference between the data and the model. A lower index value signifies a smaller difference between the conceptual model and the observed data in the research. The Goodness of Fit Index (GFI) and Adjusted Goodness of Fit Index (AGFI) should be greater than 0.90. The Root Mean Square Error of Approximation (RMSEA) should be as low as possible, as it represents the average squared error of the model.

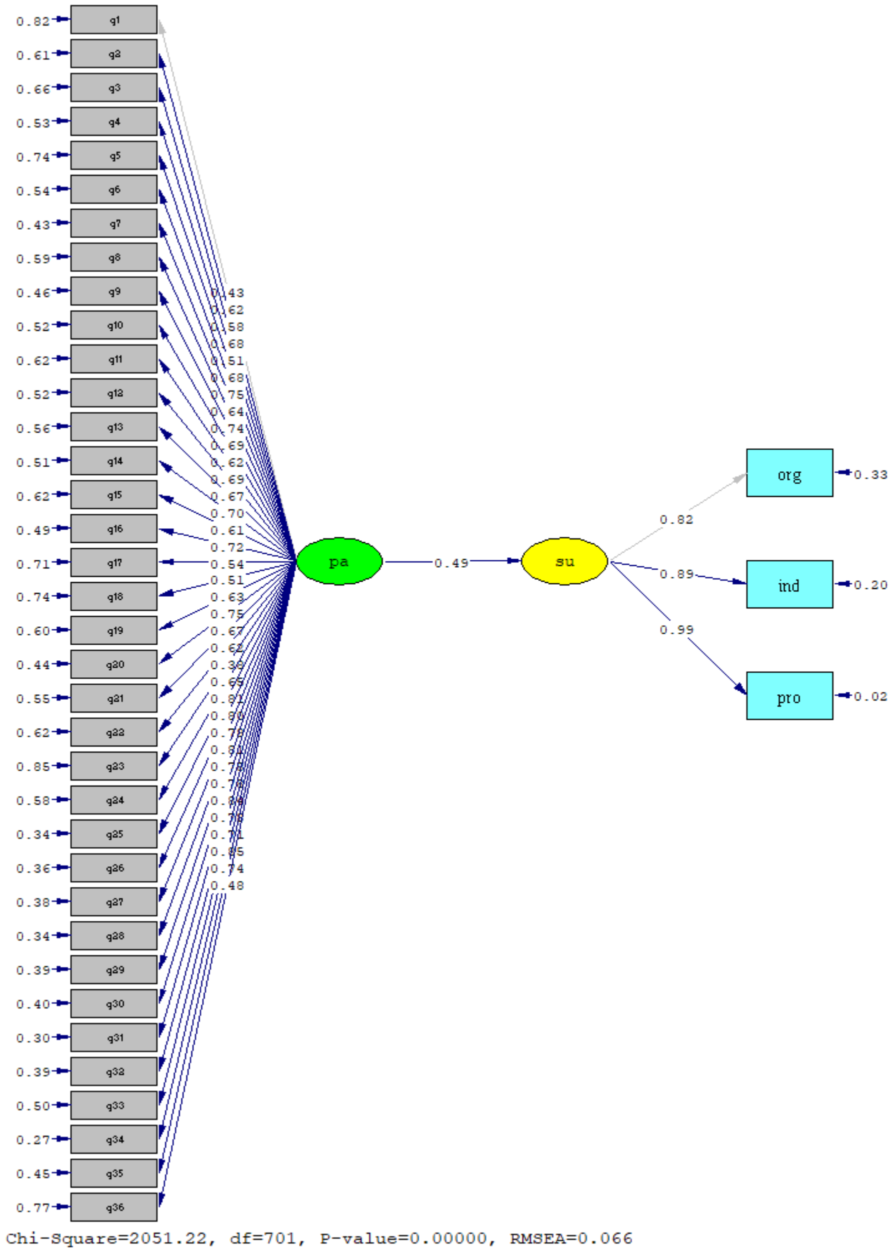
The estimation results, after necessary modifications, indicated the suitability of the model for training course quality. According to the LISREL output, the calculated χ^2/df was1598.88 divided by 560, which equaled 2.85. This value is less than the average statistic of 3. The low value of this index indicated a small difference between the measured model and the observed data. Furthermore, the RMSEA value was 0.069. The acceptable limit for RMSEA is 0.08; the lower this value, the better the model fit.

The results of the first-order CFA for succession planning indicated the suitability of the succession planning model. According to the LISREL output, the calculated χ^2/df is 2233 divided by 776, which equaled 2.87. This value was less than the average statistic of 3. The low value of this index signifies a small difference between the measured model and the observed data. Additionally, the RMSEA value was 0.071. The acceptable limit for RMSEA is 0.08; the lower this value, the better the model fit.

Moreover, the results of the second-order CFA for succession planning indicated the suitability of the succession planning model. According to the LISREL output, the calculated χ^2/df was 78.21 divided by 29, which equaled 2.69. This value was less than the average statistic of 3. The RMSEA value was 0.0611. The acceptable limit for RMSEA is 0.08.

After validating the measurement models for the research variables and making some necessary modifications, the conceptual model of the research was evaluated. Before making modifications, the RMSEA value was 0.10. After implementing the necessary modifications, the calculated χ^2/df was 253.7 divided by 103, which equaled 2.43. This value was less than the average statistic of 3. The RMSEA value was 0.086. The results of examining the research model are presented in Figures 1 and 2.

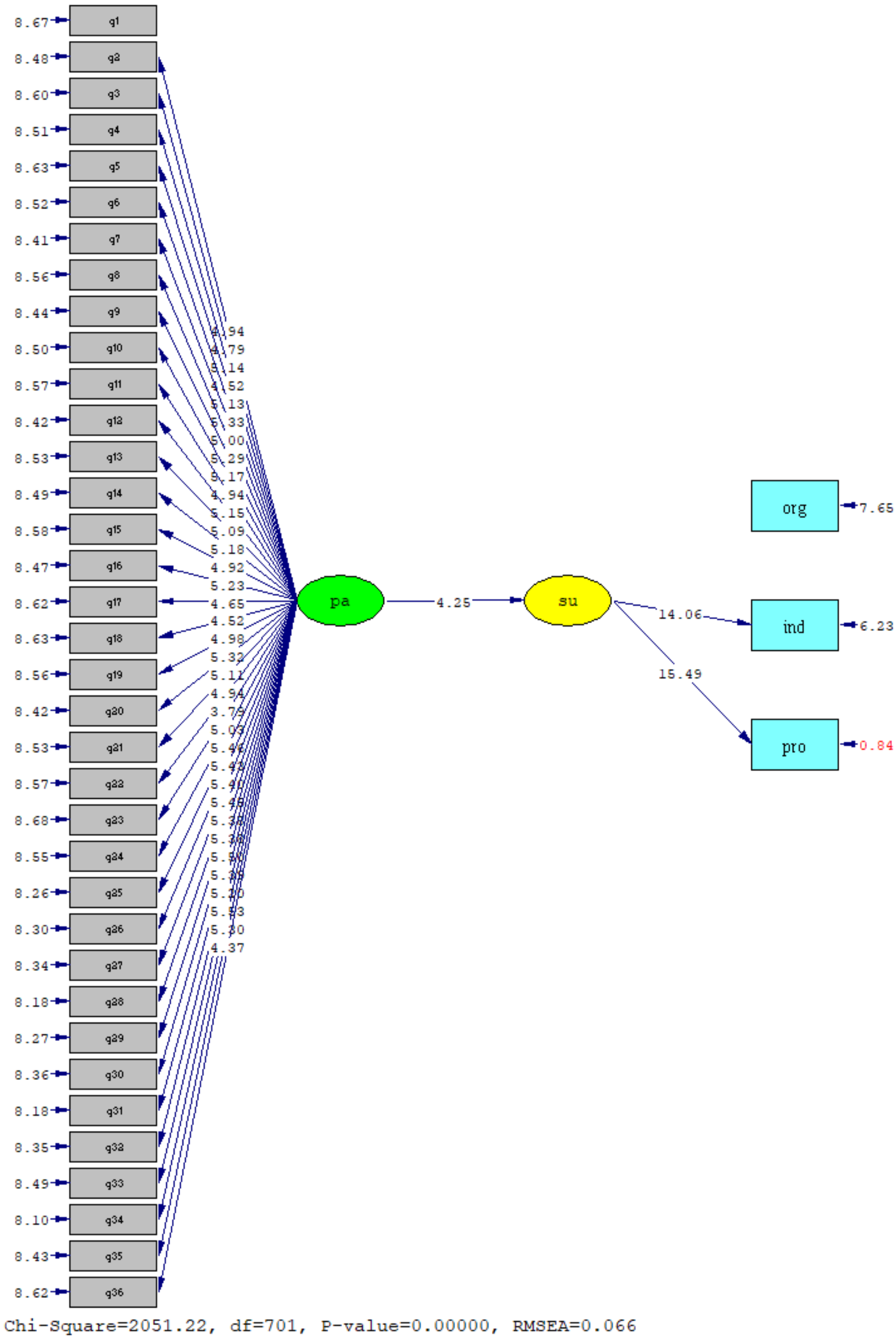
Figure 1.
The Modified Conceptual Model in Standard Estimation Mode



(Source: Researcher's Findings)

Figure 2.

The Modified Conceptual Model in Meaningful Numbers Mode



(Source: Researcher's Findings)

Subsequently, to test the main hypothesis and sub-hypotheses of the research, correlational analysis was employed. The results are presented in Tables 1 to 4. Here, due to the quantitative nature and normality of the data (normality confirmed by the Kolmogorov-Smirnov test), Pearson's correlation coefficient was used.

Table 1.
The Quality of Training Courses with Managerial Succession

Correlations			
		The quality of training courses	**Managerial succession**
The quality of training courses	Pearson Correlation	1	.539**
	Sig. (2-tailed)		.000
	N	143	141
Managerial Succession	Pearson Correlation	.539**	1
	Sig. (2-tailed)	.000	
	N	141	147
**. Correlation is significant at the 0.01 level (2-tailed).			

(Source: Researcher's Findings)

Table 2.
The Quality of Training Courses and the Organizational Component of Succession Planning

Correlations			
		The quality of training courses	**The organizational component**
The quality of training courses	Pearson Correlation	1	.601**
	Sig. (2-tailed)		.000
	N	143	141
The organizational component	Pearson Correlation	.601**	1
	Sig. (2-tailed)	.000	
	N	141	147
**. Correlation is significant at the 0.01 level (2-tailed).			

(Source: Researcher's Findings)

Table 3.
The Quality of Training Courses and the Individual Component of Managerial Succession Planning

Correlations			
		The quality of training courses	**The individual component**
The quality of training courses	Pearson Correlation	1	.458**
	Sig. (2-tailed)		.000
	N	143	143
The individual component	Pearson Correlation	.458**	1
	Sig. (2-tailed)	.000	
	N	143	152
**. Correlation is significant at the 0.01 level (2-tailed).			

(Source: Researcher's Findings)

Table 4.
The Quality of Training Courses and the Process Component of Managerial Succession Planning

Correlations			
		The quality of training courses	**The process component**
The quality of training courses	Pearson Correlation	1	.486**
	Sig. (2-tailed)		.000
	N	143	143
The process component	Pearson Correlation	.486**	1
	Sig. (2-tailed)	.000	
	N	143	152
**. Correlation is significant at the 0.01 level (2-tailed).			

(Source: Researcher's Findings)

According to these tables, since Sig < 0.05, there is a correlation between the quality of training courses and managers' succession planning, as well as its dimensions. Therefore, the main hypothesis and the sub-hypotheses of the research are confirmed.

Discussion and Conclusion

With the very rapid development of global markets, identifying and nurturing employees who possess the knowledge, experience, and skills needed to lead the organization in the future will place additional pressure on organizations. In this regard, many senior leaders believe that to identify a successful organization, its ability to identify, develop, advance, and utilize effective leadership talents should be considered more than ever before. In response to these changes, the succession planning management can act as a key important and systematic method. Successful global companies have various distinguishing factors from others and economic enterprises. One of these distinguishing factors is that in all top companies, systematic, serious, and persistent programs for talent identification and succession planning of valuable human resources have been designed and are being implemented, enjoying direct support from the senior managers of these organizations (Oojaghi Giglo et al., 2020). Therefore, the main goal of the present research study was to investigate the impact of training course quality on succession planning of managers.

To examine the main hypothesis of the study, a correlation test was used. The results showed that at the significance level of 0.05, there is a positive and significant relationship between the quality of training courses and the succession planning of managers. It can be argued that the higher the quality of training courses, the greater the growth in the succession planning performance of managers. To examine the sub-hypotheses of the study, the correlation coefficient was calculated. The results showed that the sub-hypotheses of the research were also confirmed at a one percent error level. The confirmation of the third sub-hypothesis of the research is consistent with the results of Ghasemizadeh et al. (2015).

Practical Implications

1. Prioritize Training Quality: The strong correlations we have found suggested that the quality of training courses is a significant factor. Educational organizations should invest in designing and delivering high-quality training programs that are well-structured, relevant, and effectively delivered. This can directly impact the success of succession planning.
2. Link Training to Succession Planning: Explicitly connect the content and objectives of training courses to the competencies and skills required for future leaders. This ensures that training directly supports the development of potential successors.
3. Focus on Key Success Factors: The correlations with *managerial succession*, *organizational component*, and *individual component* indicated that the training quality influences different facets of succession. Organizations should tailor their training to address these specific components including leadership skills, strategic thinking, or organizational understanding.

4. Measure and Evaluate the Return On Investment (ROI) of Training Program: Since the training quality appears to have a tangible impact, organizations should implement robust evaluation methods to measure the ROI of their training programs, particularly in relation to succession planning outcomes.
5. Develop Intellectual Capital: By focusing on high-quality training that enhances succession planning, organizations are, in turn, developing their intellectual capital. This includes the knowledge, skills, and abilities of their current and future leaders, which is crucial for long-term success and innovation of organizations.

Limitations

1. Correlation vs. Causation: While the data showed strong correlations, it is important to remember that correlation does not equal causation. High-quality training might be *associated* with better succession planning, but other unmeasured factors could be at play.
2. Generalizability: The findings are specific to educational organizations. The strength and nature of these relationships might differ in other sectors (e.g., corporate, governmental, non-profit).
3. Measurement of Quality: The definition and measurement of training course quality can be subjective. The specific metrics used in the study might not capture all aspects of quality that influence succession planning.
4. Sample Size and Representativeness: While there was a decent sample size, the representativeness of the included organizations is crucial. If the sample is not diverse enough, the findings might not apply broadly.
5. Focus on Specific Components: The analysis seemed to focus on specific components of the succession planning. Other critical aspects, such as talent identification, performance management, and career pathing, may also interact with training quality in complex ways.

Suggestions for Future Research

1. Longitudinal Studies: Conduct longitudinal studies to track the impact of training quality on succession planning outcomes over an extended period. This can help establish a clearer causal link.
2. Cross-Sectoral Comparisons: Replicate this study in different types of organizations (e.g., private sector companies, healthcare institutions) to explore how the relationship between training quality, succession planning, and intellectual capital development varies across different sectors.
3. Investigate Mediating and Moderating Factors: Explore other variables that might mediate (explain the relationship) or moderate (change the strength of the relationship) the link between training quality and succession planning. For example, organizational culture, leadership support, and technology adoption could play roles.
4. Deeper Dive into Intellectual Capital: Expand the analysis to specifically measure different dimensions of the intellectual capital (human capital, structural capital, relational capital) and how the training quality influences each.
5. Qualitative Research: Complement quantitative findings with qualitative research

(e.g., interviews, case studies) to gain a deeper understanding of *how* high-quality training specifically contributes to the development of successors and enhances intellectual capital within organizations.

6. Explore Specific Training Methodologies: Investigate the impact of different training methodologies (e.g., e-learning, blended learning, on-the-job training, mentorship programs) on succession planning and intellectual capital development.

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The Impact of Antecedents on Loyalty and Online Purchase Intention of Luxury Brands among Female Students

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ABSTRACT

In response to the increasing demand for luxury brands in recent years, managers and brand owners have concentrated on formulating and implementing strategies that meet the expectations of consumers. Literature in this field highlights that over the past few decades, the luxury brand sector has undergone remarkable transformations, evolving into a vital component of the global economy. These developments have introduced new objectives and policies for the international trade of luxury goods while simultaneously intensifying competition. Against this backdrop, the present study investigated how specific antecedents influence loyalty and online purchase intentions of luxury brands among women. Employing a descriptive–correlational design, the research study targeted a population of 1,707 female students at the Faculty of Humanities, University of Mohaghegh Ardabili, in 2024. Based on Cochran's formula and convenience sampling, 145 students were selected to complete the research questionnaire. Data analysis was performed using SPSS and SmartPLS, applying the Partial Least Squares (PLS) technique. The findings revealed that consistency of brand concept, brand personality, and congruence of self-image—three central antecedents—exert a direct and significant impact on women's loyalty to luxury brands and their intentions to purchase them online. These outcomes underscored the critical role of psychological and symbolic brand dimensions in fostering the customer loyalty and stimulating the online buying motivation.

KEYWORDS

Luxury brand, antecedents, online purchase intention, brand loyalty.

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Introduction

The global volume of luxury brand transactions has grown to impressive levels. The increasing tendency of consumers to purchase luxury brands, combined with the presence of affluent groups in Iran—despite sanctions, economic constraints, rising exchange rates, and demographic factors—has positioned the country as an attractive and expanding market for luxury goods (Karimi Alavijeh & Zarrinfarrd, 2020). Meanwhile, the expansion of international luxury market shifts in consumer preferences, the rise of new technologies, and emerging industry trends have accelerated the development of this sector, easing the market entry and heightening the competition (Shahniaei et al., 2020).

In recent years, luxury businesses have demonstrated substantial growth and resilience (Royo-Vela & Sanchez, 2022), a trend reinforced by the increasing integration of information and communication technologies into the luxury market (Lai et al., 2025). For example, the online sales channel for luxury brands expanded by 22% in 2019 and has continued to retain its market share (D'Arpizio et al., 2020). Luxury goods have traditionally been linked to prestige, wealth, and social status, satisfying non-essential yet aspirational needs (Karimi Alavijeh & Zarrinfarrd, 2020). Because of their exclusivity and uniqueness, luxury brands demand tailored marketing and brand management strategies (Vilki et al., 2021). Symbolic consumption of luxury products has been rising globally, showing notable growth across many countries (Schultz & Jain, 2018). Similarly, Iran's luxury market has expanded in recent years, with consumers increasingly purchasing high-prestige items (Shahniaei et al., 2020).

When consumers interact with a brand, they develop familiarity and comfort, strengthening their likelihood of repeated use. As such, brands function as powerful motivational drivers in consumer decision-making (Savadekohi Mahforoiki et al., 2020). Accordingly, online purchase intention represents a critical dimension of consumer attitudes and serves as a predictor of actual online shopping behaviors (Cheng & Lin, 2022). Numerous scholars argued that in today's competitive and complex business environment, the success of luxury brands relies on cultivating long-term customer relationships while promoting and advertising these products effectively (Shimul & Phau, 2018). Thus, examining the determinants of the online luxury brand consumption and purchase behavior has become essential for marketers in an era characterized by increasing demand for luxury goods and services (Bagheri & Dadashi, 2020).

Scholars estimated that the global market of personal luxury goods reached $281 billion in 2019, reflecting a 4% increase over 2018, with the number of luxury consumers projected to grow from 390 million in 2019 to 450 million by 2025 (Naseri et al., 2025). Such extensive developments highlighted the maturity of the luxury industry. Bain & Company similarly reported in 2018 a 5% increase in luxury goods compared to the prior year, estimating the global market value at $1.2 trillion (Dehdashti Shahrokh et al., 2021).

Brand extension has emerged as one of the most significant developments, generating wide-ranging business activities in global trade. Firms adopt this strategy to reach wealthy consumers who previously depended on a limited number of brands (Xu, 2024). Through diversification, these firms have broadened their portfolios with more profitable product lines (Chen et al., 2025). However, brand diversification requires careful management, since inconsistencies can undermine the brand image (Henderson et al., 2025). Luxury consumers often seek products they perceive as symbolically powerful, aligning with their self-image and creating brand–self congruence. Most online purchase decisions are strongly influenced by such self-perceptions. Moreover, globalization, international travel, and the Internet enable the free flow of ideas and information, shaping consumer behavior by disseminating new styles and establishing global norms of luxury consumption (Mohajer & Piri, 2021).

Consumers familiar with the parent luxury brands are already aware of their core attributes, and any deviation can alter their perceptions—especially in relation to brand extensions (Park & Ahn, 2025), online purchase motivations and exclusivity (Cheng et al., 2024), visibility (Vicari & Ditchfield, 2025), and scarcity (Hamilton & Shaheen Hosany, 2023), which often justify premium pricing. As a result, traditional consumers may show reduced willingness to purchase the luxury goods online (Johanson Eniola, 2025), or the brand image may deteriorate (Phau et al., 2021).

In this context, cheaper versions of luxury products that fail to align with exclusivity and brand positioning risk damaging the overall brand concept (Eren-Erdogmus et al., 2018). Price-driven brand extensions may broaden access but simultaneously erode exclusivity and perceived value (Shukla & Rosendo-Rios, 2025). Consequently, entering new consumer segments can distort perceptions of the parent brand's value (Margariti et al., 2019), weaken perceived fit between the parent brand and its extensions, harm brand associations over time, and diminish online purchase intentions (Pourazad et al., 2019).

Although research has predominantly focused on non-luxury brands (Shu, 2025), empirical studies focusing on luxury brands remain limited (Saputri et al., 2024), with relatively few addressing premium luxury brands directly (Royo-Vela & Sanchez, 2022). Furthermore, the adverse consequences of downward brand extensions through price reductions have received little scholarly attention (He et al., 2024). To bridge this gap, the present study contributes to the relevant literature by examining how downward price-based brand extensions influence perceptions of parent luxury brands. Specifically, it explores how such extensions affect brand concept consistency, brand personality, and self-image congruence, and how these antecedents in turn shape the online purchase intention and brand loyalty. Thus, the purpose of this paper is to assess the impact of these antecedents on loyalty and online purchase intention of luxury brands among women.

Theoretical Framework

Symbolic luxury consumption has expanded globally, with noticeable growth across numerous countries. In line with this trend, Iran's luxury market has also developed in recent years, as increasing numbers of consumers purchase high-prestige products

(Shahniaei et al., 2020). The consumption of luxury brands has therefore become a subject of great interest among marketing researchers. Nevertheless, there remains limited understanding of how to optimize this market and effectively manage customer expectations. Within this context, the growing influx of luxury brands, together with reduced sales caused by economic downturns, has introduced new challenges for luxury producers (Meyghani et al., 2020).

Luxury is often associated with conspicuous consumption and the lifestyles of higher social strata (Bagheri & Dadashi, 2020). Luxury items are symbols of status, highly desired but attainable only by a minority of consumers in online contexts (Kauppinen-Räisänen et al., 2018). Purchasing luxury products online is not necessarily driven by functional needs (Dhaliwal et al., 2025); rather, it is connected to the consumers' symbolic attributes, which may generate responses such as elevated self-esteem, social recognition, or the fulfillment of emotional and relational needs (Zeng & Kim, 2025). Consequently, brand and brand image represent central factors in online purchasing decisions for luxury goods (Widjaja, 2025), as consumers often strengthen their self-concept by purchasing luxury brands online (Ranakoti & Joshi, 2025).

To maintain exclusivity, luxury brands must deliver distinctive benefits unavailable elsewhere. When consumers identify these unique attributes, they perceive such products as extraordinary (Luo et al., 2025). At the same time, consumers both endorse and purchase these brands (Suardana, 2025). Prior studies revealed that when a brand's personality or image aligns with a consumer's self-concept, it exerts a positive influence on attitudes, online purchase motivation, and loyalty (Gorbaniuk et al., 2025). Loyalty emerges from favorable attitudes regarding a brand, product, or company. Thus, the brand concept and personality play a crucial role in shaping the consumer attitudes and fostering loyalty (Royo-Vela & Sanchez, 2022). Brands with consistent messaging and well-defined personalities are more likely to build loyalty, encouraging higher spending and repetitive purchasing with positive word of mouth (Hasman, 2025).

Self-image congruence exerts a direct positive effect on brand loyalty (AlQahtani, 2025). A consumer's self-concept is reinforced through the brand's personality and symbolic associations, attracting the individuals to the brand because of the perceived value it delivers in usage or online purchases (Naheen & Elsharnouby, 2024). The personality and associations of luxury brands—linked with premium prices, refinement, exclusivity, and social prestige—often necessitate inclusion in specific social groups (Castillo et al., 2024). This raises the question of whether such favorable perceptions and evaluations can be sustained when luxury brands introduce downward extensions into lower-priced segments (Park & Ahn, 2025).

Consistency of the Concept of Brand

Research on branding is fundamental for shaping effective strategies. By analyzing the current brand position and comparing it with the desired one, firms can outline development paths (Dehdashti, 2019). The concept of a brand is a central dimension that helps establish distinctiveness in consumers' minds (Vo et al., 2025). It represents the brand's essence, formed through symbols and associations (Suheri et al., 2025). A brand's concept is a unique, abstract meaning that endures when supported by integrated marketing activities, ensuring consistency across product lines (Jusuf, 2024).

In this way, it generates similar associations between consumers and the parent brand, which can shape attitudes of line extensions (Bańbuła, 2024). Luxury products which function as social markers, offer exclusive attributes that reinforce differentiation and justify higher pricing (Lee et al., 2024). As a result, the consistency of the concept of brand significantly influences how consumers evaluate extensions (Chavadi et al., 2023). Yet, when luxury brands adopt mass-marketing strategies by introducing lower-priced extensions, exclusivity may weaken. This can compromise conceptual consistency, modify product features, alter consumer evaluations, and reshape perceptions of the parent brand. If the core brand identity does not align with its extension, consumers may perceive inconsistency, which reduces purchase intention and loyalty in online settings (Royo-Vela & Sanchez, 2022).

Brand Personality

Brand personality is created when human attributes are linked to the brands, a strategy commonly applied by marketers to build favorable consumer perceptions (Khosravi et al., 2021). Effective communication efforts allow companies to develop a recognizable personality that resonates with target audiences. This connection is stronger when the brand reflects the consumer's self-concept. Acting as a bridge, brand personality ties the brand concept and brand image to the individual's self-identity. Much like human personality, it communicates through identifiable traits. Consumers compare these traits with their own; when alignment is evident, the brand becomes a symbolic extension of the self, enhancing its perceived value. Thus, the attractiveness of luxury brands in online purchases often stems from the personality traits they convey (Crener-Ricard & Phan, 2018).

The brand value, in this framework, reflects the ability of brands to embed symbolic associations into consumers' identities, making the brand part of who they are. This occurs through consumption and repeated use of brands with strong, consistent personalities. However, when luxury labels pursue downward price-based extensions, the original concepts of brand and image may shift. This change can alter the brand personality traits and reduce their alignment with consumer self-concepts (Royo-Vela & Sanchez, 2022).

The Congruence of Self-Image

Brand image refers to the consumers' perceptions, incorporating symbolic associations, attributes, and characteristics that define a brand's position in the market. It is a subjective construct, shaped by marketing strategies and influenced by consumers' individual characteristics and backgrounds (Mohit et al., 2025). When the brand image aligns with the consumer's self-concept, this creates the congruence of self-image

(Rahma et al., 2025). Based on this alignment, consumers tend to prefer brands that reflect their values and express their identities (Gorbaniuk et al., 2025).

Individuals evaluate whether a brand image reinforces their self-identity (Ayoubi et al., 2024). They are more likely to choose the brands whose images align with their own (Wiweko & Ferdinand, 2025). Conversely, when downward price-based extensions occur, brand image may weaken, diminishing alignment with the consumers' self-concepts and reducing loyalty. Essentially, luxury buyers gravitate about high-prestige brands when the brand image mirrors their self-identity, as this allows them to showcase that identity through ownership and display (Royo-Vela & Sanchez, 2022).

Literature Review

Widjaja (2025) highlighted that brand image is central in shaping trust and purchase intentions in online contexts, with product quality mediating the perception of value.

Chen et al. (2025) argued that organizational performance improvements rely on dynamic capabilities such as learning and innovation.

Castillo et al. (2024) showed that CSR communication enhances the brand image and trust when it is aligned with consumer expectations and platform features.

Nourahmadi (2024) pointed out the role of recommender systems in improving online shopping experiences by aligning products and brands with consumer preferences. In markets defined by symbolic values like luxury goods, personalized recommendations strengthen the congruence of self-image and thereby stimulate purchase intentions.

Norouzi (2024) found that digital infrastructures and online library systems facilitate consumer interactions by distributing accessible and well-structured content. The quality of such systems indirectly influences user experience, shaping trust and ultimately online purchase intentions.

Akbari Emami and Najmi (2024) studied e-commerce adoption frameworks and identified three main categories—technical, behavioral, and identity-related factors—that jointly influence online purchase intentions.

Hamilton and Hosany (2023) demonstrated that scarcity increases perceived value and purchase intentions but, if poorly managed, diminishes trust and loyalty. Just as scarcity must be strategically managed, inconsistent brand concepts or personalities can erode the consumer trust.

Chavadi et al. (2023) reported that participation in brand communities enhances trust, equity, and loyalty. When consumers feel identity alignment, they are more inclined to engage with communities and remain loyal over time.

Quach et al. (2022) investigated the art infusion in eco-friendly luxury advertising and found that it helps bridge the perceived gap between sustainability and luxury. Their findings suggested new directions for luxury marketing strategies.

Ghosh and Bhattacharya (2022) studied Gen Z in India and identified multiple antecedents of luxury brand loyalty, including CSR, product features, brand attributes, and social media engagement. While CSR had limited direct effects on trust, its combination with brand attachment was crucial in fostering loyalty. Trust mediated the link between attachment and loyalty, highlighting the layered mechanisms that support consumer commitment.

Riedmeier and Kreuzer (2022) identified four managerial roles—authoritarian guardian, intelligent guardian, agile facilitator, and connector supernova—in their study. Their contribution expands our understanding of how managers shape luxury brands strategically.

Boisvert and Ashill (2022) examined status signaling, credibility, and fit in luxury brand extensions. They reported that parent brand signaling, familiarity, and perceived quality influence credibility, while authenticity plays a decisive role in shaping the consumer attitudes. Their results also revealed cultural differences .For instance, French consumers exhibited stronger links between status signaling and credibility than American consumers, though perceived quality and familiarity had comparable effects across both groups.

Despite these contributions, research specifically addressing luxury brands remains limited. Few studies examined how antecedents such as brand concept consistency, brand personality, and the congruence of self-image influence consumer perceptions, loyalty, and online purchase intentions.

Shokri-Zadeh and Daryabaz (2021) analyzed the congruence of brand–consumer in luxury markets, highlighting factors such as brand love, affection, expectations, and image as important determinants. Their work broadened our understanding of alignment mechanisms in branding.

Porang et al. (2021) assessed the effect of brand equity on tourists' intentions in luxury tourism, with brand attitude and brand performance serving as mediators and moderators. Their findings demonstrated that the brand equity dimensions positively affected visit intention through attitudes, while performance moderated the relationship. This extended the brand equity theory to the tourism sector, emphasizing the contextual influence of brand performance.

Conceptual Model of the Research

In this study, the focus is on examining how various antecedents influence loyalty and online purchase intention of luxury brands among women. The proposed conceptual framework is presented in Figure 1. Drawing from this model, seven research hypotheses were formulated as follows:

Hypothesis 1: The consistency of brand concept has a significant relationship with online purchase intention of luxury brands.

Hypothesis 2: The consistency of brand concept has a significant relationship with loyalty to luxury brands.

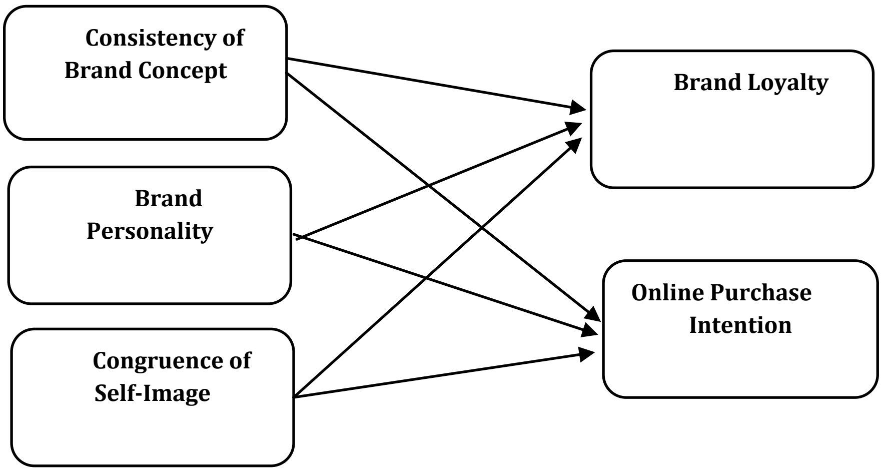
Hypothesis 3: Brand personality has a significant relationship with online purchase intention of luxury brands.

Hypothesis 4: Brand personality has a significant relationship with loyalty to luxury brands.

Hypothesis 5: The congruence of self-image has a significant relationship with online purchase intention of luxury brands.

Hypothesis 6: The congruence of self-image has a significant relationship with loyalty to luxury brands.

Figure 1.
Conceptual Model of the Research



(Source: Researcher's Findings)

Methodology

This research is applied in terms of its purpose and follows a descriptive–survey approach for data collection. The statistical population consisted of female students enrolled in the Faculty of Humanities at Mohaghegh Ardabili University. According to the official university records in 2024, the total population numbered 1,707 students. From this group, a sample of 145 students was determined using Cochran's formula and selected through convenience sampling, after which they completed the research questionnaire.

For data collection, both library research and field methods were utilized. The study variables were assessed through a localized, researcher-designed electronic questionnaire. This instrument was adapted from the work of Royo-Vela and Sanchez (2022). To measure the constructs:

- **Consistency of Brand Concept**: 3 items
- **Brand Personality**: 3 items
- **Congruence of Self-Image**: 3 items
- **Brand Loyalty**: 11 items
- **Online Purchase Intention**: 7 items

All questionnaire items were rated using a five-point Likert scale.

To ensure validity, face validity was evaluated and confirmed based on the feedback from academic professors and field experts, while content validity was assessed through the judgments of 10 experienced specialists. Reliability was examined using Cronbach's alpha coefficient, calculated via SPSS version 16. The resulting reliability indices are summarized in Table 1.

Table 1.
The Validity and Reliability of the Questionnaire

Variable	Number of Items	CVR	Cronbach's Alpha
Consistency of Brand Concept	3	0.821	0.992
Brand Personality	3	0.819	0.898
Congruence of Self-Image	3	0.776	0.916
Brand Loyalty	11	0.854	0.921
Online Purchase Intention	7	0.832	0.881

(Source: Researcher's Findings)

The results showed that the content validity, as evaluated by 10 experts, exceeded 0.6, while Cronbach's alpha coefficients for all variables were above 0.7. These findings confirmed the reliability and validity of the measurement instrument. Data were gathered using a combination of library research and fieldwork. The primary instrument was a researcher-developed questionnaire adapted from previous studies. Following data collection, the data were analyzed using Structural Equation Modeling (SEM) using the Partial Least Squares (PLS) method.

Findings

The demographic distribution of the sample in this study was evaluated based on age, education level, and experience. The results are presented in Table 2.

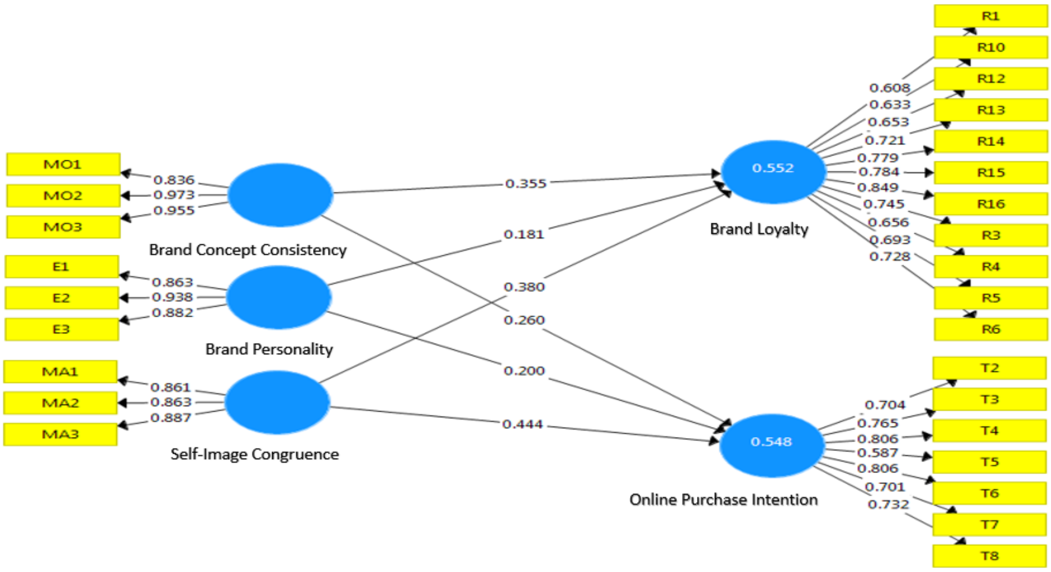
Table 2.
The Demographic Distribution of the Sample

Variable	Range	Frequency	Percentage
Age	Under 30 years	37	25.0%
	31–35 years	55	37.9%
	35–40 years	28	19.3%
	Over 40 years	25	17.2%
Education	Diploma	27	18.6%
	Associate Degree	13	9.0%
	Bachelor's	57	39.3%
	Master's	46	31.7%
	Ph.D.	2	1.4%

(Source: Researcher's Findings)

Before evaluating the model fit, factor loadings for all items were assessed based on the path coefficients. The results indicated that all factor loadings exceeded 0.4, and none of them were eliminated. The structural model derived from the path coefficients is presented in the following figure.

Figure 2.
The Path Coefficients and Factor Loadings of the Research Model



(Source: Researcher's Findings)

After confirming the adequacy of the factor loadings, the model fit was examined. The results are presented in Table 3.

Table 3.
The Estimated Values of the Research Model

Variable	Factor Loading	Cronbach's Alpha	Composite Reliability	Average Variance Extracted	R^2	Q^2	Result
Brand Self-Image	0.861	0.840	0.904	0.758	-	-	-
	0.863						
	0.861						
Consistency of Brand Concept	0.836	0.914	0.945	0.853	-	-	-
	0.973						
	0.955						
Brand Personality	0.938	0.875	0.923	0.801	-	-	-
	0.882						
	0.863						
Online Purchase Intention	0.704	0.853	0.889	0.536	0.548	0.278	Strong
	0.765						
	0.806						
	0.587						
	0.806						
	0.701						
	0.732						
Brand Loyalty	0.608	0.904	0.920	0.514	0.552	0.271	Strong
	0.633						
	0.653						
	0.721						
	0.779						
	0.784						
	0.849						
	0.745						
	0.656						
	0.693						
	0.728						

(Source: Researcher's Findings)

To assess the indices being measured and the validity of the model, indicators such as AVE, CR, and Cronbach's alpha were used. The results presented in Table 3 showed that all values exceeded the acceptable thresholds. Table 3 provides the results of the validity and reliability of the instrument.

In the present study, to evaluate the model fit, a structural model was used with two indices, R^2 and Q^2. R^2 is an indicator that connects the measurement model to the structural model and shows the effect of exogenous variables on endogenous variables. The higher the R^2 for endogenous constructs, the better the model fit. Chin (1998) indicated that values of 0.18, 0.32, and 0.66 can be used as thresholds for weak, moderate, and strong R^2, respectively. Q^2 is an indicator that examines the predictive relevance of the model. Henseler et al. (2009) suggested that values of 0.01, 0.16, and 0.36 indicate the predictive power of the model. Table 3 shows the R^2 and Q^2 values.

In this study, to evaluate the overall fit of the model, the Goodness of Fit (GOF) index was also used. The GOF in this study is 0.556, indicating a high model fit.

$$\mathrm{GOF} = \sqrt{\overline{(Communality)} \times \overline{(R\,Square)}}$$

$$\mathrm{GOF} = \sqrt{0.503 \times 0.55} = 0.525$$

In addition to what has been mentioned, there are other suitable model fit indices, the number of which has been increasing in more recent studies. However, it should be noted that there is no universal consensus on a single optimal test. Usually, using three to five indices is sufficient to confirm a model (Schumacker & Lomax, 2010). Therefore, in addition to the indices used in this study, four other well-known and important indices were also employed, including RMSEA (Root Mean Square Error of Approximation), NFI (Normed Fit Index), GFI (Goodness of Fit Index), and RMR (Root Mean Square Residual).

a) Root Mean Square Error of Approximation (RMSEA)

Unlike many other fit indices that provide only point estimates, RMSEA can be calculated for different confidence intervals, allowing the researchers to determine whether the obtained value for the model significantly differs from 0.05—a commonly used cutoff point for distinguishing good and poor models. RMSEA, which essentially measures deviation per degree of freedom, is 0.05 or lower for well-fitting models. Values above 0.08 indicate a reasonable approximation error in the population, while models with RMSEA equal to or greater than 0.10 are considered poorly fitting. It is important to note that this index can be misleading when degrees of freedom are small and the sample size is not large.

b) Normed Fit Index (NFI)

This index was first introduced by Bentler and Bonett (1980). A key limitation of NFI is its insensitivity to the addition of parameters; the index value generally increases as more parameters are incorporated. The minimum acceptable threshold for NFI is 0.90, while values of 0.95 or higher indicate a good fit.

c) Goodness of Fit Index (GFI)

Conceptually, GFI is similar to a correlation coefficient. Both GFI and correlation coefficients range from 0 to 1, although theoretically, they can assume negative values, which would indicate a definitively poor model fit. The closer the GFI is to 1, the better the model fits the observed data.

d) Root Mean Square Residual (RMR)

RMR is a fit index used to compare two different models using the same data. Its minimum value is zero, while the maximum depends on the covariances within the residual matrix and may be either small or large. Generally, a smaller RMR value in one model compared to another is considered indicative of a better model fit.

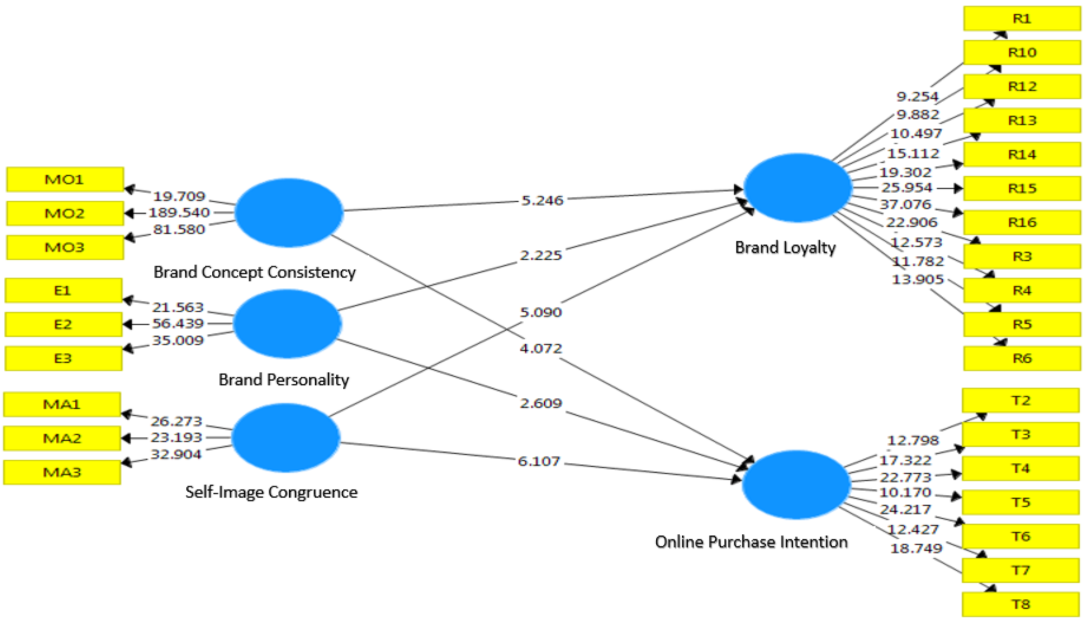
Table 4.
The Overall Fit Results (Fit Indices) of Simultaneous Relationships of Variables in the Structural Equation Model

Statistical Index	Full Name	Value	Acceptable Range (Path Analysis)	Test Result
RMSEA	Root Mean Square Error of Approximation	0.012	RMSEA < 0.09	Model Confirmed
NFI	Normed Fit Index	0.968	NFI > 0.9	Model Confirmed
GFI	Goodness of Fit Index	0.947	GFI > 0.9	Model Confirmed
RMR	Root Mean Square Residual	0.035	RMR < 0.09	Model Confirmed

(Source: Researcher's Findings)

The research hypotheses were tested using the path coefficients and t-values.

Figure 3.
The Structural Model of Direct Hypotheses



(Source: Researcher's Findings)

As shown in Figure 3, the significant effects of the consistency of brand concept, brand personality, and the congruence of self-image as antecedents influencing brand loyalty and online purchase intention for luxury brands among women were directly confirmed.

To test the significance of the hypotheses, two indicators were used: path coefficient and t-value. The t-value assesses the significance of the path coefficients. At a 95%

confidence level, if the t-value falls between ±1.96, the hypothesis is supported; otherwise, it is rejected (as indicated in Table 5). The results of the hypothesis tests, derived from the structural equation model output in Smart-PLS, are presented in Table 5.

Table 5.
The Results of the Inner Model Fit

Structural Path	Path Coefficient	t-value	p-value	Significance (α = 0.05)
Self-Image Congruence → Online Purchase Intention	0.444	6.107	0.000	Supported
Congruence of Self-Image → Brand Loyalty	0.380	5.090	0.000	Supported
Consistency of Brand Concept → Online Purchase Intention	0.260	4.072	0.000	Supported
Consistency of Brand Concept → Brand Loyalty	0.355	5.246	0.000	Supported
Brand Personality → Online Purchase Intention	0.200	2.609	0.009	Supported
Brand Personality → Brand Loyalty	0.181	2.225	0.027	Supported

(Source: Researcher's Findings)

As observed in Table 5, based on the t-statistics and p-values, all six proposed hypotheses were supported, confirming the significance of all the main paths in the model.

Discussion and Conclusion

The results of this study revealed that three main variables— congruence of self-image, consistency of brand concept, and brand personality—exert a significant positive influence on both brand loyalty and online purchase intention for luxury brands among female students. While these findings are largely consistent with the existing empirical research, they also offer some unique insights.

Among the key findings, the congruence of self-image stood out as the most influential factor. When a consumer's self-perception aligns with the identity and attributes of a brand, the probability of online purchases and repeated engagement with that brand increases substantially. This outcome is in line with the work of Sirgy et al. (1997), Kressmann et al. (2006), and Royo-Vela and Sanchez (2022), all of which emphasized the critical role of identity congruence in fostering online purchase intention and long-term loyalty. In the context of young Iranian consumers, the study suggests that the selection of luxury brands is more strongly driven by identity and social considerations than by functional benefits.

With respect to the consistency of brand concept, the findings indicated that maintaining coherence in messaging and alignment in values and brand promises enhances consumer trust and fosters stable brand relationships. These results support the views of Keller (2013) and Aaker (1996), which highlighted the brand consistency as a crucial component of symbolic brand equity. Similarly, Chavadi et al. (2023) noted that disruptions in brand consistency can undermine the consumer trust. This study corroborates these perspectives and underscores the strategic importance of managing the brand concept in competitive and sensitive markets.

Regarding the brand personality, the study showed that the personality traits attributed to a brand—although slightly less influential than the congruence of self-image or the consistency of concept—still positively impact the brand loyalty and online purchase intention. These findings resonate with prior research by Aaker (1997), Sung and Kim (2010), and Crener-Ricard and Phan (2018), suggesting that traits such as sophistication, reliability, or boldness shape consumer attitudes and behaviors. Even within the context of female students in Iran, brands that convey distinctive personalities can become integral to consumers' personal and social identity.

Comparisons with more recent studies demonstrated a notable consistency in these effects:

- Widjaja (2025), in the domain of e-commerce, highlighted that brand image is a crucial determinant of consumer trust and willingness to purchase online. The current study extended this insight by demonstrating that the congruence of self-image with the brand exerts an even stronger influence on brand loyalty.
- Hamilton and Hosany (2023) pointed out that poorly managed product scarcity can undermine the consumer loyalty. In a similar vein, the present research indicated that inconsistencies in brand concept or brand personality may threaten the consumer trust.
- Chen et al. (2025) emphasized the significance of coherence and organizational capabilities in achieving strategic success through effective business portfolio management. This aligns with the current findings, which suggested that the consistency of brand concept functions as a critical competitive capability for sustaining the consumer engagement.
- Within the context of Corporate Social Responsibility (CSR) for luxury brands, Castillo et al. (2024) showed that content aligned with consumer values strengthens trust. Correspondingly, the present study identified the brand–self congruence as the most influential factor in fostering loyalty.
- Chavadi et al. (2023) demonstrated that active participation in brand communities on social media enhances loyalty. This resonates with the current findings, as brand personality and self-image congruence provided the psychological foundation necessary for sustaining such loyalty.

Therefore, the results of this study not only corresponded with international research but also underscored the pronounced importance of the congruence of self-image within the Iranian cultural context. This suggests that young Iranian consumers often select luxury brands as a means of expressing identity and signaling social status. From a managerial perspective, these findings provided actionable guidance for luxury brand managers:

- Developing identity congruence between the brand and consumers' self-concept is critical for attracting and retaining a loyal customer base.
- Maintaining consistency and stability in the brand concept should be a central principle of brand management to cultivate enduring trust.

- Crafting a brand personality that reflects the lifestyle and psychological values of target consumers facilitates social self-expression and strengthens emotional engagement.

Nevertheless, this study has some limitations. The use of convenience sampling and the focus on a specific population (female students) constrain the generalizability of the results. Additionally, the cross-sectional design precludes examination of long-term shifts in loyalty. Future research could incorporate longitudinal designs, include more diverse samples, and examine potential mediating factors such as brand trust, emotional attachment, or perceived enjoyment to achieve a more comprehensive understanding of the interplay between brand antecedents and consumer behavior.

In conclusion, this study, alongside the existing literature, highlights that the congruence of self-image, the consistency of brand concept, and brand personality are three essential determinants of loyalty and online purchase intention for luxury brands. Addressing these factors collectively not only promotes sustainable loyalty but also strengthens brand positioning in competitive markets, ensuring repeated online purchases and long-term consumer engagement.

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Segmenting Bank Customers Based on Their Engagement in Value Co-Creation: A Decision Tree Approach

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ABSTRACT

Understanding and managing customer engagement are crucial in co-creating value and sustaining long-term customer relationships. This study develops a predictive segmentation model tailored to the banking sector, with a specific focus on emerging market contexts. Employing a mixed-methods approach, the research integrates a meta-synthesis of prior studies with a C5.0 decision tree algorithm to identify key engagement drivers. The novelty of the study lies in its integration of Relational Models Theory, Customer Lifecycle stages, and perceived emotional value into a unified predictive framework. A structured survey was administered to Iranian retail banking customers and the model segmented them based on their emotional and functional value perceptions, relational orientations, and lifecycle stages. Findings revealed that emotional value is the most influential predictor of engagement, followed by relationship stage and relational model type. Four distinct customer segments were identified, each with unique engagement profiles. The study offers practical tools for banks to personalize CRM strategies and optimize engagement efforts based on relational and behavioral insights. This research contributes to the literature by combining the relational theory and behavioral prediction within a service-dominant logic, offering actionable insights for banking institutions operating in culturally specific, emerging markets.

KEYWORDS

Customer Participation, Value Co-Creation, Decision Tree Model, Banking Sector, Customer Engagement

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Introduction

Customer segmentation is a critical tool for developing effective marketing strategies and designing customer-centric services. In the banking sector, where services are intangible and competition is intensifying, understanding customer engagement patterns has become essential (Aaker, 2001). Traditional segmentation approaches based on demographic or behavioral variables are increasingly insufficient. The rise of digital platforms and service-dominant logic (Vargo & Lusch, 2004, 2008) has brought the value co-creation to the forefront. Today, firms aim not only to serve but to co-create value with customers—particularly those who actively engage. Customer engagement has been linked to both profitability and innovation. Scholars argue that emotionally engaged customers contribute beyond transactions by providing feedback or referring to others (Kumar & Pansari, 2016). Recent research highlights the role of omnichannel consistency in strengthening this engagement (Kumar & Sharma, 2024). In service contexts, brand value is largely shaped through customer experience and interaction (Berry, 2000). Moreover, customers increasingly seek involvement in shaping the products and services they use. Kotler et al. (2010) note that in today's participatory economy, customers do not merely consume—they influence, co-create, and engage with the brand ecosystem. Customer–bank relationships also evolve across a lifecycle, and the intensity of engagement varies at each stage (Zhang et al., 2016). At the same time, Relational Models Theory (Fiske, 1991) offers insight into how customers perceive and structure interactions, from communal sharing to transactional exchanges. Despite the growing scholarly attention, there remains a significant gap in integrated models that simultaneously account for customers perceived value, relational orientations, and lifecycle stages—especially in emerging markets where cultural dynamics and trust mechanisms differ markedly from Western contexts. Most previous studies either focus on isolated predictors of engagement or are confined to digital-native, developed economies. This gap highlights the need for predictive, data-driven models that reflect the behavioral and emotional patterns of customers in culturally specific banking sectors such as Iran. This study aims to develop a decision tree model for identifying high-engagement customers based on key drivers: perceived value (functional and emotional), relational models, lifecycle stages, and demographic characteristics. The findings offer a segmentation approach aligned with engagement-based value creation.

Literature Review

Customer Engagement

Customer engagement has emerged as a multidimensional construct encompassing emotional, cognitive, and behavioral components. Bowden (2009) defined it as a psychological process by which customers evolve from awareness to loyalty. Van Doorn et al. (2010) emphasized behavioral expressions such as referrals, feedback, and content sharing, while Brodie et al. (2011) highlighted its co-creative and interactive nature. Vivek et al. (2012) underscored the emotional and cognitive depth of engagement, and Kunz et al. (2017) categorized engagement perspectives into psychological, behavioral, and motivational, offering a more nuanced framework for understanding participation. Pansari and Kumar (2017) presented an integrated view combining behavioral manifestations and affective commitments.

[Recent research also focuses on engagement in digital and AI-driven settings. Li and Zhao (2025) showed that trust in AI-powered services (e.g., banking chatbots) enhances engagement. Kumar and Sharma (2024) emphasized omnichannel consistency as a critical driver of sustained engagement in financial services. In the Iranian context, Kousheshi et al. (2020) highlighted that customer engagement in online platforms is closely linked to relationship quality—particularly trust, satisfaction, and emotional commitment. This underscores the relevance of relational dynamics and cultural expectations in shaping customer–firm interactions.]

The Value of Customer Engagement

Customer engagement generates value for firms in both direct and indirect ways. Kumar et al. (2010) introduced a widely accepted framework that categorizes this value into three dimensions ofCustomer Lifetime Value (CLV), Customer Influence Value (CIV), and Customer Knowledge Value (CKV).

CLV refers to the net present value of all future profits generated by a customer through continued transactions (Kumar & Reinartz, 2016). It captures the economic worth of a loyal customer who consistently engages in repeat purchases or expands their service usage.

CIV reflects the customer's ability to influence potential buyers via word-of-mouth, social sharing, and informal advocacy (Pansari & Kumar, 2017; Verhoef et al., 2009). Customers who voluntarily promote the brand help reduce acquisition costs and enhance brand credibility, especially in service settings.

CKV denotes the knowledge that customers share with the firm—such as feedback, innovative suggestions, or experience-based insights—that can inform product development and process improvements (Hollebeek et al., 2021; Kumar, 2019). Hartono and Wijaya (2023) showed that CKV significantly impacts the customers' intention to reuse mobile banking services.

This tripartite model allows firms to identify customers not solely based on revenue but also on their relational and intellectual contributions. The model's practical relevance has been demonstrated in customer segmentation and resource allocation across multiple industries, including banking and digital services. Overall, recognizing and leveraging engagement value can help firms tailor strategies to cultivate high-potential customers and optimize long-term performance.

Relational Models Theory

Relational Models Theory (RMT), developed by Fiske (1991), provides a comprehensive framework for understanding how individuals construct, interpret, and regulate social relationships. It posits that human interactions are governed by a limited set of relational models that guide expectations and behaviors. While six models were originally proposed, three are particularly relevant in customer–firm contexts: Communal Sharing (CS), Equality Matching (EM), and Market Pricing (MP) (Kaltcheva et al., 2014).

In the Communal Sharing model, individuals view themselves as members of a shared identity group, emphasizing unity, loyalty, and emotional connection. In business contexts, this model is evident when customers form strong affective bonds with a brand or community and participate in co-creation out of identification rather than calculation (Kaltcheva et al., 2010).

The Equality Matching model is based on balanced reciprocity, where interactions are guided by fairness and equivalence. Customers operating within this model expect mutual consideration; they are more likely to share feedback or participate in service design if their input is acknowledged and reciprocated (Bogodistov et al., 2017).

Market pricing, in contrast, is driven by cost–benefit calculations and the principle of proportionality. Customers engaging in this model evaluate interactions through utility maximization, seeking the highest return for the lowest cost (Giessner et al., 2010). Loyalty is typically contingent on perceived functional value or price advantage.

Understanding these relational orientations enables firms to tailor engagement strategies based on how customers perceive the relationship. For example, CS-oriented customers may be more responsive to emotional appeals, while MP-oriented customers may prioritize efficiency and financial incentives.

Relationship Life Cycle Framework

The relationship life cycle framework conceptualizes the evolving nature of customer–firm interactions over time. Originating from exchange theory and contract law, Dwyer et al. (1987) introduced a five-stage model of relationship development: awareness, exploration, development, maintenance, and termination. Subsequent research adapted this framework to various service contexts, emphasizing the dynamic and bidirectional nature of engagement (Palmatier et al., 2006; Zhang et al., 2016).

In the context of customer engagement, four stages are particularly relevant:

- Exploration: Initial interactions marked by uncertainty and low commitment. Customers evaluate the firm’s credibility and potential value.
- Development: Trust and satisfaction begin to form, leading to deeper engagement. Mutual expectations are shaped, and emotional attachment may emerge.
- Maintenance: A mature, stable phase characterized by high trust, relational equity, and consistent value co-creation. Engagement is typically strongest here.
- Decline: Engagement weakens due to changing needs, dissatisfaction, or better alternatives. The risk of defection increases unless proactive interventions occur.

Cambra-Fierro et al. (2018) argue that engagement is not static but fluctuates throughout the lifecycle, with the potential to regenerate or deteriorate depending on contextual and relational factors. Zhang et al. (2016) similarly emphasize that firms must tailor engagement strategies to each stage to sustain customer value and avoid premature disengagement.

In banking, recognizing a customer's position within the relationship lifecycle allows service providers to deliver personalized experiences and optimize timing for interventions, upgrades, or loyalty initiatives.

Customer Perceived Value

Customer Perceived Value (CPV) is a core construct in marketing, defined as the customer's overall evaluation of the trade-off between the perceived benefits of a service and the sacrifices made to obtain it (Zeithaml, 1988). This evaluation influences customer satisfaction, loyalty, and engagement, particularly in intangible service-based settings like banking.

The current study focuses on two primary dimensions of CPV:

- Functional Value: Refers to the utility derived from a service's practical performance, reliability, and effectiveness. Customers assess whether the service fulfills its intended purpose efficiently and meets their expectations regarding convenience and usefulness (Zeithaml et al., 2020).
- Emotional Value: Captures the affective responses generated through the customer's experience, such as feelings of trust, comfort, enjoyment, and psychological security. Emotional value often plays a stronger role than functional value in shaping the customer loyalty and advocacy behaviors (Mohammadi-Far & Poorjamshidi, 2021; Riley et al., 2015).

Research suggests that emotional value has a greater influence on sustained engagement, especially in contexts where trust and relational bonds are essential (Sánchez-Fernández & Iniesta-Bonillo, 2007). In banking, for example, even if functional performance is high, weak emotional resonance may reduce long-term commitment. Recognizing both dimensions enables firms to craft experiences that not only meet functional needs but also foster deep emotional attachment, which in turn supports more active and meaningful customer participation.

Research Gap and Study Contribution

Despite the growing literature on customer engagement, several important gaps remain. First, many studies focus exclusively on transactional metrics or affective dimensions without integrating deeper relational mechanisms such as customers' social orientation or perception of fairness. While concepts like Customer Lifetime Value (CLV) and Customer Influence Value (CIV) have been well-documented (Kumar et al., 2010), fewer empirical models capture engagement as a multidimensional behavioral and psychological construct influenced by relational models and perceived value.

Second, prior research often overlooks the temporal dimension of the customer engagement. Few frameworks explicitly consider how engagement fluctuates across different stages of relationship lifecycle, or how firms can align their strategies accordingly (Cambra-Fierro et al., 2018; Zhang et al., 2016).

Third, although the theoretical underpinnings of customer engagement are robust in Western and digital-native markets, limited empirical evidence exists in emerging economies—particularly within the banking sector of countries like Iran, where the customer behavior is shaped by unique cultural, technological, and institutional factors.

To address these gaps, this study offers a novel, data-driven segmentation approach using a decision tree model that integrates:

- Customers perceived value (emotional and functional),

- Their relational orientation (based on Relational Models Theory),
- Their current stage in the relationship lifecycle,
- And relevant demographic variables. By combining these constructs into a unified predictive model, the study provides practical tools for identifying and prioritizing high-engagement customers, optimizing resource allocation, and designing context-specific engagement strategies.

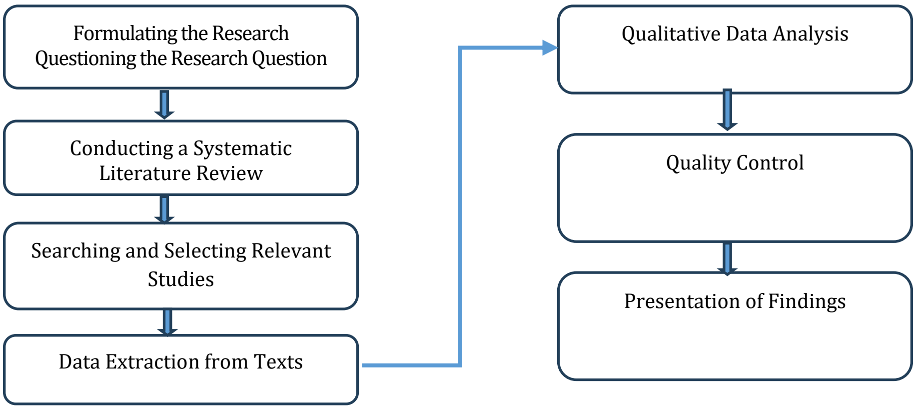
Methodology

This study adopted a mixed-methods design to investigate customer engagement segmentation in the banking sector. A meta-synthesis of prior literature was initially conducted to extract key engagement constructs, followed by a quantitative phase using a C5.0 decision tree model. Data were collected from 880 banking customers in Iran using a structured questionnaire measuring emotional and functional values, relational orientations (based on Relational Models Theory), and stages of relationship lifecycle. Due to operational constraints, convenience sampling was used, which facilitated timely data collection but may introduce selection bias and limit generalizability. The reliability index was confirmed with Cronbach's alpha values exceeding 0.70 for all constructs. To enhance validity, content validity was established through expert judgement by three academic scholars in marketing and services research, while construct validity was verified by Exploratory Factor Analysis (EFA), confirming the distinctiveness of key variables. The cleaned dataset was analyzed using IBM SPSS Modeler, and the C5.0 algorithm generated interpretable rule-based customer segments based on engagement predictors.

Qualitative Phase: Meta-Synthesis

In the first phase, meta-synthesis was employed to extract conceptual factors from previous studies indexed in databases such as Scopus, Emerald, and Science Direct between 2005 and 2023. A total of 33 relevant articles were reviewed and analyzed based on the seven-step framework proposed by Sandelowski and Barroso (2006). The process followed is illustrated in Diagram 1.

Diagram 1.
Stages of the Meta-Synthesis Method (Sandelowski & Barroso, 2007)



(Source: Researcher's Findings)

The guiding research questions for this analysis formulated around what, who, where, and how are briefly described in the text (see summary formerly shown in Table 1).

Table 1.
Research Questions (Meta-Synthesis Analysis)

Dimension	Questions	Answers
What	What are the key factors influencing customer engagement in value co-creation for banks?	Identification of determining factors from prior research on customer engagement in banking value co-creation
Who	What is the study population for identifying these factors?	Valid and credible scientific databases used in this study
When	What is the time range of the reviewed studies?	Research articles published between 2005 and 2023 from selected databases
How	What method was used to collect the relevant studies?	Qualitative data were analyzed using document analysis method

(Source: Researcher's Findings)

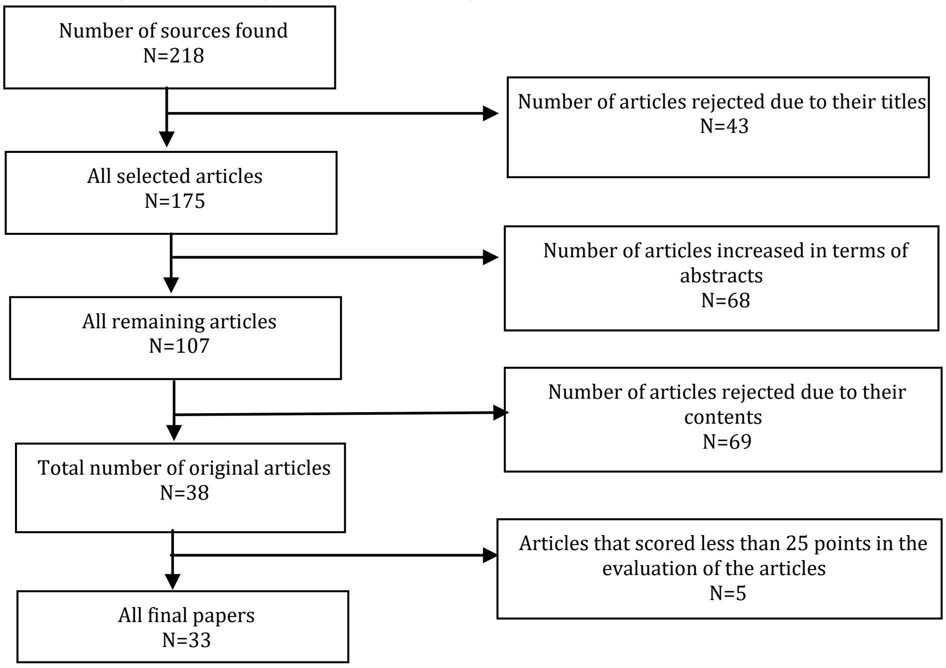
Keywords used for database searches included terms such as "customer engagement", "value co-creation", and "relational orientation" (Table 2 omitted).

Table 2.
The Keywords Searched in Academic Databases

Keywords	Databases
Customer Engagement	Scopus, Emerald, ScienceDirect
Value of Customer Engagement	
Banking Industry	

The process of screening and selecting articles is shown in Diagram 2 (Selection of the Articles for Meta-Synthesis).

Diagram 2.
The Process of Searching and Selecting Articles for Meta-Synthesis



(Source: Researcher's Findings)

Key constructs extracted from the reviewed articles are summarized in Table 3, including the perceived value (emotional and functional), relational models (communal sharing, equality matching, market pricing), stages of relationship lifecycle, and demographic attributes.

These themes served as a theoretical basis for designing the quantitative phase.

Table 3.
The Identified Factors Related to Customer Engagement and Its Value

Identified Factor	Definition	Sources
Functional Value	The value created to fulfill the customer expectations.	Prebensen et al. (2013); Pansari & Kumar (2017); Rahi (2016); Reilly et al. (2015); Naseem et al. (2015); Zeithaml (2020)
Emotional Value	The value arising from the pleasant feelings a product or service creates for the customer.	Prebensen et al. (2013); Pansari & Kumar (2017); James (2002); Choi (2017); Rahi (2016); Reilly et al. (2015); Naseem et al. (2015); Zeithaml (2020)
Communal Sharing Model	What people share and what distinguishes them from those outside their group.	Kaltcheva & Parasuraman (2009); Kaltcheva et al. (2010); Van Doorn et al. (2010); Shi et al. (2016); Carlsson (2018); Zhang (2017)
Equality Matching Model	Involves exchange of resources that are similar in type.	Giessner (2010); Bogodistov et al. (2017); Kaltcheva et al. (2014); Kaltcheva & Parasuraman (2009)
Market Pricing Model	Individuals focus on ratios and rates, calculating costs and benefits.	Giessner (2010); Bougodistou et al. (2017); Kaltcheva et al. (2014); Kaltcheva & Parasuraman (2009)
Customer Lifetime Value	Refers to the repeated selection of firm services and long-term relationship continuation.	Kaltcheva et al. (2014); Pansari & Kumar (2017)
Customer Influence Value	When customers voluntarily and without incentives share their experiences through word-of-mouth.	Verhoef et al. (2009); Kaltcheva et al. (2014); Pansari & Kumar (2017)
Customer Knowledge Value	When customers transfer their knowledge through innovative ideas or suggestions for improvement.	Hoyer et al. (2010); Joshi & Sharma (2004); Fuller et al. (2008); Kumar (2019); Kaltcheva et al. (2014); Pansari & Kumar (2017)
Relationship Life Cycle	A process through which a relationship starts, develops, matures, and eventually ends.	Palmatier (2008); Bleier et al. (2018); Cambra-Fierro (2018); Aali et al. (2019)
Demographic Characteristics	Age, gender, education level, etc.	Aali et al. (2019)

(Source: Researcher's Findings)

Quantitative Phase: Survey and Sampling

Based on the qualitative findings, a structured questionnaire was developed and validated by marketing and banking experts. The statistical population consisted of customers from Iranian commercial bank branches in Tehran. Due to the absence of an accessible sampling frame, convenience sampling was applied. Out of 1,000 questionnaires distributed over one month, 880 valid responses were used for analysis.

Data Mining Approach

Data mining refers to the process of extracting useful patterns and knowledge from large datasets (Huang et al., 2007; Witten & Frank, 2005). It supports decision-making by uncovering hidden relationships in operational data. Common techniques include decision trees, neural networks, and Bayesian networks (Lee & Tu, 2010). Among them, the C5.0 algorithm, developed by Quinlan, is favored for its high interpretability, ability to handle missing and mixed-type data, and robust classification performance (Gupta et al., 2017; Kumar & Ravi, 2007). In this study, C5.0 was applied as a data mining technique to classify customer engagement patterns based on both demographic and psychological predictors.

Measurement Instruments

Measurement items were drawn from prior studies. Perceived value was assessed with 11 items for functional and 5 for emotional values (Zeithaml et al., 2020). Relational models included 4 items for communal sharing, 3 for equality matching, and 2 for market pricing (Kaltcheva et al., 2014). The customer engagement value was based on Pansari and Kumar's (2016) model, incorporating customer lifetime, influence, and knowledge value. All items were measured on a 5-point Likert scale, except for the stage of relationship, which was assessed using a four-option nominal scale (Jap & Ganesan, 2000).

Data Analysis

Data analysis was conducted in two stages. First, basic descriptive statistics were used to evaluate data distribution. Skewness and kurtosis values were calculated to assess the normality of the data, and all values were within acceptable thresholds. Internal consistency of the constructs was confirmed using Cronbach's alpha, with all values exceeding 0.70 (see Table 6). In the second stage, a data mining technique was applied using the C5.0 decision tree algorithm to identify meaningful classification rules. This model was used to segment customers based on their engagement behavior and related predictor variables, including emotional value, stage of relationship life cycle, and relational orientation.

Findings

Operationalization of Variables

The operational definitions and measurement sources for all key constructs including emotional and functional values, relational models (communal sharing, equality matching, market pricing), stages of relationship life cycle, and customer engagement components are outlined in Table 4. These variables were used as inputs in the decision tree analysis, based on established scales adapted from prior literature.

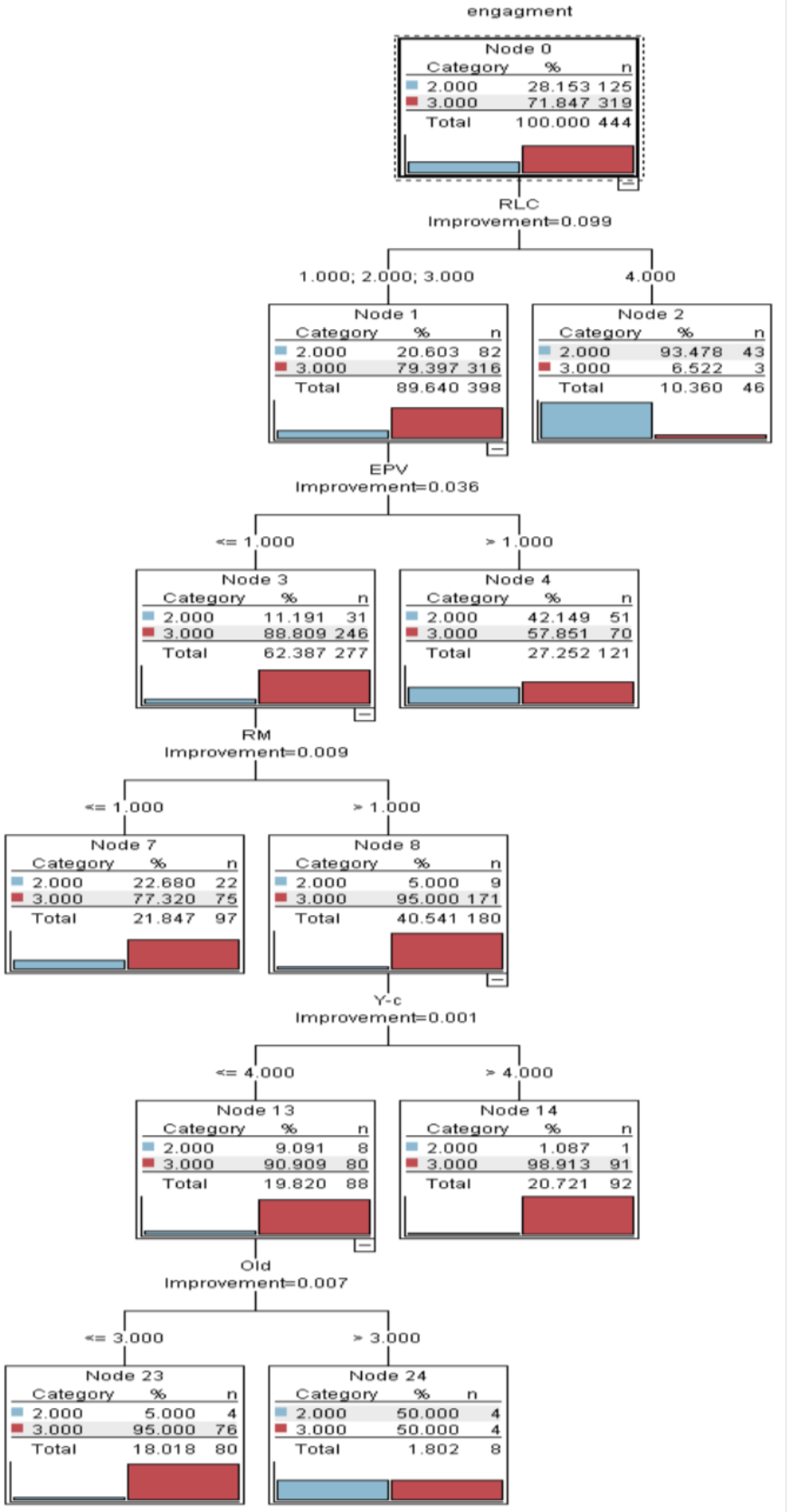
The segmentation results using the C5.0 decision tree algorithm are illustrated in Figure 1. The model identifies the relationship lifecycle (RLC), emotional perceived value (EPV), relational model (RM), and age as the primary predictors of the customer engagement.

Table 4.
The Operational Definitions of Study Variables

Variable Type	Variable Level / Name	Abbreviation	Operational Definition
Target Variable	Classification of Customers Based on Customer Engagement Value	Engagement	A binary variable operationalized based on the level of customer engagement value (customer lifetime value, customer influence value, and customer knowledge value). Calculated from the average of 9 questions: if the average is less than 3.5 (low engagement), value = 2; if between 3.5 and 5 (high engagement), value = 3.
Predictor Variables	Perceived Value - Emotional Value	EPV	A binary variable indicating the level of emotional value received by the customer from the bank. If the average score ≥ 3.5 (high emotional value), value = 1; otherwise (low emotional value), value = 2.
	Perceived Value - Functional Value	FPV	A binary variable indicating the level of functional value received by the customer from the bank. If the average score ≥ 3.5 (high functional value), value = 1; otherwise (low functional value), value = 2.
	Customer Relational Models - Communal Sharing	RM	A single-level variable corresponding to the communal sharing model. If the mean response score is greater than the average of the equality matching and market pricing models, value = 1.
	Customer Relational Models - Equality Matching		A single-level variable corresponding to the equality matching model. If the mean response score is greater than the averages of the communal sharing and market pricing models, value = 2.
	Customer Relational Models - Market Pricing		A single-level variable corresponding to the market pricing model. If the mean response score is greater than the averages of the equality matching and communal sharing models, value = 3.
	Relationship Life Cycle	RLC	A four-level variable indicating the stage of the relationship between the customer and the bank: identification stage = 1, development stage = 2, maintenance stage = 3, decline stage = 4.
	Demographic - Age	Old	A continuous variable indicating the customer’s age at the time of the study.
	Demographic - Education Level	Education	A five-level variable indicating the customer's education level: less than diploma = 1, diploma = 2, associate degree = 3, bachelor’s degree = 4, master’s degree and above = 5.
	Demographic - Gender	Gender	A binary variable: female = 1, male = 2.
	Demographic - Customer Type	T-C	A binary variable: individual (natural person) customer = 1, corporate (legal entity) customer = 2.
	Demographic - Customer Duration (Years)	Y-C	A five-level variable indicating the number of years the customer has been with the bank: less than 1 year = 1, more than 1 and up to 3 years = 2, more than 3 and up to 6 years = 3, more than 6 and up to 9 years = 4, more than 9 years = 5.
	Demographic - Percentage of Total Banking Activity	TP	A five-level variable indicating the percentage of total banking activities of the customer at Iranian commercial bank: less than 20% = 1, 21%-40% = 2, 41%-60% = 3, 61%-80% = 4, 81%-100% = 5.

(Source: Researcher's Findings)

Figure 1.
The Decision Tree Output for the Customer Engagement Segmentation



(Source: Researcher's Findings)

Demographic Profile

A total of 880 valid responses were retained. Table 5 presents the demographic information of the respondents, including gender, age, education level, and the duration of the relationship with the bank. Most participants were aged between 31 and 50 years, and a significant portion had a university-level education. These attributes provide context for the segmentation results in later stages of the analysis.

Table 5.
Descriptive Characteristics of the Respondents

Demographic Characteristics	Count	Percentage	Demographic Characteristics	Count	Percentage
Gender			Education		
Female	404	45.9%	Below Diploma	80	8%
Male	476	54.1%	Diploma	204	23.2%
Total	880	100%	Associate Degree	194	22%
Age			Bachelor’s Degree	244	27.7%
Under 25	92	10.5%	Master’s Degree and Above	168	19.1%
26 to 34	186	21.1%	Total	880	100%
35 to 44	206	23.4%	Customer Type		
45 to 54	178	20.2%	Individual (Natural Person)	564	64.1%
55 to 64	154	17.5%	Corporate (Legal Entity)	316	35.9%
Over 65	64	7.3%	Total	880	100%
Total	880	100%			

(Source: Researcher's Findings)

Descriptive Statistics and Reliability of the Instrument

As shown in Table 6, descriptive statistics indicate that the emotional value was higher than the functional value among respondents. Among relational models, communal sharing had the highest average, followed by the equality matching and market pricing. The mean values of all constructs were above the midpoint of the five-point Likert scale, confirming favorable customer perceptions.

Data normality was assessed through skewness and kurtosis values. All values were within acceptable thresholds (±3), suggesting no major deviation from normality. The reliability of the instrument was assessed using Cronbach’s alpha. All variables exceeded the 0.70 threshold, indicating high levels of internal consistency. The detailed values are included in Table 6.

Table 6.
Results of the Data Distribution Normality and Reliability of Research Variables

Variable	N	Mean	Standard Deviation	Skewness	Kurtosis	Cronbach's Alpha
Functional Value	880	3.566	0.532	-0.591	0.273	0.870
Emotional Value	880	3.646	0.608	-0.621	0.447	0.795
Communal Sharing	880	3.627	0.593	-0.522	0.149	0.755
Equality Matching	880	3.550	0.661	-0.588	0.778	0.739
Market Pricing	880	3.576	0.746	-0.429	0.364	0.721
Customer Lifetime Value	880	3.601	0.739	-0.482	0.311	0.703
Customer Influence Value	880	3.668	0.689	-0.468	-0.018	0.742
Customer Knowledge Value	880	3.821	0.627	-0.846	0.898	0.734

(Source: Researcher's Findings)

Evaluation of the Decision Tree Model Prediction Accuracy

The accuracy of predicting correct and incorrect classifications of individuals in the training group (620 cases) and the testing group (260 cases) regarding customer engagement in value co-creation was evaluated. The obtained decision tree model was able to correctly predict the occurrence of these phenomena for approximately 91.94% of individuals in the training group (samples used to build the model) and about 83.08% of individuals in the testing group.

Table 7 shows the evaluation results of the correct and incorrect predictions for the decision tree model in the training and testing groups using the C5.0 algorithm.

Table 7.
The Percentage of Correct and Incorrect Predictions of the Decision Tree Model in Training and Testing Groups

'Partition'	1_Training		2_Testing	
Correct	570	91.94%	216	83.08%
Wrong	50	8.06%	44	16.92%
Total	620		260	

(Source: Researcher's Findings)

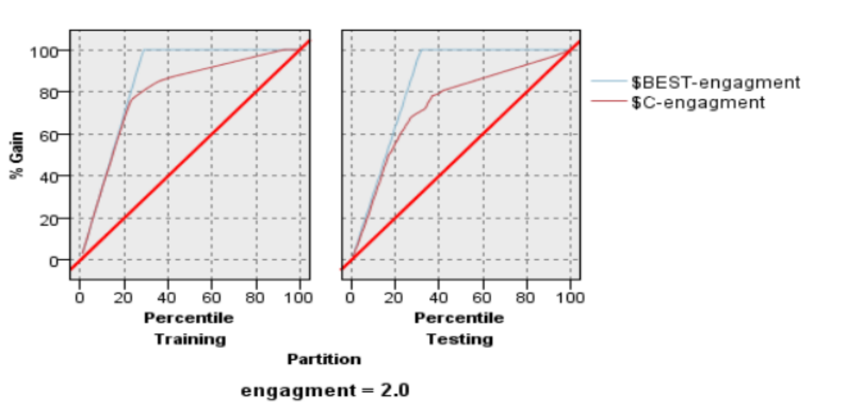
Another important evaluation criterion for decision trees is the Gain chart, which is used to assess one or more models against each other or compare a model with the theoretically best possible model.

Gain is defined as the percentage of total successes occurring within each decile, calculated as:

$$\text{Gain}=\frac{\text{Number of successes in deciles}}{\text{Total number of successes}} \times 100$$

This criterion showed favorable results for the C5.0 algorithm in both the training group (left chart) and the testing group (right chart). Overall, according to Diagram 3, the validity and power of the C5.0 model are very close to the best theoretical model, confirming the suitability of using the C5.0 algorithm in this research.

Diagram 3.
The Gain Chart of the Study Model in Training and Testing Groups under the C5.0 Algorithm



(Source: Researcher's Findings)

The importance coefficients of explanatory variables and components in the decision tree using the C5.0 algorithm are presented in Table 8, ranked from the most to the least important.

Table 8.
The Importance Degrees of the Explanatory Variables Studied

Variable Name	Importance Coefficient
Relationship Life Cycle	0.46
Emotional Value	0.23
Age	0.10
Customer Relational Models	0.08
Customer Duration (Years)	0.06
Gender	0.03
Functional Value	0.03
Percentage of Banking Activity	0.03

(Source: Researcher's Findings)

Rule Extraction: High and Low Engagement Segments

Based on the decision tree structure, conditional rules were generated to classify the customers into segments with high or low engagement in value co-creation.

Table 9.
The Rules Leading to High Engagement

Path	Rule	Engagement
1	Life Cycle: Identification/Development/Maintenance + High Emotional Value + Communal Sharing	High
2	Same Life Cycle + High Emotional Value + Equality Matching or Market Pricing + Duration < 9 years + Age < 45	Very High
3	Same Rule as #2 but Duration > 9 years	Very High
4	Same Life Cycle + Low Emotional Value	Moderate

(Source: Researcher's Findings)

Table 10.
The Rules Leading to Low Engagement

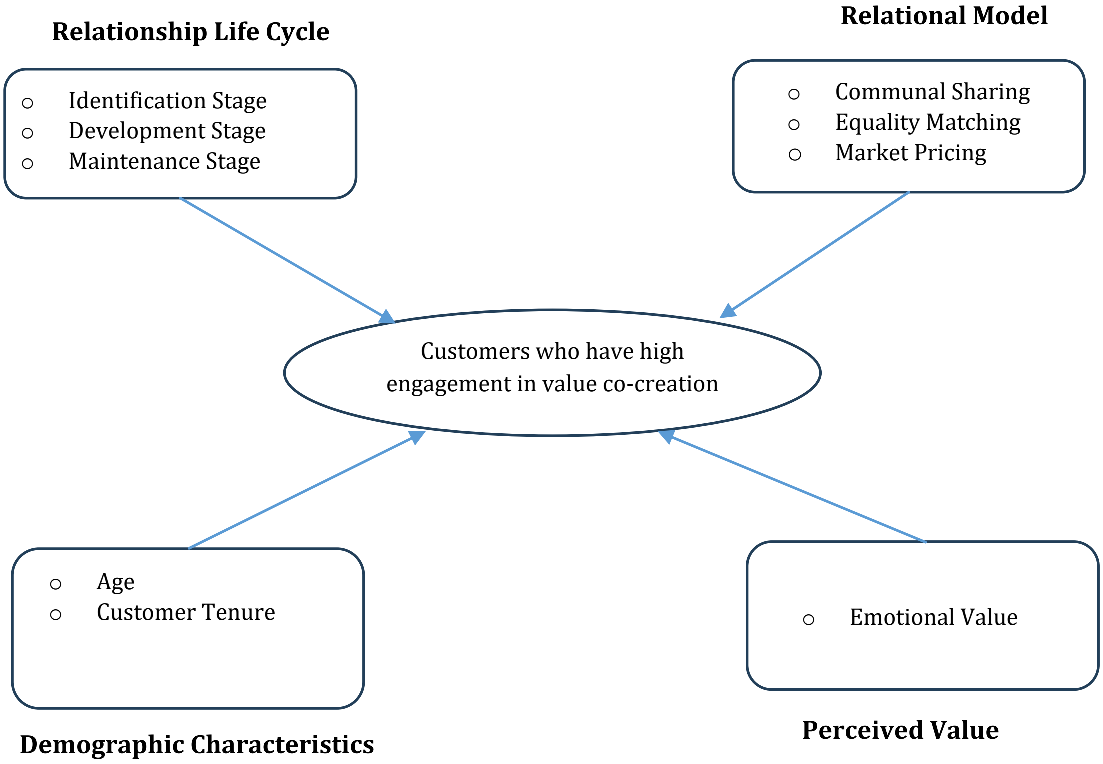
Path	Rule	Engagement
1	Same as Table 9 Rule #2 + Age > 45	Low
2	Life Cycle: Decline stage (regardless of other variables)	Very Low

(Source: Researcher's Findings)

These rules clearly demonstrate the combination of psychological, demographic, and relational factors that differentiate highly engaged customers from less engaged ones. These insights enable the design of more personalized strategies for customer engagement and resource allocation in banking.

Conceptual Model

Figure 2.
The Final Research Model Based on Target Customers in Value Co-Creation for the Bank



(Source: Researcher's Findings)

Discussion and Conclusion

Engagement Patterns and Segmentation Insights

The decision tree analysis revealed four distinct customer engagement segments shaped by emotional value, relational orientation, and stage of relationship lifecycle. The customers in the communal sharing orientation with high emotional value and established relationships demonstrated the highest levels of engagement. In contrast, the customers in the decline stage or those with transactional (market pricing) mindsets and low emotional bonds were less likely to engage deeply. This segmentation highlights that emotional connection, more than demographic or purely functional factors, predicts the customer participation in value co-creation.

The model also uncovered a high-value segment—young customers with long tenure and strong emotional ties—suggesting that emotional loyalty may develop even in early adulthood, provided the relationship continuity is sustained. Segment D, representing low-engagement customers in decline, offers a clear target for retention and win-back efforts.

Dominance of Emotional Value in Driving Engagement

Emotional value emerged as the most influential predictor of engagement, surpassing functional utility. This confirms prior findings (Mohammadi-Far & Poorjamshidi, 2021;

Sánchez-Fernández & Iniesta-Bonillo, 2007) that emotional and psychological factors such as trust, comfort, and belongingness drive sustained participation in service contexts.

In Iran's banking environment—marked by high interpersonal expectations and relational norms—emotional resonance appears even more critical. Unlike Western contexts emphasizing efficiency and speed (Li & Zhao, 2025), Iranian customers respond more to loyalty-based and trust-centered strategies. This cultural sensitivity reinforces the need to embed emotional cues into service experiences.

Strategic Implications for Customer Relationship Management

The findings offer actionable guidance for relationship marketing and CRM implementation:

- Communal Sharing customers benefit from emotionally driven strategies such as loyalty programs, appreciation gestures, and co-creation events.
- Equality Matching customers respond to fairness-based initiatives, transparent communication, and reciprocal recognition.
- Market Pricing customers value cost-efficiency, promotional clarity, and service performance.

Mapping customers by their lifecycle stage enables banks to time interventions—e.g., onboarding support, maintenance engagement, or win-back offers—with greater precision. Embedding emotional and relational logic into CRM systems can enhance the targeting accuracy and deepen the customer ties.

Theoretical and Practical Contributions

This study makes a theoretical contribution by integrating relational models, lifecycle stages, and perceived value into a unified, empirically validated segmentation framework. Unlike prior models that examine engagement in isolation, this framework reveals how relational schemas and emotional value jointly shape participation.

Practically, the study equips service firms—particularly in emerging markets—with tools to personalize engagement strategies using psychological and behavioral variables. The model's interpretability (via decision tree logic) also facilitates its operational use by managers.

Limitations and future research directions

Like all empirical studies, this research has limitations. The use of convenience sampling may introduce selection bias, and cultural context limits the generalizability beyond Iranian banking. Future studies should test this framework across industries and geographies to establish its external validity. Cross-cultural replication and longitudinal tracking of customer engagement over time would strengthen the model's robustness. Further research might also explore the integration with AI-driven CRM tools or examine how regulatory differences affect the relational dynamics.

This study demonstrates that customer engagement is best predicted through a multidimensional lens—capturing the emotional value, relational orientation, and lifecycle status. The decision tree segmentation provides both theoretical clarity and practical utility. By recognizing customers not just as buyers but as co-creators of value, firms can craft culturally informed, emotionally resonant, and lifecycle-aligned engagement strategies that enhance satisfaction and long-term loyalty. Ultimately, this research offers a replicable, analytics-based approach to engagement segmentation in emerging service markets, contributing to both marketing scholarship and strategic practice.

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