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Identifying the Components of an Intelligent Decision Support System Using a Financial Intelligence Approach (Case Study: National Banking Organizations)

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ABSTRACT

The purpose of this study was to identify the components of an intelligent decision support system using a financial intelligence approach. The study participants consisted of eight university faculty members and senior managers of national banks; the sampling method was purposive using a snowball technique, and sampling continued until theoretical saturation was achieved. In terms of purpose, the research was applied; in terms of nature, it was exploratory; based on methodology, it adopted a qualitative approach; and according to the research paradigm, it was interpretive. In this study, the qualitative thematic analysis technique was employed to identify the components of an intelligent decision support system with a financial intelligence approach. Within this technique, written texts related to the theoretical foundations and semi-structured interviews with experts were used to discover initial codes and themes; initially, 351 initial codes were identified and key themes were formed; subsequently, by identifying similarities in the underlying structure of the identified themes, 15 integrative themes were extracted; finally, by merging similar structures of the integrative themes, six overarching themes were obtained, including the primary database, decision support repository, information security and protection, knowledge management, application of the financial intelligence approach, and command processor. Based on the findings of the study, it is recommended that senior banking managers invest in the identified overarching themes in order to improve banking productivity.

Keywords: Decision Support System; Financial Intelligence; Banking System

Introduction

In recent decades, organizations have been operating in an environment characterized by increasing complexity, volatility, and uncertainty, driven by rapid technological change, intensified competition, regulatory pressures, and the exponential growth of data. In such conditions, traditional managerial decision-making approaches based on intuition or limited information are no longer sufficient to ensure organizational sustainability and competitiveness. Consequently, decision-making has increasingly become a data-driven, technology-enabled, and intelligence-oriented process, in which advanced analytical systems play a central role (1, 2). Among these systems, Intelligent Decision Support Systems (IDSS) have emerged as critical tools for enhancing the quality, speed, and consistency of managerial decisions across various organizational contexts.

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Decision Support Systems (DSS) were originally developed to assist managers in semi-structured and unstructured decision-making situations by integrating data, models, and analytical tools. With the integration of artificial intelligence (AI), machine learning, and advanced analytics, these systems have evolved into intelligent decision support systems capable of learning from data, adapting to environmental changes, and generating predictive and prescriptive insights (3, 4). IDSS are no longer limited to operational support but are increasingly used in strategic, financial, and organizational decision-making, enabling firms to respond proactively to risks and opportunities (5, 6).

The banking sector represents one of the most information-intensive and decision-sensitive environments, where the quality of decisions directly affects financial stability, customer trust, regulatory compliance, and long-term performance. Banks continuously face complex decisions related to credit allocation, risk management, liquidity management, investment strategies, fraud detection, and regulatory reporting. The growing volume and variety of financial, transactional, customer, and external economic data have made manual or conventional decision-making processes inadequate (7, 8). As a result, banks increasingly rely on intelligent decision support systems to transform raw data into actionable knowledge and to enhance decision-making effectiveness.

Parallel to the development of IDSS, the concept of **financial intelligence** has gained prominence as a multidimensional capability that combines financial literacy, analytical skills, risk awareness, and strategic thinking in financial decision-making. Financial intelligence extends beyond traditional financial analysis by incorporating behavioral, technological, and informational dimensions of financial decisions (9, 10). It enables organizations and decision-makers to interpret complex financial information, anticipate financial risks, and align financial decisions with strategic objectives (11, 12). In organizational contexts, financial intelligence is increasingly viewed as a critical competence that enhances financial performance, resilience, and adaptability.

Recent studies emphasize that the integration of financial intelligence into intelligent decision support systems can significantly improve the quality of financial and strategic decisions. AI-driven systems equipped with financial intelligence capabilities can analyze large datasets, detect hidden patterns, forecast financial outcomes, and support informed decision-making under uncertainty (13, 14). Such systems are particularly valuable in banking environments, where decisions must balance profitability, risk, compliance, and ethical considerations (15, 16).

The literature highlights several key components that contribute to the effectiveness of intelligent decision support systems. These include robust data infrastructures, advanced analytical and predictive models, knowledge management mechanisms, and secure information systems. Primary databases and decision support repositories form the foundation of IDSS by integrating internal and external data sources, such as transactional data, customer information, market indicators, and macroeconomic variables (17, 18). Without reliable and well-structured data, intelligent systems cannot deliver accurate or timely insights.

Equally important is the role of advanced analytical techniques, including artificial intelligence algorithms, machine learning models, and predictive analytics. Neural networks, decision trees, support vector machines, and hybrid AI models enable IDSS to learn from historical data, identify nonlinear relationships, and generate forecasts that support proactive decision-making (19, 20). These technologies allow banks to move from reactive decision-making toward anticipatory and adaptive strategies.

Another critical dimension of intelligent decision support systems is **knowledge management**, which involves the acquisition, processing, dissemination, and utilization of organizational knowledge. Effective knowledge management enhances organizational learning, supports innovation, and ensures that insights generated by intelligent systems are shared and applied across the organization (21, 22). In banking organizations, knowledge management plays a vital role in aligning technological capabilities with human expertise and organizational processes.

Security and information protection represent an additional foundational pillar of intelligent decision support systems, particularly in the banking sector. Given the sensitivity of financial and personal data, banks must ensure continuous monitoring, data integrity, and protection against cyber threats and unauthorized access (15, 16). Studies emphasize that the success of AI-based decision systems depends not only on analytical accuracy but also on trust, transparency, and ethical data governance (13, 14).

Despite the growing body of research on decision support systems, artificial intelligence, and financial intelligence, several gaps remain in the literature. First, much of the existing research focuses on technical or algorithmic aspects of IDSS, while fewer studies adopt a holistic perspective that integrates data infrastructure, financial intelligence, knowledge management, and security considerations into a unified framework (23, 24). Second, empirical studies specifically addressing intelligent decision support systems with a financial intelligence approach in banking organizations, particularly in developing or emerging economies, remain limited.

Moreover, the literature suggests that organizational, cultural, and contextual factors significantly influence the successful implementation of intelligent decision support systems. Human resource practices, managerial decision-making styles, and organizational readiness affect how intelligent systems are adopted and utilized (25-27). The interaction between human decision-makers and algorithmic systems also raises concerns about bias, over-reliance on automated recommendations, and the need for explainability in intelligent systems (20, 28).

From a strategic perspective, intelligent decision support systems contribute to organizational agility, strategic flexibility, and sustainable competitive advantage. By enabling faster and more informed decisions, these systems support innovation, performance improvement, and long-term value creation (8, 29). In the banking sector, where strategic misjudgments can have systemic consequences, the integration of financial intelligence into decision support systems is particularly critical (4, 30).

Recent research also underscores the importance of integrating external data sources—such as market trends, regulatory changes, and macroeconomic indicators—into intelligent decision support systems. The ability to combine internal and external data enhances the system’s predictive power and supports more comprehensive financial decision-making (3, 6). This integration aligns with the broader digital transformation of financial services and the move toward data-driven governance and risk management.

Given these developments, there is a clear need for systematic research that identifies and conceptualizes the core components of intelligent decision support systems grounded in a financial intelligence approach, particularly within banking organizations. Such research can provide a comprehensive framework that integrates technological, financial, organizational, and security dimensions, thereby offering both theoretical insights and practical guidance for managers and policymakers.

Accordingly, the aim of this study is to identify and conceptualize the core components of an intelligent decision support system based on a financial intelligence approach in banking organizations.

Methods and Materials

Based on its objective, the present study is applied, as its aim is to identify and improve the components of an intelligent decision support system using a financial intelligence approach in national banking organizations. In terms of approach and implementation, it is a qualitative study. With regard to its nature, the present research falls within the category of exploratory studies, as it seeks to identify and explore the codes, themes, and components related to an intelligent decision support system with a financial intelligence approach in national banking organizations. According to the research paradigm, the present study is positioned within the interpretive paradigm, since the data are subjective and qualitative in nature and are obtained through textual analysis and interpretation.

The research participants included relevant experts (university faculty members and senior banking managers who were familiar with decision support systems and were considered national banking experts). To include these participants in the study sample, four criteria were defined in order to select individuals with higher levels of expertise for interviews. These four criteria were: (a) university faculty membership at the rank of assistant professor or higher, (b) doctoral students with relevant research experience, (c) managerial work experience in the banking sector, and (d) expertise in the field of decision support systems.

Based on the sample inclusion criteria, ten relevant experts (university faculty members and senior banking managers familiar with decision support systems and recognized as national banking experts) were initially identified for expert interviews aimed at identifying and exploring the codes, themes, and components related to an intelligent decision support system with a financial intelligence approach in national banking organizations.

The sampling method was purposive using the snowball technique. The criterion for terminating sampling was theoretical saturation; that is, expert interviews continued until no new data or concepts emerged and the codes, themes, and components related to the intelligent decision support system with a financial intelligence approach reached repetition. Theoretical saturation was achieved with a sample size of eight participants; therefore, the final research participants consisted of eight of the aforementioned experts.

To collect data and to identify and explore the codes, themes, and components related to the intelligent decision support system with a financial intelligence approach in national banking organizations, semi-structured interviews with experts were used as the data collection instrument. After conducting the interviews, all statements made by the interviewees were transcribed with complete accuracy and without omission. To enhance the validity and accuracy of the collected data, triangulation was employed, including data source triangulation, researcher triangulation, theoretical triangulation, and methodological triangulation.

Subsequently, the qualitative thematic analysis technique was applied to identify meaningful phrases and sentences from the interview texts. In this technique, initial codes were first extracted and key themes were identified. Then, based on the relationships among the key themes, they were grouped at a higher level into specific categories, forming integrative themes. Finally, at a higher level, the integrative themes were categorized based on their similarities and interrelationships, leading to the formation of overarching themes.

The validity of the qualitative thematic analysis technique was examined and confirmed using the criteria proposed by Lincoln and Guba (1998), and the reliability of this technique was also assessed and confirmed using the inter-coder agreement coefficient (0.92).

Findings and Results

Based on the initial conceptual model held by the researcher and with the aim of eliciting expert opinions regarding influential factors, interview requests were sent to 30 individuals to invite their cooperation in this study. Ultimately, 19 individuals accepted the research team’s invitation and participated in the interview sessions.

Prior to the interview sessions, an interview protocol was developed, and in order to ensure the interviewees' preparedness, the questions and necessary explanations were sent to the participants in advance. During the interview sessions, the interview content was recorded using an audio recording device.

It should be noted that the interviews continued until theoretical saturation was achieved. After reaching theoretical saturation, the data were organized and prepared for analysis. Theoretical saturation occurred during the interview with the eighth expert; however, to ensure greater confidence, interviews were continued with two additional experts, increasing the total number of experts to ten.

As stated earlier, the qualitative thematic analysis technique was used in the present study to analyze texts (theoretical foundations and interviews). This technique consists of five main stages, as described below.

At first stage of the research, the researcher used expert interviews and a review of the collected literature as the primary sources for data collection and analysis. After reviewing all interviews and the existing literature, it became evident that a combination of these two sources should be considered.

The thematic analysis method requires repeated reading and reviewing of the data; therefore, before initiating the coding process, the entire dataset was reviewed several times. During this process, while reading the texts, certain patterns and ideas began to emerge.

Given that the interviews were recorded, the researcher first listened to each interview once, after which the recorded interviews were transcribed into Word files. In the second stage, the transcribed interviews were reviewed by the experts. In the third stage, all interview texts were fully typed and finalized. In the fourth stage, the typed and edited texts were reviewed once again.

After completing the various stages of the interview analysis process, the interview texts, along with the recorded audio files, were carefully reviewed and examined in detail. At this stage, the primary objective was to examine all details and information contained in the interviews in order to ensure that all recorded materials were accurately considered.

After ensuring the quality and accuracy of the interview content, the process of refinement and revision began. This process included correcting potential grammatical errors, organizing sentences in a logical sequence, and enhancing lexical diversity and richness within the text. The purpose of this refinement was to produce a coherent, comprehensible text that was prepared for the subsequent stages of analysis.

This procedure was conducted in order to provide a comprehensive perspective for continuing the subsequent stages of thematic analysis. At this stage, the researcher became thoroughly familiar with and immersed in the interview data.

Below, three samples of finalized texts prepared for coding—related to the first, second, and third interviewees—are presented. It should be noted that these samples were selected randomly using software.

Sample Interview 1

Hello, my name is Farzaneh Amiri.

Yes, certainly. In the optimization model of an intelligent decision support system in banking, factors such as the ability to predict risks, resource efficiency, inventory management, and the improvement of decision-making processes are among the most important aspects considered. For example, assessing various risks that may affect the bank is one of the factors that significantly contributes to enhancing banks' decision-making systems. A wide range of data is used in this model, including financial data, customer data, risk data, and so forth. These data are analyzed using artificial intelligence algorithms and related technologies in order to be applied within decision-making processes.

For instance, suppose a bank intends to develop a model to predict the probability of the salvage value of risk-sharing measures. By using neural networks, behavioral patterns and characteristics associated with these measures can be identified, and the likelihood of their occurrence can be predicted. This information helps the bank to more accurately assess the risks associated with risk-sharing measures and to implement necessary improvements in risk management processes, which in turn directly affect the bank’s financial performance. Various models are employed to optimize decision-making processes in banks, including linear and nonlinear programming models, artificial neural networks, and machine learning algorithms.

One of the main challenges in implementing these algorithms in banks is data management and data security. Given the large volume of data and the sensitivity of customers’ financial and personal information, banks must make substantial efforts to ensure data security. In addition, the need for appropriate technological infrastructure and strong computational capacity represents another major challenge in this area.

To ensure the optimal performance of the intelligent decision-making model, continuous evaluation and monitoring are required. These evaluations should be conducted periodically in order to apply necessary improvements to the system.

By implementing an intelligent decision support system in banks, significant improvements can be achieved in the performance of decision-making systems, leading to increased profitability and enhanced quality of banking services.

My experience shows that the successful implementation of such systems requires close collaboration among different teams, ranging from data analysts to information technology specialists.

Among the key points that must be considered are ensuring data quality, keeping algorithms and models up to date, and maintaining the security of customer information.

Sample Interview 2

Hello, my name is Mehdi Rezaei. I am pleased to have accepted the invitation to this interview. Yes, with pleasure.

In the optimization model of an intelligent decision support system in banks, factors such as financial supply and demand, risk, market changes, and legal and financial constraints are taken into account. In this model, various types of data are used, including financial data, customer information, market and economic data, and risk-related data. These data are utilized by data analysis algorithms and artificial intelligence techniques to make optimal decisions. Mathematical models such as linear programming, nonlinear programming, artificial neural networks, and machine learning algorithms such as decision trees and support vector machines are applied to optimize decision-making processes.

The challenges of implementing an intelligent decision support system in banks include security issues, ensuring data quality, the need for robust infrastructure such as high-speed data processing and scalable storage, and integrating artificial intelligence models with existing systems. To ensure the optimal performance of the intelligent decision-making model, continuous monitoring and evaluation of its performance, updating the model in response to market changes and conditions, and enhancing the required computational capabilities are necessary.

Implementing an intelligent decision support system in banks can lead to improved financial performance, reduced risk, increased customer satisfaction, and enhanced decision-making processes.

Sample Interview 3

Hello, my name is Leila Karimi. I am a credit analyst at a bank.

I really like the topic of your thesis. I am truly pleased to be collaborating with you.

By using predictive models and neural networks, we can achieve significant improvements in banking decision-making processes. These models are capable of identifying more complex patterns and creating effective improvements in banks' knowledge management and financial intelligence. The financial intelligence approach enables us to apply machine learning algorithms and models within banking decision-making processes through a command processor. These algorithms and models allow us to analyze and predict financial information and various risks with high accuracy and in an automated manner.

After data collection and cleansing, banks should use artificial intelligence algorithms such as neural networks, decision trees, and support vector machines to analyze data and identify customer behavioral patterns and other critical factors. These analyses directly contribute to generating more accurate forecasts and developing behavioral patterns for decision-making processes such as risk management, financial performance improvement, and resource allocation. As an example, suppose our bank intends to assess the risk and return of various investments. We can use predictive models and neural networks to analyze financial and market information and identify different risk–return behavioral patterns. Based on this information, we can make better decisions regarding future investments, which leads to increased profitability and reduced financial risk for the bank. One of the main challenges in using these models is dealing with large and complex datasets that require precise processing and analysis. Moreover, managing and ensuring data security is another major challenge that must be considered. In addition, the ability to interpret analytical results and translate them into practical, real-world decisions also requires specific expertise.

In my view, the most important point is that, in order to use these models effectively, the required data must be collected and analyzed with high accuracy and reliability. Furthermore, it is essential to remain continuously informed about technological advancements and to implement new models and algorithms that can contribute to improving banking decision-making processes.

Certainly. By using artificial intelligence algorithms and statistical techniques, we can extract important and useful information from both internal and external banking data and analyze their patterns. This information helps us make critical decisions in areas such as resource allocation, risk management, and improving banks' financial performance. Yes. The internal banking database contains information within the bank, enabling us to utilize financial data, transactions, accounts, and other internal records. On the other hand, external databases include market, economic, and customer-related information that can be used to predict customer behavior and analyze various risks. These two databases allow us to construct a decision query repository—the decision support database—and to use it for making better and more intelligent decisions.

In the table, the data were coded and a list of different codes was obtained. For the analysis, the initial codes must be examined and the manner in which different codes are combined and integrated to form concepts must be determined. Through further review and refinement of the concepts, efforts were made to ensure that the categories were sufficiently specific, distinct, non-redundant, and, at the same time, sufficiently comprehensive. Afterward, by consolidating and removing repetitive and equivalent items, the main influential indicators were developed. At this stage, 351 initial codes were extracted. Table 1 presents all extracted codes for each of the eight interviewees.

Table 1. MAXQDA Output for the Interviews

Document	Coded Segments	Codes
Expert 7, Pos. 2	In the optimization model of an intelligent decision support system in banks, the analysis of diverse data—such as financial, customer, and risk data—is utilized. By using artificial intelligence algorithms such as neural networks and predictive models, we can analyze these data and generate behavioral patterns and more accurate forecasts, which ultimately produce substantial improvements in banking decision-making processes.	Artificial intelligence algorithms and statistical techniques; Predictive models and neural networks; Primary database; External (out-of-bank) database; Banking database
Expert 4, Pos. 4	In the optimization model of an intelligent decision support system in banking, internal bank data such as banking transactions, contracts, accounts, legal and inspection files are highly valuable. These data are typically stored in the bank's operational databases and can be continuously used for analysis. For example, by analyzing patterns in banking transactions and legal files, one can support risk forecasting, detection of suspicious activities, and improvement of decision-making processes in the bank.	Primary database; External (out-of-bank) database; Initial data processing; Banking database
Expert 1, Pos. 2	In the optimization model of an intelligent decision support system in banks, factors such as financial supply and demand, risk, market changes, and legal and financial constraints are considered. In this model, various types of financial data, customer information, market and economic data, and risk-related data are used. These data are utilized by data analytics and artificial intelligence algorithms to make optimal decisions. Mathematical models such as linear programming, nonlinear programming, artificial neural networks, and machine learning algorithms such as decision trees and support vector machines are used to optimize decision-making processes.	Decision support repository; Raw decision-support data warehouse; Artificial intelligence algorithms and statistical techniques; Continuous monitoring to identify and prevent security threats; Primary database; External (out-of-bank) database; Initial data processing; Banking database; Machine learning algorithms and models
Expert 8, Pos. 5	One very important element is the decision query center. It is extremely important because the core of the decision lies in this center. Why? Because it collects data—drawing on the data repository—meaning access to a very large volume of data that has been collected over many years in relation to organizational topics, so that during querying, integration, or combination of information, it can support decision-making or decision formulation. Then it performs information refinement, keeps useful data, discards useless data, and then applies analysis using algorithms—analysis and forecasting using predictive models and neural networks—arriving at a low-risk or risk-free decision.	Raw decision-support data warehouse; Data extraction and integration operations; Predictive models and neural networks; Decision query center
Expert 7, Pos. 2	In the optimization model of an intelligent decision support system in banks, the analysis of diverse data—such as financial, customer, and risk data—is utilized. By using artificial intelligence algorithms such as neural networks and predictive models, we can analyze these data and generate behavioral patterns and more accurate forecasts, which ultimately produce substantial improvements in banking decision-making processes.	Optimization model of intelligent decision support system; Predictive models and neural networks; Primary database; External (out-of-bank) database; Banking database
Expert 7, Pos. 4	Undoubtedly, establishing a robust data repository that includes diverse, high-quality data is fundamental to the success of these models. These data must be continuously updated and accessible for analysis. Moreover, to run advanced AI models, banks require high computational capacity and appropriate technological infrastructure to process large volumes of data and perform the required analyses. Yes. Establishing a decision query repository within the decision support database enables us to collect and store the data needed for banking decisions in a central, accessible location. This helps achieve faster, more accurate, and more effective decisions. Using these models requires high-quality quantitative and qualitative data. In addition, managing and ensuring information security is a key challenge that must be considered. Furthermore, the ability to interpret analytical results and translate them into real-world actionable decisions requires specific expertise.	Raw decision-support data warehouse; Data extraction and integration operations; Predictive models and neural networks; Decision query center; Initial data processing; Command processor
Expert 5, Pos. 3	By using predictive models and neural networks, we can bring about significant improvements in banking decision-making processes. These models are capable of identifying more complex patterns and creating effective improvements	Predictive models and neural networks; Use of the financial intelligence approach; Knowledge management

	in banks' knowledge management and financial intelligence. The financial intelligence approach enables us to employ machine learning algorithms and models in banking decision-making processes through a command processor. These algorithms and models allow us to analyze and forecast financial information and various risks automatically and with high accuracy.	
Expert 5, Pos. 6	Certainly. By using artificial intelligence algorithms and statistical techniques, we can extract important and useful information from the bank's internal and external data and analyze their patterns. This information helps us make key decisions in areas such as resource allocation, risk management, and improving banks' financial performance. Yes. The banking database includes the bank's internal information, enabling us to use financial data, transactions, accounts, and other items. On the other hand, the external (out-of-bank) database includes information related to the market, the economy, and customers, which can be used to predict customer behavior and analyze various risks. These two databases enable us to build the decision query repository—the decision support database—and use it to make better and smarter decisions.	Data extraction and integration operations; Predictive models and neural networks; Decision query center; External (out-of-bank) database; Initial data processing; Banking database
Expert 3, Pos. 5	In addition to internal banking data, external (out-of-bank) data can also be effective in decision-making processes. For example, data related to economic conditions, customer behavior in the market, and other external factors can be useful in risk analysis and forecasting customer behavior.	Cost and expenditure control; Financial flexibility
Expert 2, Pos. 6	To ensure that the intelligent decision-making model operates optimally, continuous evaluation and monitoring are required. These evaluations should be conducted periodically so that necessary improvements can be applied to the system.	Informed financial decision-making
Expert 7, Pos. 2	In the optimization model of an intelligent decision support system in banks, the analysis of diverse data—such as financial, customer, and risk data—is utilized. By using artificial intelligence algorithms such as neural networks and predictive models, we can analyze these data and generate behavioral patterns and more accurate forecasts, which ultimately produce substantial improvements in banking decision-making processes.	Optimization model of intelligent decision support system; Artificial intelligence algorithms and statistical techniques; Predictive models and neural networks; Banking database
Expert 5, Pos. 4	After collecting and cleansing data, banks should use artificial intelligence algorithms such as neural networks, decision trees, and support vector machines to analyze the data and identify customer behavioral patterns and other key items. These analyses directly contribute to generating more accurate forecasts and creating behavioral patterns for decision-making processes such as risk management, financial performance improvement, and resource allocation. As an example, suppose our bank wants to assess the risk and return of its various investments. We can use predictive models and neural networks to analyze financial and market information and identify different risk–return behavioral patterns. With this information, we can make better decisions about future investments, leading to increased profitability and reduced financial risk for the bank. One of the main challenges in using these models is large and complex data that require precise processing and analysis. Additionally, managing and ensuring information security is another key challenge that must be considered. Moreover, the ability to interpret analytical results and translate them into real-world actionable decisions also requires specific expertise.	Initial data processing; Banking database
Expert 5, Pos. 6	Certainly. By using artificial intelligence algorithms and statistical techniques, we can extract important and useful information from the bank's internal and external data and analyze their patterns. This information helps us make key decisions in areas such as resource allocation, risk management, and improving banks' financial performance. Yes. The banking database includes the bank's internal information, enabling us to use financial data, transactions, accounts, and other items. On the other hand, the external (out-of-bank) database includes information related to the market, the economy, and customers, which can be used to predict customer behavior and analyze various risks. These	Decision support repository; Data extraction and integration operations; Artificial intelligence algorithms and statistical techniques; Predictive models and neural networks; Decision query center; Initial data processing; Banking database

	two databases enable us to build the decision query repository—the decision support database—and use it to make better and smarter decisions.	
Expert 4, Pos. 4	In the optimization model of an intelligent decision support system in banking, internal bank data such as banking transactions, contracts, accounts, legal and inspection files are highly valuable. These data are typically stored in the bank's operational databases and can be continuously used for analysis. For example, by analyzing patterns in banking transactions and legal files, one can support risk forecasting, detection of suspicious activities, and improvement of decision-making processes in the bank.	Optimization model of intelligent decision support system; Initial data processing; Banking database
Expert 4, Pos. 5	In addition to internal banking data, external (out-of-bank) data can also be effective in decision-making processes. For example, data related to economic conditions, customer behavior in the market, and other external factors can be useful in risk analysis and forecasting customer behavior.	Banking database
Expert 4, Pos. 6	For analysis and forecasting using internal and external bank data, predictive models and neural networks can be applied. These models use advanced algorithms to identify hidden patterns in data and provide accurate predictions that can be valuable in decision-making processes.	Initial data processing; Banking database
Expert 2, Pos. 7	By implementing an intelligent decision support system in banks, a significant improvement can be achieved in the performance of decision-making systems, and consequently, increased profitability and improved quality of banking services can be experienced.	Information security and protection; Continuous monitoring to identify and prevent security threats

After completing the refinement and revision process, the initial interview codes were extracted from the final text and placed into a table corresponding to different topics. These codes function as semantic and thematic indicators in interview analysis and facilitate subsequent stages of data analysis and interpretation.

In the first stage of coding, 351 codes were generated. At this step, some codes that were less relevant to the research topic were removed; a group of codes was merged and reorganized; and others were refined and renamed through consultation with the supervisor and research experts. After review, refinement, and consultation with experts and university faculty members, the initial codes of the present study were converted into final codes.

As shown in Table 2, based on MAXQDA software outputs, 15 integrative themes and 6 overarching themes were identified, including: (1) Primary Database, (2) Decision Support Repository, (3) Information Security and Protection, (4) Knowledge Management, (5) Use of the Financial Intelligence Approach, and (6) Command Processor. Table 2 presents the integrative and overarching themes and their repetition percentages.

Table 2. Percentage of Codes (Integrative and Overarching Themes)

Repetition (%)	Integrative Themes	Overarching Themes	Repetition (%)
50.00	Raw decision-support data warehouse	Decision support repository	50.00
50.00	Data extraction and integration operations		
87.50	Artificial intelligence algorithms and statistical techniques		
50.00	Predictive models and neural networks		
62.50	Decision query center		
25.00	Cost and expenditure control	Use of the financial intelligence approach	37.50
50.00	Financial flexibility		
12.50	Targeted investment		
37.50	Informed financial decision-making		
50.00	Continuous monitoring to identify and prevent security threats	Information security and protection	37.50
87.50	External (out-of-bank) database	Primary database	75.00
75.00	Initial data processing		
87.50	Banking database		
37.50	Machine learning algorithms and models	Command processor	37.50
50.00	Knowledge acquisition, processing, and dissemination	Knowledge management	50.00

Table 2 is the final table of the study and presents the integrative and overarching themes of the intelligent decision support system with a financial intelligence approach in national banking organizations. Based on Table 2, the most important overarching theme is the Primary Database, as 6 out of 8 interviewees (equivalent to 75%) referred to this theme. This is followed by Decision Support Repository and Knowledge Management, each mentioned by 4 out of 8 interviewees (equivalent to 50%). Next are the themes Use of the Financial Intelligence Approach, Information Security and Protection, and Command Processor, each mentioned by 3 out of 8 interviewees (equivalent to 37.5%). Additionally, among the integrative themes, Artificial Intelligence Algorithms and Statistical Techniques, External (Out-of-Bank) Database, and Banking Database jointly rank first, as 7 out of 8 interviewees (equivalent to 87.5%) referred to these themes. The theme Targeted Investment ranks last, as only 1 out of 8 interviewees (equivalent to 12.5%) mentioned it.

Step four began when the researcher proposed a set of themes and refined them. The identified themes constitute the primary source for constructing thematic networks. During this step, it became clear that some of the proposed items were not, in fact, themes.

The mental map obtained from the software is presented in Figure 1.

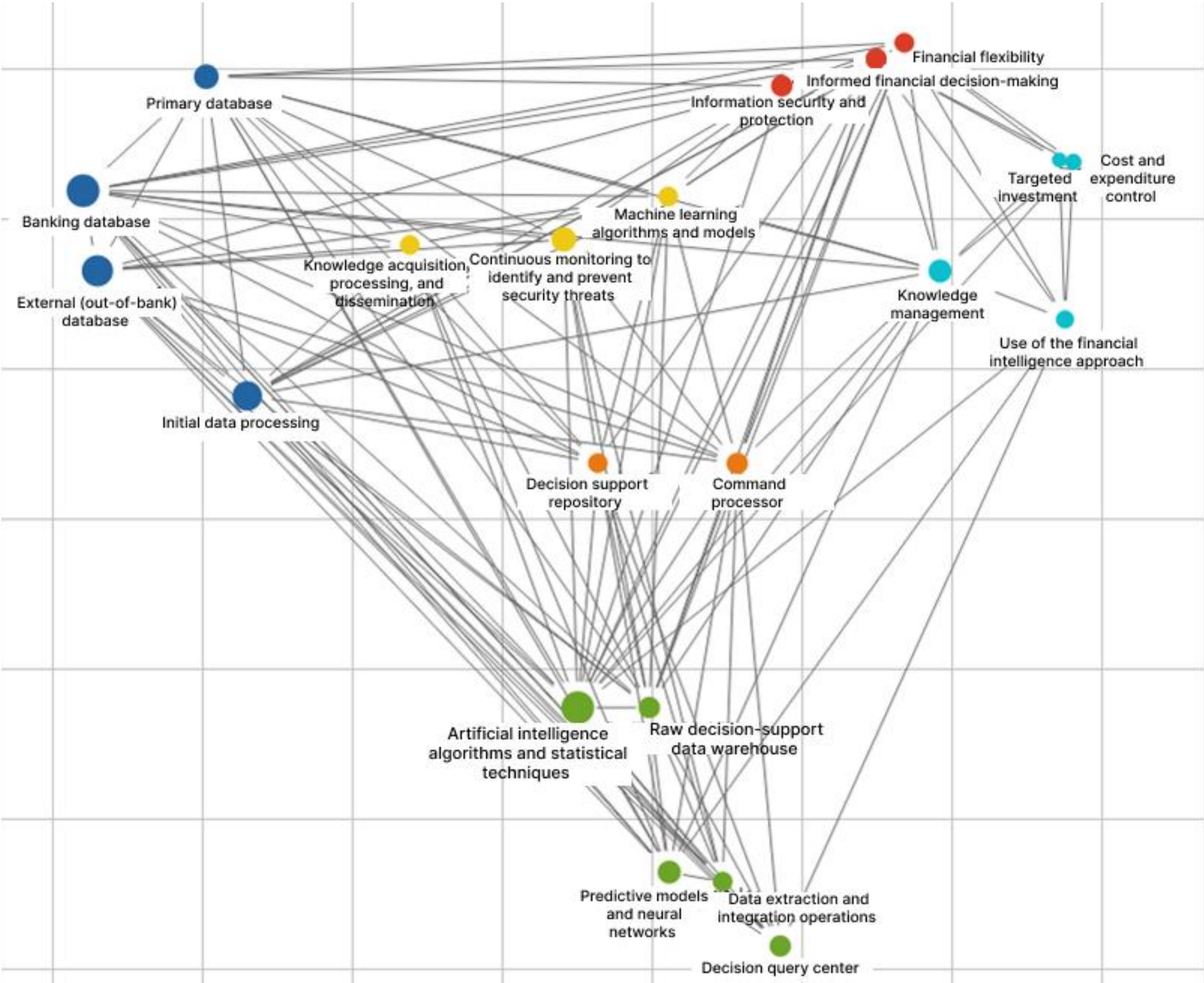

Figure 1. Thematic Network in MAXQDA Software

Next stage began when a set of indicators was identified and refined. The identified themes served as the primary source for developing the model. During this process, the indicators were refined again, and in some cases, certain indicators were merged or decomposed.

In addition, the qualitative information in this study included library-based studies, which were discussed in detail in Chapter Two. Data collection related to theoretical foundations and research literature was conducted using library resources, articles, books, journals, and the internet.

Considering the conducted literature review, research background, related models, and key indicators of the topic, the initial theoretical conceptual model of the study was influenced by theorists' perspectives, the conducted interviews as expert opinions, and finally the researcher's interpretations of the interviews as the main components of the research. The main dimensions and indicators of the study are illustrated in the following figure. The final qualitative model, developed based on Figure 1 and Table 2, is presented in Figure 2.

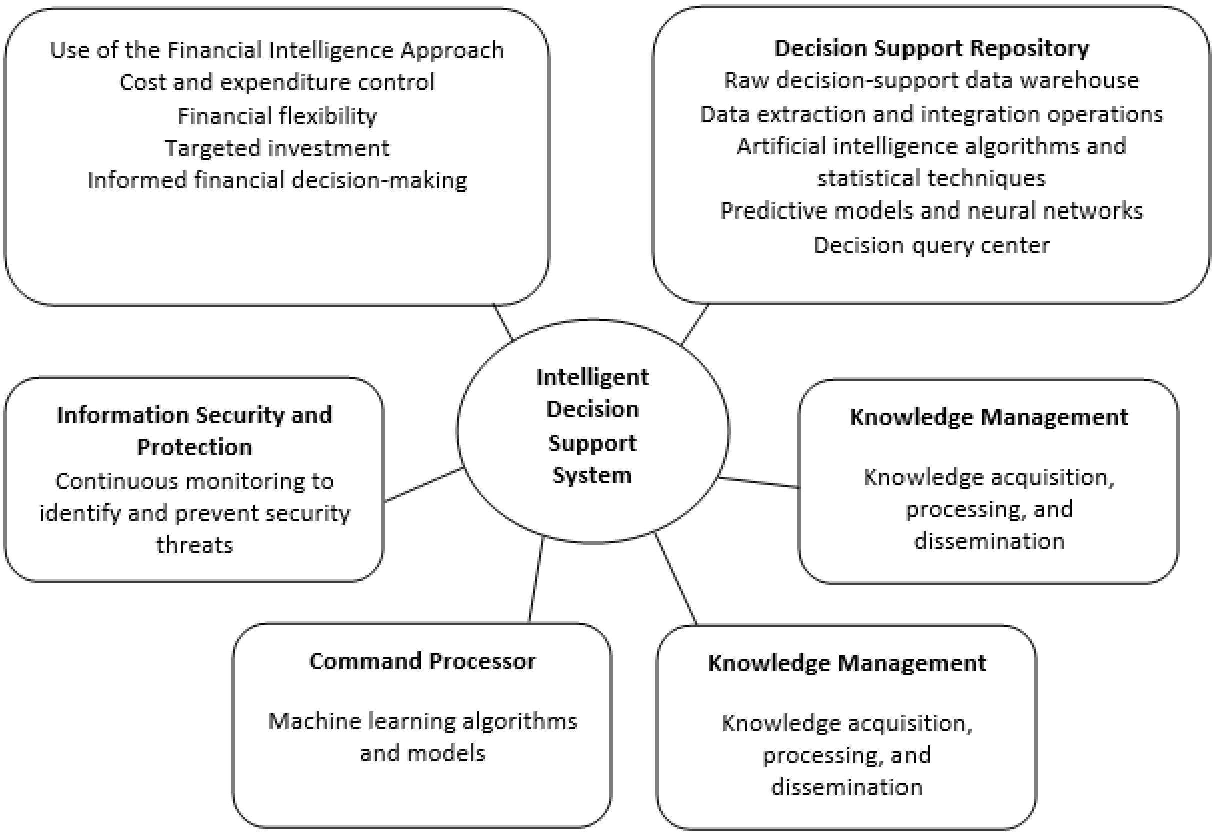

Figure 2. Model and Components of the Intelligent Decision Support System Using a Financial Intelligence Approach in National Banking Organizations

As shown in Figure 2, the overarching theme Decision Support Repository comprises five integrative themes; the overarching theme Use of the Financial Intelligence Approach comprises four integrative themes; the overarching theme Information Security and Protection comprises one integrative theme; the overarching theme Primary Database comprises one integrative theme; the overarching theme Command Processor comprises one integrative theme; and the overarching theme Knowledge Management comprises one integrative theme.

Discussion and Conclusion

The findings of the present study led to the identification of six overarching components of an intelligent decision support system based on a financial intelligence approach in banking organizations, including the primary database, decision support repository, information security and protection, knowledge management, use of the financial intelligence approach, and command processor. These results indicate that intelligent decision support in banks is not merely a technological construct but a multidimensional system that integrates data infrastructure, analytical intelligence, organizational knowledge, and governance mechanisms. This holistic perspective is consistent with recent studies emphasizing that advanced decision-making systems must be designed as socio-technical systems rather than isolated technological tools (1, 2).

One of the most prominent findings of the study is the central role of the primary database, which was the most frequently mentioned overarching theme by experts. This result highlights that the effectiveness of intelligent decision support systems fundamentally depends on the availability, quality, and integration of data. Banking organizations generate massive volumes of internal data related to transactions, accounts, contracts, and customer behavior, as well as external data related to markets, economic conditions, and regulatory environments. The emphasis placed on primary databases aligns with prior research showing that data integration and data quality are prerequisites for reliable analytics and intelligent decision-making (17, 18). Without a comprehensive and well-structured primary database, advanced algorithms and analytical models cannot function effectively, regardless of their sophistication.

Closely related to the primary database is the decision support repository, which emerged as another key overarching component. The decision support repository, encompassing raw data warehouses, data extraction and integration operations, predictive models, and decision query centers, represents the operational core of the intelligent decision support system. This finding corroborates earlier studies that emphasize the importance of centralized data repositories and analytical hubs in supporting managerial decision-making (3, 6). In the banking context, such repositories enable decision-makers to access integrated and timely information, conduct scenario analyses, and generate forecasts that support strategic and operational decisions (5). The prominence of this component reflects the shift from fragmented information systems toward integrated, analytics-driven decision infrastructures in modern banks.

The results also underscore the importance of artificial intelligence algorithms, machine learning models, and predictive analytics as integrative themes within the decision support repository and command processor components. Experts emphasized the use of neural networks, statistical techniques, and machine learning models to analyze complex financial data and generate accurate predictions. This aligns with a substantial body of literature demonstrating that AI-based decision support systems outperform traditional rule-based systems in handling uncertainty, nonlinearity, and large-scale data (19, 20). In financial and banking applications, predictive models enable proactive risk management, fraud detection, and performance optimization, which are essential for maintaining competitiveness and stability (7, 9).

Another significant finding of the study is the identification of the use of the financial intelligence approach as a distinct overarching theme. This component includes cost and expenditure control, financial flexibility, targeted investment, and informed financial decision-making. The prominence of financial intelligence reflects a growing recognition that intelligent systems must not only process data but also enhance the financial cognition and judgment of decision-makers. Previous research conceptualizes financial intelligence as the ability to interpret financial information, understand financial risks, and align financial decisions with strategic goals (10, 12). The integration of financial intelligence into decision support systems allows banks to move beyond purely technical optimization toward more strategic and value-oriented decision-making (28, 30).

The study's findings further highlight knowledge management as an essential component of intelligent decision support systems. Knowledge management, defined in this study as the acquisition, processing, and dissemination of knowledge, plays a critical role in transforming analytical outputs into organizational learning and action. This result is consistent with research emphasizing that decision support systems create value only when their outputs are effectively shared, interpreted, and embedded in organizational routines (21, 22). In banking organizations, where decisions often involve cross-functional collaboration, effective knowledge management ensures that insights generated by intelligent systems are accessible to managers, analysts, and operational staff, thereby enhancing decision coherence and consistency (25).

The identification of information security and protection as a core component reflects the heightened importance of data governance in intelligent decision support systems, particularly in the banking sector. Experts emphasized continuous monitoring to identify and prevent security threats, underscoring that trust and reliability are fundamental to the adoption and effectiveness of intelligent systems. This finding aligns with studies highlighting that data security, privacy, and ethical considerations are critical determinants of AI system acceptance in financial institutions (13, 14). Given the sensitivity of financial data and the regulatory environment in which banks operate, intelligent decision support systems must be designed with robust security mechanisms to ensure compliance, prevent misuse, and maintain stakeholder confidence (15, 16).

The command processor component, which encompasses machine learning algorithms and models that operationalize analytical insights, represents the interface between data analysis and decision execution. This component reflects the automation and semi-automation of decision processes, enabling faster and more consistent responses to dynamic conditions. Prior studies suggest that such automation enhances efficiency but also requires careful design to avoid over-reliance on algorithms and to ensure human oversight (1, 20). The findings of the present study suggest that effective command processors should support, rather than replace, managerial judgment, integrating human expertise with algorithmic intelligence.

Overall, the results of this study contribute to the literature by offering an integrated framework that combines data infrastructure, artificial intelligence, financial intelligence, knowledge management, and security considerations in the context of intelligent decision support systems for banking organizations. This framework is consistent with recent calls for multidimensional and context-sensitive models of decision support that reflect the realities of digital transformation in financial services (2, 8). By grounding the model in expert insights, the study provides empirical support for the argument that intelligent decision support systems must be designed as comprehensive organizational systems rather than isolated technological solutions.

Despite its contributions, this study has several limitations. First, the research was conducted using a qualitative approach with a limited number of expert participants, which may restrict the generalizability of the findings to all banking contexts. Second, the study focused primarily on banking organizations, and the identified components may not fully capture the specific requirements of other industries. Third, the reliance on expert perceptions means that the findings reflect subjective interpretations, which, although valuable, may differ from insights derived from large-scale quantitative data.

Future studies could build on the findings of this research by empirically testing the proposed model using quantitative methods such as structural equation modeling. Comparative studies across different countries or financial systems could also provide insights into the contextual factors influencing intelligent decision support systems. Additionally, future research may examine the interaction between human decision-makers and intelligent systems, particularly issues related to trust, explainability, and ethical decision-making.

From a practical perspective, banking managers should prioritize the development of integrated data infrastructures and invest in advanced analytical capabilities while simultaneously strengthening knowledge management and information security practices. Organizations should also focus on enhancing financial intelligence among decision-makers to ensure that analytical outputs are effectively translated into strategic actions. Finally, banks are encouraged to adopt a balanced approach that combines algorithmic intelligence with human expertise to achieve sustainable and responsible decision-making.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

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

Transparency of Data

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

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