





# Applying Meta-Synthesis Techniques in Identifying Optimization Components of FinTech Based on Artificial Intelligence Indicators in the Financial Market

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## Article Info

### Article type:

Original Research

### How to cite this article:

Ghasemzadeh, E., Keramati, M. A., Mehrinejad, S., & Mehrani, A. (2024). Applying Meta-Synthesis Techniques in Identifying Optimization Components of FinTech Based on Artificial Intelligence Indicators in the Financial Market. *International Journal of Innovation Management and Organizational Behavior*, 4(3), 173-179.  
<https://doi.org/10.61838/kman.ijimob.4.3.20>



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## ABSTRACT

**Objective:** The purpose of this research is to apply the meta-synthesis technique to identify optimization components of FinTech based on artificial intelligence (AI) indicators in the financial market. AI offers the financial industry a unique opportunity to reduce costs, improve customer experience, and increase operational efficiency, among other benefits. Financial companies can provide excellent financial services to their clients. Various features of AI are used by different FinTech companies worldwide to make operations safer and more efficient.

**Methodology:** The researcher employed a systematic review and meta-synthesis approach to analyze the results and findings of previous researchers. By following the seven-step method of Sandelowski and Barroso, the researcher identified influential factors. Out of 198 articles, 35 were selected based on the CASP method. The validity of the analysis was confirmed using Holsti's coefficient, Scott's Pi coefficient, Cohen's kappa index, and Krippendorff's alpha. For reliability measurement and quality control, the transcription method was used, which was found to have an excellent agreement level for the identified indicators. The results from the data analysis, conducted using MAXQDA software, led to the identification of 21 initial codes in four categories.

**Findings:** Based on the meta-synthesis method, 21 codes were identified in four categories. The validity and reliability of the research findings were confirmed. The identified categories include machine learning algorithms, text analysis and information extraction, portfolio optimization, and recommender systems. In FinTech optimization, one of the fundamental components is machine learning algorithms.

**Conclusion:** The use of artificial neural networks for predicting market prices, detecting price patterns, and structuring an optimal investment portfolio has

significantly improved the performance of capital management systems. Additionally, genetic and evolutionary algorithms have been effective in optimizing parameters and structures of financial models, aiding in achieving optimal investment solutions. However, it is essential to recognize that while AI indicators can enhance financial system performance, one must also be aware of the associated limitations and risks. These include issues such as model complexity, sensitivity to input data, and risks related to machine decision-making.

**Keywords:** *FinTech optimization, artificial intelligence indicators, financial market.*

## 1 Introduction

The necessity for increased transparency, cost reduction, reduced intermediation, and timely access to information are significant challenges for system-oriented organizations (Ozkaya & Demirhan, 2023). In the current era, advancements in information technology have led to the development and expansion of financial services, auditing, insurance, and banking. Investors in emerging markets seek to achieve innovations using creative technologies and FinTech startups. The financial industry represents the broadest and deepest application of artificial intelligence (AI). Its participants include not only technology companies that provide AI services to financial institutions but also traditional financial institutions that employ technology, emerging financial formats, and financial regulatory authorities (Hamill & Gilbert, 2015). Considering the various financial services that use AI technology, the intelligent financial model can be divided into smart investment advisory, smart customer services, smart risk control, smart marketing, and more (Singh et al., 2022).

FinTech, or more precisely, financial technology, is a new term associated with mobile and internet and is widely used in the financial industry (Ali & Suri, 2022). This term refers to the use of technology to enhance and improve financial services, including sending and receiving money, remote banking, online investing, electronic payments, and other financial services. Over the past decade, with technological advancements, FinTech has become one of the most significant change factors in the financial industry. This term encompasses a wide range of technologies such as AI, blockchain, cloud computing, data processing, virtual reality, and the Internet of Things, which are used to develop and improve financial services. The use of FinTech leads to cost reductions, increased speed, and better access to financial services, allowing individuals and companies to manage money and investments in new ways. However, attention to security issues and privacy preservation in this field is also essential (Parida et al., 2022).

AI transforms the financial industry by increasing the speed, accuracy, and efficiency of financial services. AI technologies are used to create innovative solutions that improve customer experiences, reduce costs, and drive growth. Currently, AI plays a significant role (He et al., 2021). It helps FinTech companies automate routine processes and enhance results on a scale beyond human intelligence. The primary application of AI enables FinTech companies to identify threats, prevent fraud, automate daily tasks, and improve service quality. All these lead to improved efficiency and higher profits (Almansour, 2023). AI applications in the financial market include price prediction, capital management, market data analysis, identifying composite patterns, and recognizing intersections of various events in financial markets (Choi et al., 2022). Techniques used in this area include machine learning, neural networks, genetic algorithms, and optimization methods such as evolutionary algorithms. These technologies aid in risk management, quick decision-making, and enhancing efficiency in the financial market (Firdaus et al., 2020).

One of the significant applications of AI in the financial market is price prediction. By using machine learning algorithms and neural networks, complex patterns in market data can be identified, allowing for future price predictions. This information can assist investors and traders in making quick and accurate decisions. In addition to price prediction, AI also aids in improving capital management processes. Technologies used in this area include investment optimization models that help investors select the optimal combination of assets for maximum profit and minimum risk using evolutionary algorithms or reinforcement learning. AI assists in analyzing market data and identifying hidden patterns. These patterns can provide valuable information that helps investors and traders better understand market trends and opportunities (Ahmed et al., 2022; Ishwarappa & Anuradha, 2021).

AI offers the financial industry a unique opportunity to reduce costs, improve customer experience, and increase operational efficiency, among other benefits. Financial

companies are capable of providing excellent financial services to their clients (Ribes, 2022). Various features of AI are used by different FinTech companies worldwide to make operations safer and more efficient (Cao et al., 2021). All these solutions have an important goal: to increase the efficiency of FinTech companies. By using automation tools for data analysis and chatbots, companies can significantly reduce their employees' workload (Chang et al., 2022). Therefore, considering all the stated points, it can be said that the use of AI capabilities in FinTech is inevitable, making the optimization of the FinTech model based on AI crucial (Mohammadi et al., 2022).

FinTech is one of the highly successful startups in AI and financial markets, using advanced technologies for analyzing financial data and predicting market trends. AI indicators used by FinTech include neural networks, machine learning algorithms, and natural language processing techniques. The first indicator used in FinTech is machine learning algorithms (Craja et al., 2020). These algorithms can recognize complex patterns in financial data and provide accurate predictions for future market behaviors through data analysis. The second indicator is neural networks. These networks are models of the human brain's structure, capable of deep learning and complex information processing. FinTech uses these networks to analyze large and complex financial data to identify important patterns in financial markets and predict future trends.

The third indicator is natural language processing techniques. These techniques help FinTech analyze information in texts, news, financial reports, and other human language sources to extract important information. This information can positively or negatively impact financial market behavior, and FinTech uses these techniques to gain a deeper understanding of market behavior, allowing for quick and accurate responses to market changes. Therefore, this research seeks to answer the question: what are the optimization components of FinTech based on AI indicators in the financial market?

## 2 Methods and Materials

This research, aiming to identify the optimization components of FinTech based on AI indicators in the financial market, is a qualitative study using a library research method with the meta-synthesis technique in the field of smart production. Meta-synthesis is a subset of meta-study methods that systematically review resources to extract, evaluate, combine, and, if necessary, statistically

summarize research previously conducted on a specific subject area. In meta-synthesis, information and findings extracted from other related and similar studies are reviewed and analyzed. The data collected from these studies are qualitative rather than quantitative. Consequently, the sample for meta-synthesis is selected based on its relevance to the research question. Meta-synthesis is not merely an integrated review of qualitative principles or secondary and primary data analysis from selected studies but an analysis of the findings of these studies. In other words, meta-synthesis is the combination of interpretations of the primary data of selected studies. The ATLAS.ti software was used for analysis.

The first step in the Sandelowski and Barroso method is to formulate the research questions. These questions are generally based on the four parameters of what, who, when, and how. After the research questions are formulated based on the research objective, the systematic review of the literature begins.

To collect the research data, secondary data named past documents and records are used. As previously mentioned, the research databases of interest are two prominent databases, Scopus and Web of Science, focusing particularly on the following publication databases: Emerald Insight, Springer Link, Science Direct, Taylor & Francis Online, SAGE Journals, and Wiley Online Library.

Additionally, regarding Persian articles, the databases of the Scientific Information Database (SID) and the Comprehensive Portal of Humanities were considered.

To refine the articles extracted from the literature, four stages were followed, with the final stage based on the opinions of five expert observers in this research. These experts provided their assessments for each final screened article based on a forthcoming approach, and articles that scored lower than the set threshold were excluded from the process.

After eliminating studies that were inconsistent with the research objectives and questions, the researcher must assess the methodological quality of the studies. The purpose of this step is to eliminate studies whose findings are not trusted by the researcher. The tool commonly used for evaluating the quality of initial qualitative research studies is the Critical Appraisal Skills Programme (CASP), which helps determine the accuracy, validity, and importance of qualitative research through ten questions. These questions focus on the following: 1. Research objectives 2. Methodological rationale 3. Research design 4. Sampling method 5. Data collection 6. Reflexivity (referring to the relationship

between the researcher and participants) 7. Ethical considerations 8. Data analysis precision 9. Clear and transparent presentation of findings 10. Research value.

The next step involves reviewing the remaining articles and extracting texts for coding in the next step. This step focuses on separating the results and outputs and interpreting these outputs alongside the researchers' final discussion and conclusions. At this stage, 35 articles were entered into the MAXQDA software, and to familiarize the researcher with

the existing data, some articles were randomly and selectively reviewed, and random and scattered coding was done. This allowed the researcher to become acquainted with the generalities of the discussion and the prevailing environment.

### 3 Findings and Results

Table 1 specifies the concept of the codes:

**Table 1**

#### *Initial Code Extraction*

Component	Concept
Artificial Neural Networks	Artificial neural networks can identify complex patterns in financial market data and aid in decision-making for transactions. They can use recursive algorithms like LSTM to understand temporal patterns in financial data.
Decision Trees	These algorithms use tree-based approaches to analyze financial market data. They can present simple and understandable patterns useful for financial decision-making.
Support Vector Machines (SVM)	SVMs use linear and nonlinear separation between financial data to predict market changes. They can be effective in cases with more complex patterns and nonlinear interactions.
Adversarial Learning Methods	These methods use experience to improve financial decision-making. The machine model learns how to optimize future performance based on past experiences.
Ensemble Learning Methods	These methods combine multiple machine learning models to improve the accuracy and robustness of financial predictions. Examples include methods like random forests and gradient boosting machines.
Hidden Markov Models (HMM)	These models are used to model market processes that are not directly observable (such as hidden states in the market).
Natural Language Processing (NLP)	Using NLP, we can analyze news, tweets, and texts related to financial markets to extract useful information and evaluate risks and market predictions.
Clustering Techniques like K-Means	These techniques use market data to group different investments and recognize behaviors of different market groups.
Text Analysis and News Agencies	By using NLP algorithms, you can gather and analyze financial news and market analyses from various sources (e.g., social media, news sites, blogs) to extract useful information for investment and business decisions.
Concept Extraction and Sentiment Analysis	These techniques help you extract sentiments and attitudes from texts and opinions related to financial markets, providing a better understanding of their impact on market behavior.
Social Network Analysis Techniques	Reviewing and analyzing social networks related to the financial market and various companies can help better understand patterns and changes in the market.
Visual Analysis	Using visual analysis techniques, you can extract useful information from charts, images related to financial reports, and even images related to company activities.
Data Mining	Using data mining techniques can help you discover hidden information and patterns in financial data that can be useful for investment decision-making.
Automated Risk Management Methods	These methods include using automated algorithms to manage and control risk in portfolios, including techniques for risk balance management and systematic risk management.
Diversified Strategies	Using diverse and combined strategies, including model-based and signal-based strategies, can improve FinTech portfolio performance and reduce investment risk.
Market Changes	Since financial market conditions may continuously change, portfolio optimization models must adapt to market changes. Using machine learning-based methods can serve as a fundamental approach to improving portfolio performance against financial market changes.
Limitations and Risks	In portfolio optimization, various constraints such as financial limitations, risk constraints, and transaction volume constraints must be considered. These constraints can be managed using optimization techniques like genetic algorithms.
Algorithmic Architecture	This includes various AI algorithms used for data processing and financial market analysis. Examples include artificial neural networks, machine learning algorithms, decision tree algorithms, and evolutionary algorithms.
Data and Inputs	This includes financial market data (e.g., prices, transaction volumes, interest rates, company news) and other market-related inputs. These data may be collected from various sources such as financial databases, social media, and other online sources.
Prediction Models	This includes models that use data and inputs to predict market behavior and future changes. These models may include simple statistical models, probabilistic models, or more complex AI-based models.
Market-Making System	This includes algorithms and methods used for executing trades and creating market dynamics. This includes order management algorithms, trading strategies, and trade execution systems.

The researcher, during the analysis, looks for themes that have emerged among the existing studies in the meta-

synthesis. This is known as (thematic review). Once the themes are identified and specified, the reviewer forms a

classification and places similar and related classifications in a theme that best describes them. The themes provide the basis for creating explanations, patterns, theories, or hypotheses. In this research, all factors extracted from the studies were initially considered as identifiers, and then, considering the meaning of each, identifiers were defined in

a similar concept; then, similar concepts were categorized into explanatory categories to identify the explanatory axes of the research indicators in the form of main and sub-components. In Table 2, in the source column, each article is indicated with the letter C and the article number.

**Table 2**

*Main Categories and Corresponding Codes*

Dimensions	Component	Source
Machine Learning Algorithms	Artificial Neural Networks	S1-S2-S3-S4-S5-S6-S7-S8-S9-S10-S11-S12-S13-S14-S15-S16-S17-S18-S19-S21-S22-S23-S24-S25-S26
	Decision Trees	S34-S35-S26-S18-S22-S26-S29
	Support Vector Machines (SVM)	S32-S33-S21-S22-S26-S30
	Adversarial Learning Methods	S19-S20-S35-S17-S31-S32
	Ensemble Learning Methods	S9-S20-S35-S5
	Hidden Markov Models (HMM)	S21-S20-S35-S27
	Natural Language Processing (NLP)	S7-S8-S9-S10-S11-S12-S1-S2-S6-S19-S21
Text Analysis and Information Extraction	Clustering Techniques like K-Means	S17-S16-32-S23-S28-S24
	Text Analysis and News Agencies	S34-S35-S16
	Concept Extraction and Sentiment Analysis	S34-S35-S17-S8-S9-S20
	Use of Social Network Analysis Techniques	S37-S38-S39-S40-S41-S42
Portfolio Optimization	Visual Analysis	S1-S2-S3-S4-S5-S6-S7-S8-S9-S10-S11-S12-S13-S14-S15-S16-S17-S18-S19-S21-S22-S23-S24-S25-S26
	Data Mining	S19-S33-S34-S41-S42
	Automated Risk Management Methods	S7-S12-S13-S14-S20-S21-S24
	Diversified Strategies	S1-S2-S3-S5-S8-S9-S11-S13-S21-S19
Recommender Systems	Market Changes	S2-S3-S13-S14-S6-S8-S10-S14
	Limitations and Risks	S9-S10-S6-S7-S17-S18
	Algorithmic Architecture	S28-S29-S32-S33-S34-S15-S10
	Data and Inputs	S19-S23-S15-S11-S12
	Prediction Models	S33-S25-S4-S6-S8-S19
	Market-Making System	S20-S10-S11-S14-S24

#### 4 Discussion and Conclusion

The aim of this research was to identify the optimization components of FinTech based on AI indicators in the financial market. Based on the meta-synthesis method, 21 codes in four categories were identified. The validity and reliability of the research findings were also confirmed. The identified categories are machine learning algorithms, text analysis and information extraction, portfolio optimization, and recommender systems. In FinTech optimization, one of the fundamental components is machine learning algorithms. These algorithms use financial and market data to predict future behaviors and improve the performance of financial systems. These methods utilize various types of

machine learning models such as neural networks, decision trees, and ensemble learning methods.

Text analysis and information extraction are also important components in FinTech optimization. By analyzing texts related to news, tweets, company reports, and other sources, useful information such as market sentiment, events, and economic conditions can be extracted. This information is automatically processed and used for financial decision-making. Portfolio optimization is another important component in FinTech optimization. This process includes selecting the best combination of assets and allocating capital to maximize returns and reduce risks. Portfolio optimization algorithms use financial data and mathematical decision-making methods to automatically model optimal portfolios. Recommender systems also play a

significant role in FinTech optimization. These systems provide investment or trading suggestions based on the analysis of financial data and previous investor behavior. Machine learning algorithms and portfolio optimization methods are used to provide accurate and effective recommendations.

In recent research, many efforts have been made to identify the optimization components of FinTech using AI indicators in the financial market. AI indicators such as artificial neural networks, genetic algorithms, evolutionary algorithms, and machine learning have been used. The results of these studies show that using these AI indicators can significantly improve the performance of capital management systems and investment decision-making in the financial market.

In this context, it has been found that using artificial neural networks for market price prediction, pattern recognition, and structuring an optimal investment portfolio has significantly improved the performance of capital management systems. Additionally, genetic and evolutionary algorithms have also been effective in optimizing parameters and structures of financial models, helping to achieve optimal investment solutions. However, it is crucial to be aware that although AI indicators can improve financial system performance, the associated limitations and risks must also be recognized. These include issues such as model complexity, sensitivity to input data, and risks associated with machine decision-making. Therefore, balancing model accuracy and risk acceptance is necessary when using these indicators.

FinTech optimization, or the improvement of financial processes and decision-making using modern technologies, can leverage various AI components. Below are practical suggestions for each of the mentioned components:

**Machine Learning Algorithms:**

**Stock Price Prediction:** Machine learning algorithms like neural networks and decision trees can help predict prices by analyzing financial market data and related indicators.

**Risk Management:** Using machine learning models, risky patterns can be identified, and optimal management of different risks in investment portfolios can be achieved.

**Text Analysis and Information Extraction:**

**Market News and Analysis:** By using text analysis and information extraction, market news and analyses can be automatically reviewed, and useful information can be extracted.

**Company Health Assessment:** By aggregating and analyzing textual information related to company

performance from various sources, a more precise and rapid assessment of company health can be achieved.

**Portfolio Optimization:**

**Portfolio Adjustment:** Using optimization algorithms, improvements in asset composition and capital allocation can be achieved for greater efficiency and reduced risks.

**Periodic Portfolio Rebalancing:** Optimization algorithms can be used to periodically rebalance portfolios to respond to market changes and new conditions.

**Recommender Systems:**

**Asset Recommendations:** AI-based recommender systems can provide investors with suggestions tailored to their goals and risk profiles.

**Portfolio Management:** Recommender systems can offer suggestions for managing and improving various portfolios, helping investors make better decisions.

### Authors' Contributions

All authors have contributed significantly to the research process and the development of the manuscript.

### Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

### Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

### Acknowledgments

We would like to express our gratitude to all individuals helped us to do the project.

### Declaration of Interest

The authors report no conflict of interest.

### Funding

According to the authors, this article has no financial support.

### Ethical Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were observed.

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