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THE IMPACT OF ARTIFICIAL INTELLIGENCE-SUPPORTED DECISION MODELS ON EMERGING MARKETS: A BEHAVIORAL FINANCE PERSPECTIVE

Yapay Zekâ Destekli Karar Modellerinin Gelişen Piyasalar Üzerindeki Etkisi: Davranışsal Finans Perspektifi

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ABSTRACT

This study examines the interaction between artificial intelligence (AI)-supported decision models, investor behavior, and market conditions in emerging financial markets, with particular emphasis on Türkiye. The research adopts a qualitative document analysis approach supported by a systematic literature review, and the literature selection process was structured in line with PRISMA principles. Studies published between 2020 and 2025 were identified through YÖK National Thesis Center, DergiPark, Google Scholar, academic publisher platforms, institutional repositories, and open-access academic sources. After applying inclusion criteria related to behavioral finance and AI-supported financial decision-making, 20 studies were included in the final analysis. The selected studies were coded according to publication characteristics, research methods, data structures, AI techniques, and behavioral finance themes. The findings indicate that AI-based forecasting and risk management models provide stronger decision support than traditional econometric approaches, especially under volatile market conditions. However, algorithmic opacity, bias, data quality, explainability, legal liability, and regulatory uncertainty remain critical limitations. Overall, AI should be considered a complementary socio-technical decision-support tool rather than a substitute for human judgment.

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ÖZ

Bu çalışma, yapay zekâ destekli karar modellerinin yatırımcı davranışları ve piyasa koşullarıyla olan etkileşimini, özellikle Türkiye ve gelişmekte olan finansal piyasalar bağlamında incelemektedir. Araştırma, sistematik literatür taramasıyla desteklenen nitel doküman analizi yöntemiyle yürütülmüş; literatür seçim süreci PRISMA ilkeleri doğrultusunda yapılandırılmıştır. 2020–2025 yılları arasında yayımlanan çalışmalar YÖK Ulusal Tez Merkezi, DergiPark, Google Scholar, akademik yayınevi platformları, kurumsal açık erişim arşivleri ve açık erişimli akademik kaynaklar üzerinden belirlenmiştir. Davranışsal finans veya yapay zekâ destekli finansal karar verme boyutu içeren 20 çalışma nihai analize dâhil edilmiştir. Seçilen çalışmalar yayın özellikleri, yöntem, veri yapısı, kullanılan yapay zekâ teknikleri ve davranışsal finans temaları açısından kodlanmıştır. Bulgular, yapay zekâ tabanlı tahmin ve risk yönetimi modellerinin özellikle oynak piyasa koşullarında geleneksel ekonometrik yaklaşımlara kıyasla daha güçlü karar desteği sağlayabildiğini göstermektedir. Ancak algoritmik şeffaflık, yanlılık, veri kalitesi, açıklanabilirlik, hukuki sorumluluk ve düzenleyici belirsizlikler önemli sınırlılıklar oluşturmaktadır. Sonuç olarak yapay zekâ, insan kararını ikame eden değil, tamamlayan sosyo-teknik bir karar destek aracı olarak değerlendirilmelidir.

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1. Introduction

Artificial intelligence has become one of the most influential technological forces reshaping contemporary economic and financial systems. Advances in machine learning, deep learning, big data analytics, algorithmic trading, robo-advisory systems, and data-driven modelling have transformed the ways in which financial information is processed, risks are evaluated, investment alternatives are compared, and decisions are supported in financial markets. These technologies are increasingly used in areas such as price forecasting, portfolio optimization, credit evaluation, fraud detection, risk management, customer profiling, and investment advisory services. As a result, artificial intelligence is no longer treated only as a technical forecasting tool; rather, it has become a strategic decision-support infrastructure affecting both institutional financial actors and individual investors.

Emerging markets provide a particularly relevant context for examining the influence of AI-supported decision models. These markets are often characterized by structural volatility, information asymmetry, sensitivity to global economic developments, rapidly changing investor sentiment, and evolving regulatory frameworks. Such conditions create a complex decision environment in which traditional financial assumptions and AI-based tools are simultaneously tested under pressure. In markets such as Türkiye, where financial digitalization, fintech applications, algorithmic trading, robo-advisory discussions, and AI-supported investment tools are gaining visibility, the interaction between technological capability and investor behaviour becomes especially important. Therefore, the analysis of AI-supported decision models in emerging markets requires attention not only to model performance, but also to behavioural responses, institutional readiness, regulatory capacity, and data infrastructure.

Traditional finance largely assumes that investors behave rationally and that markets operate efficiently. According to the efficient market hypothesis, asset prices reflect all available information, and consistently obtaining above-market returns is considered highly difficult. However, real market observations such as herd behaviour, overconfidence, loss aversion, speculative bubbles, excessive reactions, and momentum effects show that financial markets frequently deviate from this idealized rational structure. Behavioural finance emerged in response to these limitations by emphasizing that psychological tendencies, cognitive biases, emotions, and bounded rationality systematically shape financial decisions. From this perspective, investment decisions are not determined only by available information or statistical models; they are also shaped by how investors perceive, interpret, trust, or reject financial information and decision-support outputs.

In this context, AI-supported decision models create both opportunities and risks for behavioural finance. On the one hand, AI systems can process large and diverse datasets that exceed individual analytical capacity, identify nonlinear patterns, improve forecasting performance, classify investor behaviour, and support more disciplined decision-making. Techniques such as sentiment analysis, text mining, machine learning-based classification, and predictive modelling may also make behavioural tendencies such as herd behaviour, risk perception, overconfidence, and technology acceptance more observable and measurable. On the other hand, AI systems may introduce new forms of risk. Algorithmic opacity, biased training data, overfitting, weak explainability, data quality limitations, excessive reliance on automated outputs, and unclear legal responsibility may reproduce or intensify behavioural and institutional vulnerabilities. Therefore, the critical question is not whether AI is simply superior to human judgment, but under what conditions AI supports, reshapes, or distorts financial decision-making.

This issue becomes particularly significant in emerging markets, where limited information structures, high volatility, regulatory transformation, uneven data quality, and rapid digital adoption create both opportunities and vulnerabilities. AI-supported decision models may enhance predictive accuracy, improve resource allocation, support portfolio management, and contribute to financial stability. However, inappropriate use, weak governance, or misinterpretation of AI-generated recommendations may intensify systemic fragilities and investor-level risks. For this reason, AI-supported financial decision models should be evaluated as socio-technical systems operating at the intersection of algorithms, investor psychology, institutional structures, and market conditions.

This study examines these dynamics by analysing how AI-supported financial decision models interact with behavioural patterns, financial decision processes, institutional characteristics, and emerging market conditions. By integrating perspectives from artificial intelligence and behavioural finance, the study aims to clarify the opportunities, risks, and governance challenges associated with AI-supported decision-making in emerging financial markets, with particular attention to Türkiye. In this respect, the study contributes to the literature by moving beyond a purely technical evaluation of AI performance and proposing a broader interpretive framework that considers investor behaviour, trust, cognitive bias, robo-advisory systems, explainability, regulatory uncertainty, and market structure together.

2. Artificial Intelligence and Finance

2.1. Artificial Intelligence and Application Models

The idea of artificial intelligence began to take shape in 1950 with Alan Turing's well-known question: "Can machines think?". A few years later, the term gained formal recognition during the 1956 Dartmouth Workshop led by John McCarthy (Gülşen, 2019, p. 410). As the concept developed, machine learning emerged as an approach focusing on algorithms that analyze existing data in order to predict situations that have not yet been observed (Çolakoğlu, 2020, p. 8). In general terms, artificial intelligence refers to the capacity of machines to learn from past experiences and make decisions based on acquired knowledge (Kurbanoğlu, 1992, p. 189). Within this framework, machine learning encompasses algorithms that model problems according to their associated data (Atalay & Çelik, 2017). These algorithms rely on statistical reasoning and can operate even when no explicit instruction exists for a specific task (Bingöl et al., 2020, p. 2201).

As machine learning practices advanced, relationships within available data became central to the learning process. Modern datasets possess considerable size and variety (Atalay & Çelik, 2017). This growth facilitated the development of deep learning, which relies on layered structures connecting large volumes of data to artificial neural networks inspired by the human brain. Deep learning is regarded as an advanced method within artificial neural networks (Craft, 2018) and is widely applied to complex problems requiring high computational capacity (Akerkar, 2019). Its performance improves as algorithms encounter richer datasets. Access to large-scale data sources is often achieved through data mining, defined as the discovery of knowledge from databases. Data mining is considered a subfield of machine learning and focuses on exploratory data analysis through unsupervised techniques (Küçük & Arıcı, 2018, p. 77).

Artificial intelligence has also been interpreted through attempts to model physiological and neurological structures associated with human intelligence. These include the nervous system, genetic structures and various natural processes that are transferred to machines, computers and software systems (Pomerol, 1997, p. 4). In this context, artificial intelligence systems may display behaviors associated with intelligence, either by imitating human thinking and actions, or by following rational decision processes. Systems that behave as if they are intelligent are generally described as weak artificial intelligence whereas systems capable of exhibiting human-like mental characteristics are defined as strong artificial intelligence (Ünver & Altunok, 2020, p. 484). Overall, artificial intelligence refers to enabling computers or computer-supported machines to perform cognitive activities such as learning, analyzing, understanding, creating meaning, forming judgments, generalizing and recognizing patterns (Öztürk & Şahin, 2018, p. 24).

Following these developments in artificial intelligence and machine learning, attention gradually shifted toward systems capable of imitating the decision-making ability of human experts, bringing expert systems into focus.

2.2. Expert Systems

Expert systems were developed by embedding into computer programs the qualities associated with expertise, including deep knowledge of a specific problem field and the ability to perform tasks effectively (Lawrence, 1991, p. 202). They address problems that require expert level competence by applying stored information together with logical inference processes. When new situations arise, they rely on previously stored knowledge to form conclusions and aim to combine human style reasoning with the speed and reliability of computers (Demirhan et al., 2010, p. 31).

In practice, expert systems can function as independent decision units or serve as supportive tools that provide recommendations in complex problem settings. Their primary distinction from decision support systems lies in their knowledge bases and inference mechanisms, which allow access to expert reasoning and specialized insights (Kurbanoğlu, 1992, p. 189). Although they reduce costs and enhance quality, they remain limited because they cannot replicate the creativity of human experts or renew themselves through continuous learning (Başoğlu &

Bulut, 2017, p. 577). These limitations prompted interest in more flexible intelligent models and opened the path toward artificial neural networks.

2.3. Artificial Neural Networks

Artificial neural networks emerged as models that imitate the neural structure of the human brain and learn through interconnected neural receptors. They generate new information from classified datasets and make decisions based on learned patterns (Keskenler & Keskenler, 2017, p. 10). The networks consist of artificial neural cells connected to one another, with knowledge stored in the weight values assigned to these connections (Öztemel, 2012, p. 41). Each artificial neural cell collects incoming signals through a summation function, processes them with an activation function and transfers the output to subsequent cells. A typical network includes an input layer, one or more hidden layers, and an output layer. Information flows from the input layer to the hidden layers, and finally reaches the output layer (Atalay & Çelik, 2017, p. 162). Producing accurate output depends on the correct adjustment of weight values. Initially assigned at random, these weights are modified throughout training until the network produces correct results for all training examples. When the model responds accurately to the test set, learning is considered complete. Because information is distributed across many weighted connections and because interpreting these weights is difficult, neural networks are often referred to as a black box (Öztemel, 2012, p. 57). Difficulties associated with interpreting neural networks encouraged researchers to explore alternative optimization approaches, which led naturally to the adoption of genetic algorithms.

2.4. Genetic Algorithms

Genetic algorithms are "population-based" heuristic optimization methods inspired by natural evolutionary processes. They generate new candidate points in the search space through selection and crossover (Özçalıcı & Ayrıçay, 2016, p. 281). Their use expanded over time, and they became a preferred approach for multivariable optimization problems that challenge traditional methods. The initial population is created randomly from a subset of all possible solutions, and consists of individuals represented within the 0 to 1 range. Chromosome-like sequences are rounded to 0 or 1, and evaluated through a fitness function tailored to the specific problem. Selection increases the probability that individuals with higher fitness values advance to the next generation. Selected individuals then undergo crossover, in which gene segments are exchanged. The number of chromosomes involved depends on the crossover rate. Mutation alters a gene element when a change in search direction is needed, and the mutation rate determines how many chromosomes undergo this alteration. Population size remains constant because new individuals replace older ones. Identifying the individual with the highest fitness value corresponds to determining the optimal solution, and each application produces a single final result (Daş et al., 2006, pp. 168-169).

2.5. Behavioral Finance Approach

Financial markets have relied on standard models for many years, and these models rest on assumptions that have shaped modern finance. The efficient market hypothesis together with mainstream theory argues that an investor holding a well-diversified portfolio will obtain a return close to the market portfolio. Yet the extent to which these assumptions hold under real market conditions has long been questioned. Present-day markets display determinism, overconfidence and herding behaviors that require attention (Cross et al., 2004, p. 1). As discussions continued, modern finance maintained the view that the price of a security equals the sum of the present values of its future cash flow (Daniel, 2004, p. 1). Within this framework, the probability of achieving extraordinary returns is regarded as zero. Outcomes with negative covariance with marginal utility are expected only in risky assets. A central criticism concerns the difficulty of measuring marginal utility directly since accurate measurement requires additional economic and financial indicators. These issues reveal weaknesses in the efficient market hypothesis. Although the hypothesis offers mathematical solutions for specific problems, it assumes that investors consistently behave in a correct manner. Its dependence on historical information for forecasting also implies that future price movements reflect past trends, an assumption that overlooks human free will. A more accurate evaluation of investor behavior therefore requires addressing these limitations, and this need encourages the emergence of behavioral finance.

Behavioral finance offers an alternative by challenging the classical premise that rational investors always maximize expected utility. The field integrates psychology with decision-making science and broadens the understanding of financial behavior (Fuller, 2000, p. 1). It investigates the origins of biases within financial settings and examines how decision makers commit systematic thinking and judgment errors. This perspective differs sharply from the efficient market hypothesis. While the hypothesis assumes zero transaction costs, no market segmentation and easy entry into securities markets, behavioral finance argues that investors aim to maximize portfolio value and act in line with their own interests (Fuller, 2000, p. 1). Two central dimensions shape the field. One dimension focuses on perception, meaning how individuals interpret information. The other addresses limit to arbitrage, referring to conditions under which markets fail to remain efficient (Ritter, 2003, p. 1). These distinctions help explain why modern finance, through the efficient market hypothesis, maintains that abnormal gains occur only when investors possess superior information and operate in highly competitive environments (Ritter, 2003, p. 1). The hypothesis attributes rationality to markets rather than individuals and suggests that unbiased expectations about the future can be formed. Growth trends, macroeconomic indicators and historical return indices play major roles in shaping these expectations. Behavioral finance challenges this view by arguing that information used in financial markets may lose efficiency under certain circumstances.

The argument behind behavioral finance also recognizes that misjudgments do not arise only from psychological factors. Imbalances in supply and demand can produce similar errors. The Istanbul Stock Exchange index is calculated from firm values derived by multiplying share quantities with market prices and weighing them by firm values and trading volumes. Firms' future cash flows are not directly incorporated into the calculation. When a new firm offers shares to the public, excessive demand often drives prices upward, after which weakening demand can cause sharp declines. Such fluctuations may lead investors to make incorrect decisions.

3. Artificial Intelligence-Supported Decision Models

3.1. Decision Support Systems

Businesses have always encountered simple, complex, ordinary and extraordinary problems that require a wide range of decisions. Managers in particular must cope with the risk of making incorrect choices due to environmental influences, personal biases and intuition. As a result, the decision process becomes challenging. Decision support systems were developed to ease this difficulty, yet understanding these systems first requires clarifying the concepts of decision, decision making and management.

The Turkish Language Association defines a decision as a final judgment formed after examining an issue. Decision has been described as a series of dynamic elements and activities that begin with identifying the factors required for action and end with forming a clear judgment (Mintzberg, 1976, as cited in Tekin & Ehtiyar, 2010, pp. 3394–3414). The decision making process involves identifying alternatives for solving a problem, evaluating them, and selecting the most appropriate one (Çelik, 2018). Another view considers it a behavioral pattern displayed by decision makers when choosing among alternatives to achieve a goal (Çelikten et al., 2019, pp. 581-592). Within, a business the most active area of decision making is the management level. Managers guide decision processes as part of their managerial functions. Management is therefore defined as coordinating and using organizational elements to achieve objectives effectively and efficiently (Tekin & Ehtiyar, 2010, pp. 3394-3414). In other words, management requires choosing how to use all necessary resources to reach organizational goals. The strong link between the words, manager and decision, stems from this connection. The accuracy of managerial decisions heavily influences the success and longevity of businesses. Managers must therefore make choices that enhance survival, improve competitiveness, increase profitability and guide performance (Emhan, 2007, pp. 212-224). Successful firms differ from others by making better, faster and more timely decisions, and by implementing them effectively (Tekin & Ehtiyar, 2010, pp. 3394-3414).

In real business settings, many decision makers struggle to extract meaningful results from large and complex datasets and to integrate such information into decision processes. Managers also face uncertainty about whether they possess adequate data for reliable decisions. Intuition is often used; however, intuition alone is insufficient under competitive, dynamic and uncertain conditions (Çelik, 2006). Decision makers also operate within boundaries that influence outcomes. These boundaries include cognitive limits, such as restricted capacity to store and process data, and economic limits, such as the cost of acquiring, storing, processing, transmitting and distributing information (Daniela, 2019, pp. 76-82). Such limitations created demand for technological structures supported by mathematical tools to reduce decision related problems. This demand initiated the development of modern decision support systems.

Advances in technology have had a positive impact on business processes. Technological systems are widely used to support rapid and accurate decisions, increase efficiency, reduce costs and strengthen competitive advantage. A major benefit of these systems is the support they provide in accessing data and information. Without adequate information, managers cannot perform decision processes effectively. Firms must therefore collect information continuously from both internal and external environments. Organizations that prioritize technological investments gain rapid access to needed data. However, collected data must be processed and transformed into usable information. For this reason, businesses establish management information systems that convert raw data into meaningful information and integrate it into organizational processes.

Management information systems collect, store, process, generate and share data and information while supporting decision processes (Dizman & Özen, 2017, pp. 137-152). They provide strategic information that enables managers to make timely and effective decisions (Anameriç, 2005, pp. 25-43). Their main components include data, data warehouses, information and data mining. Data represent recorded elements that form the basis of information (Karagül, 2006). Their own data do not produce information and must be processed through input, processing and output stages. Information refers to processed outputs that carry meaning for users (Karagül, 2006). A data warehouse is an integrated, time-oriented repository that supports managerial decision making (Yaldır & Taşer, 2016, pp. 153-171). Data mining identifies relationships among seemingly unrelated data and generates meaningful results that support accurate future decisions (Dural, 2015). Several software tools assist data mining, including online analytical processing, which allows users to perform extensive analyses and calculations.

The increasing needs of decision makers for timely and understandable information led to the development of management information systems adapted to organizational requirements. This evolution brought decision support systems into prominence. These systems emerged in the 1960s as tools supporting managerial decision processes. They collect, organize and analyze needed data through interactive software structures. With these capabilities, they visualize future trends, generate useful information, and integrate with human reasoning (Daniela, 2019, pp. 76–82). Their origins are linked to computer-based decision analysis at Carnegie Institute of Technology. Interest in grew significantly during the 1980s, when attention shifted toward business-oriented decision support. Over time, individual, group and management-oriented decision-making systems were developed. Today, these systems also include analytics and data-driven solutions (Uyanık, 2016). Michael Scott Morton provided the first definition, describing decision support systems as interactive computer structures that assist decision makers in solving semi-structured and unstructured problems through data and models (Yaldır & Taşer, 2016, pp. 153-171). Another definition emphasizes their ability to enable users to access, summarize and analyze data while offering statistical methods, graphical tools, models, tables and reports (Dural, 2015). George (1992) describes them as combinations of computer and communication technologies used to coordinate decision processes across functional areas and hierarchical levels (George, 1992, pp. 109-125).

Decision support systems appear in four main forms. Model-based systems use models to answer what-if questions (Yıldız et al., 2008, pp. 239-248). Knowledge-based systems rely on tools also known as intelligent decision support systems and provide specialized solutions for smaller groups (Dural, 2015). Document-based systems analyze written, visual and audio materials such as interviews, news clips, advertisements, reports, catalogs, letters and emails (Çelik, 2006; Uyanık, 2016). Data-based systems analyze internal and external data using online analytical processing and data mining (Daniela, 2019, pp. 76-82). Data stored in repositories can be combined to examine relationships among them (Dural, 2015).

3.2. Integration of Artificial Intelligence Technologies Into Decision Support Systems (DSS)

AI-based decision support systems analyze heterogeneous data structures to develop predictive models and provide users with more effective decision-making capabilities. These systems are generally designed with a multilayered architectural structure. The core architecture of AI-DSS is represented as follows (Kostopoulos et al., 2024, p. 2842):

[Data Sources]

↓

[Data Pre-Processing Module]

↓
[AI/ML Module (Prediction/Recommendation Generation)]

↓
[Explainability Layer (XAI Interpretation)]

↓
[Decision Support Panel (Result Presentation)]

↓
[User-Driven Decision Making]

This sequence introduces the operational flow of AI-DSS and highlights the functional role of each component. Data Sources form the foundation of AI-enhanced DSS structures and include structured data such as database systems and spreadsheet tools as well as unstructured data such as text, image and audio inputs, which provide the initial inputs required for the system to generate decisions. The Data Pre-Processing Module ensures that data are accurate, complete and meaningful through cleaning, normalization and feature selection, improving system performance and preparing the data for model training (Soori et al., 2024, pp. 206-225). The Machine Learning/Artificial Intelligence Layer employs machine learning (ML) and deep learning (DL) algorithms for prediction or classification, with model parameters adjusted dynamically according to user requirements to adapt to different operational contexts. The Explainability Layer (XAI) addresses transparency and interpretability through techniques such as SHAP and LIME to clarify how model outputs are produced and strengthen accountability. The Decision Support Panel presents model recommendations in a clear and intuitive format using visualization tools and user-oriented interfaces to improve decision quality. In the final layer, User Interaction and Decision Making, users assess model recommendations and make choices aligned with their institutional context, leaving human judgment essential while AI operates as a supportive analytical tool. This multilayered architecture is designed to meet requirements such as technical transparency, user interaction and operational efficiency and appears in different forms across sectoral applications examined in subsequent sections (Onwujekwe, G. & Weistroffer, 2025, pp. 15-32).

4. The Use of AI and ML in The Financial Sector

Since information processing constitutes a core function of financial markets, the financial sector serves as a useful laboratory for exploring the potential effects of artificial intelligence (Desai, 2023). AI and ML systems require large volumes of data for training. The sector collects and processes data from individual consumers and businesses, indicators related to economic activity, financial markets, payments, financial transactions and many other sources. The sector's traditional role as an intermediary generates substantial data, creating a favorable environment for AI and ML applications (Tierno, 2024, p. 5).

Compared with other sectors of the economy, the adoption and diversification of AI-based applications in finance have developed more slowly. The primary reason is that financial activities constitute one of the most heavily regulated areas. Financial regulations aim to ensure market integrity, consumer protection, financial stability, institutional trust, risk management, and transparency, yet they also impose obligations that may not align with advanced AI tools. Risks related to breaches of data privacy, lack of explainability in AI models, the obligation of financial service providers to act in clients' best interests, and the need to avoid misleading outputs and risks that advanced AI tools may pose for consumers limit the expansion of AI use in the sector. Broader adoption may accelerate once regulations addressing these risks become operational (OECD, 2023, pp. 11-12). An important supply-side driver is technology. Rapid developments in information processing have increased the volume of data that can be processed, and reduced processing time (IOSCO, 2017, p. 6). Growing digitalization and web-based services have expanded datasets available for learning and prediction. Rising processor speeds, declining hardware costs, and improved access to computing power through cloud services have enabled efficient data processing. Advances in databases, software and algorithms have lowered the cost of storing, segregating, and analyzing data.

The data-intensive structure of the financial sector constitutes a second supply-side factor supporting AI and ML adoption. Technological developments in financial services have enhanced the infrastructure and datasets used by institutions, resulting in a favorable environment for AI and ML. Digitalized financial data can be used for ML, and market automation enables AI algorithms to interact directly with markets and, with minimal human intervention, issue real-time complex buy–sell orders based on sophisticated decision processes. Retail credit scoring systems have become machine-readable. In addition to market data, online search trends, browsing patterns and social media information have rapidly expanded the data universe available for ML-enhanced scoring, thereby accelerating AI and ML adoption (Financial Stability Board, 2017, pp. 8–9). On the demand side, the primary driver is profit maximization. Financial institutions use AI to optimize costs. A 2023 survey conducted by NVIDIA reported that 36 percent of financial services professionals observed more than a 10 percent reduction in annual costs due to AI applications (Pressley, 2024). Cost reductions arise from multiple channels: AI automates data processing, document handling, recruitment, customer interactions and similar processes, reducing errors and saving time across operational levels. AI-powered chatbots reduce personnel needs in customer interactions. The ability of AI to analyze large datasets and detect unusual patterns reduces fraud and irregularities, enhances transaction security, and limits losses from operational risks. AI also strengthens anti-money laundering efforts by improving transaction monitoring and reducing compliance costs and potential losses (Pressley, 2024).

A second demand-sided driver is the concern of falling behind competitors using similar tools. Financial institutions adopt AI and ML to keep pace in optimizing decision processes, developing new products and services and improving operational efficiency (Financial Stability Board, 2017, p. 9). A third driver is compliance with administrative and regulatory requirements. Advances in AI and ML have transformed the role of technology in regulation. After the 2008 global financial crisis, tighter regulations increased compliance costs, prompting a shift toward regulatory technologies supported by AI and ML. Banks and financial institutions use AI-driven tools for prudential compliance, anti-money laundering measures and efficient data reporting (Boukherouaa & Shabsigh, 2021, p. 11). Supervisory authorities have also turned to AI/ML tools as they face larger, faster and more complex datasets, integrating these tools into monitoring and oversight systems (Financial Stability Board, 2017, p. 10). These factors have expanded AI use across banking, asset management, securities and insurance, and throughout different stages of the financial value chain. In retail and corporate banking, AI is used for customer acquisition, credit analysis, customer support, recruitment, anti–money laundering, compliance and fraud detection. In asset and portfolio management, it is used for stock selection and risk management. In algorithmic and high-frequency trading, it supports liquidity management. In insurance, AI contributes to customer relations, risk analysis and claims assessment. Generative AI and LLMs are used in sales and marketing, customer support, operations, data management, and software development. Financial institutions are expected to further expand AI-based capabilities (OECD, 2023, p. 13).

AI and ML models offer flexibility compared with traditional statistical and econometric models, identify complex variable relationships and strengthen institutional analytical tools. ML methods are designed to learn complex patterns from historical data and avoid the tendency of traditional models to overemphasize past relationships when forecasting. Research shows that ML methods outperform linear regression-based approaches in prediction accuracy and robustness (Bolhuis & Rayner, 2020, p. 4). A 2023 KPMG survey of financial sector firms reported preferred areas for generative AI use as follows: Operations (56 percent), Information Technology (IT) (56 percent), Marketing and Sales (42 percent), Product Development and Research and Development (R&D) (40 percent), Customer Management (40 percent), Finance and Accounting (19 percent), Human Resources (16 percent) and Risk Management and Legal (14 percent). These results show that 56 percent of participants prioritized generative AI in operations and IT, while 42 percent prioritized its use in marketing and sales (KPMG, 2023, p. 6).

AI and ML applications in finance can be considered under four main categories (van der Burgt, 2019, p. 25; Financial Stability Board, 2017, p. 11):

- Customer-focused use (front office): credit scoring, insurance, chatbots.
- Operational use (back office): capital optimization, risk management, market impact analysis.
- Use in asset and portfolio management and financial market trading.
- Compliance by financial institutions and use in supervision by regulatory authorities.

In customer-focused use, the initial application involved processes related to *know-your-customer* principles including identification, verification, collection and processing of personal information. Such applications eliminate the need for physical interaction, reduce time and costs for both banks and customers, and facilitate customer acquisition (van der Burgt, 2019, p. 26). Chatbots that imitate human speech through text and voice commands and interact with users online, for example by engaging in conversation and providing answers, represent the next stage of AI-supported customer interaction. These systems use machine learning to draw on responses from previous interactions to improve their performance. Bank chatbots operate on a 24/7 basis, evaluate customer queries, provide information on account balances and transaction histories, and guide users through various banking processes, which shorten waiting times (Tierno, 2024, p. 7).

The evolution of chatbots has moved toward recommending products and services and encouraging customers to purchase them (Zhu, Vigren et al., 2024). Through chatbots, financial institutions support customers in financial decision-making processes, and, through these interactions, they also gather information about clients and expand their data capacity (Financial Stability Board, 2017, pp. 14-15). AI also plays a central role in credit analysis. Banks have largely automated credit decision processes through scoring applications that assess client creditworthiness. Structured and quantifiable data, such as credit and bill payment history, outstanding debt, overdue or unpaid loans and account activity, have until recently been the primary determinants of credit scores. AI and ML-based credit scoring systems now incorporate unstructured and wide-ranging data, including visual elements, social media activity, posts and networks, alongside structured data. This integration increases the accuracy of credit scores and supports partial mitigation of potential risk. Applying ML algorithms to new datasets facilitates the assessment of qualitative factors such as consumer behavior and willingness to pay. The ability to exploit these additional data sources enables more accurate, faster and cheaper measurement and classification of borrower risk and supports quicker and more reliable credit decisions (Cooper, 2023, p. 1; Financial Stability Board, 2017, pp. 12–13; OECD, 2021a, p. 44; Tierno, 2024, pp. 6–7).

5. Analysis and Findings

5.1. Research Design

This study adopts a qualitative research design based on systematic literature review procedures and document analysis to examine the literature on artificial intelligence-supported investment decisions from a behavioural finance perspective, with particular attention to Türkiye and other emerging markets. The study does not aim to conduct a full-scale bibliometric mapping analysis, citation network analysis, or meta-analysis. Rather, it provides a transparent, systematic, and thematically structured review of the selected literature.

Document analysis is a qualitative method that enables the systematic examination, interpretation, and synthesis of written materials in order to identify patterns, themes, conceptual orientations, methodological tendencies, and analytical gaps within a body of literature (Bowen, 2009; Creswell, 2021; Yıldırım & Şimşek, 2016). In the present study, document analysis was employed to evaluate the conceptual, methodological, empirical, behavioural, and regulatory characteristics of studies dealing with AI-supported financial decision-making and behavioural finance-related dimensions.

To increase methodological transparency and replicability, the stages of identification, screening, eligibility assessment, and inclusion were reported in line with the PRISMA 2020 framework (Moher et al., 2009; Page et al., 2021). In this study, PRISMA was used as a reporting and selection-transparency tool guiding the review process, rather than as evidence of meta-analysis or advanced bibliometric design. Accordingly, the study is positioned as a qualitative systematic review supported by document analysis, descriptive classification, and thematic coding.

The document analysis process was guided by the following methodological principles:

Table 1. Methodological Principles Guiding the Document Analysis

Methodological Principle	Application in This Study
Document identification	Relevant studies were identified through database and supplementary searches focusing on AI-supported financial decision-making, behavioural finance, robo-advisory systems, machine learning-based forecasting, and emerging markets.
Eligibility and relevance assessment	Studies were assessed according to publication year, full-text accessibility, financial decision-making relevance, and the presence of a behavioural finance or AI-supported decision-making dimension.
Systematic organization	The selected studies were organized by publication type, year, research method, data structure, AI technique, behavioural finance theme, and main finding.
Coding and classification	Each study was coded through a structured coding form to enable comparison across methodological, conceptual, technological, behavioural, and regulatory dimensions.
Thematic synthesis	Recurring themes such as forecasting, investor bias, trust, risk perception, cognitive bias, robo-advisory systems, technology acceptance, explainability, legal liability, and regulation were synthesized thematically.
Transparency and traceability	The identification, screening, eligibility, and inclusion stages were reported through PRISMA-based tables to make the review process transparent and replicable.
Interpretive analysis	The findings were interpreted in relation to the interaction between AI-supported decision models, investor psychology, institutional structures, regulatory capacity, and emerging market conditions.

Note: These principles were derived from qualitative document analysis and systematic qualitative review procedures suggested by Bowen, Creswell, and Yıldırım and Şimşek. They were used to ensure systematic document identification, transparent selection, structured coding, thematic synthesis, and interpretive consistency.

5.2. Literature Search Strategy

The literature search was conducted accross the YÖK National Thesis Center, DergiPark, Google Scholar, academic publisher platforms, institutional repositories, author profile pages, and open-access academic sources. These sources were selected because they provide broad access to graduate theses, peer-reviewed journal articles, book chapters, nationally relevant academic publications, and practice-based sources concerning Türkiye and emerging markets. In response to the reviewer's recommendation, the search scope was expanded beyond the initial databases in order to include additional studies and sources relevant to artificial intelligence-supported financial decision-making, behavioural finance, robo-advisory systems, machine learning-based forecasting, investor trust, technology acceptance, and regulatory implications.

The search was limited to studies published between 2020 and 2025, as this period corresponds to the accelerated diffusion of artificial intelligence applications in finance, including machine learning-based forecasting, robo-advisory systems, algorithmic trading, big data analytics, and AI-supported investment tools. The search process used combinations of the following keywords: "artificial intelligence and finance," "AI investment decisions," "machine learning in finance," "algorithmic trading," "robo-advisors," "behavioural finance and AI," "AI in financial decision making," "AI and finance," "behavioral finance and AI," "AI-supported portfolio management," "investor trust and artificial intelligence," "machine learning-based financial forecasting," and "AI regulation in financial markets."

Only full-text accessible studies were considered for detailed review so that each study could be systematically coded and compared across common analytical categories. In addition to journal articles and graduate theses, book chapters and one practice-based sectoral source were included where they directly contributed to the conceptual or contextual understanding of AI-supported financial decision-making. The practice-based source was retained only for contextual enrichment due to its relevance to robo-advisory and AI-supported portfolio management and was not treated as equivalent to peer-reviewed empirical evidence.

Table 2. Search Strategy and Database Coverage

Database / Source	Rationale for Inclusion	Example Search Strings	Type of Records Retrieved
YÖK National Thesis Center	To capture graduate-level research conducted in Türkiye	artificial intelligence and finance; AI investment decisions; behavioural finance and AI	Master's theses and doctoral dissertations
DergiPark	To identify peer-reviewed national journal publications	AI in financial decision making; machine learning in finance; algorithmic trading	Peer-reviewed journal articles
Google Scholar	To broaden retrieval across interdisciplinary academic outputs	AI and finance; robo-advisors; behavioral finance and AI	Journal articles, theses, book chapters, and other academic outputs
Academic publisher platforms	To identify relevant book chapters and edited academic volumes	behavioural finance and artificial intelligence; investor bias and AI; cognitive bias and financial decision-making	Book chapters and edited-volume chapters
Institutional repositories	To verify graduate theses, open-access records, and institutionally archived academic outputs	fintech and artificial intelligence; AI investment decisions Türkiye; financial decision-making and AI	Theses, institutional records, and open-access academic outputs
Author profile pages	To verify author-based publication records and recently published academic works	artificial intelligence finance author profile; behavioural finance AI publication	Author-verified academic publications and publication metadata
Open-access academic sources	To expand the dataset with recent AI–finance studies and practice-relevant outputs	machine learning financial decision-making; AI-supported portfolio management; robo-advisory systems	Journal articles, academic outputs, and practice-based sectoral sources

Note: The search strategy was designed to capture studies at the intersection of artificial intelligence, behavioural finance, and financial decision-making, with particular attention to Türkiye and emerging market contexts. In response to the reviewer's recommendation, the search scope was expanded beyond the initial databases to include academic publisher platforms, institutional repositories, author profile pages, and open-access academic sources. The final sample was restricted to full-text accessible studies published between 2020 and 2025. The database search was conducted between 1 September 2025 and 31 October 2025, and the final screening process was completed in November 2025.

5.3. Inclusion and Exclusion Criteria

To ensure analytical relevance and comparability, explicit inclusion and exclusion criteria were applied during the title–abstract screening and full-text eligibility assessment stages. The criteria were revised in line with the expanded dataset so that peer-reviewed journal articles, academic book chapters, graduate theses, and one practice-based sectoral source could be evaluated transparently within the same review framework.

Studies were included if they:

(i) were published between 2020 and 2025;

(ii) examined artificial intelligence techniques in finance, investment, financial markets, or financial decision-making;

(iii) addressed at least one behavioural finance-related dimension, such as investor behaviour, herd behaviour, overconfidence, loss aversion, cognitive bias, trust, risk perception, technology acceptance, or investor decision-making;

(iv) were published as peer-reviewed journal articles, academic book chapters, graduate theses, or university portal research reports; in addition, one practice-based sectoral source was retained for contextual enrichment due to its direct relevance to robo-advisory systems and AI-supported portfolio management; and

(v) were available in full-text format or provided sufficient accessible content for systematic coding and thematic comparison.

Studies were excluded if they:

(i) focused exclusively on technical algorithm performance without linking the analysis to investor behaviour, behavioural finance, or financial decision-making;

(ii) addressed AI applications outside the financial domain;

(iii) discussed finance only indirectly without a clear connection to investment decisions, financial decision support, or market behaviour;

(iv) lacked sufficient methodological, conceptual, or thematic detail for structured coding and comparison;

(v) were identified as duplicate records during screening; or

(vi) were not available in full-text form and did not provide sufficient accessible information for reliable analysis.

These criteria ensured that the final analytical corpus reflected the relationship between AI-supported systems, investor behaviour, and financial decision-making under emerging market conditions, rather than AI applications in finance in a broad and undifferentiated sense. The inclusion of one practice-based sectoral source was methodologically limited to contextual enrichment and was not treated as equivalent to peer-reviewed empirical evidence.

5.4. Literature Selection Process (PRISMA)

The literature selection process followed four PRISMA-based stages: identification, screening, eligibility, and inclusion. During the identification stage, 104 records were retrieved through searches in the YÖK National Thesis Center, DergiPark, Google Scholar, academic publisher platforms, institutional repositories, author profile pages, and open-access academic sources. After duplicate removal, 84 records remained for title and abstract screening. At this stage, 47 records were excluded because they did not directly match the research focus. The remaining 37 full-text studies were assessed for eligibility. During the eligibility assessment, 17 studies were excluded because they lacked a behavioural finance dimension, focused only on technical algorithm performance, addressed AI outside the financial decision-making context, or did not provide sufficient methodological or conceptual detail for structured coding and comparison. Consequently, 20 studies were included in the final review dataset. The final dataset consisted of peer-reviewed journal articles, book chapters, master's theses, one university portal research report, and one practice-based sectoral source included for contextual enrichment due to its relevance to robo-advisory and AI-supported portfolio management. This staged procedure strengthened the transparency and traceability of the review process.

Table 3. PRISMA-Based Literature Selection Summary

Stage	Description	Number of Records
Identification	Records identified through database and supplementary searching	104
Screening	Records remaining after duplicate removal	84
Screening	Records excluded after title and abstract screening	47
Eligibility	Full-text studies assessed for eligibility	37
Eligibility	Full-text studies excluded	17
Inclusion	Studies included in the final review	20

Note: The literature selection process was reported in line with the PRISMA 2020 framework to improve methodological transparency and traceability. The search scope was expanded beyond the initial databases by including academic publisher platforms, institutional repositories, author profile pages, and open-access academic sources. The final dataset comprised 20 studies published between 2020 and 2025.

Table 4. Reasons for Exclusion at the Full-Text Eligibility Stage

Exclusion Reason	Explanation	Number of Studies Excluded
No behavioural finance dimension	The study focused on AI in finance but did not address investor behaviour, cognitive bias, risk perception, trust, technology acceptance, or related behavioural finance variables.	9
Technical performance focus only	The study evaluated AI models only in terms of predictive or algorithmic performance and did not sufficiently connect findings to financial decision behaviour or behavioural finance.	5
Outside the financial decision-making scope	The study addressed AI applications outside the financial decision-making context or discussed finance only indirectly.	1
Insufficient methodological/conceptual detail	The full text did not provide sufficient detail for systematic coding and comparative analysis.	2
Total		**17**

Note: These exclusion categories were used to ensure that the final dataset reflected the intersection of artificial intelligence, behavioural finance, and financial decision-making in emerging markets. The revised exclusion structure also reflects the expanded search scope and the inclusion of additional sources relevant to robo-advisory systems, machine learning-based forecasting, investor trust, and regulatory implications.

5.5. Data Collection and Coding Procedure

After the final sample had been identified, a structured coding form was developed to analyse the selected studies systematically. For each study, the following categories were recorded: publication type, publication year, research method/design, sample or study group, data type/data source, AI technique(s) used, behavioural finance theme(s) addressed, and principal findings/conclusions. This coding structure enabled cross-study comparison in terms of conceptual orientation, methodological tendencies, AI application areas, and behavioural dimensions, and it provided the basis for the structured summary tables presented in the findings section.

Table 5. Coding Framework Used in the Review

Coding Category	Description	Analytical Purpose
Publication type	Journal article, academic book chapter, graduate thesis, university portal research report, or practice-based sectoral source	To distinguish different forms of academic and contextual output
Publication year	Year of publication	To observe recent research concentration
Research method / design	Qualitative, quantitative, applied, review, legal analysis, etc.	To identify methodological tendencies
Sample / study group	Investors, firms, institutions, datasets, or literature corpus	To clarify analytical focus
Data type / source	Survey data, financial time series, bibliographic data, secondary data, legal texts, etc.	To compare empirical and conceptual evidence bases
AI technique(s) used	ANN, deep learning, LSTM, XGBoost, robo-advisors, hybrid models, etc.	To map technological approaches
Behavioural finance theme(s)	Herd behaviour, overconfidence, trust, risk perception, loss aversion, technology acceptance, etc.	To identify recurring behavioural patterns
Key findings / conclusions	Main arguments and reported outcomes	To support thematic synthesis and comparative interpretation

Note: The coding framework was developed to support descriptive and thematic analysis of the selected studies and to increase transparency in how the review findings were generated.

5.6. Data Analysis

The collected data were analysed through descriptive analysis and thematic classification. The purpose of the analysis was not to produce bibliometric network visualizations, citation mapping, or co-occurrence analysis, but to identify recurrent themes, methodological patterns, AI application areas, and behavioural finance dimensions across the selected studies. In this respect, the study should be understood as a qualitative systematic review based on document analysis, rather than as a full-scale bibliometric study.

Within this framework, the reviewed studies were categorized according to publication characteristics, research methods, data structures, AI techniques, and behavioural finance themes. The resulting patterns were synthesized and presented through structured summary tables. This approach allowed the study to identify thematic intersections between artificial intelligence, investor behaviour, and emerging market dynamics without making claims associated with advanced bibliometric mapping methods. More specifically, the analysis pursued three interrelated aims: (i) to classify the selected studies descriptively, (ii) to compare them in methodological and thematic terms, and (iii) to interpret how the literature conceptualizes the relationship between AI-supported decision models, behavioural finance, and emerging market conditions.

5.7. Limitations of the Study

This study has several limitations. First, the final analytical corpus consists of 20 studies published between 2020 and 2025. Although the dataset was expanded in response to reviewer feedback, the number of studies remains relatively limited because the literature at the intersection of artificial intelligence, behavioural finance, and emerging-market financial decision-making is still developing. Therefore, the findings should be interpreted as a structured qualitative synthesis rather than as statistically generalizable evidence.

Second, although the search scope was expanded beyond the initial databases, the review was still limited to full-text accessible studies identified through the YÖK National Thesis Center, DergiPark, Google Scholar, academic publisher platforms, institutional repositories, author profile pages, and open-access academic sources. As a result, studies indexed exclusively in subscription-based international databases or not available in full text may not have been captured.

Third, the expanded dataset includes peer-reviewed journal articles, book chapters, master's theses, one university portal research report, and one practice-based sectoral source. The university portal research report and the practice-based sectoral source were included only for contextual enrichment because of their relevance to Borsa Istanbul-based AI-supported forecasting, robo-advisory systems, and AI-supported portfolio management. These sources were not treated as equivalent to peer-reviewed empirical evidence. This distinction is important because the sources included in the review do not all carry the same methodological or empirical weight.

Finally, because this study is designed as a qualitative systematic review based on document analysis, its aim is not to generate statistical generalizations, meta-analytic effect sizes, or bibliometric network outputs. Rather, it seeks to provide a conceptually and methodologically structured interpretation of the existing literature. Despite these limitations, the selected studies offer a meaningful overview of current research trends, methodological patterns, and thematic gaps regarding AI-supported financial decision-making in emerging markets.

5.8. Findings

Table 6. Reviewed Studies

Category	Codes
Articles	M1, M2, M3, M4, M5, M6, M8, M10, M11, M14, M16, M17, M18
Book Chapters	M7, M13, M15
Research Report / University Portal Source	M9
Sectoral / Practice-Based Source	M12
Theses	T1, T2

Table 6 presents the classification of the studies included in the final dataset according to publication type. Codes beginning with M represent journal articles, academic book chapters, one university portal research report, and one practice-based sectoral source, whereas codes beginning with T correspond to graduate theses. The expanded dataset consists of 20 studies and provides a broader representation of the literature on artificial intelligence-supported financial decision-making, behavioural finance, robo-advisory systems, machine learning-based forecasting, technology acceptance, and regulatory implications.

Compared with the initial dataset, the revised corpus includes not only peer-reviewed articles and theses, but also academic book chapters, one university portal research report, and one practice-based source retained for contextual enrichment. This expansion strengthens the thematic coverage of the review by incorporating additional perspectives on investor psychology, cognitive bias, algorithmic decision-making, user trust, machine learning-based financial prediction, AI-supported portfolio management, and Borsa Istanbul-based AI-supported forecasting. This is particularly relevant for Türkiye and other emerging market contexts, where academic, regulatory, institutional, and practice-based discussions on AI-supported investment decision processes are still developing.

Table 7. Objectives

Code	Objective
M1	To discuss the strategic importance of AI applications in business decision-making and question whether decisions can be made without the human factor.
M2	To conceptually examine the advantages, challenges, and strategic implications of AI in the financial sector and provide a decision-support framework for managers.
M3	To conduct a bibliometric analysis of AI–finance studies in Scopus from 1977 to 2024 and reveal the evolution of the literature.
M4	To bibliometrically analyse behavioural finance studies in seven emerging economies using Web of Science and identify thematic trends and gaps.
M5	To map the literature at the intersection of AI and financial behaviour, identifying themes, research networks, and future opportunities.
M6	To discuss the interaction between behavioural finance models and AI-based algorithmic trading and assess potential impacts on market stability.
M7	To explain the potential of AI and machine learning to monitor and model investor biases.
M8	To design an AI-supported corporate decision support system and demonstrate its contribution through an applied model.
M9	To introduce AI-supported forecasting and risk management approaches using Borsa Istanbul data and compare them with traditional methods.
M10	To analyse the legal nature and liability boundaries of AI-driven investment advice and propose suitable regulatory solutions.
M11	To examine the impact of AI techniques on investment decisions in the Turkish financial sector.
M12	To discuss robo-advisory, fund robots, and AI-supported portfolio management as practice-based examples of algorithmic financial decision support.
M13	To examine the interaction between behavioural finance and artificial intelligence in financial decision-making processes.
M14	To evaluate the opportunities, risks, and regulatory implications of artificial intelligence, machine learning, and big data in the financial sector.
M15	To discuss cognitive biases, behavioural finance, market anomalies, and machine learning-based approaches in financial decision-making.
M16	To systematically review the use of artificial intelligence technologies in the finance literature.
M17	To examine user perceptions, trust, and acceptance of artificial intelligence applications in finance and banking.
M18	To analyse machine learning-based forecasting and strategy development approaches in financial decision processes.
T1	To examine the role of fintech and AI applications in investment evaluation in the Turkish financial markets.

Code	Objective
T2	To identify the factors influencing individual investors' acceptance of ChatGPT-like AI tools in financial decision-making.

Table 7 summarizes the primary research objectives of the reviewed studies. The analysis reveals four broad orientations in the expanded literature. The first consists of conceptual and theoretical studies examining the relationship between artificial intelligence, behavioural finance, and financial decision-making. The second includes bibliometric and systematic review studies that evaluate broader publication trends, research clusters, and thematic gaps. The third consists of empirical and applied studies focusing on forecasting, decision support systems, user acceptance, and technology adoption. The fourth includes legal, regulatory, and practice-based studies that address explainability, robo-advisory systems, AI-supported portfolio management, and investor protection. Across these groups, artificial intelligence is treated not merely as a technical instrument, but as a strategic, behavioural, institutional, and regulatory factor shaping contemporary financial decision-making processes.

Table 8. Methodological Characteristics of the Reviewed Studies

Code	Method	Design / Study Type
M1	Qualitative	Conceptual study / literature review
M2	Qualitative	Conceptual review
M3	Quantitative	Bibliometric analysis
M4	Quantitative	Bibliometric analysis
M5	Quantitative	Bibliometric analysis / scientific mapping
M6	Qualitative	Literature review
M7	Qualitative	Review / book chapter
M8	Qualitative	Model design with example application
M9	Applied	Financial forecasting model
M10	Qualitative	Doctrinal legal analysis
M11	Qualitative	Conceptual study with case/application analysis
M12	Practice-based	Sectoral evaluation / robo-advisory discussion
M13	Qualitative	Book chapter / conceptual evaluation
M14	Qualitative	Conceptual and policy-oriented review
M15	Qualitative	Book chapter / conceptual discussion
M16	Qualitative	Systematic literature review
M17	Quantitative	Survey-based field research
M18	Applied / quantitative	Machine learning-based forecasting and strategy development
T1	Qualitative	Master's thesis / literature-based evaluation
T2	Quantitative	Survey-based quantitative study / Technology Acceptance Model

Table 8 presents the methodological characteristics of the reviewed studies. The expanded dataset reveals a multidisciplinary methodological structure. Qualitative conceptual studies provide the theoretical foundation of the AI–behavioural finance relationship, while bibliometric and systematic review studies contribute to mapping the evolution of the field. Applied and quantitative studies focus on machine learning-based forecasting, financial strategy development, AI-supported decision systems, and technology acceptance. Legal and policy-oriented studies address questions of explainability, liability, investor protection, and regulatory adaptation. The inclusion of one practice-based source also reflects the practical development of robo-advisory and AI-supported portfolio management, although this source is used only for contextual enrichment and not as equivalent to peer-reviewed empirical evidence.

Table 9. Data Structure and Source Scope of the Reviewed Studies

Code	Data Type	Data Source / Scope
M1	Theoretical	Literature and conceptual discussions
M2	Theoretical + statistical indicators	Sector reports and secondary data
M3	Bibliometric data	Scopus, 1977–2024, AI–finance articles
M4	Bibliometric data	Web of Science, 1999–2025, seven emerging economies
M5	Bibliometric data	International citation databases
M6	Theoretical	Example scenarios involving interest rate decisions and algorithmic trading
M7	Theoretical	Behavioural finance and AI literature
M8	Corporate secondary data	Historical sales and expense data of the sample firm
M9	Financial time-series / report-based data	Borsa Istanbul-related financial indicators and AI-supported forecasting examples presented in a university portal research report
M10	Theoretical / legal	Legislation, secondary sources, and foreign regulations
M11	Theoretical + literature	Academic studies, EU regulations, and Turkish applications
M12	Practice-based secondary data	Robo-advisory, fund robots, and AI-supported portfolio management examples
M13	Theoretical	Behavioural finance and artificial intelligence literature
M14	Theoretical + policy-oriented	Finance, AI, machine learning, big data, and regulatory discussions
M15	Theoretical	Behavioural finance, cognitive bias, market anomaly, and machine learning literature
M16	Literature corpus	Studies on artificial intelligence technologies in finance
M17	Survey data	Users of finance and banking services
M18	Financial / model-based data	Machine learning-based prediction and strategy development models
T1	Secondary / literature-based data	Turkish financial markets and fintech applications
T2	Survey data	Online survey administered to individual investors

Table 9 summarizes the data structures and source scopes of the reviewed studies. The findings show that the literature operates across theoretical, bibliometric, empirical, applied, legal, report-based, and practice-based evidence bases. Bibliometric studies rely primarily on international databases such as Scopus and Web of Science, whereas conceptual and legal studies draw on secondary literature, regulatory documents, and policy discussions. Empirical and applied studies focusing on Türkiye use localized data sources such as Borsa Istanbul-related financial indicators, firm-level data, investor survey data, and financial user responses.

The expanded dataset also includes sources addressing robo-advisory systems, user trust, behavioural bias, machine learning-based financial strategy development, and university portal-based AI-supported forecasting examples. This diversity indicates that AI-supported financial decision-making can be examined at multiple levels, from macro-level publication trends to investor behaviour, institutional practice, Borsa Istanbul-based financial forecasting, and regulatory governance.

Table 10. Main Findings of the Reviewed Studies

Code	Main Finding	Reported Evidence / Analytical Basis
M1	AI applications accelerate decision-making, improve access to information, and are increasingly positioned as integral components of future decision processes.	Conceptual finding based on managerial and strategic evaluation of AI-supported decision environments.
M2	AI in the financial sector provides operational advantages such as cost reduction, fraud detection, and improved customer experience, while simultaneously creating challenges related to bias, transparency, and workforce transformation.	Conceptual and sector-based assessment supported by secondary evidence and sectoral discussion.

Code	Main Finding	Reported Evidence / Analytical Basis
M3	The AI–finance literature has expanded rapidly, especially after 2017, with publication and citation activity concentrated in a limited number of countries and institutions.	Bibliometric evidence derived from publication, citation, and productivity patterns.
M4	Behavioural finance research in emerging economies is concentrated around themes such as investor bias, sentiment, and financial literacy, with uneven geographical distribution.	Bibliometric and thematic mapping evidence focusing on emerging market research patterns.
M5	The literature at the intersection of AI and financial behaviour clusters around decision-making, inclusive finance, ethics, regulation, and algorithmic bias.	Scientific mapping and thematic cluster analysis.
M6	AI-supported algorithmic trading may reduce the effects of emotional trading, overreaction, and speculative instability under certain conditions.	Conceptual evaluation of the interaction between behavioural finance and algorithmic trading systems.
M7	AI techniques such as sentiment analysis, text mining, and machine learning enable the identification of investor biases including overconfidence, herd behaviour, and risk avoidance.	Review-based synthesis showing the use of AI for bias detection, behavioural analysis, and predictive support.
M8	AI-supported decision support systems can improve tactical decision quality under uncertainty by converting historical and integrated institutional data into flexible managerial outputs.	Applied model-based evidence; the study develops and demonstrates an expert-system-supported decision support design for mid-level managerial use.
M9	In the Borsa Istanbul context, AI-supported forecasting models are reported to outperform traditional statistical approaches by producing lower forecasting error and stronger risk-management support across firm-level financial indicators.	Comparative empirical evidence based on financial data from Borsa Istanbul companies.
M10	AI-driven investment advice creates legal uncertainty because existing liability regimes are not fully compatible with black-box decision systems.	Doctrinal legal analysis centred on fault attribution, causality, explainability, and investor protection.
M11	AI techniques are reported to perform better than conventional models in investment decision contexts such as portfolio optimization, forecasting, and related analytical applications in Turkish finance.	Conceptual and application-based assessment linked to Turkish financial sector practice.
M12	Robo-advisory systems show how AI can be used in risk profiling, fund selection, and portfolio management.	Practice-based discussion of fund robots and AI-supported financial advisory systems.
M13	Behavioural finance and AI intersect around investor psychology, decision errors, and technology-supported financial judgement.	Conceptual book chapter linking behavioural finance and artificial intelligence.
M14	AI, machine learning, and big data create opportunities in the financial sector but also raise risks related to algorithmic bias, transparency, data governance, and regulation.	Conceptual and policy-oriented assessment.
M15	Cognitive biases and market anomalies can be reinterpreted through modern data-driven and machine learning-based approaches.	Conceptual synthesis of behavioural finance and machine learning perspectives.
M16	The finance literature increasingly examines AI technologies in prediction, risk analysis, investment decisions, and financial technologies.	Systematic literature review evidence.
M17	User trust and acceptance are critical for the adoption of AI applications in finance and banking.	Survey-based evidence from finance and banking users.
M18	Machine learning models can support forecasting and strategy development in financial decision processes.	Applied model-based evidence using machine learning approaches.
T1	Fintech and AI applications are associated with improvements in investment evaluation, banking efficiency, and financially relevant decision processes in the Turkish context.	Thesis-based analysis of fintech and AI applications in Türkiye.
T2	Intention to use ChatGPT-like AI tools is associated with perceived usefulness, ease of use, trust, social influence, and perceived risk.	Survey-based behavioural evidence grounded in technology acceptance variables.

Table 10 summarizes the main findings of the reviewed studies and shows that the expanded literature converges around four core result areas. First, AI-supported systems are associated with stronger analytical performance in forecasting, optimization, risk management, and strategy development, especially in volatile financial environments. Second, AI increasingly enables the measurable analysis of investor behaviour through sentiment analysis, text mining, machine learning-based classification, and user acceptance models. Third, robo-advisory systems and AI-supported portfolio management show that algorithmic decision support is becoming visible not only in academic discussion but also in practice. Fourth, the reviewed studies consistently emphasize that these analytical gains are accompanied by major concerns related to explainability, accountability, legal responsibility, algorithmic bias, data governance, and investor trust. Taken together, the findings indicate that artificial intelligence is reshaping financial decision-making at technical, behavioural, institutional, and regulatory levels.

Table 11. Main Conclusions of the Reviewed Studies

Code	Conclusions
M1	AI applications have become a strategic necessity in decision-making, yet the human factor should not be entirely removed.
M2	Financial institutions cannot achieve sustainable success in AI adoption without strong data governance, ethical principles, and regulatory compliance.
M3	The AI–finance literature is growing rapidly but remains geographically and thematically uneven; future studies should focus more on risk management and crisis periods.
M4	Behavioural finance research provides important policy insights for emerging economies; neuro-finance, digital behaviour, and machine learning are likely to gain further importance.
M5	The influence of AI on financial behaviour will continue to increase; ethical design, transparency, and financial literacy are essential for inclusive and fair financial ecosystems.
M6	Effective use of AI and algorithmic trading can reduce investor errors and increase market stability, although model selection and implementation must be handled with caution.
M7	AI can support more rational investor decision-making, though ethical, privacy, and explainability issues remain unresolved.
M8	AI-supported decision support systems offer substantial benefits for mid-level tactical decisions, suggesting that firms should invest more in such systems.
M9	AI-based forecasting and risk management approaches provide more accurate risk measurement and improved portfolio management in the Borsa Istanbul context.
M10	A hybrid liability regime centred on explainability is needed for AI-driven investment advice; the regulatory role of the Capital Markets Board is therefore critical.
M11	AI techniques should be expanded in the Turkish financial sector, although important challenges remain in regulation, infrastructure, and human capital.
M12	Robo-advisory and AI-supported portfolio tools indicate that algorithmic systems are becoming visible in practical investment decision environments.
M13	AI should be interpreted together with human psychology, behavioural bias, and investor judgement rather than only as a technical tool.
M14	Sustainable AI use in finance requires regulatory clarity, explainability, data governance, and institutional oversight.
M15	Behavioural finance remains essential for understanding financial anomalies, but machine learning offers new tools for identifying and modelling these patterns.
M16	AI technologies are increasingly embedded in finance research, yet methodological consistency and context-sensitive evaluation remain necessary.
M17	Trust, perceived usefulness, and user acceptance are decisive for the successful diffusion of AI in finance and banking.
M18	Machine learning-based forecasting and strategy models can strengthen financial decision support when supported by appropriate data and model validation.
T1	Fintech and AI applications are transforming investment evaluation in Turkish financial markets, but regulatory and infrastructural gaps continue to limit their full potential.

Code	Conclusions
T2	ChatGPT-like tools can reduce investors' cognitive load; however, without stronger trust and liability safeguards, widespread and healthy adoption will remain limited.

Table 11 presents the principal conclusions derived from the reviewed studies. Overall, the literature suggests that artificial intelligence has evolved from a complementary analytical instrument into a strategic component of contemporary financial decision-making systems. At the same time, the studies consistently emphasize that human judgment remains essential, particularly in environments characterized by uncertainty, behavioural bias, regulatory complexity, and information asymmetry. The expanded dataset also shows that responsible AI adoption in finance depends on explainability, ethical design, data governance, user trust, legal clarity, and institutional oversight. In the context of Türkiye, the literature indicates that AI offers important opportunities for improving forecasting accuracy, portfolio management, banking efficiency, investor support, and financial decision quality; however, these benefits remain conditional upon regulatory modernization, technological infrastructure, and the development of specialized expertise.

Table 12. Thematic Intersections of Behavioural Finance, Artificial Intelligence, and Emerging Markets

Code	Behavioural Finance Themes	AI Dimension	Türkiye / Emerging Markets Link
M1	Decision errors, cognitive load, human intuition	Automation of decision-making with AI applications	General; adaptable to Türkiye as a conceptual framework
M2	Investor trust, risk perception	AI integration in the financial sector, ethics, and transparency	Policy implications for Türkiye and the global financial system
M3	Financial decision behaviour, indirectly	Trends in AI use within finance	Global; includes implications relevant to emerging markets
M4	Investor biases, financial literacy, sentiment	Machine learning and digital behaviour as emerging themes	Focus on Türkiye and six other emerging economies
M5	Decision-making, inclusive finance, ethical bias	AI-based decision systems and algorithmic bias	Global; emphasizes disadvantaged groups and developing regions
M6	Overreaction, price bubbles, herd behaviour	Algorithmic trading and AI-based strategies	General; includes implications for emerging markets and crises
M7	Cognitive biases, herd behaviour, loss aversion	Sentiment analysis, text mining, and machine learning	Global literature; adaptable to Türkiye and emerging regions
M8	Corporate decision-making under uncertainty	AI-supported decision support and expert systems	Model developed based on a firm in Türkiye
M9	Risk perception, return expectations	AI-supported financial forecasting and risk management	Directly focused on Türkiye / Borsa Istanbul
M10	Investor protection, trust, information asymmetry	AI-driven robo-advisory, black-box models, explainable AI	Turkish capital markets; comparative with EU/US
M11	Investor behaviour, portfolio selection biases	Neural networks, genetic algorithms, and robo-advisory applications	Turkish financial sector and EU regulatory context
M12	Trust, risk profiling, investor guidance	Robo-advisory and AI-supported portfolio management	Türkiye-focused practice-based source
M13	Investor psychology, decision bias, behavioural judgement	AI and behavioural finance interaction	Conceptually relevant to Türkiye and emerging markets
M14	Algorithmic bias, trust, risk perception, regulatory uncertainty	AI, machine learning, big data, explainability	Türkiye and policy-making relevance
M15	Cognitive biases, anomalies, irrational decision-making	Machine learning-based interpretation of market patterns	Adaptable to emerging market behaviour
M16	Financial technology adoption, prediction, risk analysis	AI technologies in finance literature	Broad relevance to Türkiye and developing financial systems
M17	Trust, user acceptance, technology adoption	AI use in finance and banking	Directly relevant to Turkish financial users

Code	Behavioural Finance Themes	AI Dimension	Türkiye / Emerging Markets Link
M18	Forecasting, risk perception, strategy formation	Machine learning-based prediction and strategy development	Relevant to data-driven financial decision-making
T1	Investor behaviour, adoption of new financial technologies	Fintech and AI applications in investment evaluation	Turkish financial markets example
T2	Technology acceptance, trust, social influence	Use of ChatGPT-like generative AI tools	Individual investors in Türkiye

Table 12 provides an integrated overview of the intersections between behavioural finance, artificial intelligence, and emerging markets. The reviewed studies show that investor biases and behavioural patterns are increasingly analysed through data-driven techniques such as machine learning, sentiment analysis, text mining, robo-advisory systems, and technology acceptance models. In emerging markets, where financial systems are shaped by volatility, structural fragility, information asymmetry, and regulatory transformation, these analytical tools become especially relevant for understanding herd behaviour, trust, risk perception, cognitive bias, and financial technology adoption. At the same time, the literature consistently highlights challenges related to algorithmic bias, ethical governance, explainability, legal liability, data quality, and investor protection. Within this broader landscape, Türkiye emerges as a particularly relevant case because Borsa Istanbul applications, fintech diffusion, AI-supported investment tools, and ongoing regulatory discussions illustrate how emerging financial systems are gradually integrating artificial intelligence into financial decision-making processes. Taken together, these intersections suggest that the relationship between behavioural finance, AI, and emerging markets constitutes a promising and expanding research agenda.

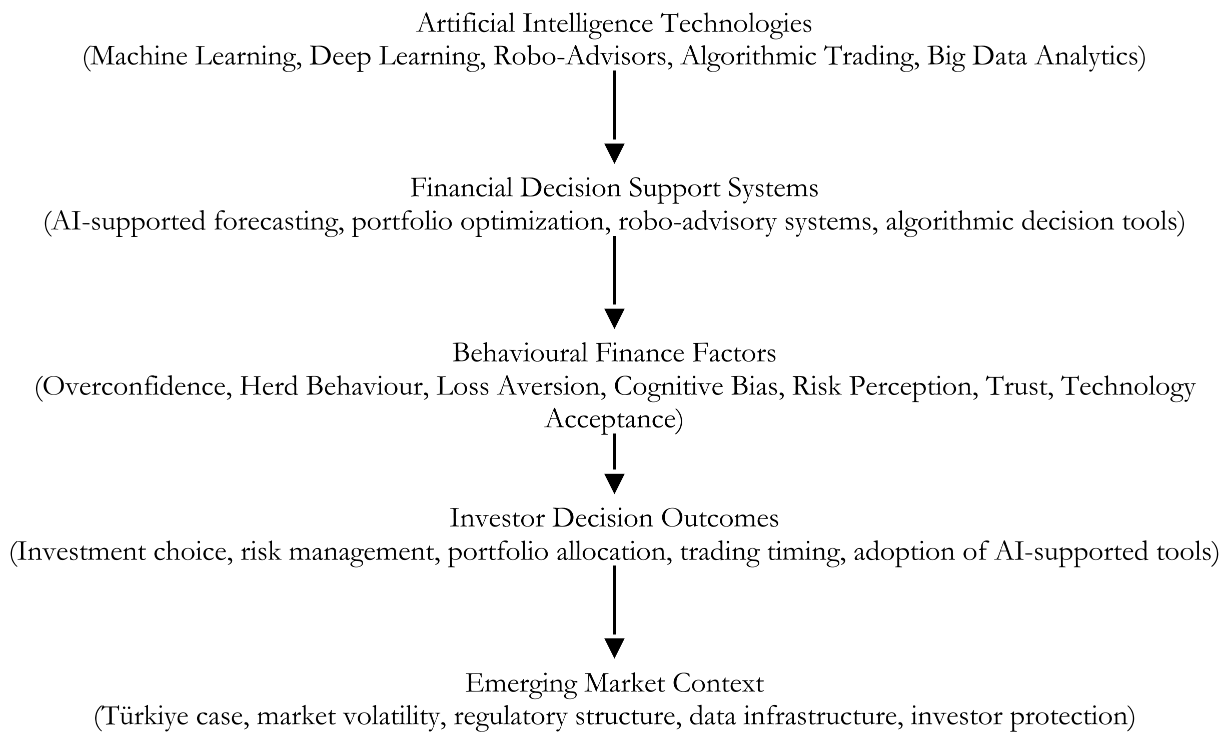

Figure 1. Conceptual Framework of the Interaction Between Artificial Intelligence, Behavioural Finance, and Emerging Market Dynamics

Figure 1 illustrates the conceptual interaction between artificial intelligence technologies, behavioural finance factors, investor decision outcomes, and emerging market dynamics. At the first level, AI technologies including machine learning algorithms, deep learning models, robo-advisory systems, algorithmic trading mechanisms, and big data analytics form the technological basis of modern financial decision-support systems. At the second level, these systems transform large-scale financial and behavioural data into actionable outputs through forecasting, optimization, classification, recommendation, and portfolio management mechanisms. However, financial decisions are not shaped by technological systems alone. The third level therefore highlights the role of behavioural finance factors, including overconfidence, herd behaviour, loss aversion, cognitive bias, trust, risk perception, and technology acceptance. These factors influence how investors interpret, accept, resist, or over-rely on AI-generated recommendations. At the fourth level, the interaction between technological outputs and behavioural responses produces concrete investor decision outcomes such as portfolio allocation, trading timing, risk management, investment selection, and adoption of AI-supported tools. Finally, these relationships are situated within the broader context of emerging markets, where volatility, evolving regulatory structures, data infrastructure, financial literacy, and investor protection significantly shape the adoption and effectiveness of AI-driven financial systems. In this respect, the framework offers a conceptual basis for understanding AI-supported decision models as socio-technical systems operating in continuous interaction with investor psychology, institutional capacity, and market structure.

6. Discussion and Conclusion

The findings of this study indicate that the relationship between artificial intelligence (AI) and behavioural finance in emerging markets should be interpreted not merely as a matter of technological improvement, but as a multi-layered transformation involving technical capability, investor behaviour, institutional regulation, and practical adoption. Across the expanded review dataset, AI-supported systems are consistently associated with stronger analytical capacity, faster information processing, enhanced forecasting, portfolio support, and broader decision-support potential (Çevik & Vuran, 2025; Elmacı, 2025; Gedik, 2025; İnce et al., 2021; Şahin, 2024). At the same time, however, the literature also shows that these advantages do not automatically eliminate behavioural distortions, nor do they remove the need for explainability, legal accountability, investor protection, and human supervision (Demir, 2025; Kumar & Kumar, 2022; Şahin, 2024). In this respect, the present study argues that AI-supported financial decision models in emerging markets must be evaluated simultaneously at the technical, behavioural, institutional, and regulatory levels.

The specific contribution of this study is to propose an integrated interpretive framework for understanding AI-supported financial decision models in emerging markets, while positioning Türkiye as an analytically significant case rather than a merely local illustration. Unlike studies that focus only on forecasting performance or algorithmic accuracy, this review brings together multiple dimensions of the literature, including machine learning-based prediction, robo-advisory systems, behavioural bias, technology acceptance, investor trust, algorithmic opacity, legal liability, and data governance. Thus, the study contributes to the literature by conceptualizing AI-supported financial decision-making as a socio-technical process shaped not only by algorithms, but also by investor psychology, institutional capacity, and market structure.

A first key conclusion concerns the performance dimension of AI-supported systems. Several studies in the reviewed corpus suggest that AI-based forecasting, optimization, and decision-support tools can outperform conventional approaches in price forecasting, portfolio support, and risk management, particularly in volatile settings such as Borsa Istanbul and other emerging-market environments (Alp Coşkun, 2022; Çevik & Vuran, 2025; Elmacı, 2025). Nevertheless, the literature does not present these gains with the same degree of methodological precision. In some studies, superiority is expressed through lower prediction error or stronger analytical performance, whereas in others it is discussed more broadly in terms of flexibility, efficiency, or managerial usefulness (Dönerçark & Tecim, 2020; Gedik, 2025; Yıldız, 2022). This indicates that the literature is promising, yet not fully standardized. Accordingly, while the present study confirms the positive potential of AI-supported decision systems, it also emphasizes that claims of superiority should be interpreted cautiously unless they are supported by clearly reported comparative metrics, transparent model validation, and context-specific evidence.

A second major conclusion concerns the behavioural dimension. The reviewed studies show that AI increasingly enables the measurable analysis of investor behaviour through sentiment analysis, text mining, machine learning-based classification systems, technology acceptance models, and user trust research (Aydın, 2025; Demir, 2025; Gümüş et al., 2020; Metin, 2025). Biases such as herd behaviour, overconfidence, loss aversion, risk perception, cognitive bias, and technology acceptance become more visible when investor actions are analysed through dynamic or large-scale data structures. Yet the literature does not support the simplistic conclusion that AI necessarily reduces irrationality. Some studies suggest that algorithmic systems may reduce emotional decision-making by imposing analytical discipline, especially in trading, forecasting, and portfolio management contexts (Aktaş, 2022; Ayar, 2024; Elmacı, 2025). Other studies imply the opposite risk: AI may reproduce or intensify distortions through opaque model logic, biased training data, weak interpretability, or excessive investor trust in automated outputs (Bayakhmetova et al., 2025; Gedik, 2025; Şahin, 2024). This tension is one of the most important findings of the present article because it shifts the debate away from the question of whether AI is simply "better" than human judgment and toward the more relevant question of under what conditions AI changes behavioural outcomes positively or negatively.

A third conclusion relates to the institutional and regulatory dimension. The reviewed corpus consistently identifies explainability, accountability, legal liability, data governance, algorithmic bias, and investor protection as critical issues in AI-supported financial decision-making, especially in relation to black-box systems and robo-advisory applications (Demir, 2025; Gedik, 2025; Şahin, 2024). In this sense, the spread of AI in finance creates a governance challenge as much as a technological opportunity. The issue is no longer only whether AI can improve decision quality, but whether algorithmic recommendations can be supervised, interpreted, audited, and legally situated within existing financial systems. This is particularly important in emerging markets, where institutional asymmetries, evolving regulation, limited technical capacity, and uneven data infrastructures may magnify the risks associated with weakly governed AI systems (Alp Coşkun, 2022; Gedik, 2025; Metin, 2025). Thus, the findings of the present study support the view that the future of AI in finance depends not only on algorithmic sophistication, but also on the quality of regulatory adaptation and institutional oversight.

A fourth conclusion concerns practical adoption and investor-facing AI systems. The expanded dataset shows that robo-advisory systems, AI-supported portfolio tools, and ChatGPT-like financial decision aids are becoming increasingly visible in both academic and practice-based discussions (Aktaş, 2022; Demir, 2025; Gümüş et al., 2020). These tools may reduce information-processing burdens, support risk profiling, and make investment guidance more accessible. However, their effectiveness depends heavily on trust, perceived usefulness, perceived ease of use, risk perception, and users' ability to critically evaluate AI-generated recommendations. Therefore, AI adoption in finance should not be treated only as a technological diffusion process. It should also be understood as a behavioural and educational process in which investors learn how to interpret, question, and responsibly use automated decision-support outputs.

Within this broader framework, Türkiye emerges as a particularly important analytical case rather than merely a local example. The reviewed studies indicate that the Turkish financial environment offers both a meaningful testing ground and a revealing constraint structure for AI adoption. On the one hand, Borsa Istanbul applications, fintech diffusion, robo-advisory discussions, and growing interest in AI-assisted investment decisions create a favourable environment for experimentation and applied financial modelling (Aktaş, 2022; Çevik & Vuran, 2025; Elmacı, 2025; Öztürk, 2024). On the other hand, the literature repeatedly points to regulatory lag, infrastructure limitations, uneven data quality, legal uncertainty, and shortages of specialized expertise as barriers to sustainable adoption (Alp Coşkun, 2022; Gedik, 2025; Şahin, 2024). More specifically, the Turkish case can be differentiated along three dimensions. First, at the regulatory level, questions of liability, explainability, auditability, and investor protection remain insufficiently clarified in relation to AI-supported advisory services. Second, at the investor level, trust, perceived usefulness, risk perception, digital literacy, and technology acceptance appear to play a decisive role in shaping behavioural adoption. Third, at the infrastructural level, the sustainability of AI integration depends on data quality, institutional interoperability, model validation capacity, and the availability of specialized expertise. This threefold structure makes Türkiye analytically important for emerging-market finance because it reveals how technological opportunity and institutional readiness do not always develop at the same pace.

6.1. Expanded Dataset and Contextual Enrichment

The core conclusions of this article are derived from the 20 studies included in the expanded review dataset. In response to the reviewer's recommendation, the original corpus was broadened by incorporating additional studies and sources relevant to behavioural finance, AI-supported financial decision-making, robo-advisory systems, investor trust, machine learning-based forecasting, cognitive bias, user acceptance, and regulatory implications. Among these sources, one practice-based sectoral source was retained for contextual enrichment due to its direct relevance to robo-advisory systems and AI-supported portfolio management. This distinction is methodologically important because it clarifies that not all sources carry the same empirical weight, while still allowing the review to reflect the practical development of AI-supported financial decision systems.

Overall, the expanded review shows that AI transforms financial decision-making at four interconnected levels. At the technical level, AI improves forecasting, classification, optimization, risk analysis, and analytical speed. At the behavioural level, it increases the observability of investor bias, trust, risk perception, and adoption patterns, but does not fully eliminate behavioural distortions. At the institutional level, it generates new demands for regulation, explainability, transparency, data governance, and accountability. At the practical level, it reshapes investor-facing services through robo-advisory systems, AI-supported portfolio tools, and generative AI-based financial decision aids. This four-level interpretation constitutes the principal conceptual contribution of the study.

Rather than merely summarizing recent literature, the article proposes an integrated way of understanding AI-supported financial decision models as socio-technical systems shaped simultaneously by algorithms, investor psychology, institutional arrangements, regulatory capacity, and market conditions. In this sense, the article contributes to the literature not by introducing a new econometric model, but by clarifying the conceptual architecture through which the AI–behavioural finance relationship can be interpreted in emerging-market settings.

In conclusion, AI should not be treated simply as a superior forecasting device or as a substitute for human judgment. In emerging markets, and especially in the case of Türkiye, AI-supported decision systems operate within environments defined by volatility, behavioural asymmetry, regulatory evolution, institutional unevenness, and varying levels of investor trust. For this reason, the sustainable adoption of AI in finance depends not only on model performance, but also on data quality, behavioural awareness, legal clarity, institutional trust, investor education, and governance capacity. The literature reviewed in this study suggests that AI has significant potential to improve financial decision-making in emerging markets; however, this potential can be realized only when technological capability is matched by behavioural awareness, regulatory clarity, institutional trust, and context-sensitive governance.

6.2. Policy Implications and Recommendations

Based on the reviewed literature, several implications can be proposed for regulators, financial institutions, investors, and future research.

First, regulatory authorities in emerging markets should establish clearer AI governance standards for financial services. These standards should address explainability, auditability, accountability, liability, data quality, algorithmic bias, and investor protection, particularly in areas such as robo-advisory systems and AI-supported investment recommendations (Demir, 2025; Gedik, 2025; Şahin, 2024). In the case of Türkiye, this implies that financial regulation should move beyond general digitalization rhetoric and develop more explicit rules concerning AI-supported advisory systems, model transparency, data governance, and responsibility for algorithmic outputs in capital markets. Without such reforms, the rapid diffusion of AI may deepen legal ambiguity rather than reduce uncertainty.

Second, financial institutions should adopt hybrid decision architectures instead of fully automated decision regimes. The reviewed studies suggest that AI is most effective when used as a decision-support mechanism that improves analytical quality while preserving human judgment in final evaluation (Alp Coşkun, 2022; Dönerçark & Tecim, 2020; İnce et al., 2021). This is especially important in volatile and behaviourally sensitive markets, where algorithmic outputs may be informative but not sufficient on their own. Accordingly, banks, brokerage firms, portfolio managers, fintech platforms, and robo-advisory service providers should combine AI-based recommendations with expert validation, internal monitoring routines, explainability mechanisms, and investor suitability checks. Such hybrid models are more consistent with the evidence reviewed in this study than visions of complete automation.

Third, investment in AI should include human capital as well as technological infrastructure. The reviewed literature repeatedly suggests that the value of AI depends on the presence of professionals capable of interpreting outputs, identifying model risks, understanding behavioural implications, and evaluating the limits of prediction (Alp Coşkun, 2022; Çevik & Vuran, 2025; Gedik, 2025). For this reason, organizations should strengthen training not only in data analytics and machine learning, but also in behavioural finance, model-risk management, explainable

AI, financial regulation, and AI governance. In the Turkish context, where expertise gaps are repeatedly noted, this recommendation is especially important for sustainable and responsible adoption.

Fourth, investor education should be treated as a strategic component of AI adoption in finance. The literature indicates that trust, perceived usefulness, risk perception, digital literacy, and technology acceptance significantly influence whether investors adopt AI-supported financial tools (Demir, 2025; Gümüş et al., 2020). Therefore, investor education programs should not only encourage digital finance participation, but also explain the limits of automated recommendations, the risks of overreliance on algorithmic outputs, the possibility of algorithmic bias, and the continuing need for critical financial judgment. In emerging markets such as Türkiye, where digital trust and financial literacy may vary across investor groups, such educational efforts are likely to influence whether AI diffusion becomes inclusive and stabilizing or fragmented and risk-prone.

Fifth, future research should produce more methodologically comparable empirical evidence. One of the recurring limitations identified in the reviewed literature is that claims of AI superiority are not always supported by clearly comparable performance metrics. Future research should therefore report standardized indicators more consistently, distinguish more clearly between technical model performance and behavioural outcomes, and examine when AI reduces, fails to reduce, or unintentionally intensifies behavioural bias. Comparative studies across different emerging markets would be especially valuable for understanding how institutional structure, regulatory quality, data infrastructure, and investor characteristics shape the real effects of AI adoption in finance.

Sixth, future review-based studies may benefit from stronger evidence-tracking tools and more transparent screening procedures. The use of automated retrieval, duplicate filtering, reference management systems, and PRISMA-compatible evidence tracking can increase methodological transparency and replicability. In addition, future studies may distinguish more explicitly between peer-reviewed empirical studies, theoretical studies, book chapters, theses, policy documents, and practice-based sources. Such distinctions would help clarify the evidential weight of different source types and prevent conceptual or methodological overgeneralization.

In practical terms, the most immediate priorities for emerging markets are: (i) regulatory clarification for AI-supported advisory and recommendation systems, (ii) institutional investment in explainable and auditable AI infrastructures, (iii) development of human capital in AI governance and behavioural finance, and (iv) investor education focused on trust, risk awareness, digital literacy, and the responsible use of AI-supported financial tools.

Taken together, these implications reinforce the main conclusion of the study: the future of AI-supported financial decision-making in emerging markets will depend not merely on stronger algorithms, but on the strength of the behavioural, legal, educational, institutional, and technological ecosystems within which those algorithms are deployed. In this respect, AI should be approached as a complementary socio-technical decision-support infrastructure, not as a self-sufficient replacement for judgment, governance, and responsibility.

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APPENDICES

Appendix 1 – Studies Included in the Research

Code	Title	Author(s)	Year	Type
M1	Yapay Zeka Uygulamalarının Karar Verme Üzerine Etkileri: Kavramsal Bir Çalışma	Hüseyin İnce; Sena Esin İmamoğlu; Salih Zeki İmamoğlu	2021	Article
M2	Finans Sektöründe Yapay Zekâ Avantajları, Zorlukları ve Stratejileri Üzerine Kavramsal Bir Değerlendirme	Yasemin Gedik	2025	Article
M3	Finans Alanında Yapay Zekâ Uygulamalarına İlişkin Bibliyometrik Bir Analiz	Turan Öndeş; Osman Can Barakalı	2025	Article
M4	Gelişmekte Olan Piyasalarda Davranışsal Finans: Trendler, Boşluklar ve İş Birlikleri	Tuğçe Metin	2025	Article
M5	Artificial Intelligence in Financial Behavior: Bibliometric Ideas and New Opportunities	Bayakhmetova A.; Rudenko L.; Krylova L. et al.	2025	Article
M6	Davranışsal Finans Temelinde Yapay Zekânın Algoritmik Trading ile Etkileşiminin Geleceği Üzerine Bir Değerlendirme	İlkcan Ayar	2024	Article
M7	Davranışsal Finans Alanında Yapay Zekâ Uygulamaları	Salih Aydın	2025	Book Chapter
M8	Kurumsal Karar Destek Sistemlerinde Yapay Zekâ Kullanımı: Tasarım ve Uygulama	Mert Dönerçark; Vahap Tecim	2020	Article
M9	Yapay Zeka Destekli Finansal Tahmin ve Risk Yönetimi: Borsa İstanbul Örneği	Orhan Elmacı	2025	Research Report / University Portal Source
M10	Yapay Zekâ Destekli Yatırım Tavsiyelerinin Hukuki Niteliği: Sermaye Piyasasında Sorumluluğun Sınırları	Şamil Demir	2025	Article
M11	The Role of Artificial Intelligence in Investment Decisions and Applications in the Turkish Finance Industry	Esra Alp Coşkun	2022	Article
M12	Para Yöneten Robotlar: Robo-Danışmanlık, Fon Robotları ve Yapay Zekâ Destekli Portföy Yönetimi	Zeynep Candan Aktaş	2022	Sectoral / Practice-Based Source
M13	Davranışsal İktisadın Gelişimi ve Uygulamaları İçinde Davranışsal Finans ve Yapay Zekâ	Mehmet Hakan Bilgin	2023	Book Chapter
M14	Finans Sektöründe Yapay Zekâ ve Makine Öğrenmesi Uygulamaları: Fırsatlar, Riskler ve Düzenleyici Yaklaşımlar	Fuat Şahin	2024	Article
M15	Davranışsal Finansta Piyasa Anomalileri, Bilişsel Sapmalar ve Makine Öğrenmesi Temelli Yaklaşımlar	Yusuf Kırık	2025	Book Chapter
M16	Finans Alanında Yapay Zekâ Teknolojilerinin Kullanımı: Sistematik Literatür İncelemesi	Ayşe Yıldız	2022	Article
M17	Finans ve Bankacılık Sisteminde Yapay Zekâ Kullanımı: Kullanıcı Güveni ve Kabulü Üzerine Bir Araştırma	Selçuk Gümüş; Bahadır Medetoğlu; Erdinç Tutar	2020	Article
M18	Finansal Karar Süreçlerinde Makine Öğrenimi Tabanlı Tahmin ve Strateji Geliştirme Yaklaşımları	Mahmut Emin Çevik; Bengü Vuran	2025	Article
T1	Finans Piyasalarında Yatırımların Değerlendirilmesinde Fintech ve Yapay Zekâ Uygulamaları: Türkiye Örneği	Hatice Öztürk	2024	Master's Thesis
T2	Bireysel Yatırımcıların Finansal Yatırım Kararlarında Yapay Zekâ Kullanım Kabullerinin İncelenmesi: ChatGPT Örneği	Fatih Demir	2025	Master's Thesis

GENİŞLETİLMİŞ ÖZET

Amaç

Son yıllarda yapay zekâ teknolojilerinde yaşanan hızlı gelişmeler, finansal piyasaların işleyişini, yatırım kararlarının alınma biçimini ve finansal bilgiye dayalı karar destek mekanizmalarını önemli ölçüde dönüştürmüştür. Makine öğrenmesi, derin öğrenme, algoritmik işlem sistemleri, büyük veri analitiği, duygu analizi ve robo-danışmanlık gibi uygulamalar; finansal verilerin daha hızlı işlenmesine, piyasa hareketlerinin daha sistematik biçimde tahmin edilmesine ve yatırım kararlarının daha veri temelli alınmasına katkı sağlamaktadır. Bununla birlikte finansal karar alma süreçleri yalnızca teknik göstergelerden ve sayısal modellemelerden ibaret değildir. Yatırımcıların risk algısı, güven düzeyi, bilişsel yanlılıkları, aşırı güven eğilimleri, kayıptan kaçınma davranışları, sürü psikolojisi ve teknolojiye yönelik kabul düzeyleri de yatırım kararları üzerinde belirleyici etkiye sahiptir.

Bu çalışmanın temel amacı, yapay zekâ destekli yatırım karar modellerini davranışsal finans perspektifi çerçevesinde incelemek ve özellikle Türkiye gibi gelişmekte olan piyasalarda bu teknolojilerin yatırımcı davranışlarıyla nasıl etkileşime girdiğini ortaya koymaktır. Çalışma, yapay zekâyı yalnızca teknik bir tahmin veya otomatik işlem aracı olarak değil; yatırımcı psikolojisi, finansal teknoloji kabulü, güven, açıklanabilirlik, algoritmik şeffaflık, hukuki sorumluluk ve kurumsal yönetişim boyutlarıyla birlikte değerlendirilmesi gereken sosyo-teknik bir karar destek sistemi olarak ele almaktadır.

Yöntem

Araştırma, nitel araştırma yaklaşımı kapsamında doküman analizi yöntemiyle yürütülmüştür. Çalışmada, yapay zekâ destekli finansal karar modelleri ile davranışsal finans arasındaki ilişkiyi ortaya koyan akademik ve kurumsal kaynaklar sistematik biçimde incelenmiştir. Literatür tarama sürecinde yöntemsel şeffaflığı artırmak amacıyla PRISMA raporlama çerçevesi dikkate alınmıştır.

Araştırma kapsamında 2020–2025 yılları arasında yayımlanan çalışmalar taranmıştır. Kaynak taraması; YÖK Ulusal Tez Merkezi, DergiPark, Google Scholar, akademik yayınevi platformları, kurumsal açık erişim arşivleri ve açık erişimli akademik kaynaklar üzerinden gerçekleştirilmiştir. Tarama sürecinde yapay zekâ, makine öğrenmesi, derin öğrenme, algoritmik finans, robo-danışmanlık, yatırım kararları, davranışsal finans, yatırımcı davranışı, risk algısı, güven, sürü davranışı ve bilişsel yanlılıklar gibi anahtar kavramlar kullanılmıştır.

Çalışmaya dâhil edilecek kaynakların belirlenmesinde belirli ölçütler esas alınmıştır. Buna göre, yapay zekâ destekli finansal karar verme süreçlerini ele alan; davranışsal finans, yatırımcı psikolojisi veya finansal teknoloji kabulü boyutlarından en az birini içeren; yatırım kararları, portföy yönetimi, risk yönetimi, piyasa tahmini veya robo-danışmanlık konularına katkı sağlayan çalışmalar değerlendirmeye alınmıştır. Buna karşılık yalnızca teknik algoritma performansına odaklanan, davranışsal finans boyutu taşımayan veya finansal yatırım kararlarıyla doğrudan ilişkili olmayan çalışmalar kapsam dışında bırakılmıştır. Hakem önerisi doğrultusunda veri seti genişletilmiş ve nihai analiz 20 çalışma üzerinden yürütülmüştür. Bu veri seti; hakemli makaleler, kitap bölümleri, yüksek lisans tezleri ve robo-danışmanlık ile yapay zekâ destekli portföy yönetimi bağlamında katkı sunduğu değerlendirilen bir sektör/pratik kaynaktan oluşmaktadır.

Bulgular

Araştırma bulguları, yapay zekâ destekli modellerin finansal tahmin, risk yönetimi, portföy optimizasyonu, algoritmik işlem ve yatırım stratejisi geliştirme süreçlerinde giderek daha önemli bir karar destek aracı hâline geldiğini göstermektedir. Özellikle yüksek piyasa oynaklığının bulunduğu dönemlerde makine öğrenmesi ve derin öğrenme tabanlı modellerin, geleneksel ekonometrik yöntemlere kıyasla daha esnek ve güçlü tahmin kapasitesi sunabildiği görülmektedir. Büyük veri analitiği, alternatif veri kaynaklarının kullanımı, duygu analizi ve metin madenciliği uygulamaları; finansal piyasalardaki fiyat hareketlerini, yatırımcı beklentilerini ve piyasa duyarlılığını daha bütüncül biçimde analiz etme imkânı sağlamaktadır.

Davranışsal finans açısından değerlendirildiğinde, yapay zekâ uygulamalarının yatırımcı davranışlarının daha ölçülebilir hâle gelmesine katkı sunduğu tespit edilmiştir. Sosyal medya paylaşımları, haber metinleri, arama eğilimleri, piyasa verileri ve yatırımcı işlem davranışları üzerinden geliştirilen modeller; güven, risk algısı, aşırı güven, sürü davranışı, kayıptan kaçınma ve bilişsel yanlılıklar gibi davranışsal unsurların analiz edilmesine olanak tanımaktadır. Bu yönüyle yapay zekâ, yalnızca piyasa hareketlerini tahmin eden bir araç değil, aynı zamanda yatırımcı psikolojisini anlamaya ve karar süreçlerini daha rasyonel zemine taşımaya yardımcı olan bir analitik altyapı olarak öne çıkmaktadır.

Bulgular ayrıca robo-danışmanlık sistemlerinin ve yapay zekâ destekli portföy yönetimi uygulamalarının bireysel yatırımcılar açısından yeni fırsatlar sunduğunu göstermektedir. Bu sistemler, yatırımcı profiline uygun portföy önerileri sunabilmekte, risk toleransını dikkate alabilmekte ve yatırım kararlarını daha sistematik hâle getirebilmektedir. Ancak bu fırsatların yanında önemli sınırlılıklar ve riskler de bulunmaktadır. Algoritmik şeffaflık eksikliği, kara kutu model yapıları, veri kalitesi sorunları, algoritmik yanlılık, aşırı otomasyon güveni, yatırımcının model çıktılarını sorgulamadan kabul etmesi, hukuki sorumluluk belirsizliği ve düzenleyici çerçevenin yetersizliği bu risklerin başında gelmektedir.

Türkiye bağlamında değerlendirildiğinde, Borsa İstanbul uygulamaları, fintech ekosisteminin gelişimi, dijital yatırım platformlarının yaygınlaşması ve robo-danışmanlık tartışmaları yapay zekâ destekli finansal karar modelleri için önemli bir potansiyel oluşturmaktadır. Bununla birlikte Türkiye'de bu alanın henüz gelişim aşamasında olduğu; veri altyapısı, düzenleyici çerçeve, teknik uzmanlık, algoritmik denetim ve yatırımcı güveni konularında geliştirilmesi gereken alanların bulunduğu görülmektedir.

Sonuç

Çalışmanın sonuçları, yapay zekânın finansal karar alma süreçlerinde insan yargısını tamamen ikame eden bir teknoloji olarak değil, insan kararını güçlendiren tamamlayıcı bir karar destek aracı olarak değerlendirilmesi gerektiğini ortaya koymaktadır. Yapay zekâ modelleri, büyük veri setlerini işleyebilme, karmaşık örüntüleri tespit edebilme ve hızlı tahmin üretebilme açısından önemli avantajlar sunsa da finansal kararların etik, psikolojik, hukuki ve kurumsal boyutları göz ardı edilmemelidir.

Davranışsal finans perspektifi, yapay zekâ destekli yatırım modellerinin daha sağlıklı değerlendirilmesi açısından kritik bir çerçeve sunmaktadır. Çünkü yatırım kararları yalnızca rasyonel fayda maksimizasyonuna dayalı olarak alınmamakta; yatırımcıların duyguları, algıları, beklentileri, yanlılıkları ve teknolojiye duydukları güven de karar süreçlerini doğrudan etkilemektedir. Bu nedenle yapay zekâ sistemlerinin yatırımcı davranışlarını analiz ederken açıklanabilir, denetlenebilir, etik ilkelere uygun ve yatırımcıyı koruyucu bir anlayışla geliştirilmesi gerekmektedir.

Türkiye gibi gelişmekte olan piyasalarda yapay zekâ destekli finansal karar modellerinin önemli fırsatlar sunduğu, ancak bu fırsatların etkili biçimde değerlendirilebilmesi için güçlü veri altyapısına, düzenleyici netliğe, finansal okuryazarlık düzeyinin artırılmasına ve algoritmik yönetişim mekanizmalarının geliştirilmesine ihtiyaç duyulduğu sonucuna ulaşılmıştır. Özellikle robo-danışmanlık, algoritmik yatırım tavsiyeleri ve yapay zekâ destekli portföy yönetimi uygulamalarında yatırımcıların korunması, sorumluluk alanlarının belirlenmesi ve model çıktılarının denetlenebilir hâle getirilmesi büyük önem taşımaktadır.

Özgün Değer

Bu çalışmanın özgün değeri, yapay zekâ destekli yatırım karar modellerini yalnızca teknik performans veya tahmin başarısı üzerinden değil, davranışsal finans perspektifiyle birlikte değerlendirmesinden kaynaklanmaktadır. Literatürde yapay zekâ uygulamaları çoğunlukla algoritmik başarı, tahmin doğruluğu, portföy optimizasyonu veya piyasa performansı açısından ele alınırken; bu çalışma yatırımcı psikolojisi, bilişsel yanlılıklar, güven, teknoloji kabulü, açıklanabilirlik, hukuki sorumluluk ve kurumsal yönetişim boyutlarını aynı kavramsal çerçevede bir araya getirmektedir.

Çalışma ayrıca gelişmekte olan piyasalar bağlamına odaklanması bakımından da katkı sunmaktadır. Türkiye özelinde fintech ekosistemi, Borsa İstanbul uygulamaları, dijital yatırım platformları ve robo-danışmanlık tartışmaları dikkate alınarak yapay zekâ destekli finansal karar modellerinin fırsatları ve sınırlılıkları bütüncül biçimde değerlendirilmiştir. Bu yönüyle araştırma hem akademik literatüre hem de finansal teknoloji uygulayıcılarına kavramsal ve pratik bir çerçeve sunmaktadır.

YAZARLARIN BEYANI / DECLARATION OF THE AUTHORS	
Katkı Oranı Beyanı	☒ Yazar, çalışmanın tümüne tek başına katkı sağlamıştır. ☐ Yazarlar çalışmaya eşit oranda katkı sağlamıştır. ☐ Çalışmaya birinci yazar %XX oranında, ikinci yazar %XX oranında, üçüncü yazar %XX oranında katkı sağlamıştır.
Declaration of Contribution Rate	☒ The author contributes the study on his/her own ☐ The authors have equal contributions. ☐ The first author contributes XX%, the second author contributes XX%, the third author contributes XX%.
Çatışma Beyanı	☒ Çalışmada herhangi bir potansiyel çıkar çatışması söz konusu değildir. ☐ Yazarlar, çalışmadan XXX (firması, kurumu, kişisinin) etkilenebileceğini ve ortaya çıkacak çıkar çatışması durumunu yönetmek için onaylanmış bir planının olduğunu beyan etmektedir.
Declaration of Conflict	☒ There is no potential conflict of interest in the study. ☐ Authors declare that XXX (firm, institution, person) may be affected from the study and in case of a conflict of interest they have a confirmed plan in order to administer the case.
Yayın Etiği Beyanı	☒ Çalışmada etik dışı bir husus bulunmadığını, araştırma ve yayın etiğine özenle uyulduğunu beyan ederiz. ☒ Bu çalışma, etik kurul belgesi gerektiren bir çalışma değildir. ☐ Bu çalışma için _______ Üniversitesi, Bilimsel Araştırma ve Yayın Etiği Kurulundan __/__/____ tarih ve ______ sayılı kararı ile etik kurul onayı alınmıştır.
Declaration of Publication Ethics	☒ We hereby declare that the study has not unethical issues and that research and publication ethics have been observed carefully. ☒ This study does not require ethics committee approval. ☐ Ethical approval for this study was obtained from the Scientific Research and Publication Ethics Committee of ______ University with decision number ______ dated __/__/___.
Üretken Yapay Zekâ Kullanım Beyanı	☐ Bu çalışmanın hiçbir aşamasında üretken yapay zekâ araçlarından faydalanılmamıştır. ☒ Bu çalışmanın hazırlanması sırasında yazar, yalnızca dil kontrolü ve yazım düzeltme amacıyla ChatGPT'den faydalanmıştır. ChatGPT, çalışmanın fikir, analiz, yorum, bulgu veya akademik içeriğinin oluşturulmasında kullanılmamıştır. Çalışmanın tüm akademik içeriği ve sorumluluğu tamamen yazara aittir. Yazar, dil düzenleme sonrasında metni gözden geçirmiş ve yayımlanan makalenin içeriği konusunda tüm sorumluluğu üstlenmiştir.
Declaration of Generative AI Use	☐ No generative artificial intelligence tools were used at any stage of this study. ☒ During the preparation of this study, the author used ChatGPT solely for language editing and proofreading. ChatGPT was not used to generate the ideas, analyses, interpretations, findings, or academic content of the study. All academic content and responsibility belong entirely to the author. The author reviewed the text after language editing and takes full responsibility for the content of the published article.
Destek ve Teşekkür Beyanı	☒ Çalışmada herhangi bir kurum ya da kuruluştan mali destek alınmamıştır. ☐ Bu çalışma, X Projesi (Proje No: XXXXX) tarafından desteklenmektedir. ☐ Diğer (Belirtiniz) ……….
Declaration of Support and Acknowledgments	☒ No financial support is taken from any institution or organization. ☐ The study is supported by X Project (Project No: XXXXX). ☐ Others (Specify) ……….