
| RESEARCH ARTICLE

Soft Computing in Financial Technology: A Survey of Fuzzy, Evolutionary and Neuro-Fuzzy Methods

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| ABSTRACT

Financial problems are rarely crisp. Borrower creditworthiness must often be judged under vagueness, financial markets exhibit nonlinear and non-stationary behavior, and portfolio and trading decisions must be made within large, uncertain search spaces. Soft computing, which comprises fuzzy logic, neural networks, evolutionary computation, and swarm intelligence, was conceived to handle exactly this kind of imprecision, and for three decades it has been applied to financial problems. This survey classifies the soft-computing paradigms, reviews their applications across six areas of financial technology (credit scoring, fraud detection, forecasting, portfolio optimization, bankruptcy prediction, and financial statement analytics), and compares them along dimensions that matter in financial practice. The review finds that no single paradigm suits every financial problem; hybrid methods, particularly neuro-fuzzy systems, frequently offer the best balance between predictive accuracy and interpretability. The survey closes by discussing open challenges, including explainability, non-stationarity, class imbalance, and integration with deep learning.

| KEYWORDS

soft computing; fuzzy logic; neuro-fuzzy systems; evolutionary computation; financial technology; credit risk

| ARTICLE INFORMATION

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1. Introduction

Conventional computing methods find exact solutions to problems that are stated precisely. Financial problems are rarely of this type. A credit decision must be made about a borrower whose behavior is uncertain. A trader must make predictions in a nonlinear and non-stationary market. A portfolio must be constructed to meet uncertain and conflicting objectives. Accepting approximation, uncertainty, and nonlinearity is therefore a requirement of financial problem solving. Soft computing, as defined by Zadeh, encompasses a family of techniques, including fuzzy logic, neural networks, and evolutionary computation, that are designed to handle these challenges (Zadeh, 1994).

Soft computing has been applied extensively in financial technology over the past three decades (Bahrammirzaee, 2010). Despite this growth, the literature is difficult to navigate because the methods and their applications are so diverse. This article addresses that problem. Section 2 reviews the soft-computing paradigms and critically evaluates prior surveys of the field, identifying the gap this study fills. Section 3 describes the review methodology. Section 4 presents the findings: applications in six financial-technology areas, a comparative analysis of the paradigms with reported results, and open challenges. Section 5 concludes. The article is intended for researchers and practitioners interested in applying soft computing to financial problems, including readers who are not specialists in the field.

2. Literature Review

2.1 Soft-computing paradigms

The soft-computing paradigms include fuzzy logic, neural networks, evolutionary computation, swarm intelligence, and neuro-fuzzy systems. Figure 1 illustrates these methods.

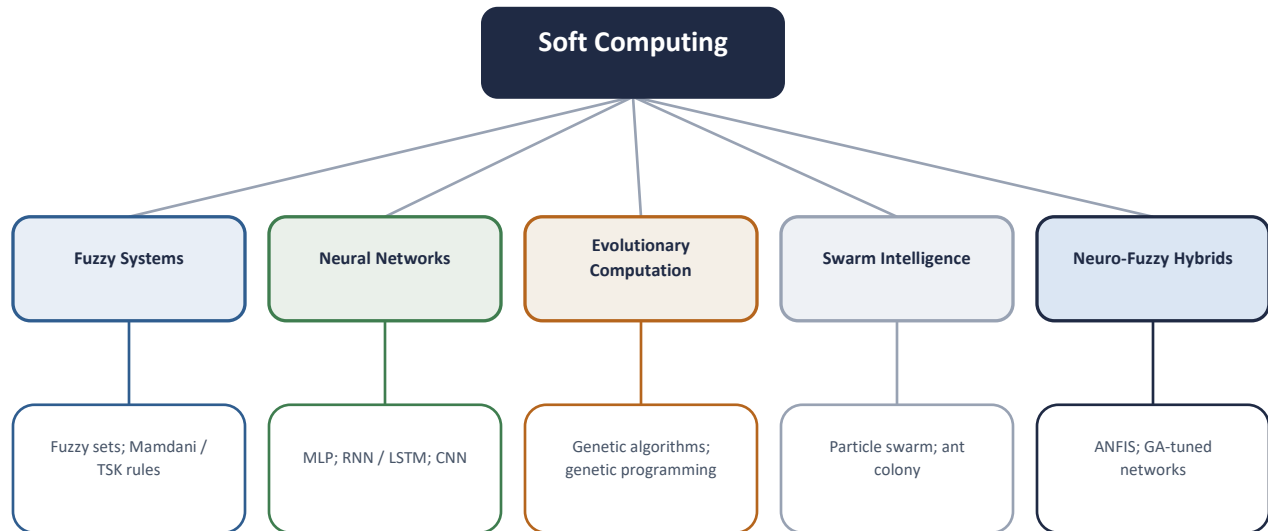


Figure 1. A taxonomy of soft-computing paradigms and representative methods. The paradigms are complementary rather than competing, and the most effective financial applications frequently combine them, most notably in neuro-fuzzy hybrids.

Fuzzy set theory, introduced by Zadeh, allows an element to belong to a set to a degree between 0 and 1 rather than simply belonging or not belonging (Zadeh, 1965). Fuzzy rule-based systems combine such sets through linguistic IF–THEN rules (for example, “IF debt ratio is high AND income is unstable THEN risk is high”) to map imprecise inputs to outputs. Because these rules are readable, fuzzy systems are often preferred where decisions must be explained to customers or regulators.

2.1.2 Neural networks

Neural networks learn complex, nonlinear relationships directly from data. They are well suited to forecasting and classification, although their limited interpretability is a recognized drawback, and they have been applied to business and financial problems for more than two decades (Tkáč & Verner, 2016).

2.1.3 Evolutionary computation

Evolutionary computation methods, including genetic algorithms and genetic programming, search a problem space using mechanisms inspired by natural selection (Goldberg, 1989; Holland, 1975/1992). In finance, they are applied mainly to optimization and model discovery (Aguilar-Rivera et al., 2015).

2.1.4 Swarm intelligence

Swarm intelligence methods, such as particle swarm optimization (PSO), are inspired by the collective behavior of social organisms such as bird flocks and fish schools, in which simple individuals sharing information produce an effective group-level search (Kennedy & Eberhart, 1995). Like evolutionary computation, these methods are best suited to optimization problems.

2.1.5 Neuro-fuzzy and hybrid systems

Neuro-fuzzy systems combine fuzzy systems and neural networks (Jang, 1993). The fuzzy component supplies interpretable rules, while the neural component supplies the ability to learn those rules from data. Other hybrids use evolutionary algorithms to tune neural networks or fuzzy systems (Bahrammirzaee, 2010). All such methods aim to combine the complementary strengths of the individual paradigms.

2.2 Prior surveys of soft computing in finance

Zadeh (1994) framed soft computing as a partnership of fuzzy logic, neural networks, and probabilistic reasoning, arguing that tolerance for imprecision is a strength rather than a flaw. Finance quickly became one of its most active application areas. Several surveys have since reviewed parts of this literature, but each is limited in scope, in paradigm coverage, or in recency.

Bahrammirzaee (2010) is the closest in spirit to the present study. It compares artificial neural networks, expert systems, and hybrid intelligent systems across credit evaluation, portfolio management, and financial prediction, and concludes that hybrid systems generally outperform single techniques. Its value lies in showing, early on, that combining paradigms pays off in finance. However, it predates much of the evolutionary, swarm, and neuro-fuzzy work of the past fifteen years, treats evolutionary methods only briefly, and does not examine interpretability as a design criterion.

Atsalakis and Valavanis (2009) surveyed more than one hundred studies applying soft computing to stock market forecasting and found that neural and neuro-fuzzy models usually outperformed conventional statistical models. Their review is thorough within its domain and is candid that differing datasets, horizons, and error measures make studies hard to compare. Its limitation is its restriction to a single application, which leaves open whether its conclusions transfer to credit, fraud, or portfolio problems.

Tkáč and Verner (2016) reviewed two decades of neural network research in business, showing that finance is among the dominant application areas and that multilayer perceptrons trained by backpropagation remained the most common architecture. The survey is valuable for its breadth across business functions, but because it is confined to one paradigm, it cannot say how neural networks compare with fuzzy or evolutionary alternatives on the same problems.

Several surveys focus on a single financial problem. Thomas (2000) reviewed statistical and operational-research methods for credit and behavioral scoring, noting neural networks and genetic algorithms as emerging alternatives and observing that competing methods often achieved broadly similar accuracy. Lessmann et al. (2015) updated this picture with a large benchmark of classification algorithms on multiple credit-scoring datasets, finding that ensemble methods performed best and arguing that the evaluation measures used in earlier studies had distorted conclusions. Their benchmark is methodologically rigorous but concerned with predictive accuracy rather than the interpretability that lenders and regulators require. Ravi Kumar and Ravi (2007) reviewed statistical and intelligent techniques for bankruptcy prediction in banks and firms, covering studies from 1968 to 2005, and found that intelligent techniques, and hybrids especially, tended to outperform statistical models. Their review remains a standard reference for that domain but does not cover more recent neuro-fuzzy and swarm-optimized models.

Other surveys focus on a single family of methods. Aguilar-Rivera et al. (2015) surveyed genetic algorithms and related Darwinian approaches across financial applications, including portfolio optimization and trading-rule discovery. Ponsich et al. (2013) concentrated on multiobjective evolutionary algorithms for portfolio optimization and related problems in economics. Both are authoritative on the optimization side of finance, but neither addresses classification tasks such as credit scoring or fraud detection, and neither considers how evolutionary methods combine with fuzzy or neural models.

More recent reviews center on deep learning. Sezer et al. (2020) systematically reviewed deep learning for financial time-series forecasting published between 2005 and 2019, finding recurrent architectures such as LSTM to be dominant. Ozbayoglu et al. (2020) extended the review to deep learning across financial applications more broadly. Thivaos et al. (2026) surveyed machine learning and deep learning for financial fraud detection, emphasizing class imbalance, concept drift, and the gap between benchmark results and deployment. These reviews document a clear shift in research attention toward deep models, but they largely treat fuzzy and neuro-fuzzy methods as background and give limited attention to how interpretable soft-computing components might complement deep architectures.

2.3 Research gap

Taken together, prior surveys are either confined to one paradigm (Aguilar-Rivera et al., 2015; Ponsich et al., 2013; Tkáč & Verner, 2016), confined to one financial problem (Atsalakis & Valavanis, 2009; Lessmann et al., 2015; Ravi Kumar & Ravi, 2007; Thivaos et al., 2026; Thomas, 2000), or centered on deep learning (Ozbayoglu et al., 2020; Sezer et al., 2020). The one broad comparative survey (Bahrammirzaee, 2010) is now more than fifteen years old. No recent review compares fuzzy, neural, evolutionary, swarm, and neuro-fuzzy methods side by side across multiple financial-technology applications while treating interpretability as a criterion alongside accuracy. The present survey addresses that gap. Table 1 summarizes the prior surveys and their limitations relative to this study.

Table 1. *Prior surveys of soft computing and related methods in finance.*

Survey	Scope	Paradigms covered	Limitation relative to this study
Bahrammirzaee (2010)	Multiple finance areas	Neural networks, expert systems, hybrids	Predates recent neuro-fuzzy and swarm work; little on evolutionary methods
Atsalakis & Valavanis (2009)	Stock forecasting	Neural, neuro-fuzzy	Single application
Tkáč & Verner (2016)	Business, including finance	Neural networks only	Single paradigm
Thomas (2000)	Credit scoring	Statistical, operational research, early soft computing	Single application; dated
Lessmann et al. (2015)	Credit scoring	Wide range of classifiers	Accuracy-focused; interpretability not assessed
Ravi Kumar & Ravi (2007)	Bankruptcy prediction	Statistical and intelligent techniques	Single application; covers studies to 2005
Aguilar-Rivera et al. (2015)	Multiple finance areas	Genetic and evolutionary algorithms	Single paradigm; optimization only
Ponsich et al. (2013)	Portfolio optimization	Multiobjective evolutionary algorithms	Single paradigm and application
Sezer et al. (2020)	Time-series forecasting	Deep learning	Soft computing treated as background
Ozbayoglu et al. (2020)	Multiple finance areas	Deep learning	Soft computing treated as background
Thivaos et al. (2026)	Fraud detection	Machine and deep learning	Single application; neuro-fuzzy not central

3. Methodology

3.1 Review design

Sources were identified through Google Scholar and IEEE Xplore searches combining "soft computing," "fuzzy," "neuro-fuzzy," and "evolutionary computation" with each application area, supplemented by citation tracing from the surveys in Table 1. Studies were included if they applied a soft-computing method to a financial problem or reported a quantitative baseline comparison; non-English and purely theoretical works were excluded.

3.2 Selection of sources

The review draws on foundational works for each paradigm (Goldberg, 1989; Holland, 1975/1992; Jang, 1993; Kennedy & Eberhart, 1995; Zadeh, 1965, 1994), on earlier surveys of artificial intelligence and soft computing in finance (Atsalakis & Valavanis, 2009; Bahrammirzaee, 2010; Ozbayoglu et al., 2020; Sezer et al., 2020; Tkáč & Verner, 2016), and on representative application studies in credit scoring (Ayed & Bougatef, 2024; Lessmann et al., 2015; Ong et al., 2005; Thomas, 2000; West, 2000), forecasting (Boyacioglu & Avci, 2010; Mohamed et al., 2025), portfolio optimization (Aguilar-Rivera et al., 2015; Ponsich et al., 2013), bankruptcy prediction (Ravi Kumar & Ravi, 2007), fraud detection (Thivaos et al., 2026; Wang et al., 2025), and financial statement analytics (Liu, 2025). Studies were selected for their influence on the field or because they report quantitative comparisons against conventional baselines.

3.3 Analytical framework

Each study was classified by paradigm (Section 2.1) and by application area. The paradigms were then compared on four dimensions relevant to financial practice: ability to handle uncertainty, ability to learn from data, interpretability, and primary financial role (Table 2). Quantitative results were extracted as reported by the original authors and are presented without re-analysis (Table 4). Because the underlying datasets, baselines, and metrics differ, these figures are treated as indicative rather than directly comparable.

4. Results and Findings

4.1 Applications of soft computing in financial technology

4.1.1 Credit scoring and lending risk

Credit scoring is one of the most established application areas of soft computing in finance (Thomas, 2000). Neural networks have proved effective as credit-scoring classifiers (West, 2000), fuzzy systems can make scores more interpretable, and genetic programming can construct scoring models automatically (Ong et al., 2005). Large benchmarks show that advanced and ensemble methods often outperform simpler models (Lessmann et al., 2015). Neuro-fuzzy systems are attractive here because lending decisions must be explainable: on consumer loans from a Tunisian Islamic bank, ANFIS matched logistic regression in discriminating power while producing the lowest misclassification cost and, unlike a neural network, allowed the bank to justify rejections (Ayed & Bougatef, 2024).

4.1.2 Fraud and anomaly detection

Fraud detection requires identifying a small number of fraudulent transactions within very large transaction volumes. Neural networks, including deep and graph-based architectures, dominate recent work, alongside metaheuristic feature selection (Thivaïos et al., 2026). Neuro-fuzzy approaches have also been applied; for example, an enhanced ANFIS combining wavelet decomposition with temporal attention has been used to study credit-card fraud (Wang et al., 2025). The area is characterized by severe class imbalance, concept drift, and a need for explainable alerts.

4.1.3 Financial forecasting and time-series prediction

Forecasting financial time series is a central problem in financial technology. Studies applying neural and neuro-fuzzy models generally report better performance than conventional linear models (Atsalakis & Valavanis, 2009). Recent reviews show a clear shift toward deep learning (Ozbayoglu et al., 2020; Sezer et al., 2020), while neuro-fuzzy models remain competitive, particularly when their parameters are tuned by swarm or evolutionary optimizers (Boyacioglu & Avci, 2010; Mohamed et al., 2025).

4.1.4 Portfolio optimization and algorithmic trading

Portfolio optimization seeks the best allocation across assets while balancing risk and return (Aguilar-Rivera et al., 2015; Ponsich et al., 2013). Multiobjective evolutionary algorithms are the most widely applied soft-computing approach, with swarm intelligence methods such as PSO as a common alternative (Aguilar-Rivera et al., 2015; Ponsich et al., 2013). These methods are valued because they find high-quality solutions to problems whose realistic constraints defeat exact optimization.

4.1.5 Bankruptcy and financial-distress prediction

Bankruptcy and financial-distress prediction is another established application (Bahrammirzaee, 2010). Reviews show that neural networks and hybrid intelligent systems generally outperform traditional statistical methods (Ravi Kumar & Ravi, 2007). Fuzzy and neuro-fuzzy systems suit the problem well because the factors that lead to financial distress are imprecise and are often expressed in vague terms by analysts (Bahrammirzaee, 2010).

4.1.6 Financial decision and statement analytics

Soft-computing methods have also been applied to financial decision and statement analytics. Liu (2025) proposes a hybrid framework combining ANFIS with quantum-inspired genetic optimization and deep fuzzy reinforcement learning for automated financial statement analysis, reporting better accuracy and convergence than ANFIS alone on data from Chinese firms.

4.2 Comparative analysis

Table 2 compares the soft-computing paradigms, and Table 3 maps each financial application area to its dominant methods. Together they show that no single soft-computing method is ideal for all financial problems; instead, there is a trade-off between accuracy and interpretability. Neural networks are accurate but difficult to interpret. Fuzzy systems are easy to interpret but, on their own, less accurate. Neuro-fuzzy systems aim to combine the advantages of both. Evolutionary and swarm intelligence methods are less commonly used for classification but are well suited to the optimization problems that arise in these areas, such as portfolio construction and model tuning.

Table 2. *Soft-computing paradigms compared on dimensions that matter in financial practice.*

Paradigm	Handles uncertainty	Learns from data	Interpretability	Primary financial role
Fuzzy logic	High	No (rule-based)*	High	Encoding expert knowledge under vagueness
Neural networks	Implicit (noise-tolerant)	Yes	Low	Learning nonlinear patterns; classification
Evolutionary computation	Indirect	Search / optimize	Medium	Optimization, feature and model selection
Swarm intelligence	Indirect	Search / optimize	Medium	Optimization in large, dynamic spaces
Neuro-fuzzy hybrids	High	Yes	Medium–High	Learned models that remain interpretable

*Fuzzy systems become data-adaptive when combined with learning, as in neuro-fuzzy models.

Table 3. *Financial-technology application areas mapped to dominant soft-computing methods.*

Application area	Dominant soft-computing methods	Representative literature
Credit scoring & lending	Neural networks; fuzzy rule systems; genetic programming; neuro-fuzzy	Thomas (2000); West (2000); Ong et al. (2005); Lessmann et al. (2015); Ayed & Bougatef (2024)
Fraud & anomaly detection	Neural (incl. deep/graph); evolutionary feature selection; neuro-fuzzy	Thivaos et al. (2026); Wang et al. (2025)
Financial forecasting	Neural networks; fuzzy-neural; ANFIS; deep learning	Atsalakis & Valavanis (2009); Sezer et al. (2020); Ozbayoglu et al. (2020); Mohamed et al. (2025)
Portfolio optimization & trading	Multiobjective evolutionary algorithms; PSO; genetic algorithms	Ponsich et al. (2013); Aguilar-Rivera et al. (2015)
Bankruptcy / distress prediction	Neural networks; fuzzy-neural; hybrid intelligent systems	Ravi Kumar & Ravi (2007); Bahrammirzaee (2010)
Financial decision & statement analytics	Fuzzy logic; hybrid intelligent systems	Bahrammirzaee (2010); Liu (2025)

4.3 Reported performance

No single figure captures the benefit of soft computing in finance, because studies use different datasets, metrics, and baselines. Nonetheless, the literature consistently reports gains in accuracy, interpretability, or optimization quality over classical methods. Neuro-fuzzy methods such as ANFIS, for instance, have reported high accuracy in forecasting stock-index returns (Boyacioglu & Avci, 2010), competitive discrimination with the lowest misclassification cost in consumer default prediction (Ayed & Bougatef, 2024), improved fraud-related prediction (Wang et al., 2025), and lower forecasting error when tuned by a swarm optimizer (Mohamed et al., 2025). Table 4 summarizes representative results.

Table 4. Representative quantitative results reported for soft-computing methods in finance (each from its own study and dataset; not directly comparable).

Task/domain	Soft-computing method	Reported result	Source
Stock-index return forecasting	ANFIS (neuro-fuzzy)	~98.3% accuracy	Boyacioglu & Avci (2010)
Consumer default prediction	ANFIS vs LR / ANN / FIS	AUC $\approx$ 0.90 (tied with LR); lowest misclassification cost	Ayed & Bougatef (2024)
Credit-card fraud detection	Enhanced ANFIS	Higher AUC-ROC/F1 than LightGBM, TabNet and others; RMSE – 17.8% vs neuro-fuzzy and LSTM baselines	Wang et al. (2025)
Stock-index forecasting	Swarm-optimized ANFIS	$\approx$ 13–32% lower RMSE than standard ANFIS, depending on index	Mohamed et al. (2025)
Bankruptcy / distress forecasting	Fuzzy-neural systems	Outperform ARMA, logit, probit baselines	Ravi Kumar & Ravi (2007)

Results are as reported by the cited studies on their own datasets; differences in data and evaluation make the figures indicative rather than head-to-head comparisons.

4.4 Open challenges and future directions

4.4.1 Explainability and accountability

Credit and fraud decisions increasingly require explanations for customers and regulators, yet the deep models now dominating the literature are largely opaque (Ozbayoglu et al., 2020). Neuro-fuzzy systems retain a rule structure (Jang, 1993), but rule bases grow rapidly with the number of inputs, eroding the interpretability that motivated their use. Compact rule learning and explanation methods for hybrid models remain open problems.

4.4.2 Non-stationarity

Financial markets shift between regimes, and fraud patterns evolve as fraudsters adapt to detection systems (Thivaïos et al., 2026). Most reported studies evaluate on static train and test splits (Sezer et al., 2020), which overstates real-world performance. Adaptive and evolving fuzzy and neuro-fuzzy systems that update their rules online are a promising direction.

4.4.3 Class imbalance

Defaults, bankruptcies, and fraudulent transactions are rare, so accuracy is a misleading metric. Cost-sensitive learning and evaluation based on precision and recall or on misclassification cost are needed (Thivaïos et al., 2026), and benchmark studies show that conclusions about which classifier is best depend heavily on evaluation choices (Lessmann et al., 2015).

4.4.4 Integration with deep learning

Deep learning now dominates financial forecasting research (Ozbayoglu et al., 2020; Sezer et al., 2020). Soft computing can complement rather than compete with it: evolutionary and swarm methods can search architectures and hyperparameters (Aguilar-Rivera et al., 2015), and fuzzy layers can add interpretable structure to deep models.

4.4.5 Reproducibility and comparability

As Table 4 shows, reported gains come from different datasets and metrics and cannot be compared directly. Shared benchmark datasets and standardized evaluation protocols, as advocated in credit scoring (Lessmann et al., 2015), would allow soft-computing methods to be assessed on equal terms.

5. Conclusion

Financial problems are characterized by uncertainty, nonlinearity, and imprecision, and soft-computing methods are well suited to address them. This article has reviewed the soft-computing paradigms, critically evaluated prior surveys, and examined applications across six areas of financial technology. No single method is ideal for all financial problems; however, hybrid methods that combine

the strengths of different paradigms, particularly neuro-fuzzy systems, frequently offer the best balance of accuracy and interpretability. As soft computing becomes increasingly integrated with deep learning, it is likely to remain an important part of financial technology, especially where decisions must be explained.

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