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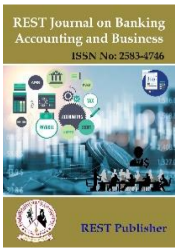

Quantitative Assessment Framework for Machine Learning Applications in Finance Using WSM

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Abstract. *This study evaluates the interoperability and performance of machine learning (ML) applications across different sectors of finance using the Weighted Sum Model (WSM) methodology. These sectors are assessed based on four key factors: application types, innovative activities, economic forecasting challenges, and new econometric tools. The results indicate notable differences in ML performance across the finance sectors. Financial institutions and services (G2) scored the highest in the WSM analysis, with a score of 1.24575, reflecting strong performance in overall applications and econometric tools. Corporate finance and governance (G3) followed closely with a score of 1.24447, excelling in economic forecasting. Public financial markets (G1) ranked third with a score of 1.22720, demonstrating a balanced performance across the criteria. Household finance (G5) ranked fourth with a score of 1.03080, showing strength in developing innovative measures but falling short in econometric tools. Behavioural finance (G4) ranked the lowest with a score of 0.83299, indicating limited alignment across the assessment criteria. The normalized data analysis reveals the interaction between ML applications, with G5 leading in innovative metrics development, G3 excelling in forecasting accuracy, and G2 showing robust overall scope and econometric tool usage. The study applied balanced weighting (0.45) across all domains and criteria to ensure a fair assessment of ML applications. The findings highlight the transformative potential of ML in the financial sector, particularly in enhancing decision-making, risk assessment, and the creation of advanced metrics. These findings add to the growing body of research on ML applications in finance and provide valuable insights for practitioners looking to implement ML solutions in specific financial domains. Future research should focus on addressing the "black box" issue in complex ML models, developing more interpretable methods that maintain predictive accuracy while improving transparency and trust in automated financial systems.*

Keywords: *Spectral Performance Differentiation, Methodological Optimization, Predictive Accuracy Enhancement, Innovation Leadership, Econometric Tool Integration*

1. INTRODUCTION

The application of machine learning in financial services demonstrates considerable promise, especially when leveraging unconventional data to develop advanced and innovative metrics. Its clear advantages over traditional econometric methods—coupled with the surge in related academic publications and its increasing presence in leading scholarly journals—underscore the field's robust and ongoing expansion. [1] The finance industry is currently undergoing a transformation driven by technological innovations based on machine learning. Established institutions and emerging disruptors are competing to explore, develop, and deploy computer-assisted financial decision-making. Despite the significant hype surrounding the role of ML in finance, there have been notable achievements. This article reviews ten key investment challenges for which machine learning has provided excellent solutions. [2] This review explores recent developments in quantum algorithms tailored for financial applications, emphasizing scenarios where machine learning (ML) offers effective solutions. The significance of ML in finance has grown due to improvements in algorithm efficiency; Common ML methods in finance include regression for asset valuation, classification for optimizing portfolios, among others. [3] In recent years, machine learning (ML) has seen rapid growth, transforming various business functions, particularly within the Banking, Financial Services, and Insurance (BFSI) sector. ML is increasingly leveraged to boost operational efficiency, elevate customer experience, and strengthen risk management. Its widespread adoption in the BFSI industry is driven by its capacity to automate tasks, aid in decision-making, enhance client engagement, and identify fraudulent activities. This study employs bibliometric analysis to present a thorough overview of current research trends and ML applications in the financial domain. [4] This paper aims to explore whether data-driven machine learning investment strategies can be used to select high-performing stocks that outperform the market index. To validate the effectiveness and reliability of the method, three top-performing stocks were selected and simulated through paper trading, allowing assessment of the profitability and stability of the chosen stock portfolios. [5] This paper investigates the use of machine learning (ML) in addressing key challenges within financial research. The study makes three primary contributions: first, it introduces the fundamentals of machine learning; second, it examines a range of R packages used for financial applications and offers a classification of current and emerging ML use cases in the sector; and third, it evaluates the potential impact of ML in finance. The paper also discusses various ML techniques, presents a case study focused on credit risk, and outlines current limitations and future directions. The conclusion summarizes the main insights, constraints, and prospective developments in this field. [6] Machine learning (ML) has introduced a novel approach to the financial sector, enhancing the potential of business operations. Many organizations have achieved competitive advantages by incorporating ML into their workflows, with its growing adoption across various business functions resulting in notable successes and returns. [7] The application of machine learning (ML) in finance serves as a valuable tool for analyzing vast economic datasets, detailing its methodologies, and advocating its integration into econometric analysis. In contrast, Mullainathan emphasizes forecasting as a primary application of ML in economics, offering perspectives on both existing and emerging use cases. [8] In certain respects, the absence of strict regulations underscores the urgency for banks and financial institutions to address cybercrime by adopting machine learning (ML) technologies.. As conventional security measures prove increasingly inadequate against the growing number of cyber attacks, ML techniques are being deployed for malware classification and the efficient identification of emerging threats. [9] The authors conducted a comparative study to highlight the limitations of traditional approaches in capturing the dynamics of real-time time series. They also explored the benefits of using machine learning (ML) techniques in quantitative finance. While traditional methods produce useful results, they are mainly used in static settings, serving only as approximations of complex real-world situations. The increasing automation of processes and rapid technological advances has paved the way for the adoption of ML-based methods in various fields, including finance. [10] Machine learning in financial services provides valuable insights by training algorithms to analyze unstructured data, identify nonlinear relationships between variables, and predict outcomes. It learns from complex interactions and recommends appropriate actions. Below are some of the most common applications of ML in financial services. [11] Machine learning (ML)-based predictive techniques are gaining widespread acceptance in various fields, including finance. However, their complexity often leads to challenges in interpreting and validating their predictions, a phenomenon known as the “black box” problem. [12] Machine learning (ML) applications have attracted significant attention in finance, financial accounting, and particularly in industrial engineering. This research investigates the application of ML models for cost estimation and financial forecasting within industrial engineering companies. [13] Financial institutions are increasingly adopting machine learning (ML) solutions to enhance security, meet regulatory requirements, and strengthen customer trust. However, this shift also introduces several challenges, such as concerns over data privacy, the necessity for high-quality datasets, and the potential drawbacks of excessive dependence on automated systems. [14] Machine learning applications in finance often yield superior performance compared to those applied to linear or homogeneous datasets. Despite this, white-box models remain more widely used due to their transparency and ease of interpretation. Many financial models depend on annual data, as it holds greater relevance for shareholders. Additionally, the authors have included insights from social media platforms, especially investor forums, to enrich their analysis. [15]

2. MATERIAL AND METHOD

Alternative

General Financial Markets (G1): General financial markets, often abbreviated as "G1", refer to the broad concept of Markets for trading financial assets—such as stocks, bonds, currencies, and derivatives—play a vital role in the financial system. They function as key platforms where buyers and sellers exchange various financial instruments.

Financial Institutions and Services (G2): In the context of business and software reviews, "Financial Institutions and Services (G2)" generally refers to the classification of software and services associated with.G2 provides user reviews and ratings for a variety of financial services software, including tools for banking, investment management, and CRM systems.

Corporate Finance and Governance (G3): Corporate governance in finance involves the framework of rules and procedures that govern how individuals within an organization are expected to act. These principles aim to ensure transparency, fairness, and accountability in a company's interactions with all stakeholders.

Behavioural Finance (G4): Behavioural finance examines how psychological factors can influence market outcomes. It analyzes various sectors and industries to understand how psychological biases influence financial decisions and market behaviour, playing a key role in explaining deviations from traditional financial theory.

Housing Finance (G5): Household finance, which examines how households use financial markets to achieve their goals, has emerged as a distinct field of study in recent years. The area has received significant attention and has developed its own identity, focus, and research agenda, addressing both ethical and positive aspects of household financial decision-making.

Evolution

All types: The term "all types", depending on the context, refers to a wide range of different types or categories. It refers to diversity or a wide range of objects, for example "all types of people", which refers to a variety of people with different characteristics. In some contexts, it can also refer to specific categories, such as "all types of Pokémon".

Advanced and innovative metrics: "Advanced and innovative metrics" generally refers to methods or metrics that are useful and well-defined, but also provide a new or innovative approach. This indicates that the new method is more precise, accurate, or insightful than existing methods, often providing improved results or a better understanding of a particular subject

.**Economic forecasting problems:** Economic forecasting faces inherent challenges due to the complexity and ever-changing nature of economies. Unexpected events, policy changes, and global conditions can significantly affect forecasts, even those made using sophisticated models. In addition, human behaviour and expectations can influence economic outcomes, making accurate forecasting difficult.

New econometric tools: The primary method employed in econometrics is the linear multiple regression model, which systematically analyzes how variations in an independent economic variable influence a dependent variable, while accounting for the impact of other relevant factors. Emerging econometric tools seek to enhance or expand upon these traditional approaches, offering more advanced techniques for interpreting economic data
.

WSM method

The Weighted Sum Model (WSM) is a widely adopted and well-known approach for supporting decision-making processes. It provides a simple approach for assessing multiple alternatives based on different decision criteria. In this model, we assume there are m alternatives and n criteria to consider. It operates on the premise that higher values for all benefit criteria are preferable. Furthermore, the performance of each alternative is evaluated according to these criteria. [16] The Weighted Sum Model (WSM) helps companies identify the most suitable supplier, enhance productivity, and improve customer satisfaction. The ideal supplier is one who provides the right product at the right time and place, while meeting the required quantity. Known for its simplicity and adaptability, WSM is widely applied in various fields, including robotics, data processing, and other sectors. The Weighted Sum Model (WSM) is a commonly utilized and straightforward technique for assessing alternatives according to defined criteria. It is applicable only when all data can be represented in a single unit or dimension. Although WSM is not limited to one-dimensional problems, it is generally less effective for multidimensional cases where variables have different units. In this study, the researchers employed a well-established method to aid decision-making. Recognized for its simplicity and ease of implementation, the Weighted Sum Model (WSM) is commonly applied in one-dimensional analyses. It is a standard tool used across various fields, including robotics, computer systems, and beyond. The research process is depicted through a flowchart provided in the corresponding section. In this study, the researchers utilized the WSM approach. The results produced by this method offer recommendations that align with the coach's standards. The goal of the research is to apply the WSM technique to select football players based on predefined player profiles. This system is designed to assist coaches in making more objective, data-driven decisions during the selection process. [17] The Weighted Sum Method (WSM), also referred to as linear secularization, is a method used to convert a multi-objective optimization problem (MOP) into a single-objective problem by aggregating multiple objectives through assigned weighting factors. Although WSM can yield Pareto-optimal solutions in specific cases, it also has certain limitations. Weighted sum model (WSM) is a widely used approach in decision making, especially within the framework of multi-criteria decision making (MCDM). It involves calculating the score of each alternative by multiplying the weight of each criterion (W) with the corresponding alternative value (I), enabling a structured evaluation of various options. This study offers a comparative evaluation of different approaches using the Weighted Scoring Model (WSM) [18-19]. The analysis starts by identifying key comparison criteria and explaining each one. These criteria, along with others not explicitly mentioned, were drawn from previous comparative studies. Using the WSM method, weighted scores are calculated for each approach, and the final results are visually presented and thoroughly analyzed. This paper examines the differences in performance between connection members using these methods. Welded angle section connections are selected for the design, and the analysis considers varying angle section thicknesses. The study explores the applicability of the WSM method under multiple loading scenarios. Through numerical analysis, the safety and suitability of bolted versus welded connections are evaluated to determine the most effective approach for connection design. He thermo physical properties of nanoparticles a crucial role in the heat transfers of nanofluids. The Weighted Sum Model (WSM) is favoured for its simplicity and dependability in conducting such evaluations [20-24]. The evaluation will be based on thirteen carefully chosen criteria, reflecting both the characteristics of the debris and the requirements of the removal missions. A pro-rata method will be applied to assign weights to the criteria. Subsequently, A Weighted Sum Model (WSM) is a decision-making technique that evaluates and ranks multiple alternatives by assigning weights to various criteria and summing the weighted scores This research paper describes how the issue can be addressed by combining principles from business analysis and design methodologies. The initial ideas are derived from the Work Systems Method (WSM), a theoretical framework originally developed to create a systems analysis approach tailored for business professionals, which later evolved into the WSM The Weighted Sum Model (WSM) is a widely recognized and simple approach in decision theory. used to rank different options based on multiple criteria to support decision-making. Additionally, it is assumed that all criteria are specific to the application, with higher values being regarded as more favourable. WSM evaluates the likelihood of candidate arguments based on a verb and its related argument. While previous research, such as priority selection or semantic law acquisition, has utilized supervised resources or made independent predictions for arguments, this study takes a different approach. It focuses on extracting plausible arguments by solely relying on the information from the dependent parser and analyzing their co-relation. The WSM image polarization was chosen individually for the specified study area. On average, eight images were utilized each day. However, the dataset is limited by the orbital inclination of the ENVISAT satellite, which restricts image acquisition, particularly in certain regions. Images are captured only up to a certain latitude (known as the polar aperture), which means that some parts of the study area may not be covered by WSM images [25-28].

3. RESULT AND DISCUSSION

TABLE 1. Machine learning application finance

	All types	Superior and novel measures	Economic prediction problems	New econometric tools
General financial markets (G1)	98.000	46.090	70.000	34.900
Financial institutions and services (G2)	120.200	22.350	98.450	20.000
Corporate finance and governance (G3)	67.450	45.670	36.890	50.000
Behavioural finance (G4)	22.900	30.700	46.900	60.000
Household finance (G5)	67.900	56.780	65.980	120.000

Table 1 The WSM methodology reveals that machine learning applications in finance are strongly interoperable across various areas, with housing finance (G5) taking the lead due to its high values in innovative metrics and econometric tools

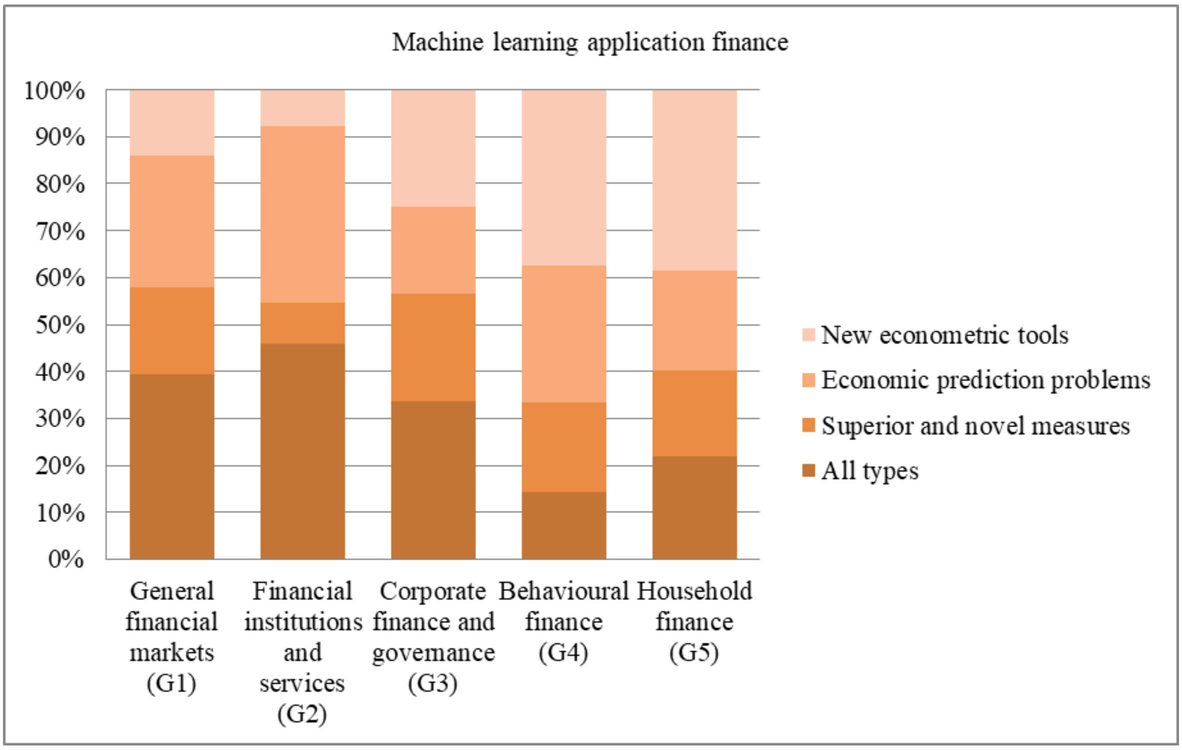

FIGURE 1. Machine learning application finance

Figure 1 illustrates how machine learning applications in financial sectors interact with each other, with G5 excelling in innovative methods and econometric tools, while G2 dominates in aggregate applications and economic forecasting capabilities.

TABLE 2. Normalized data

	Normalized data			
General financial markets (G1)	0.81531	0.81173	0.52700	0.57307
Financial institutions and services (G2)	1.00000	0.39362	0.37471	1.00000
Corporate finance and governance (G3)	0.56115	0.80433	1.00000	0.40000
Behavioural finance (G4)	0.19052	0.54068	0.78657	0.33333
Household finance (G5)	0.56489	1.00000	0.55911	0.16667

Table 2 shows how machine learning applications perform against each other in normalized terms, with G5 leading in new metrics, G3 leads in prediction accuracy, and G2 excelling in overall scope and econometric tools

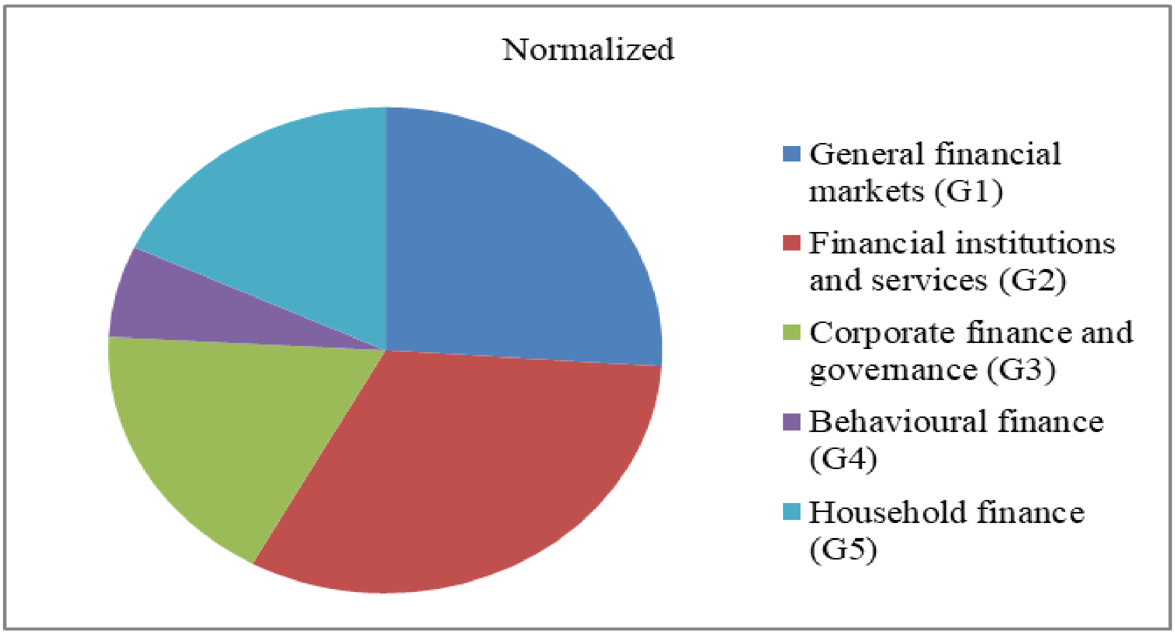

FIGURE 2. Normalized data

Figure 2 highlights t interoperability machine learning in finance, with G2 and G3 excels in key areas, while G5 shows strong innovation but little impact on econometric tools.

TABLE 3. Weight

Weight			
0.45	0.45	0.45	0.45
0.45	0.45	0.45	0.45
0.45	0.45	0.45	0.45
0.45	0.45	0.45	0.45
0.45	0.45	0.45	0.45

Table 3 demonstrates balanced interplay in WSM method, where equal weights (0.45) are assigned across all financial domains and criteria, ensuring a balanced evaluation of machine learning applications.

TABLE 4. Weighted normalized decision matrix

	Weighted normalized decision matrix			
General financial markets (G1)	0.36689	0.36528	0.23715	0.25788
Financial institutions and services (G2)	0.45000	0.17713	0.16862	0.45000
Corporate finance and governance (G3)	0.25252	0.36195	0.45000	0.18000
Behavioural finance (G4)	0.08573	0.24331	0.35396	0.15000
Household finance (G5)	0.25420	0.45000	0.25160	0.07500

Table 4 reveals how machine learning applications perform with weighted normalized values, with G2 and G5 achieving strong performance in selected areas, while G3 leads in prediction performance under symmetric WSM weighting.

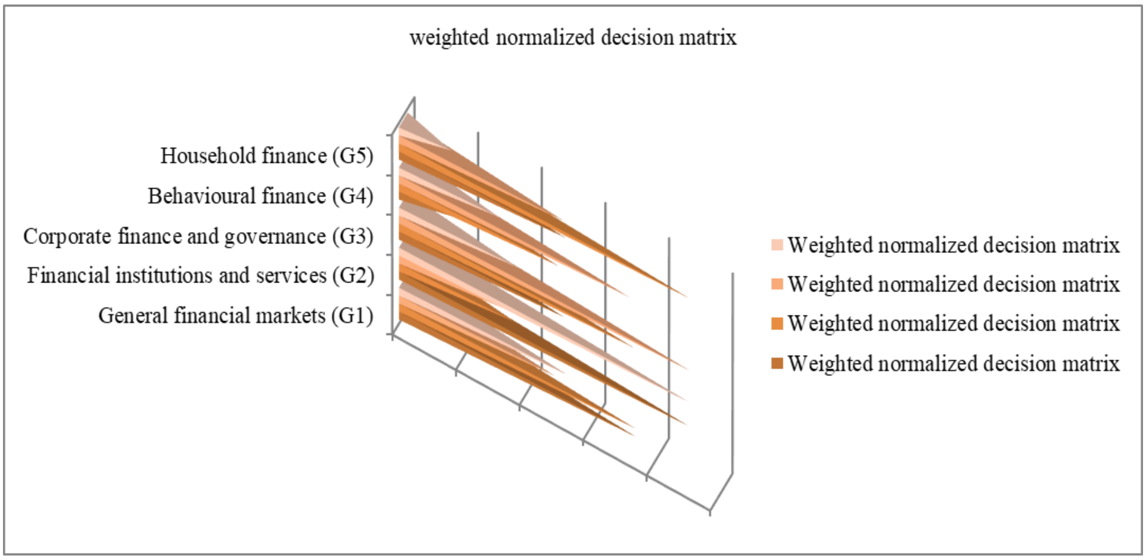

FIGURE 3. Weighted normalized decision matrix

Figure 3 demonstrates the operation using a decision matrix that has been weighted and normalized. Where G2 and G3 stand out for econometric robustness and predictive accuracy, while G5 shows leadership in new applications.

TABLE 5. Preference score & Rank

	Preference Score & Rank	
General financial markets (G1)	1.22720	3
Financial institutions and services (G2)	1.24575	1
Corporate finance and governance (G3)	1.24447	2
Behavioural finance (G4)	0.83299	5
Household finance (G5)	1.03080	4

Table 5 shows the interoperability by priority scores, with G2 ranking highest in machine learning performance, followed by G3, while G4 ranks lowest, indicating limited convergence across key criteria.

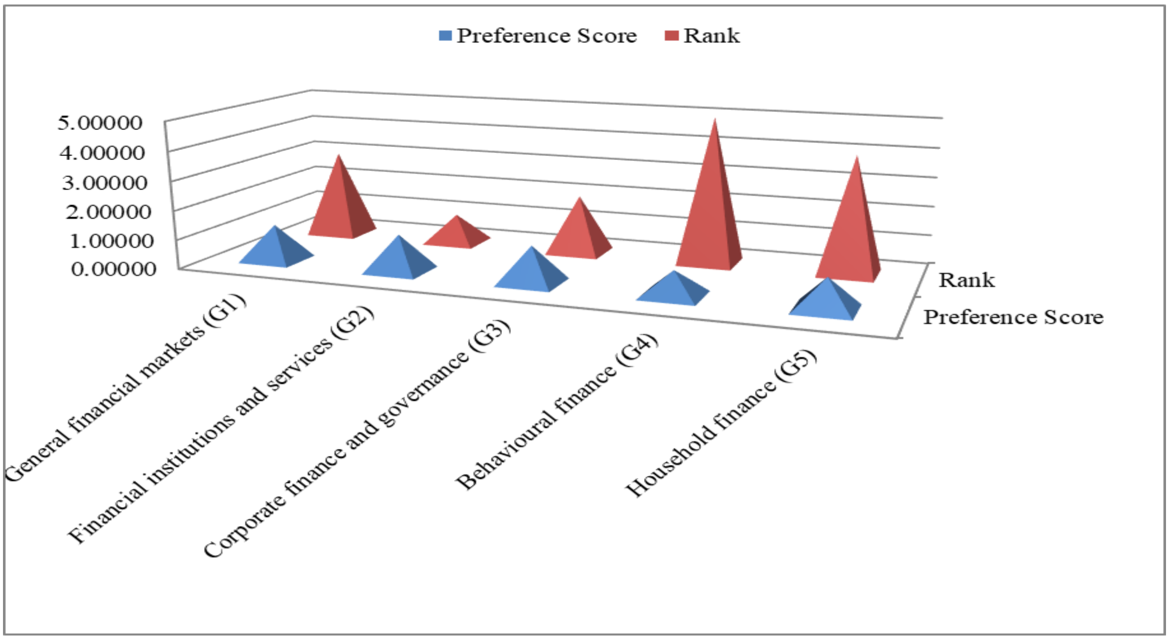

FIGURE 4. Preference score and Rank

Figure 4 highlights the interoperability of machine learning in the financial sector, with G2 and G3 receiving high rankings, indicating better integration, while G4 lags behind, reflecting limited performance across the assessed criteria

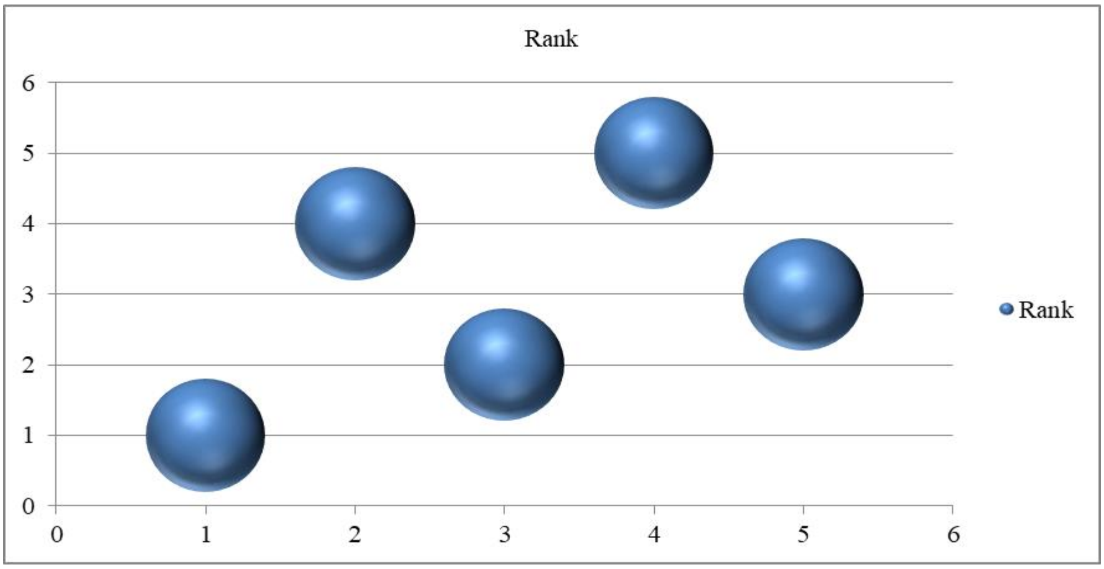

FIGURE 5. Rank

Figure 5 presents the ranking. of financial domains based on the WSM method, with G2 leading, followed by G3. G4 ranks lowest, showing its relatively weak performance in machine learning applications.

4. CONCLUSIONS

A comprehensive analysis of machine learning (ML) applications in various financial sectors using the Weighted Sum Model (WSM) methodology highlights notable variations in performance and efficiency. Financial Institutions and Services (G2) stands out with the highest preference score of 1.24575, demonstrating outstanding capabilities in integrating comprehensive applications and econometric tools. Corporate Finance and Governance (G3) closely follows with a score of 1.24447, excelling particularly in economic forecasting accuracy. Public Financial Markets (G1) holds a respectable third place with a score of 1.22720, reflecting balanced performance across all evaluation criteria. Housing Finance (G5) ranks fourth, scoring 1.03080, with strength in developing innovative metrics but limited effectiveness in applying econometric tools. Behavioral Finance (G4) lags behind with a score of 0.83299, showing considerable room for improvement in integrating ML across all criteria. Normalized data analysis offers deeper insights into the unique strengths of each sector. Household finance leads in innovative measurement development, showcasing creativity in creating new approaches. Corporate finance excels in economic forecasting, while financial institutions demonstrate robust overall application and strong econometric tool integration. ML techniques are particularly valuable in improving decision-making, enhancing risk assessment practices, and developing advanced financial metrics that capture complex market dynamics. Despite the promising outcomes, challenges remain. The "black box" issue continues to limit the transparency of complex ML models, hindering interpretation and validation. Future research should focus on creating more interpretable methods that preserve predictive accuracy while enhancing computational transparency as the finance industry undergoes continued technological transformation; the integration of ML across all sectors is expected to accelerate. Financial institutions should prioritize investment in ML capabilities, particularly in areas with strong performance potential, while addressing challenges in emerging areas such as behavioral finance.

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