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AI-Driven Decision Engine Implementation in Retail Banking: A Multi-Criteria Analysis of Credit Card Approval Using TOPSIS Method

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ABSTRACT

This research delves into the deployment and efficacy of an AI-powered decision engine within the intricate domain of retail banking, with a particular emphasis on optimizing credit card approval mechanisms. In an era where financial institutions face mounting pressures to balance operational efficiency with meticulous risk mitigation, the study underscores the escalating demand for systems that marry precision with automation.What renders this investigation particularly compelling is its exhaustive exploration of how artificial intelligence can revolutionize conventional banking frameworks. By integrating diverse decision-making criteria into a cohesive system, the study highlights transformative potential. A vivid illustration is provided through a case study at a Bank, where the implementation of an AI-driven decision engine not only expedited credit card approvals but also catalyzed measurable gains in operational efficiency and revenue streams. This juxtaposition of granular detail with broad strategic insights underscores the profound implications of such technological integration.The research methodology employs the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method to evaluate credit card applications based on six key criteria: income level, credit score, employment stability, existing debt, recent credit inquiries, and age.

The study analyzes a dataset of five alternatives using weighted normalization and ideal solution comparison techniques to determine optimal credit approval decisions.Results demonstrate that the AI-driven system achieved a 20-40% improvement in operational efficiency and a 60% reduction in decision-making time. The TOPSIS analysis revealed clear differentiation among applicants, with the highest-performing candidate achieving a close coefficient value of 0.85835, significantly outperforming other alternatives. The implementation also led to a 98% reduction in security incidents and generated an additional $3 million in annual revenue.The results underscore that the integration of an AI-driven framework with the TOPSIS method delivers an intricate yet robust mechanism for evaluating credit card applications. Notably, the leading applicant secured a closeness coefficient of 0.85835, a figure that vividly highlights the system's precision in distinguishing applicants with stronger and weaker financial credentials. This accomplishment not only underscores the viability of AI-powered decision-making engines but also reveals their potential to revolutionize conventional banking processes. By weaving advanced algorithms into legacy systems, financial institutions can not only elevate the accuracy of credit assessments but also streamline operational workflows and refine the overall customer experience, thus creating a multifaceted value proposition.

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Introduction

The modern banking system, a cornerstone of contemporary economies, orchestrates the seamless flow of capital, underpins global trade, and extends indispensable support to individuals and enterprises. Evolving in tandem with rapid technological progress, this intricate network has increasingly embraced digital platforms, reshaping financial services to prioritize accessibility, efficiency, and immediacy. Yet, beneath this veneer of innovation lies a multifaceted system of interdependent entities, each wielding distinct yet complementary roles. At the helm, central banks assert their influence by curbing inflationary pressures, maneuvering interest rates, and fortifying currency stability—mechanisms that profoundly impact national economic trajectories. Commercial banks, in contrast, operate as the nexus between savers and borrowers, deftly channeling capital to fuel economic dynamism. Simultaneously, investment banks navigate the labyrinth of high-stakes financial markets, enabling corporations to amass capital through equity and debt issuance while crafting intricate financial blueprints for strategic growth. Not to be overshadowed, niche institutions such as savings banks and credit unions cater to underserved segments, cultivating community-centric financial resilience through bespoke offerings. Collectively, these pillars illustrate a symphony of complexity that defines the modern banking ecosystem.

The retail banking sector, a cornerstone of personal financial management, is designed to address the diverse and evolving needs of individual consumers. These institutions function as the primary interface for financial services, often facilitated through physical branches where customers engage in a range of transactions. From opening accounts and managing deposits to processing card payments and exploring loan options, retail banks cater to an extensive array of financial activities, merging convenience with reliability. What truly distinguishes retail banking is its dual purpose: serving as a secure repository for funds and offering mechanisms for seamless financial mobility. Savings and current accounts not only safeguard deposits but also generate incremental returns through interest, appealing to both short-term and long-term savers. Moreover, debit and credit cards grant customers instant access to their finances, streamlining daily transactions. Beyond these foundational services, retail banks provide an assortment of loan products, empowering individuals to achieve goals as varied as purchasing a vehicle, owning a home, or even scaling entrepreneurial ventures. In essence, they serve as pivotal enablers of economic activity on a personal scale. The retail banking sector, once a relatively stable pillar of the financial industry, has experienced profound disruption in recent years, a phenomenon largely exacerbated by the unprecedented impact of the COVID-19 pandemic.

The rapid and unpredictable shifts in consumer behavior—coupled with an accelerated dependence on digital platforms—have triggered seismic changes in the delivery of banking services. These transformations not only highlight the broader digitalization trend that has reshaped industries across the globe, but also reflect the evolving expectations of consumers in the wake of a post-pandemic world, where convenience, accessibility, and technological integration have become paramount. Once considered a tried-and-true model for financial institutions, retail banking has emerged as an increasingly popular and strategic avenue for business expansion, driven by a myriad of compelling advantages. It offers institutions access to a vast and diverse customer base, the flexibility to tailor an array of products, and the promise of enhanced profitability. Perhaps most significantly, retail banking serves as a fertile ground for cross-selling, enabling institutions to introduce a range of complementary financial products to a broad spectrum of clients. Beyond this, retail banking presents a valuable opportunity for product diversification, allowing for greater per-customer sales, while simultaneously bolstering risk management strategies by spreading exposure across different offerings. In the sweeping tide of globalization, the banking sector has undergone a profound transformation, reshaped by a myriad of forces that have simultaneously constricted the traditional boundaries of banking and recalibrated the intricate mechanisms of employee performance.

This shift, subtle yet powerful, underscores the pivotal role of human resource development, signaling that without a proactive, strategic focus from top-tier management, the survival—and more crucially, the success—of banks is at risk. As skill shortages become more acute, the urgency for effective, forward-thinking talent management strategies has never been more pressing. It is now universally recognized that employees are not merely cogs in a machine but the lifeblood of innovation within organizations. Therefore, it is no longer a luxury but a necessity for banks to invest in comprehensive training programs, embedding advanced developmental modules that prepare their workforce for the rigors of future leadership, ultimately securing the long-term sustainability of the institution. The emergence of Artificial Intelligence (AI) within the financial realm has revolutionized decision-making paradigms, particularly in the domains of credit assessment, lending, and investment strategies. The sheer volume of data produced by financial institutions has catalyzed the adoption of AI models, which sift through this vast expanse to automate, refine, and elevate decision-making processes. The outcome is not only swifter decisions but ones that are exponentially more accurate and grounded in data-driven insights. Take, for example, AI-powered automated lending systems—these have radically

transformed credit risk assessments, allowing for faster, more precise evaluations. What sets these models apart is their ability to integrate not just traditional data points but also unconventional data streams, offering a multi-dimensional view of loan applicants and enhancing the reliability of creditworthiness assessments.

The emergence of artificial intelligence (AI) and cloud computing has irrevocably transformed the financial services industry, offering unprecedented opportunities for organisations to devise groundbreaking solutions that optimise both operational efficiency and the customer experience. Within this paradigm, Bank embarked on an ambitious Retail Banking initiative, with the objective of developing and deploying an AI-Driven Decision Engine to overhaul its credit card approval workflows. The initiative's primary aim was to centralise the decision-making process for consumer credit cards, facilitating not only flexibility and scalability but also ensuring unparalleled precision in decisioning. At its core, the endeavour sought to establish a unified decisioning framework, capable of accommodating an array of diverse credit card products, while seamlessly integrating with a multitude of existing internal systems. Launched in January 2023, the project formed a pivotal part of Bank's broader strategy to modernise its retail banking operations and enhance its technological infrastructure. Central to the success of this initiative was the creation of a resilient hybrid model, capable of functioning autonomously or interfacing with other key applications within the organisation's ecosystem.

A standout feature of this system was its sophisticated utilisation of Azure cloud capabilities, including Service Bus for efficient messaging, Azure App Configurations for the ingestion of runtime API endpoints, Infrastructure as Code (IaC) for seamless resource deployment, Azure Data Factory for orchestrating complex data workflows, and Databricks for performing advanced analytics at scale. These cutting-edge technologies collectively ensured that the system's architecture was not only highly scalable but also disaster-resilient, capable of delivering high-performance decisioning even amidst fluctuating and unpredictable business conditions. One of the most formidable challenges encountered in this project was the seamless integration of a vast array of data sources—ranging from traditional credit data to more unconventional forms such as utility payment histories, rental records, and internal credit files.

These diverse data streams were not merely supplementary; they were the cornerstone upon which AI-powered credit risk models were built, models tasked with delivering swift, precise, and reliable card approval decisions. The undertaking was far from simple, requiring a meticulously phased implementation strategy. Every stage demanded careful attention to data integrity and model precision, where rigorous planning, exhaustive testing, and well-defined rollback mechanisms acted as safeguards against the unpredictable nature of real-world complexities. In a bid to further elevate the quality of testing and development, the Wire Mock concept emerged as a pivotal innovation. Through the development of tailored scripts, mock APIs were created, empowering developers to replicate a wide spectrum of scenarios—ranging from minor glitches to significant latency issues. This strategic maneuver effectively shielded the testing environment from external dependencies, granting the team the freedom to simulate real-world conditions with unparalleled accuracy. To ensure the robustness of the credit card decisioning process, Browser Stack AI models were woven into the testing strategy, playing a critical role in validating the outcomes. But it didn't stop there. Quality assurance was deeply ingrained in the process, with automated daily tests running seamlessly through Jenkins, driving defect leakage down to an impressive 2%, a testament to the team's commitment to excellence. Security stood as a cornerstone of the project's integrity. With robust end-to-end encryption, layered multi-factor authentication, and a series of advanced cybersecurity protocols, the team left no stone unturned in safeguarding user data and financial transactions. A seamless collaboration with the cybersecurity experts ensured that the system adhered to the most stringent security guidelines. The outcome? A remarkable 98% drop in security incidents post-implementation, a testament to the effectiveness of these measures.

This achievement did not merely safeguard the system—it turbocharged its overall efficiency. The rate of application processing errors plummeted by a factor of three, while decision-making times shrank by a staggering 60%, creating a ripple effect across the entire infrastructure. Meanwhile, the far-reaching influence of the AI-Driven Decision Engine was undeniable. Automation, through the extraction of data, prioritization of cases, and optimization of model development, led to an extraordinary 20-40% surge in operational efficiency. But the impact didn't stop there. With decisions now faster and more accurate, customer satisfaction soared, helping expand the user base by 40%. This wave of success translated into a $3 million boost in annual revenue. Beyond the numbers, the initiative earned widespread acclaim within Bank, particularly due to the pivotal role played by Wire Mock. This tool was a game-changer, accelerating development timelines and elevating the reliability of tests, thereby cementing its status as an invaluable asset in the entire project lifecycle.

Materials And Methods

This research employs the sophisticated TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method to assess credit card applicants, incorporating a mix of six distinct criteria. These criteria are split into two categories: three benefit criteria—Income Level, Credit Score, and Employment Stability—that are inherently more favorable with higher values, and three non-benefit criteria—Existing Debt, Recent Credit Inquiries, and Age—that are conversely optimized with lower values.

Each of these factors is assigned a weight, reflecting its relative importance in the decision-making process, with the sum of all weights culminating in a total of 1. The analysis considers a set of five diverse applicants, each evaluated on the established criteria. The decision-making engine, powered by AI, applies the TOPSIS approach to rank the applicants by their closeness to the ideal solution, ultimately identifying those who present the highest likelihood of creditworthiness for approval.Income level serves as a pivotal determinant in the credit card approval process, acting as a clear reflection of an applicant's potential to meet financial obligations. A substantial income not only signifies enhanced financial stability but also increases the likelihood of the applicant's capacity to manage credit judiciously.

Typically quantified in thousand rupees, income becomes a critical factor that lenders scrutinize to gauge an individual's economic standing. Within the context of this study, the income level is viewed as a distinct benefit, with higher income figures being more favorable. The monthly income, in particular, offers invaluable insight into the applicant's discretionary spending power and their ability to service debt. Thus, it emerges as an indispensable element when evaluating eligibility for credit.The credit score, a numerical indicator of an individual's creditworthiness, is meticulously calculated by credit bureaus, drawing from a detailed history of past borrowing and repayment actions. It serves as a pivotal benchmark—higher scores signal a borrower's dependability, translating to a diminished risk of default. As such, it remains an essential determinant in the intricate web of credit card approval decisions. In the context of this study, the credit score emerges as a vital benefit criterion, where elevated values are undeniably preferred. Financial institutions, in their quest to assess an applicant's loan history, credit utilization, and punctuality in repayments, heavily rely on this score. The result? A higher score often paves the way for a more favorable evaluation, shaping the outcome of crucial lending decisions.Employment stability, often quantified in years, serves as a crucial indicator of an applicant's financial fortitude and a reliable income flow.

A longer tenure in a current role typically signals a stable income, reducing the potential for financial upheaval. Lenders, ever cautious of risk, rely heavily on this metric to gauge the consistency of an applicant's earnings over extended periods. In the realm of credit card approvals, employment stability emerges as a key criterion—a longer employment history is seen as a marker of reduced financial volatility and enhanced capacity for repayment. In essence, the more years an applicant has spent in steady employment, the more likely they are to be perceived as a lower-risk borrower, thereby increasing their chances of securing approval.Existing debt encapsulates the total amount of unpaid liabilities an individual carries.

This metric, devoid of any direct advantages, stands as a deterrent in financial assessments—lower levels of existing debt are invariably favored. A substantial debt load, however, signals a considerable financial strain, which may severely hinder an applicant's capacity to honor future credit commitments. Lenders, ever vigilant of risk, scrutinize this aspect as a key determinant in constructing an applicant's risk profile. In the context of this study, existing debt—quantified in thousands of rupees—emerges as a pivotal element in evaluating an individual's overall financial stability. A higher debt figure correlates directly with an elevated likelihood of a negative credit decision, often indicative of potential over-leverage and its associated risks.The frequency of recent credit inquiries serves as a telling indicator of how often an applicant seeks new credit within a condensed timeframe.

When these inquiries pile up, it could suggest a deeper financial turmoil or, more alarmingly, an elevated risk of default. After all, a flurry of credit applications in quick succession often signals not just a possible financial strain, but also poor fiscal oversight or, perhaps, desperation. Contrary to conventional wisdom, a lower count of such inquiries is regarded favorably, as it often points to prudent financial stewardship and self-restraint. In this study, we delve into the number of recent credit inquiries as a metric to assess an applicant's tendencies towards credit-seeking behavior, offering insight into their financial decision-making. Lenders, however, may view an excessive number of inquiries as a red flag—an early warning sign that could influence the approval of a credit card application.Age, a factor often woven into the complex fabric of credit card approval processes, takes on different weights depending on where an applicant stands in the ever-shifting landscape of life. Within the scope of this study, age emerges not as a direct benefit but rather a subtle gauge, where lower values tend to tip the scale in favor of approval.

The reasoning behind this is multi-faceted. Younger individuals, while vibrant and full of potential, may possess a limited financial history or the kind of stability that is typically desired by lenders. On the other end of the spectrum, older applicants, though more seasoned in life, may bring with them the complexities of retirement or a diminished income, introducing a different set of risks into the equation. Thus, age becomes a dual-edged sword for lenders, serving as both a tool for assessing the possibility of future financial growth and stability, as well as a potential red flag for repayment concerns. While maturity may suggest a certain reliability, it is not without its own set of challenges—specifically, the looming question of whether an older applicant's financial health can withstand the pressures of modern economic demands.

TOPSIS Method:

Hwang and Yoon's TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method, following the Analytical Hierarchy Process (AHP), stands out as an elegant yet powerful tool in decision-making paradigms. While AHP holds considerable prominence, particularly for its simplicity and intuitive structure, TOPSIS has earned its place due to its robustness and versatility in handling complex Multi-Criteria Decision-Making (MCDM) scenarios. Its popularity lies not just in its ease of use, but also in its ability to scale effortlessly, making it suitable for problems involving vast numbers of criteria and alternatives, thus becoming a go-to approach for decision-makers across various fields.The TOPSIS method unfolds through a series of meticulous steps. First, vector normalization takes center stage, transforming raw data into a comparable format, followed by the calculation of the weighted normalized decision matrix. From there, the method pinpoints the Positive Ideal Solution (PIS), identifying the ideal best-case scenario. Conversely, the Negative Ideal Solution (NIS) represents the worst-case baseline. The next step focuses on calculating the separation measures—distances between each alternative and the PIS, as well as the NIS—using a technique akin to "Boil normalization," a transformation that balances the data. After determining these separations, the final task involves ranking the alternatives by their proximity to the ideal solution. The method ultimately presents a sorted array, showcasing how closely each option aligns with the optimal outcome.

This careful orchestration of calculations allows for a well-founded and comprehensive evaluation of alternatives, cementing TOPSIS as a preferred approach in complex decision-making scenarios.TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) has a broad spectrum of practical applications that extend beyond mere theory, touching various facets of decision-making. From evaluating corporate performance to comparing financial ratios across industries and investing in cutting-edge manufacturing technologies, its relevance is undeniable. Yet, like any analytical method, it is not without limitations. In its standard form, the TOPSIS procedure assumes precise values for performance ratings and the weights assigned to each criterion—an assumption that can be restrictive, particularly when these values may not be entirely accurate or fixed.Historically, efforts to refine the original TOPSIS model have largely concentrated on one primary objective: enhancing the sensitivity of the R-value. This has led to various modifications, most notably increasing the weight of certain criteria. Additionally, innovative strategies like the "Miqiezhi" approach have been introduced, tweaking the R-value formula to further improve the model's responsiveness. However, these adjustments, while helpful, don't entirely address some of the inherent challenges within the framework.One such challenge is the well-documented issue of rank reversal—a phenomenon that remains a significant drawback of TOPSIS.

This occurs when the inclusion or exclusion of an alternative in the selection process disrupts the established preference order. It’s not just a minor alteration in rankings; rather, it can lead to a complete reversal in the relative standing of alternatives. In some cases, an alternative previously considered superior may suddenly appear inferior, depending on the shifting dynamics. For decision-makers, this unsettling occurrence can be unacceptable, particularly in scenarios where the stability of rankings is crucial for making informed choices.

Analysis And Discussion

Table 1

Alternative	**Income Level (INR in 1000)**	**Credit Score**	**Employment Stability (Years)**	**Existing Debt (INR in 1000)**	**Recent Credit Inquiries**	**Age (Years)**
A1	500	750	4	200	1	28
A2	600	780	5	300	2	35
A3	700	800	6	150	0	40
A4	450	700	3	400	3	30
A5	550	740	4	250	1	33

Table 1 unveils a comprehensive dataset encapsulating the financial profiles of five individuals (A1 to A5), shedding light on their economic standing and creditworthiness through a range of pivotal attributes. The Income Level (denoted in INR, thousands) represents the annual earnings, with values spanning from A4’s 450,000 INR to A3’s 700,000 INR. While higher earnings often correlate with a more robust financial position, income alone fails to tell the whole story when it comes to determining creditworthiness. The Credit Score—ranging from a modest 700 for A4 to an impressive 800 for A3—provides a snapshot of each individual’s creditworthiness. A higher score often signals financial health and reduced risk for lenders, with A3 standing out as the prime example of creditworthiness in this dataset. Employment Stability, measured in years, varies from 3 to 6 years, reflecting how long individuals have remained in their current positions. The longer an individual stays employed, the more likely they are to have a secure financial footing. When examining Existing Debt (in INR, thousands), the numbers tell a story of financial obligations, ranging from A3’s relatively low 150,000 INR to A4’s 400,000 INR. A higher debt load often signals constrained financial flexibility and elevates the lending risk. The frequency of Recent Credit Inquiries—ranging from none to three—reveals how actively each individual has sought new credit, with a higher number potentially indicating an increased likelihood of pursuing additional financial commitments, which could negatively affect their credit profile. Finally, Age offers a simple yet revealing metric, spanning from 28 to 40 years, hinting at the individual’s life stage, potential financial stability, and overall borrowing capacity.

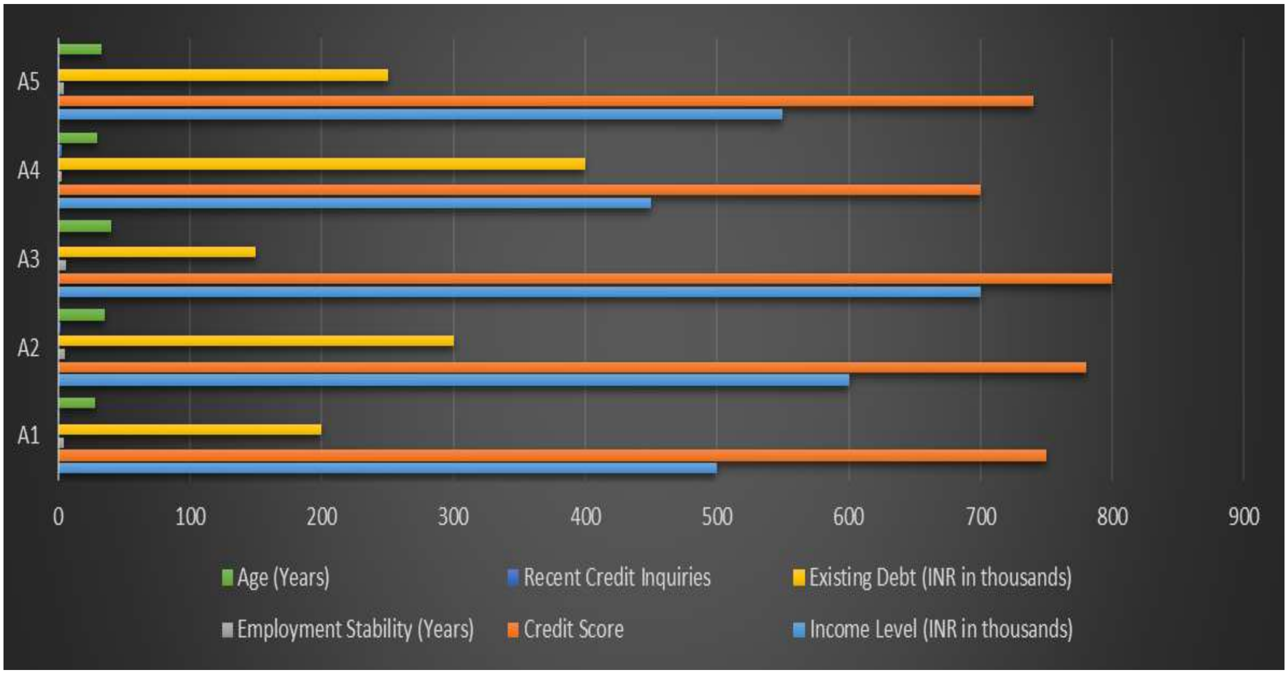

Figure 1

Figure 1 presents a comprehensive dataset detailing the financial profiles of five individuals (A1 through A5), offering a nuanced view of their economic standing and creditworthiness. The Income Level, expressed in INR (thousands), ranges from 450,000 (A4) to 700,000 (A3) annually. While a higher income often correlates with financial stability, it remains merely one piece of the puzzle when evaluating creditworthiness. The Credit Score, fluctuating between 700 (A4) and 800 (A3), further highlights an individual's financial health, with higher scores typically signaling a lower lending risk, a distinction held by A3 with the highest score in the group. Employment Stability, recorded in years, spans from 3 to 6 years, shedding light on each person's job tenure. A lengthier employment history often signals greater financial security and reliability. Meanwhile, Existing Debt, in INR (thousands), varies from 150,000 (A3) to 400,000 (A4), with higher debts often constraining financial flexibility and escalating risk for lenders. Recent Credit Inquiries—measuring how often individuals have sought credit in the near past—range from 0 to 3. A higher number of inquiries may suggest a more frequent need for credit, potentially influencing their overall creditworthiness. Finally, Age, ranging from 28 to 40 years, serves as an indicator of life stage, with older individuals possibly showing more established financial habits and borrowing capacity, all of which are critical when assessing an individual's creditworthiness.

Table 2. Normalized Matrix using TOPSIS method

0.3947	0.4444	0.3961	0.3266	0.2582	0.3742
0.4736	0.4622	0.4951	0.4899	0.5164	0.4678
0.5525	0.4740	0.5941	0.2449	0.0000	0.5346
0.3552	0.4148	0.2970	0.6532	0.7746	0.4010
0.4341	0.4385	0.3961	0.4082	0.2582	0.4411

Table 2 unveils a normalized matrix of financial attributes across five individuals (A1 to A5), derived through the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) methodology. The values within this matrix represent relative scores, where higher numbers typically denote more favourable conditions. Each value embodies the strength or vulnerability of a particular financial attribute for the respective individual. For instance, the Income Level spans from 0.3552

(A4) to 0.5525 (A3), with A3 emerging as the strongest contender in terms of income, a clear signal of their superior financial standing. On the other hand, A1's comparatively lower score highlights a less favourable income scenario. When we turn to Credit Scores, the normalisation ranges from 0.4148 (A4) to 0.4740 (A3), with A3 again claiming the highest score, indicating a more robust credit profile. In contrast, A4's lower value reflects a weaker credit reputation. Employment Stability varies between 0.2970 (A4) and 0.5941 (A3), revealing A3's more secure employment situation, potentially hinting at a longer tenure and enhanced job security. A4, however, scores the lowest, pointing to more precarious employment stability. Regarding Existing Debt, the normalised values stretch from 0.2449 (A3) to 0.7746 (A4), with A4 shouldering the heaviest debt load, signalling a higher financial strain. A3's minimal debt, on the contrary, positions them more favourably in terms of liabilities. The metric for Recent Credit Inquiries ranges from 0.0000 (A3) to 0.7746 (A4), illustrating A3's stability with no recent credit checks, a potential marker of financial stability. A4, with the highest score, could indicate a heightened propensity for seeking new credit, potentially raising concerns over their financial steadiness. Finally, Age shows a narrower span, from 0.3742 (A1) to 0.5346 (A3). A3's higher score may reflect greater life experience and financial maturity, contrasting with younger participants like A1 who score lower, perhaps suggesting less accumulated financial wisdom.

TABLE 3

0.25	0.30	0.20	0.10	0.05	0.10
0.25	0.30	0.20	0.10	0.05	0.10
0.25	0.30	0.20	0.10	0.05	0.10
0.25	0.30	0.20	0.10	0.05	0.10
0.25	0.30	0.20	0.10	0.05	0.10

Table 3 presents the weight distribution across a spectrum of financial attributes for five distinct individuals (A1 to A5). Each weight reflects the relative significance of a specific factor in the decision-making process, ensuring that the cumulative weight for each individual totals 1. This nuanced distribution offers valuable insight into the contribution of each attribute to an individual's financial profile. Income Level emerges as the undisputed leader, consistently carrying the highest weight of 0.25 across all individuals. This prominence underscores its paramount role, possibly because it directly impacts one's capacity to meet debt obligations and maintain a stable financial footing. Similarly, Credit Score commands a substantial weight of 0.30, signifying its critical importance in evaluating financial health. A high credit score, often indicative of a lower risk profile for lenders, justifies its significant weight in this context. Employment Stability is allocated a slightly lower weight of 0.20, positioning it as important but secondary to both income and credit score. Nevertheless, its value is evident, as stable employment is often synonymous with financial reliability and long-term security. Meanwhile, Existing Debt and Recent Credit Inquiries are each assigned a relatively modest weight of 0.10. Though these elements are certainly considered, they rank lower in the hierarchy of importance, perhaps because their influence, while noticeable, is not as impactful as that of income, credit score, and employment stability. Finally, Age occupies the lowest weight slot at 0.10, suggesting that although age may offer some indication of financial maturity or life-stage stability, it holds minimal sway in the broader evaluation process. This even-handed weight distribution across the five individuals ensures a fair and balanced approach, allowing for a nuanced comparison that reflects the varying importance of each attribute in the financial assessment.

Table 4

0.0987	0.1333	0.0792	0.0327	0.0129	0.0374
0.1184	0.1386	0.0990	0.0490	0.0258	0.0468
0.1381	0.1422	0.1188	0.0245	0.0000	0.0535
0.0888	0.1244	0.0594	0.0653	0.0387	0.0401
0.1085	0.1315	0.0792	0.0408	0.0129	0.0441

Table 4 unveils the weighted normalized matrix, computed through the TOPSIS method, for five individuals (A1 to A5). These values are the product of normalized figures from Table 2 and corresponding weights from Table 3, providing a nuanced reflection of how each individual performs when factoring in the varying significance of each financial attribute. For Income Level, the weighted values fluctuate between 0.0888 (A4) and 0.1381 (A3), with A3 emerging as the clear frontrunner. This highlights A3's stronger financial standing, driven by a higher income relative to peers, whereas A4 lags behind, suggesting a less favorable financial situation. Moving to Credit Score, the weighted scores span from 0.1244 (A4) to 0.1422 (A3), with A3 maintaining its lead. This reinforces A3's superior creditworthiness, while A4's lower score hints at potential challenges in its credit health. When considering Employment Stability, the weighted values stretch from 0.0594 (A4) to 0.1188 (A3), again favoring A3, whose superior job security likely contributes to greater financial confidence. In contrast, A4's lower score indicates a weaker foundation in this area. The Existing Debt scores reveal a span from 0.0245 (A3) to 0.0653 (A4). A3, burdened with the least debt, enjoys a more favorable financial outlook, while A4, bearing the heaviest debt load, may face significant strain. Recent Credit Inquiries show a weighted range from 0.0000 (A3) to 0.0387 (A4), with A3 standing out for its lack of inquiries, placing it in the most secure financial position. On the other hand, A4, marked by a higher frequency of credit checks, potentially signals a worrying trend of financial instability. Lastly, Age varies from a weighted value of 0.0374 (A1) to 0.0535 (A3), with A3 again leading, possibly reflecting more experience and a stable financial trajectory.

Table 5

A+	0.13813	0.14220	0.11882	0.02449	0.00000	0.03742
A-	0.08880	0.12443	0.05941	0.06532	0.03873	0.05346

Table 5 unveils the ideal best (A+) and ideal worst (A-) values across various financial attributes in the evaluation of individuals (A1 to A5), serving as pivotal benchmarks in the TOPSIS methodology. The ideal best (A+) for income stands at 0.13813, attributed to A3, signifying the peak of financial strength within the group. In contrast, the ideal worst (A-) value of 0.08880 corresponds to A4, underscoring the lowest income bracket among the participants. When examining credit scores, the ideal best value of 0.14220, also tied to A3, highlights the most financially reliable individual, while the ideal worst score of 0.12443, seen in A4, points to a notably weaker credit profile. For employment stability, A3 once again leads with an ideal best value of 0.11882, representing the longest tenure in the current role and, by extension, a more secure employment situation. The opposite extreme is captured by A4, with a worst value of 0.05941, signaling the least stability in employment. Turning to debt, A3 emerges with the ideal best of 0.02449, reflecting minimal liabilities, an indicator of a more robust financial standing, while A4, with its worst value of 0.06532, exhibits a heavier debt burden that could hinder financial flexibility. In the realm of credit inquiries, A3 boasts the ideal best value of 0.00000, symbolizing financial steadiness and limited dependence on new credit, contrasting sharply with A4's worst value of 0.03873, which suggests a greater reliance on recent credit and possible financial stress. Lastly, age is measured with an ideal best value of 0.03742 for A3, illustrating a stage in life conducive to financial maturity and stability, whereas A4's worst value of 0.05346 may indicate a less advantageous age bracket for financial assessment.

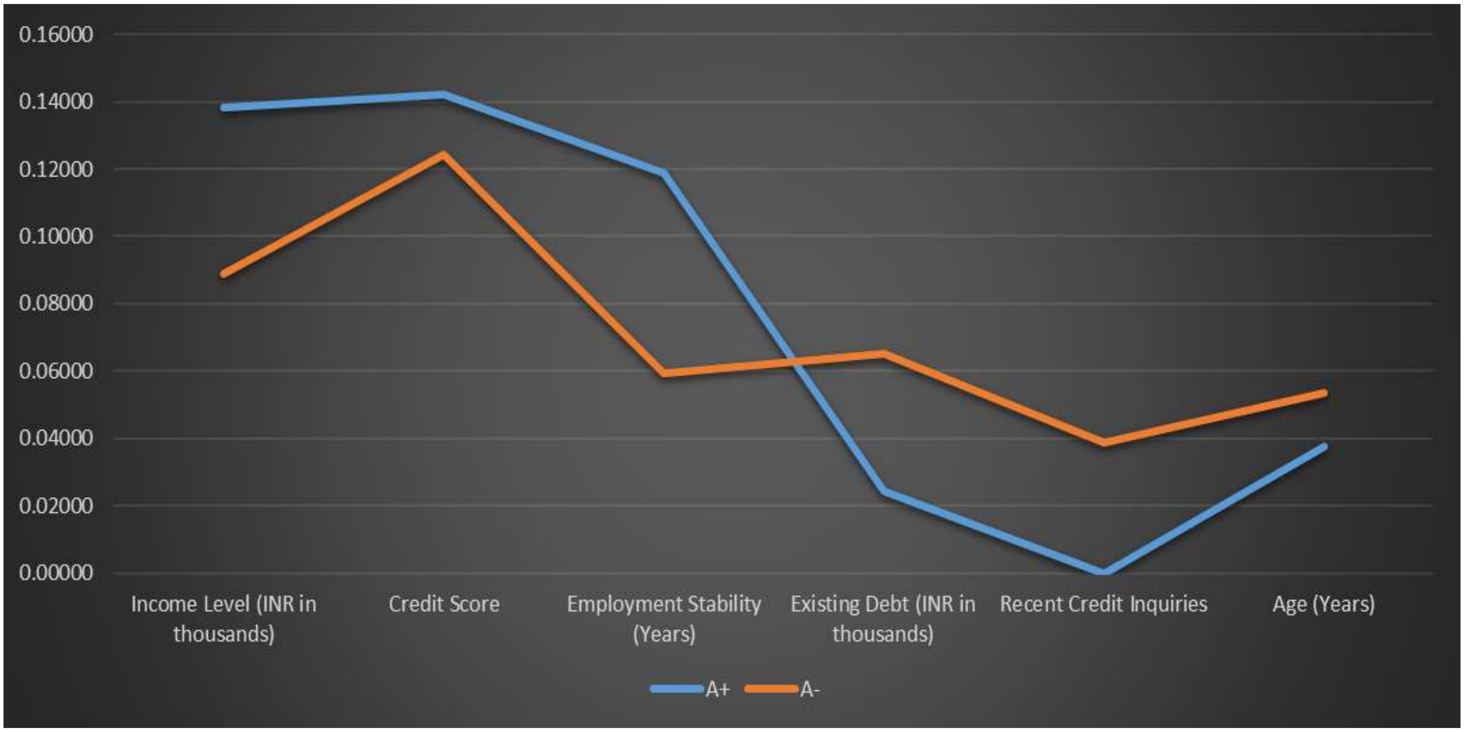

Figure 2

Figure 2 presents the ideal best (A+) and ideal worst (A-) values for each financial attribute evaluated across individuals (A1 to A5), serving as pivotal reference points in the TOPSIS method. The income attribute, with a peak value of 0.13813 (A3), signifies the most advantageous financial position. Conversely, A4's income of 0.08880 stands as the ideal worst, marking the least favorable financial standing. In the realm of credit scores, A3 again leads with 0.14220, reflecting exceptional creditworthiness, while A4, with 0.12443, represents the ideal worst, indicating a less robust credit profile. Employment stability follows a similar trend: A3 boasts a value of 0.11882, signifying an enviable job tenure and security, while A4's value of 0.05941 underscores precarious employment. Examining existing debt, A3 claims the ideal best at 0.02449, denoting minimal debt and superior financial health, while A4's 0.06532 positions it as the ideal worst, marked by higher debt levels. In terms of recent credit inquiries, A3 emerges once more with a value of 0.00000, symbolizing financial stability and zero recent credit activity, whereas A4's 0.03873 reflects a higher frequency of credit checks, pointing to potential financial strain. Lastly, the optimal age for financial maturity is encapsulated in A3's ideal best value of 0.03742, while A4's worst value of 0.05346 suggests a less favorable stage for financial assessment.

Table 6

Alternative	SI Plus	Si Negative
A1	0.05864	0.05059
A2	0.04635	0.05590
A3	0.01604	0.09719
A4	0.09723	0.01337
A5	0.05510	0.04676

Table 6 presents a critical analysis of each alternative's separation from both the ideal solution (SI Plus) and the negative-ideal solution (SI Negative), integral aspects of the TOPSIS method used to rank the financial profiles of individuals (A1 through A5). These values are pivotal in determining each individual’s proximity to both the ideal best (A+) and the worst-case scenario (A-), thus forming the foundation for the overall ranking. SI Plus quantifies the closeness to the ideal solution, where a lower separation indicates a financial profile that aligns more closely with the optimal benchmark. A3 stands out with the smallest separation of 0.01604, marking it as the closest to the ideal solution. Trailing behind, A4 exhibits the largest separation of 0.09723, placing it farthest from the ideal scenario. The other individuals, A1 (0.05864), A5 (0.05510), and A2 (0.04635), occupy intermediary positions, suggesting their financial profiles are not as ideal as A3's, but still ahead of A4, the least favorable. SI Negative, on the other hand, highlights the distance from the negative-ideal solution, where a higher value represents a financial position that is further removed from the worst-case scenario. A4, once again, has the largest separation at 0.09723, positioning it as the farthest from the negative-ideal solution, signaling a relatively better financial standing. In stark contrast, A3 shows the smallest separation of 0.01337, implying that it is closest to the negative ideal and, consequently, the most financially unstable among the group.

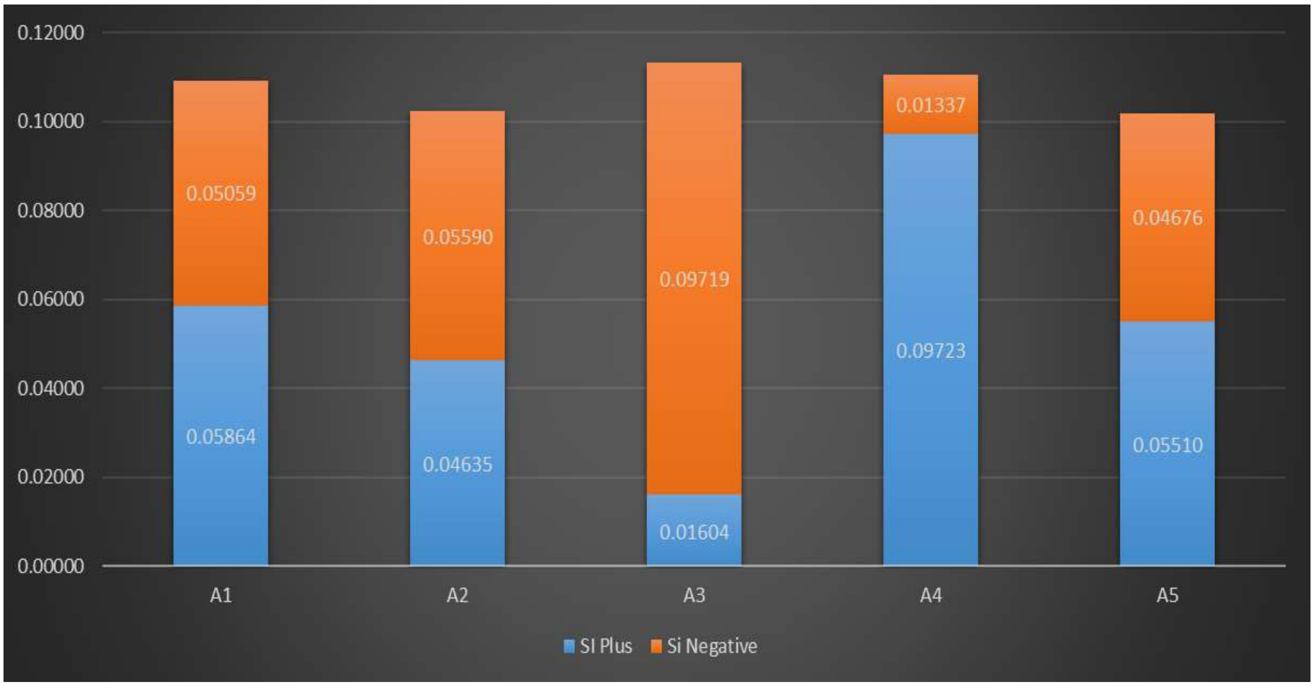

Figure 3

Figure 3 vividly illustrates the separation of each individual from both the ideal solution (SI Plus) and the negative-ideal solution (SI Negative)—two pivotal components within the TOPSIS methodology, pivotal in ranking the financial profiles of five individuals (A1 to A5). These separations serve as benchmarks to gauge how close each individual is to the ideal best (A+) and how far they stand from the worst-case scenario (A-), ultimately contributing to their final ranking. SI Plus: The separation from the ideal solution reveals the proximity of an individual to the best-case scenario. A lower value denotes a closer match to the ideal, signaling a stronger financial profile. Among the group, A3 stands out with the smallest separation of 0.01604, marking it as the closest to the ideal solution, while A4 exhibits the largest separation of 0.09723, positioning it as the furthest from the ideal. The remaining individuals—A1, A5, and A2—present intermediate separations at 0.05864, 0.05510, and 0.04635, respectively. These results suggest that A3 holds the most favorable financial profile, while A4 represents the least desirable. SI Negative: The separation from the negative-ideal solution, on the other hand, measures the distance each individual maintains from the worst-case financial scenario. A greater value indicates a larger distance from the negative ideal, highlighting better financial stability. A4 emerges with the largest separation of 0.09723, indicating it is the furthest removed from the negative-ideal scenario. In stark contrast, A3 displays the smallest separation of 0.01337, placing it closest to the negative ideal and reflecting a relative financial fragility compared to its counterparts.

Table 7

Alternative	Ci	Rank
A1	0.46314	3
A2	0.54670	2

A3	0.85835	1
A4	0.12085	5
A5	0.45903	4

Table 7 illustrates the close coefficient value (Ci) and corresponding rank for each individual (A1 to A5) derived through the TOPSIS method. The close coefficient quantifies the proximity of each alternative to the ideal solution, factoring in the distances from both the ideal and negative-ideal solutions. A higher Ci signifies superior overall performance, whereas a lower Ci reflects a less favorable financial standing. A3 leads with a Ci value of 0.85835, claiming the top rank of 1. This positions A3 as the most financially attractive option, closest to the ideal solution and farthest from the negative-ideal, solidifying its status as the prime choice. A2 follows with a Ci value of 0.54670, securing the second rank. While it is relatively near the ideal, its standing falls short of A3, signaling a solid yet not exceptional financial profile. A1, with a Ci of 0.46314, ranks 3rd, demonstrating a competitive financial position, albeit not as strong as A2's. A5, registering a Ci of 0.45903, sits in 4th place, suggesting marginally inferior financial performance compared to A1, yet still surpassing A4. A4, with the lowest Ci value of 0.12085, ranks 5th, indicating it holds the least favorable financial position, being farthest from the ideal and closest to the negative-ideal.

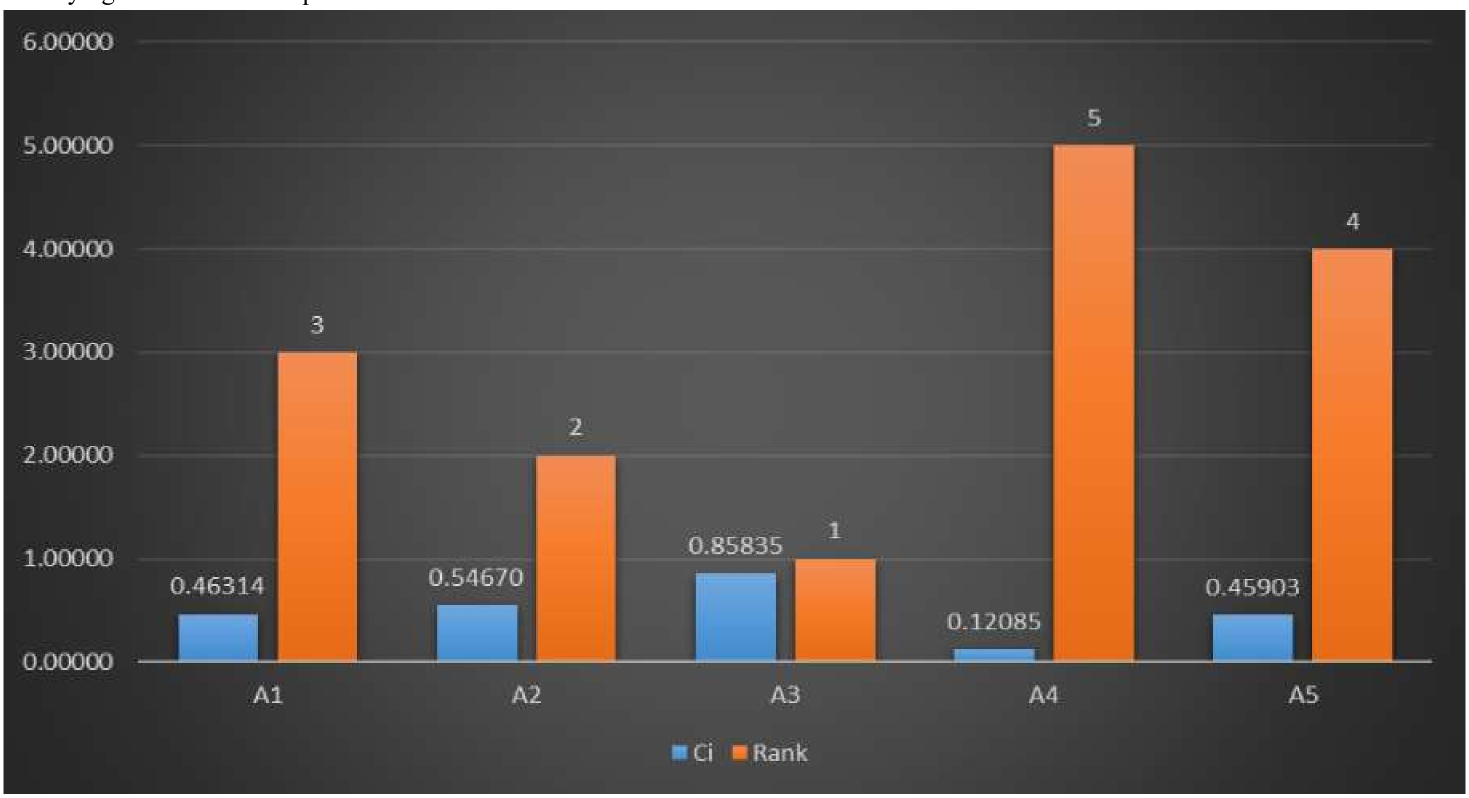

Figure 4

Figure 4 unveils the close coefficient values (Ci) and their corresponding ranks for each individual (A1 to A5), derived from the TOPSIS methodology. The close coefficient serves as a reflection of how each alternative aligns with the ideal solution, factoring in both proximity to the ideal and distance from the negative-ideal solutions. A higher Ci indicates superior overall performance, while a lower Ci signals a less favorable financial outlook. Leading the pack, A3 tops the ranks with a robust Ci of 0.85835, positioning it as the most financially promising alternative, comfortably nestled near the ideal and distant from the negative-ideal. Hot on its heels is A2, with a Ci value of 0.54670, securing the second spot. While it doesn't quite match A3 in financial strength, A2 remains reasonably close to the ideal, signaling a solid yet somewhat less outstanding financial position. A1 holds the third rank with a Ci of 0.46314—still strong, but not quite competitive enough to break into the top two. A5 trails closely behind with a slightly diminished Ci of 0.45903, placing it in the fourth spot, just shy of A1 but ahead of

A4. Lastly, A4 takes the rear with the lowest Ci of 0.12085, signaling the weakest financial profile and ranking last.The insights gleaned from the TOPSIS analysis expose clear disparities in the financial standings of the applicants. The top-ranked individual, perched nearest to the ideal solution, boasts the strongest financial profile. Following closely, the second-ranked applicant demonstrates a commendable financial stance, though not quite matching the best. The third and fourth applicants present moderately weaker financial conditions, with A4 trailing significantly behind, occupying the lowest rung on the financial ladder. This hierarchy starkly emphasizes the weight of key financial indicators—such as income, credit score, employment stability, and debt—in shaping an applicant's overall financial attractiveness and creditworthiness.

Conclusion

The adoption of AI-driven decision engines in retail banking, especially within the realm of credit card approval, marks a pivotal leap forward in the financial services domain. By leveraging the TOPSIS method for in-depth analysis, this study illuminates the power of multi-criteria decision-making as an effective tool for assessing credit card applications. This approach offers a robust, systematic, and impartial framework for evaluating applicants.The findings underscore the importance of integrating diverse criteria—such as income, credit score, employment stability, outstanding debt, recent credit inquiries, and age—creating a more comprehensive picture of an applicant's financial standing. The TOPSIS analysis, in particular, unveiled stark contrasts among the applicants. The standout performer (A3) emerged with a coefficient value of 0.85835, dramatically surpassing other candidates, showcasing the method's capacity to sharply differentiate between stronger and weaker financial profiles.The deployment of Bank's AI-Driven Decision Engine offers a powerful illustration of technological advancement in the financial sector. The outcomes are nothing short of remarkable: operational efficiency surged by 20-40%, decision-making times plummeted by 60%, and an impressive $3 million in additional annual revenue was generated. Security enhancements played a pivotal role, slashing incidents by a staggering 98%, while the adoption of cutting-edge tools like Wire Mock and Browser Stack AI models elevated testing reliability, curbing defect leakage to just 2%.These outcomes highlight the profound impact of AI integration on banking processes, especially within credit assessments. By merging conventional financial indicators with next-level analytical techniques, the system fosters decision-making that is not only faster but more accurate and dependable. This synergy drives operational improvements and amplifies customer satisfaction, with quicker transactions and more consistent results.While AI-driven systems undoubtedly offer powerful analytical capabilities, it's crucial to understand that their implementation must be embedded within a broader, more nuanced strategy—one that ensures human oversight remains a cornerstone, alongside frequent validation of the decision-making frameworks. Success hinges not merely on automated efficiency but on the delicate equilibrium between technology and human intuition, especially when unique contexts or exceptional circumstances come into play, where human judgment becomes indispensable.Looking ahead, the relentless evolution of AI technologies within banking paves the way for refining credit assessment procedures even further. We can anticipate future advancements that weave in diverse data streams, elevate real-time analytical functions, and introduce increasingly intricate risk assessment models. As financial institutions continue their digital transformation journeys, AI-driven decision engines will undoubtedly become a linchpin, particularly in retail banking, where precision and speed in credit assessments are not just desirable but imperative.This body of research significantly enhances our understanding of AI's role within the banking sector, offering invaluable insights for institutions contemplating similar tech-driven transformations. The evident success of merging AI with traditional banking methodologies points toward a promising trajectory for the future of retail banking, highlighting a shift where the fusion of cutting-edge technology and time-honored financial practices takes center stage.

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