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Designing an Intelligent Scoring System for Crediting Manufacturers and Importers of Goods in Industry 4.0

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Abstract: *Background*: The modern credit card system is critical, but it has not been fully examined to meet the unique financial needs of a constantly changing number of manufacturers and importers. *Methods*: An intelligent credit card system integrates the features of artificial intelligence and blockchain technology. The decentralized and unchangeable ledger of the Blockchain technology significantly reduces the risk of fraud while maintaining real-time transaction recording. On the other hand, the capabilities of AI-driven credit assessment algorithms enable more precise, effective, and customized credit choices that are specifically tailored to meet the unique financial profiles of manufacturers and importers. *Results*: Several metrics, including predictive credit risk, fraud detection, credit assessment accuracy, default rate comparison, loan approval rate comparison, and other important metrics affecting the credit card system, have been investigated to determine the effectiveness of modern credit card systems when using Blockchain technology and AI. *Conclusion*: The study of developing an intelligent scoring system for crediting manufacturers and importers of goods in Industry 4.0 can be enhanced by incorporating user adoption. The changing legislation and increasing security threats necessitate ongoing monitoring. Scalability difficulties can be handled by detailed planning that focuses on integration, data migration, and change management. The research may potentially increase operational efficiency in the manufacturing and importing industries.

Keywords: intelligent credit card system; blockchain integration; AI in finance; financial innovation; risk management; financial operations

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1. Introduction

In the current era, the financial services landscape is undergoing a profound transformation, particularly influenced by the evolving needs of manufacturers and importers of goods [1]. These key economic players are increasingly confronted with complex financial challenges that traditional banking systems and credit tools fail to adequately address. This gap in the financial services market represents a critical scientific problem that our paper seeks to explore and address. Our research is centered on the development of an intelligent credit card system (ICCS), which is meticulously designed to cater to the specific needs of these sectors [2]. The main research question guiding our study is how can the integration of blockchain technology and artificial intelligence (AI) create a more effective and secure financial system for manufacturers and importers? This question stems from the recognition of the limitations of existing financial solutions and the potential of emerging technologies to fill this void [3]. In addressing this question, our paper delves into the application of blockchain, known for its robust security and transparent transaction capabilities [4], and AI, renowned for its efficiency in credit assessment and risk management [4]. This dual integration forms the crux of the ICCS, aiming to revolutionize how financial transactions and credit decisions are handled in these sectors.

Furthermore, the paper sets out to achieve two primary objectives: first, to propose a comprehensive framework for the ICCS, detailing its conceptualization, development, and potential applications for manufacturers and importers [5]; and second, to rigorously evaluate the impact of this innovative system on the overall efficiency, security, and risk management in the financial operations of these sectors [6]. By undertaking this research, we aspire to contribute significantly to the field of financial technology. We aim to provide a robust theoretical and practical framework that not only addresses the current gap in financial services for manufacturers and importers but also sets the stage for future technological advancements in this domain. Through our comprehensive analysis and evaluation, this paper intends to offer insightful and actionable recommendations for industry stakeholders, thereby empowering them to navigate the complexities of the modern financial landscape.

Figure 1 provides an overview of the dynamic landscape of financial services, highlighting the growing complexities faced by manufacturers and importers. It visually represents the need for innovative solutions and the role of the proposed ICCS underpinned by blockchain and AI in streamlining financial operations and enhancing risk management.

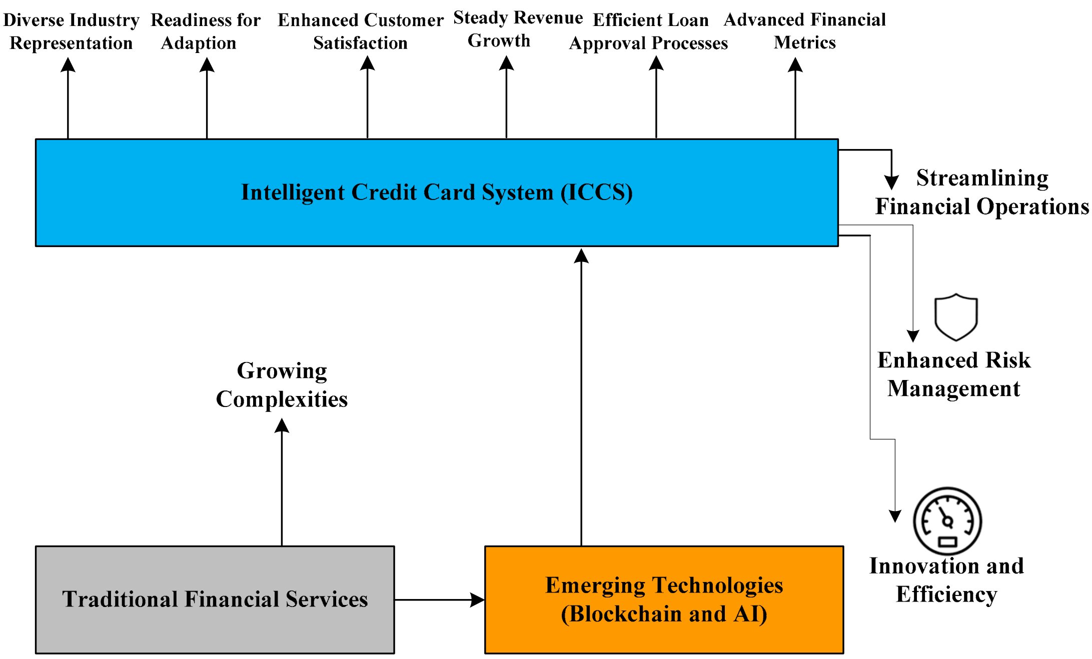


Figure 1. Evolving financial services landscape.

This research makes several significant contributions to the field of financial technology, particularly in the context of credit card systems for manufacturers and importers. The contributions can be summarized as follows:

- The proposed study sheds light on the potential for advanced technologies like blockchain and AI to significantly enhance financial performance metrics, including credit scores, loan approval rates, default rates, revenue growth, and customer satisfaction. These findings underscore the transformative capabilities of modern financial systems.
- This research highlights the potential of the intelligent credit card system to enhance the precision of credit assessments, which is of paramount importance to credit-dependent industries.

- Efficient loan-approval processes are introduced that reveal the positive influence of blockchain and AI integration on loan approval efficiency, presenting practical insights for expediting and streamlining financial workflows in the manufacturing and importing sectors.
- A risk mitigation component is introduced that shows that the system effectively reduces default rates, which is crucial for ensuring the stability of financial operations. This mitigation of credit risks has the potential to reduce financial losses for manufacturers and importers.
- Steady revenue growth is employed that demonstrates how the upward trajectory in revenue growth signifies the long-term financial benefits of implementing advanced technologies in financial systems. This finding provides a roadmap for achieving sustained financial prosperity.
- An enhanced customer satisfaction metric is used to highlight the system's role in building stronger customer relationships, which can lead to increased business growth and brand loyalty.
- Readiness for adoption is used to reveal the readiness of a significant portion of participants to embrace innovative technology in their respective industries. This readiness underscores the potential for the rapid adoption and integration of advanced financial systems.

These contributions collectively highlight the potential of the intelligent credit card system to revolutionize financial operations for manufacturers and importers, emphasizing the significant role of advanced technologies in shaping the future of financial services.

Paper Organization

The remainder of the paper is as follows. Section 2 reviews existing credit card systems, identifying limitations in the context of manufacturing and importing sectors, and explores blockchain and AI integration. Section 3 details the research methodology, including the design, data collection, and analysis. Section 4 presents the proposed method for the ICCS, emphasizing blockchain technology and AI in credit assessment. Section 5 presents the testing process, along with the experimental setup and results. Section 6 summarizes the entire paper and provides future research direction, research limitations, and implications for both Industry 4.0 manufacturers and importers.

2. Related Work

This section discusses the salient features of the existing approaches. The prevalent credit card systems, predominantly tailored for individual consumers and retail transactions, exhibit inherent limitations when applied to the intricate financial needs of manufacturers and importers. Traditional systems often lack transparency, which is something that is crucial for large-scale financial operations Tingfei et al. [7]. Moreover, credit assessment within these systems can be inadequate for assessing the unique financial profiles of manufacturers and importers, potentially leading to inefficiencies in risk management Rao et al. [8]. These limitations underscore the need for innovative financial solutions tailored to the sector. Blockchain technology has gained traction in the financial sector due to its transformative potential. It offers inherent security and transparency through its decentralized and immutable ledger system Patel et al. [9]. Within finance, blockchain finds applications in cryptocurrency, digital identity verification, and smart contracts An et al. [10]. Blockchain's decentralized nature reduces the risk of fraudulent activities, and its real-time transaction recording enhances transparency Zetzsche et al. [11]. Artificial Intelligence and machine learning have reshaped financial services by bolstering risk assessment and decision-making processes Truby et al. [12]. AI-driven credit assessment algorithms analyze vast datasets to provide more accurate and timely credit decisions Jaiwant [13], identifying nuanced patterns in financial behavior and thus improving risk management Ahmad et al. [14]. The convergence of blockchain and AI technologies presents a compelling opportunity to address the shortcomings of traditional credit card systems. Integrating blockchain enhances the security and transparency of credit card transactions Wan et al. [15], while AI-powered credit assessment augments risk evaluation (Yu et al. 2021) [16]. Additionally, blockchain's real-time transaction recording and validation mitigate risks associated with fraudulent activities, enhancing transparency Bonyuet [17].

In a similar vein, the application of the Internet of Things (IoT) in the manufacturing industry, as explored in Kalsoom et al. [18], reveals a parallel scenario in terms of the need for context-specific technological solutions. The study's identification of key IoT technologies that enhance supply chain visibility, as well as its elucidation of the benefits and challenges, parallels our exploration of blockchain and AI in finance. In light of global challenges, the need for resilience and adaptability in business operations has been further highlighted, with the fourth industrial revolution demanding strategic shifts towards more resilient and adaptable business practices Ahmed et al. [19]. This aligns with the transformative potential of blockchain and AI in financial operations. Furthermore, the role of blockchain in transforming supply chains is significant, extending beyond financial transactions and cryptocurrencies Azmat and Evanthia [20]. Its applications in enhancing supply chain resilience and agility, as well as in contractual processes within supply chains, offer insights into how blockchain can transform financial operations Azmat et al. [21]. The integration allows for efficient payment processing and real-time transaction tracking Chen et al. [22]. These interdisciplinary approaches streamline financial operations and catalyze innovation in risk management within the industry and manufacturing and importing sectors. Existing studies have begun to explore the synergy between blockchain and AI in the context of financial services. Research by Smith [23] demonstrates how blockchain's secure data sharing can enhance the training of AI models for improved credit assessment and the potential for smart contracts on blockchain to automate credit-related transactions, reducing administrative overhead.

In summary, the exploration of blockchain and AI technologies within this literature review illuminates a pivotal shift in financial services, addressing the complex needs of manufacturers and importers that traditional credit systems fail to meet. The parallels drawn with the internet of things (IoT) in manufacturing, as well as the broader implications of the fourth industrial revolution, highlight a cross-industry movement towards more resilient, adaptable, and technologically advanced operations. The convergence of blockchain and AI not only promises enhanced security and efficiency in financial transactions but also suggests a broader applicability of these technologies in improving operational transparency and risk management across various sectors. In conclusion, this review underscores the transformative impact of emerging technologies in financial operations. The integration of blockchain and AI, mirroring advancements in other sectors, like manufacturing and supply chain management, is not just an evolution of existing systems but a necessary revolution to meet the dynamic demands of the modern business world. Our research contributes to this ongoing discourse, providing insights into the future of financial services in an increasingly interconnected and technologically sophisticated global economy. Table 1 shows the characteristics and limitations of the state-of-the-art approaches.

Table 1. Existing approaches and the proposed approach to credit card systems for manufacturers and importers.

Approaches	Proposed Solutions	Features/Characteristics	Limitations
Tingfei et al. [7]	The increasingly critical issue of credit card fraud is being analyzed and detected through the application of machine-learning techniques.	It suggests an oversampling strategy based on variational automatic coding (VAE) in conjunction with traditional deep learning methods.	The suggested approach is restricted to a publicly available credit card fraud dataset that includes purchases made by cardholders in Europe. Lacks customization for B2B use and is limited for small-scale financial operations.
Rao et al. [8]	Designed for transparency in the credit card system, especially in transaction details.	Focuses on transaction detail transparency for small business management.	Limited to real-time transaction for small- and medium-sized enterprises; does not cover the large financial operations.

Table 1. *Cont.*

Approaches	Proposed Solutions	Features/Characteristics	Limitations
Patel et al. [9]	Designed to offer a content analysis and bibliometric study of blockchain technology in banking and finance that are often inadequate for assessing unique financial profiles of manufacturers and importers.	Focuses on the effects on financial applications, regulation and cybersecurity, sustainable blockchain, and financial intermediation.	Limited to bibliometric review and content analysis of scholarly works addressing the causes, effects, and applications of blockchain-based technology adoption in various intricately linked sectors, especially focusing on banking and finance; insufficient data points for customized credit evaluation; and does not cover financial growth for manufacturers and importers
An et al. [10]	Developed with consideration for the benefits and drawbacks of using AI technology to asset management, lending platforms, and banking.	Explains the fundamentals of artificial intelligence (AI), blockchain, and cryptocurrencies, as well as how they are in to the financial industry.	Limited to central bank digital currency and decentralization and consensus, which are two ideas that are related to the benefits of blockchain applications.
Zetzsche et al. [11]	Designed for the FinTech and sustainable development goals in the digital transformation.	Supports the UN Sustainable Development Goals (SDGs), in the FinTech industry; and uses progressive approach to the development of the underlying infrastructure needed to enable the digital financial transformation.	Limited to FinTech and Sustainable Development Goals (SDGs) for the digital financial transformation.
Truby et al. [12]	Automation in credit-related transactions.	Designed for automated credit processes for credit transactions to reduce excessive administrative workload and controls on the unprecedented risks to consumers.	Limited to increased administrative overhead and financial stability for consumers.
Jaiwant [13]	Designed with AI in banks to improve client support and customers with a tailored experience.	Focuses on AI in banks to improve client support and providing customers with a tailored experience, mainly concentrating on the idea of AI in the banking industry and increased the effectiveness and success of IoT banking operations.	Limited to AI applications for banking sector in general and does not cover the industry at large and manufacturers and importers and credit assessment; and may not address financial needs.
Ahmed et al. [14]	AI models adapt to specific financial dynamics.	Improves efficiency of energy management usage and transparency in industry 4.0.	Limited to AI applications for energy and management in financial sector and does not cover manufacturers and importers.
Wan et al. [15]	Integrating blockchain enhances security and transparency	Examines network delay that affects the behavior of blockchain forks and protects transaction histories.	Limited to blockchain security for network latency and transactions.
Yu et al. [16]	Designed for blockchain-enhanced security access control system	Focuses on the tracking and revocation of malicious users and allows for revocability and traceability.	Limited to data encryption and decryption for enhanced data sharing.
Bonyuet [17]	Blockchain's real-time transaction recording mitigates risks in auditing.	Enhances transparency and credit assessment, optimizing credit decisions.	Limited to blockchain and real-time transactions for auditing; does not cover complexities in implementation.
Kalsoom et al. [18]	Examines IoT's impact on supply chain visibility and manufacturing.	Identifies key IoT technologies for supply chain visibility and their benefits and challenges.	Limited to IoT applications in manufacturing; does not directly address financial operations.
Ahmed et al. [19]	Addresses the need for resilience in business operations due to global challenges.	Aligns with the transformative potential of blockchain and AI in financial operations.	Focuses on strategic shifts in business practices; limited coverage of specific financial solutions.
Azmat and Evanthia [20]	Blockchain's role in transforming supply chains beyond financial transactions.	Enhances supply chain resilience and agility; applicable in contractual processes within supply chains.	Primarily focused on supply chain applications; limited discussion on direct financial operations impacts.

Table 1. *Cont.*

Approaches	Proposed Solutions	Features/Characteristics	Limitations
Azmat et al. [21]	Investigates blockchain's impact on supply chain finance and contractual processes.	Highlights the potential of blockchain-enabled smart contracts in supply chain design.	Limited to supply chain finance and contractual processes; broader implications for financial operations not fully explored.
Chen et al. [22]	Integration of Blockchain and AI for Payment Processing	Efficient payment processing and real-time transaction tracking.	Limited to auto real industry and supply chain finance; does not cover interdisciplinary approach within the manufacturing and importing sectors.
Smith [23]	Demonstrates how blockchain's secure data sharing can enhance the training of AI models for improved credit assessment.	Highlights the potential for smart contracts on blockchain to automate credit-related transactions, reducing administrative overhead.	Limited to the practical exploration of blockchain and AI integration in financial operations and administrative overhead and does not cover manufacturer and importers in Industry 5.0.
Our Solution	Designed for manufacturers and importers, addressing complex financial needs.	Designed with the capacity of cutting-edge technologies such as blockchain and AI to substantially elevate financial performance metrics. These encompass credit scores, loan approval rates, default rates, revenue growth, customer satisfaction, etc.	Limited to streamlining financial processes within the manufacturing and importing sectors through the integration of blockchain and AI, resulting in more efficient workflows.

3. Research Methodology

This study employed a comprehensive mixed-methods research design, blending qualitative and quantitative approaches to explore the implementation and impact of an intelligent credit card system tailored for manufacturers and importers of goods. The qualitative component comprises a systematic literature review, meticulously analyzing existing credit card systems, blockchain technology, and artificial intelligence applications in the financial sector. This review aims to identify the gaps in the current systems and opportunities for innovation through the integration of blockchain and AI. For the quantitative aspect, we designed and administered a structured survey targeting a specific group of manufacturers, importers, and financial institutions. The criteria for selecting these respondents were based on their involvement in financial operations and their potential to be impacted by the adoption of an ICCS. The survey focused on gathering data about current credit card system preferences, the challenges faced with existing systems, and the perceived benefits and concerns regarding the integration of blockchain and AI technologies. The indicators for evaluating the effectiveness of the ICCS in this study include transaction efficiency, fraud detection rate, user satisfaction, and the overall cost-effectiveness of financial operations. These indicators were chosen to provide a comprehensive understanding of the system's performance from both a technical and user-centric perspective. This dual-method approach allows for a thorough exploration of the topic, combining empirical data from the surveys with insights from the literature review. The combination of these methodologies is intended to provide a holistic view of the potential and challenges of implementing an ICCS in the manufacturing and import sectors, ensuring that the research findings are well-grounded and applicable to real-world scenarios.

Figure 2 demonstrates the research methodology for investigating an intelligent credit card system for manufacturers and importers. The study applies statistical tests like chi-square, regression analysis, Cohen's d, covariance, and ANOVA to assess relationships and differences among groups. It provides a systematic approach to understanding credit card system adoption and preferences, aiming to offer valuable insights to manufacturers, importers, and financial institutions.

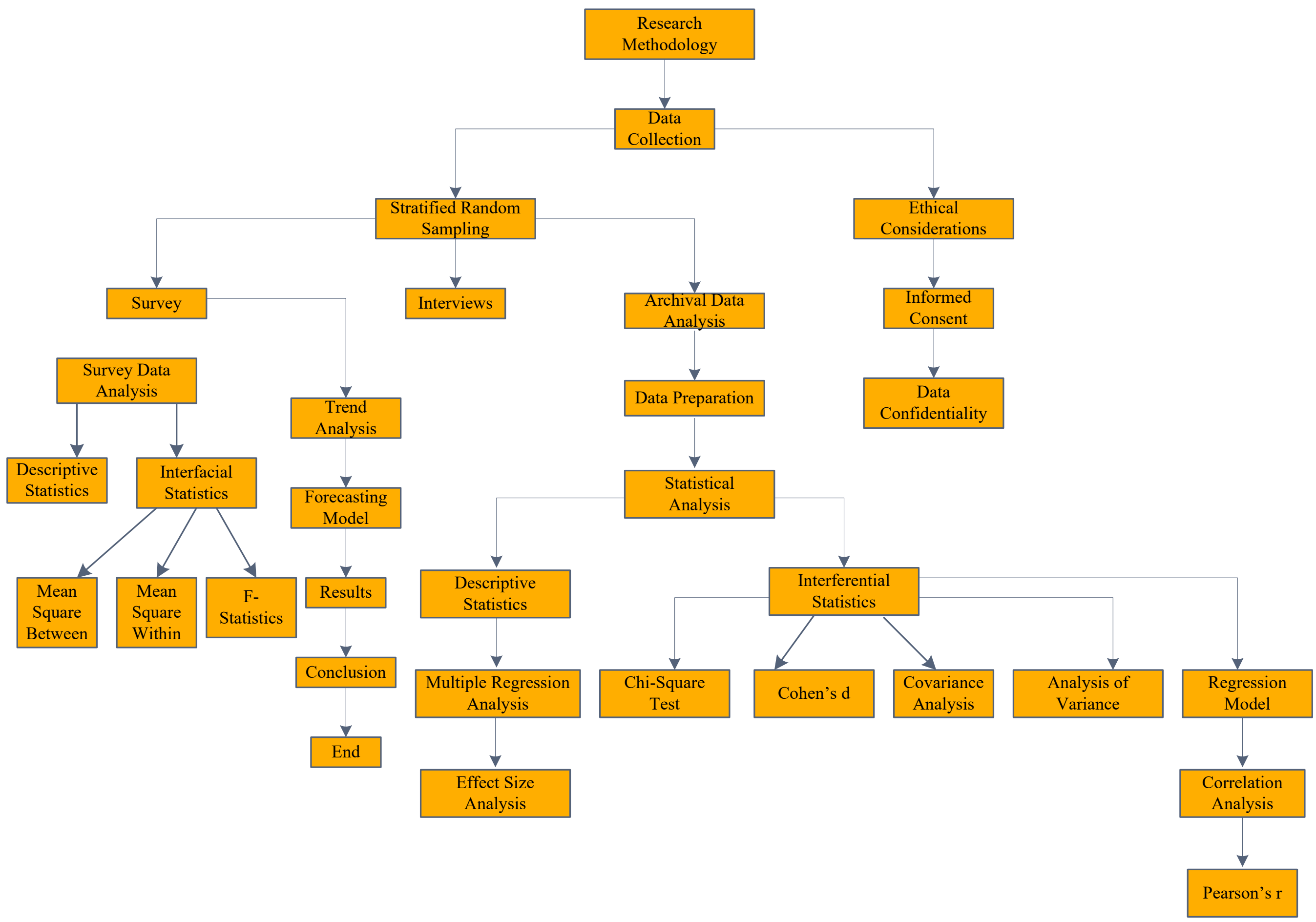


Figure 2. Research methodology for an intelligent credit card system.

3.1. Data Collection Methods

Primary data were collected through structured surveys distributed electronically to a representative sample of manufacturers, importers, and financial professionals. These surveys facilitate efficient data collection and analysis. The survey questions cover a range of topics, including system preferences, challenges faced, and opinions on the integration of blockchain and AI in credit card systems. In addition, in-depth interviews were conducted with key industry experts and stakeholders to provide qualitative insights. The interview topics are aligned with the survey questions, allowing for richer, context-specific responses. Furthermore, archival data from financial records and transaction histories were analyzed to supplement survey and interview data, enhancing the robustness of the findings. We utilize Equation (1) to determine the sample size, S_s, for every stratum, S:

$$S_s = \frac{z.P^2(1-P)}{E^2} \tag{1}$$

where z denotes the score (corresponding to the desired confidence level), P is the estimated proportion of the population, and E is the margin of error.

We partitioned the target population into distinct subgroups based on specific and relevant criteria. These criteria were carefully selected to encompass the essential dimensions of heterogeneity within our research context. The identified criteria included industry types, company sizes, geographical locations, and years of operation. By stratifying the population in this manner, we aimed to ensure that each subgroup represented a meaningful segment of the overall population. This process enables us to account for variations and characteristics specific to different segments, ultimately enhancing the precision and reliability of our research findings. The categorization by years of operation was performed to see how the credit card system's acceptance and efficacy changed over time in various industries. In our research, we employed a comprehensive and systematic approach to sample stratification to ensure that our findings are relevant and applicable to a diverse range of manufacturers, importers, and financial institutions. The sample was stratified across four industry types, manufacturing, importing, IT, and retail, allowing us to consider the unique financial practices and challenges in each sector. Company size was categorized into small (fewer than 50 employees or less than KRW 10 million annual revenue), medium (50-to-250 employees or from KRW 10 to KRW 50 million annual revenue), and large (over 250 employees or more than KRW 50 million annual revenue) to examine the impact of organizational scale. We also divided the sample into four geographical regions, North, South, East, and West, to capture regional economic variances. Finally, companies were grouped by their years of operation (1–5 years, 6–10 years, and 11+ years), enabling us to analyze the evolution of credit card system adoption over time. This detailed stratification provides a balanced representation across different dimensions.

The sample size was determined using Equation (1) to achieve a 95% confidence level and a 5% margin of error, accounting for the strata created during the stratification process. This formula ensures that each stratum had an adequate representation within the sample, allowing for robust sector-specific analyses. The data collection methods for different strata can be described mathematically as follows:

$$C_s = \sum_{i=0}^{t_s} i\{S_v + I_n + D_a\} \tag{2}$$

where C_s denotes stratum for the data collection process, S_v denotes survey, I_n represents interview, t_s denotes total stratums, and D_a denotes archival data analysis.

The probability, P_b, of credit card system adoption within each stratum can be estimated as follows:

$$P_b = \sum_{i=0}^{S} (P_s)i + (A_s)i \tag{3}$$

where P_s denotes for total number of participants in stratum, and A_s represents for number of adopters in stratum.

A multiple regression analysis is employed to assess the influence of multiple independent variables on credit card system adoption. Thus, adoption that represents the dependent variable, A_d, can be determined as follows:

$$A_d = \left\{E_f, U_e, O_f, E_t\right\} \tag{4}$$

where E_f denotes for economic factor; U_e denotes for user experience; O_f denotes other factors that signify the strength and direction of their influence on credit card system adoption; and E_t represents the error term, encompassing unexplained variations or factors, which are not considered in the model.

Equation (4) helps us assess the complex relationship between various factors and the adoption of the credit card system, allowing us to gain insights into the significance and direction of these relationships. We employ a multiple regression analysis to assess the influence of multiple independent variables on credit card system adoption. Throughout the sampling and data collection processes, ethical considerations are paramount. Informed consent was obtained from all survey and interview participants, guaranteeing their voluntary participation and anonymity. Data confidentiality was rigorously maintained, and all research activities adhered to relevant ethical guidelines and regulations.

3.2. Data Analysis Method

We utilized specialized software to conduct both descriptive and inferential statistical analyses of the survey responses. The descriptive statistics were employed to provide a comprehensive overview of the participants' demographics and their preferences regarding the credit card system. This included calculating measures such as mean, median, mode (to identify central tendencies), standard deviation, range (to understand variability), and frequency distributions (to understand the distribution of responses across various categories). Inferential statistics were applied to assess the significance of various factors influencing the adoption of the intelligent credit card system and to gauge the potential benefits of integrating blockchain and AI technologies into this system. This involved the use of statistical tests such as chi-square tests for categorical data analysis, t-tests and ANOVA for comparing group means, and regression analysis for examining relationships between variables. Furthermore, the margin of error (E) in our study was calculated in a manner akin to determining a confidence interval. This calculation was crucial for establishing the range within which we can reasonably expect the true population parameter to fall. The margin of error serves as a critical gauge for assessing the precision of our findings, thus ensuring that our results accurately represent the broader population of manufacturers, importers, and financial institutions. Such an approach in statistical analysis ensures a robust and comprehensive understanding of the data, enabling well-substantiated conclusions to be drawn from our research, ensuring that the results accurately represent the broader population of manufacturers, importers, and financial institutions.

$$C_i = \frac{z.\sigma}{\sqrt{n}} \tag{5}$$

where C_i is the confidence interval that is a range of values which provide a level of confidence about where the true population parameter is likely to be. It helps estimate the precision of a statistical result. The z-sore is the value that corresponds to various confidence levels of confidence; σ is the standard deviation, which represents the amount of variation or dispersion in a set of data; and $\sqrt{n}$ is the square root of the sample size, S_s.

We collected data on the adoption rates of the intelligent credit card system among various manufacturers, importers, and financial institutions. We are interested in assessing how dispersed these adoption rates are within each group. The adoption rates within each group are similar. Therefore, the margin of error, E, can be determined as follows:

$$E = \forall\gamma \times \sqrt{\frac{\sigma^2}{S_s}} \tag{6}$$

where $\forall\gamma$ denotes the quantiles which are points in a distribution that represent the rank order of its products, and S_s is sample size.

In our study, the margin of error, E, helps determine the precision of our estimates regarding the ICCS's adoption rates among manufacturers, importers, and financial institutions. Thus, there is a need for a central statistical measure that can be determined as follows:

$$\overline{X} = \frac{1}{n}\sum_{i=0}^{n} X_i \tag{7}$$

where X_i denotes data values and then dividing the total by the number of data points (n). This measure serves as a representation of the average value, a fundamental component for analyzing the various aspects of credit card system preferences and adoption among manufacturers, importers, and financial institutions.

Understanding the spread and consistency of data points regarding credit card system preferences and adoption among manufacturers, importers, and financial institutions is crucial. The standard deviation (σ) is a pivotal statistical measure for this purpose. It quantifies the variability of data, providing valuable insights into how tightly or loosely data points are distributed around the mean $(\overline{X})$.

A small standard deviation indicates that most companies have adoption rates close to the mean, creating a precise and focused cluster. Conversely, a large standard deviation implies that adoption rates vary widely from the mean, forming a more dispersed distribution.

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2} \tag{8}$$

We utilize the standard deviation (σ) as a pivotal statistical measure. This metric plays a crucial role in quantifying the dispersion or variability of data points. It is computed by taking the square root of the average of the squared differences between each data point and the mean ($\overline{X}$). The application of standard deviation is integral to our data analysis, as it allows us to assess the spread and consistency of credit card system preferences and adoption among manufacturers, importers, and financial institutions.

Variance (Var(X) measures are employed to measure the average of the squared differences between each data point and the mean. This is like assessing how much the adoption rates of the intelligent credit card system differ from the average. A small variance suggests that most data points are close to the mean, while a larger variance indicates a broader spread.

$$\mathrm{Var}(X) = \frac{1}{n}\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2 \tag{9}$$

Variance (Var(X)) serves as a fundamental measure that assesses how data points deviate from the mean ($\overline{X}$). This critical statistical metric is calculated as the average of squared differences between each data point and the mean. Variance plays a central role in our data analysis, allowing us to understand the extent to which credit card system preferences and adoption vary among manufacturers, importers, and financial institutions.

Pearson's correlation coefficient (r) assesses the linear relationship between two variables (e.g., intelligent credit card system adoption and economic factors); it allows us to measure the relationship. If r is close to 1, it means a strong positive linear relationship, much like when one variable increases and the other does too. If r is close to -1, it indicates a strong negative linear relationship, where one variable decreases as the other increases. When r is close to 0, there is little-to-no linear relationship.

$$r = \frac{\frac{1}{n}\sum_{i=1}^{n}\left(X_i - \overline{X}\right)\left(Y_i - \overline{Y}\right)}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2\sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2}} \tag{10}$$

Equation (10) is used to compute descriptive statistics, assess the correlation between variables, and derive meaningful insights from the data. The Pearson's correlation coefficient (r) plays a crucial role in understanding the relationships between variables in our study. This analysis provides valuable insights into the interplay between different variables and their impact on the intelligent credit card system.

3.3. Data Calculation Model

The data calculation model plays a vital role in the credit card system. Thus, assessing the independence of categorical variables is necessary. It is used to compare observed and expected frequencies in a contingency table. The chi-square test assesses if there is a significant relationship between these variables. We employ the chi-square (X^2) test to assess the independence of categorical variables within a contingency table.

$$X^2 = \sum \frac{\left(O_i - E_i\right)^2}{E_i} \tag{11}$$

where O_i denotes the observed frequencies with their expected counterparts (E_i) in each cell. By doing so, we can gain insights into how different factors impact the intelligent credit card system's preferences and adoption among manufacturers, importers, and financial institutions. Thus, an affect size represents the standardized difference between two means ($\overline{X}1$ and $\overline{X}2$), and it can be determined as follows:

$$d = \frac{\overline{X}1 - \overline{X}2}{s} \tag{12}$$

A negative covariance implies an inverse relationship, where higher credit card adoption is associated with lower revenue.

$$\mathrm{Cov}(X, Y) = \frac{1}{n}\sum_{i=1}^{n}\left\{\left(X_{\mathrm{i}} - \overline{X}\right)\left(Y_{\mathrm{i}} - \overline{Y}\right)\right\} \tag{13}$$

Covariance (Cov) measures how two variables, X and Y, change together. It indicates whether they have a positive or negative relationship. In this equation, we calculate Cov(X, Y) by taking the average of the product of the deviations of each data point from their respective means. A positive Cov(X, Y) suggests that when X increases, Y tends to increase, and vice versa. A negative value implies an inverse relationship between X and Y. This equation helps us understand how different factors relate to credit card system preferences and adoption among manufacturers, importers, and financial institutions.

We can determine whether any observed differences in their adoption rates are likely to be representative of broader trends. This enables us to draw meaningful conclusions about the impact of various factors on credit card adoption in these groups.

$$t = \frac{\overline{X}1 - \overline{Y}2}{\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \tag{14}$$

In our proposed study, we compare various characteristics, such as preferences or perceptions, between different groups within our sample, like manufacturers, importers, and financial institutions. It helps us identify if certain variables significantly influence credit card system adoption. The differences among means are necessary when dealing with more than two groups. In the context of our research, we utilize this equation to determine whether there are statistically significant differences in credit card system preferences or adoption across various categories, such as industry types. The F-statistic serves as a critical tool for identifying variations in the data and comprehending how these variations relate to our research variables.

$$\mathrm{F} = \frac{MSB}{MSW} \tag{15}$$

where F-statistic (F) is a statistical measure used to assess whether there are significant differences among the means of more than two groups.

In Equation (15), we divide the variance between the group means by the variance within each group. The F-statistic provides a ratio of these two variances. If this ratio is sufficiently large, it suggests that there are significant differences between the group means, indicating that the groups are not similar due to random variation. In our research, we use this F-statistic to assess whether there are statistically significant differences in credit card system preferences or adoption across various categories, such as industry types.

In our case, the credit card system adoption can be elucidated by the independent variables. A high R^2 value indicates a well-fitting model, implying that the independent variables effectively expound the variation in credit card system adoption.

$$R^2 = 1 - \frac{SSR}{SST} \tag{16}$$

The R^2 value represents the goodness of fit of a regression model. It quantifies the proportion of the variation in the dependent variable (credit card system adoption) that can be explained by the independent variables. A high R^2 indicates a well-fitting model, implying that the independent variables effectively explain the variation in credit card system adoption.

We refine the understanding of credit card system preferences and adoption, *P (A/B)*, as new information or data become available that can be calculated as follows:

$$P\ (A/B) = \frac{P\left(\frac{B}{A}\right)\ P\ (A)}{P\ (B)} \tag{17}$$

We assessed whether two independent groups exhibit significant differences. Within our study, we compared credit card system adoption or preferences between distinct categories, such as manufacturers and importers. It helped us determine whether there are significant differences in the preferences of these groups.

$$U = n_1 n_2 + \frac{n_1(n_1+1)}{2} - R_1 \tag{18}$$

where U represents a statistic used to compare the preferences of two independent groups; $n_1 n_2$ represents the sample sizes of the two independent groups being compared in our research, such as manufacturers and importers; and R_1 is the sum of the ranks of the group with the smaller sample size (n_1) in a ranked dataset.

We also need to determine whether significant differences exist in credit card system adoption or preferences across multiple categories, such as industry types or geographical regions. Equation (19) can be instrumental in identifying variations among these groups, *H*.

$$\mathrm{H} = \frac{12}{k(k+1)} \sum r_i^2 - 3(k+1) \tag{19}$$

where k denotes the number of groups or categories under consideration; and the symbol ($\sum$) signifies the summation of a series of values**,** which specifically involves the summation of the squared ranks (r_i) within each group. Here, (r_i) represents the rank assigned to individual data points within their respective groups. We can determine whether there are substantial differences in credit card system adoption or preferences across multiple categories, such as various industry types or geographical regions. We should understand how different factors influence the frequency of credit card system adoption, providing valuable insights into its determinants.

$$P(Y = y) = \frac{e^{-\lambda}\ \lambda^y}{y!} \tag{20}$$

where P denotes the probability that observes a specific count (y) based on a given rate parameter (λ).

Finally, we also need to analyze trends and patterns related to credit card system adoption over time. It helps identify potential trends and patterns in the data, facilitating better decision-making and a better understanding of how adoption may evolve in the future forecasted value, given by the following:

$$F\ (t) = \alpha Y\ (t) + (1-\alpha) F\ (t-1) \tag{21}$$

where $F\ (t)$ represents the forecasted value at a specific time point, t; $Y\ (t)$ is the actual observation or data point at that time; and $F\ (t-1)$ is the forecasted value at the previous time point. The (alpha) is a smoothing factor, which determines the weight given to the most recent observation ($Y\ (t)$) versus the previous forecast ($F\ (t-1)$). A smaller α places more weight on past forecasts, while a larger α emphasizes the most recent data point. The choice of α depends on the characteristics of the time series data and the level of responsiveness desired in the forecast.

Our research methodology provides a comprehensive framework for analyzing credit card system preferences and adoption.

4. Proposed Method for the Intelligent Credit Card System

The intelligent credit card system represents a groundbreaking approach to financial services tailored to meet the distinctive demands of manufacturers and importers. This section outlines the proposed method, emphasizing the key components that underpin the ICCS, offering security, transparency, and efficiency in credit card transactions. The ICCS represents a paradigm shift in the world of financial services, meticulously engineered to meet the distinctive demands of manufacturers and importers. At its core, the system embodies a synergistic blend of cutting-edge components, each meticulously selected to fortify financial operations, enhance risk management strategies, and provide an exceptional user experience. Blockchain technology lies at the heart of the ICCS, symbolizing the very foundation upon which its security and transparency are built. This revolutionary technology ensures that every transaction, the lifeblood of financial operations, is conducted within a secure and transparent environment. The mathematical essence of blockchain's role, B_r, for manufacturers and importers, $\ddot{Y}$, can be expressed as follows:

$$B_r = \left(\sum_{i=1}^{\forall\ddot{Y}} S_t.K\right)\left(\sum_{i=1}^{\forall\ddot{Y}} T_r.\tau\right)\left(\sum_{i=1}^{\forall\ddot{Y}} I_t.bl.ld\right) \tag{22}$$

where S_t denotes the security, T_r is the transparency, I_t denotes immutability, τ denotes the transparency features, $\forall\ddot{Y}$ denotes the total numbers of the manufacturers and importers, K is the secret key, bl denotes the blocks, and ld is the ledger.

Utilizing advanced cryptographic algorithms, blockchain guarantees the integrity and security of transactions. It secures each financial interaction with an unbreakable digital seal, rendering tampering and fraud virtually impossible. The decentralized nature of blockchain permits real-time tracking and verification of every credit card transaction. This transparency is indispensable for a sector that thrives on timely and trustworthy transactions.

Smart contracts, integral to the ICCS, exemplify the embodiment of automation and efficiency within the system. Thus, smart contracts can be summarized as follows:

$$S_C = \{A_t, E_c, T_i\} \tag{23}$$

where S_C represents smart contracts, which are self-executing digital agreements that automate credit-related transactions. They consist of A_t, which denotes automation, signifying that smart contracts automate financial processes; E_c represents the streamlined and efficient execution of credit-related transactions; and T_i denotes trustlessness. By automating credit-related transactions, smart contracts reduce administrative overhead, resulting in cost savings and minimized error rates. The ICCS employs AI to perform credit assessments, providing precision and timeliness, which are paramount in an ever-evolving sector. The mathematical essence of AI and machine learning within the system can be expressed as follows:

$$AI\_ML = \{P_n, T_s, A_t\} \tag{24}$$

where AI_ML denotes AI and machine learning; P_n stands for precision, which indicates the high level of accuracy and precision; T_s denotes timeliness that highlights their ability to provide real-time credit decisions; and A_t signifies the adaptability that AI and machine-learning algorithms can adapt to changing conditions within the financial sector, ensuring continued relevance and accuracy. Data security is a non-negotiable aspect of the ICCS, reflecting its commitment to safeguarding sensitive financial information. The data security within the system can be obtained as follows:

$$D_s = \{C_e, A_c, E_n\} \tag{25}$$

where C_e which denotes confidentiality and signifies the encryption and protection of sensitive financial data to maintain its confidentiality; A_c denotes access control, emphasizing the stringent control over who can access and manipulate financial data; and E_n stands for encryption, which is a crucial measure to ensure that sensitive information remains indecipherable to unauthorized parties, even if intercepted during transmission. The proposed ICCS recognizes the importance of user satisfaction, offering extensive customization options and a user-friendly interface. This dedication to user-centric design ensures that each user's unique financial requirements are met. The user-centric features, U_c, could be determined as follows:

$$U_c = \{C_n, U_y, S_n\} \tag{26}$$

where C_n represents the customization that enables the users to tailor the system to their specific financial needs; U_y, denotes usability, which signifies the user-friendly interface; and S_n indicates the focus on enhancing user satisfaction by placing users at the center of the system's design.

Figure 3 demonstrates the core components of the intelligent credit card system designed to meet the specific requirements of manufacturers and importers. The ICCS integrates blockchain technology, ensuring the security and transparency of transactions and smart contracts for automating processes, while ensuring trust. AI and machine learning are utilized for precision and real-time credit assessments.

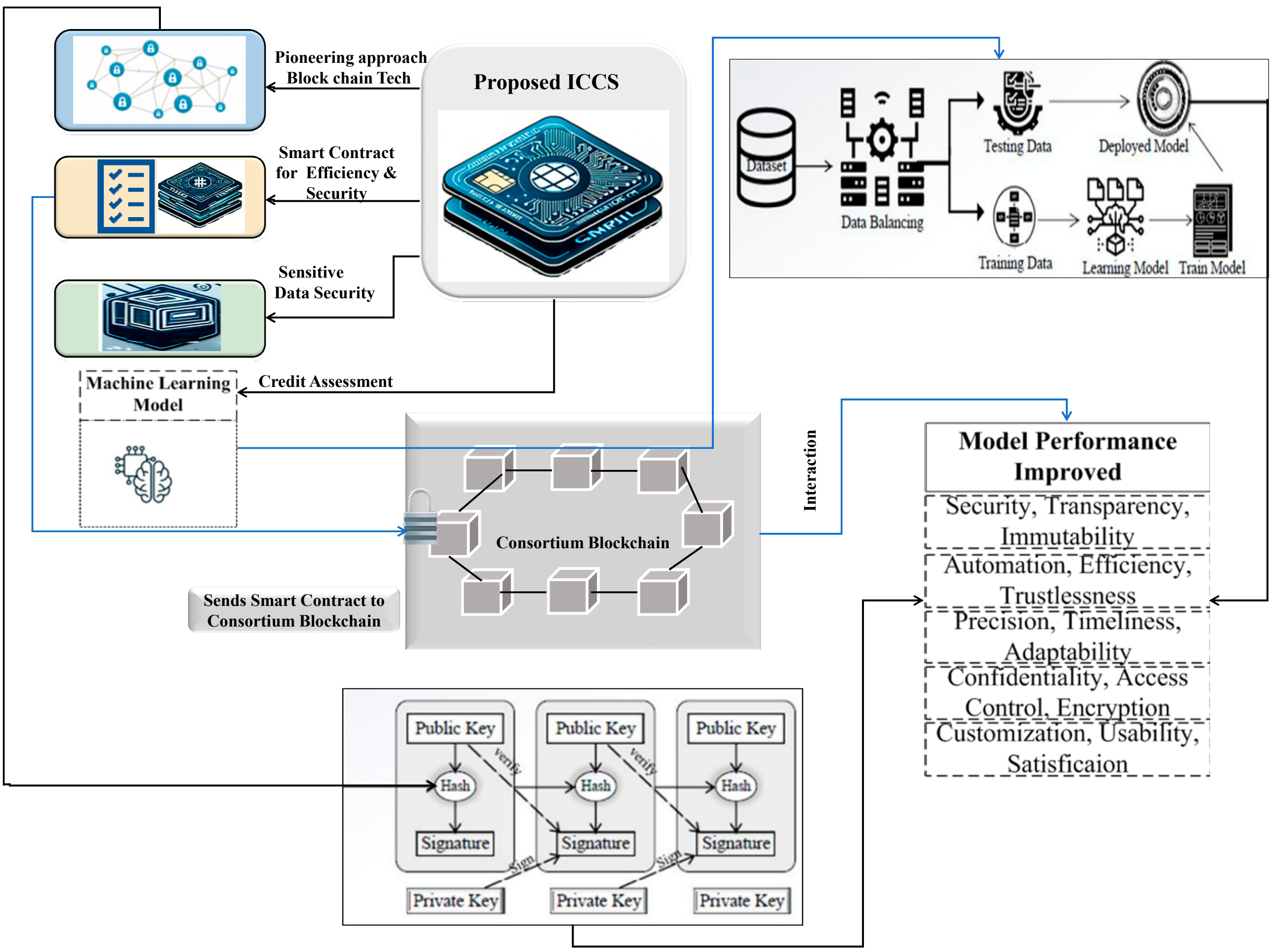


Figure 3. Intelligent credit card system with blockchain and AI integration.

4.1. Blockchain-Based Security in Credit Cards

Blockchain technology in the intelligent credit card system plays a pivotal role in preserving the integrity of financial transactions while instilling an atmosphere of trust and transparency [24,25]. This immutability starts with the creation of unalterable transaction records. Each new transaction is cryptographically linked to the previous data, creating an unbreakable chain of records.

$$B_t = \{T_n, I_m, L_k\} \tag{27}$$

where B_1 denotes the blockchain transaction data linkage; T_n denotes transaction data, representing the specific information related to a financial transaction; I_m represents immutability; and L_k denotes the linkage, which emphasizes the cryptographic linking of new transaction data with the previous data, creating an unbreakable chain of records. The blockchain transaction data linkage signifies that each new transaction datum is cryptographically linked to the previous data that form an unbreakable chain [26–28].

The significance of this immutability extends to safeguarding against unauthorized modifications. Thus, the financial data within the intelligent credit card system remain incorruptible. It provides a resilient and dependable foundation upon which the financial transactions of manufacturers and importers can be conducted with a high degree of confidence and security.

4.1.1. Security Distribution for Unassailable Transactions

This feature contributes significantly to enhancing the security of financial transactions within the system. The absence of a central authority is a defining characteristic of blockchain. This decentralization ensures that there is no single entity with the power to control or manipulate transaction data [29,30]. Thus, a single point of failure is eliminated. This feature is particularly important in a sector where substantial financial transactions occur, as it mitigates risks associated with fraud, collusion, or data breaches. One of the key benefits of decentralization is the elimination of central points of vulnerability. By distributing transaction data across a network of nodes, blockchain reduces the likelihood of malicious attacks or unauthorized access. The decentralization can be determined as follows:

$$D = \{A_a, D_d, R_m\} \tag{28}$$

where A_a denotes the absence of central authority, an attribute which signifies the core principle of blockchain technology; D_d denotes the distribution of transaction data that decentralization involves in the distribution of transaction data across a network of nodes, enhancing the system's security and reliability; and R_m represents risk mitigation. The decentralization effectively mitigates risks associated with fraud, collusion, or data breaches by eliminating central points of vulnerability, and it can be determined as follows:

$$C_m = \{M_a, N_n, L_a\} \tag{29}$$

where C_m denotes the consensus mechanism, M_a denotes a majority agreement, N_n denote network nodes which represent the various participants in the blockchain network, and L_a represents ledger accuracy. The decentralization within the blockchain framework forms the backbone of security in the intelligent credit card system. It ensures that financial transactions are conducted with the highest level of security, which reduces the risks associated with centralization and offers a robust and dependable foundation for financial activities in the manufacturing and importing sectors. Thus, the blockchain decentralization mechanism can be constructed as follows:

$$D_m = \{N_n, C_s, V_y\} \tag{30}$$

where N_n denotes the nodes, which signifies the multiple participants or computers that form the network; C_s denotes for consensus, which defines the mechanism by which nodes agree on the validity of transactions; and V_y denotes the vulnerability reduction, which underlines the benefit of distributing transaction data across nodes to reduce the risk of attacks and unauthorized access.

4.1.2. Safeguarding Sensitive Financial Data

Blockchain technology uses advanced cryptographic algorithms to secure the security of the intelligent credit card system [31,32]. These cryptographic measures are essential in protecting the sensitive financial information of users. One of the primary methods employed is data encryption, which is determined as follows:

$$C_y = \{E_n, D_t, A_c\} \tag{31}$$

where C_y denotes cryptographic security measures, which are essential for protecting sensitive financial information; E_n denotes the encryption process that transforms data into an unintelligible format, which ensures confidentiality; D_t signifies data transmission security; and A_c denotes the access control that indicates rigorous control over who can view and manipulate financial data. These cryptographic measures provide a multi-layered defense against potential threats and data breaches.

Encrypting sensitive data and protecting data transmission ensure that consumers' financial information is secure. This comprehensive approach to cryptographic security greatly improves the system's overall security and integrity [33,34]. Blockchain technology's role in ensuring security within the intelligent credit card system extends to its use of advanced cryptographic techniques. Cryptography is utilized to encrypt sensitive financial data, rendering them indecipherable to unauthorized parties [35,36].

4.1.3. Financial Transformation Using Smart Contracts

Smart contracts constitute a groundbreaking feature of the blockchain-based security within the ICCS. These self-executing contracts bring about a paradigm shift in the way financial agreements are facilitated and enforced. One of the central advantages of smart contracts is their capability for automated agreement execution. Traditional financial agreements often necessitate intermediaries and manual execution, leading to potential delays and disputes [37]. In contrast, smart contracts eliminate the need for intermediaries and automate the execution of predefined credit terms. This automation significantly reduces the potential for disputes and errors, streamlining financial transactions within the system.

$$S_c = \{A_u, T_s, U_t\} \tag{32}$$

where S_c represents smart contracts for automated transactions; A_u denotes automated execution, which highlights the self-executing nature of smart contracts; T_s signifies the transaction streamlining; and U_t denotes user trust, which emphasizes that smart contracts operate with transparency and trustlessness. These attributes enhance efficiency and security in financial interactions.

Moreover, smart contracts operate with transparency and trustlessness. They are designed to function openly and transparently on the blockchain. The code that governs these contracts is visible to all parties involved, and its execution is trustless. This means that parties can rely on the code's execution without the need for intermediaries or third parties to oversee the process. The self-executing nature of smart contracts ensures that the terms of credit agreements are enforced as intended.

4.1.4. Fostering Trust and Accountability Process

The trust and accountability can be fostered by employing the transparency that is a foundational characteristic of blockchain technology, which serves as a cornerstone for enhancing security within the intelligent credit card system. It ensures that users have real-time visibility of all credit card transactions. Therefore, transparency for real-time monitoring (T_r) within the system (S) can be determined as follows:

$$T_r = \left(\sum_{i=1}^{S} R_t F_t \right) \left(\sum_{i=1}^{S} I_h F_t \right) \tag{33}$$

where R_t denotes the real-time visibility, which allows the users to instantly access and monitor detailed information about their financial transactions, F_t; and I_h denotes the immutable transaction history, which ensures the trustworthiness and authenticity of all transactions. Users of the intelligent credit card system benefit from real-time visibility into their financial transactions [38]. This means that they can instantly monitor and access detailed information about their financial activities. The real-time transparency empowers users with immediate insights into their financial dealings. The transparency within the intelligent credit card system provides users with a real-time view of their financial transactions, enabling them to promptly identify any irregularities. The immutable transaction history is recorded on the blockchain, which reinforces trust and accountability by allowing users and stakeholders to verify the authenticity of all transactions. In this setting of credit cards, blockchain technology provides enhanced security, transparency, and trust in financial transactions. It reduces the risk of fraud, minimizes the need for intermediaries, and ensures that transaction histories are reliable and immutable [39–42]. Manufacturers, importers, and financial institutions can benefit significantly from these blockchain advantages in credit card transactions [43–46].

Figure 4 illustrates how blockchain technology is leveraged to enhance security in credit card transactions. It is concluded that the blockchain's decentralized nature, cryptographic security measures, and smart contracts play pivotal roles in ensuring the integrity of financial operations. Decentralization eliminates central points of vulnerability, reducing the risk of fraud and data breaches. Advanced cryptographic techniques, including data encryption and access controls, safeguard sensitive financial information. Smart contracts automate the execution of credit terms, streamlining transactions and reducing the potential for disputes. The transparency inherent in blockchain allows users to have real-time visibility regarding their transactions, fostering trust and accountability. Algorithm 1 explains how blockchain technology works in order to secure commodities.

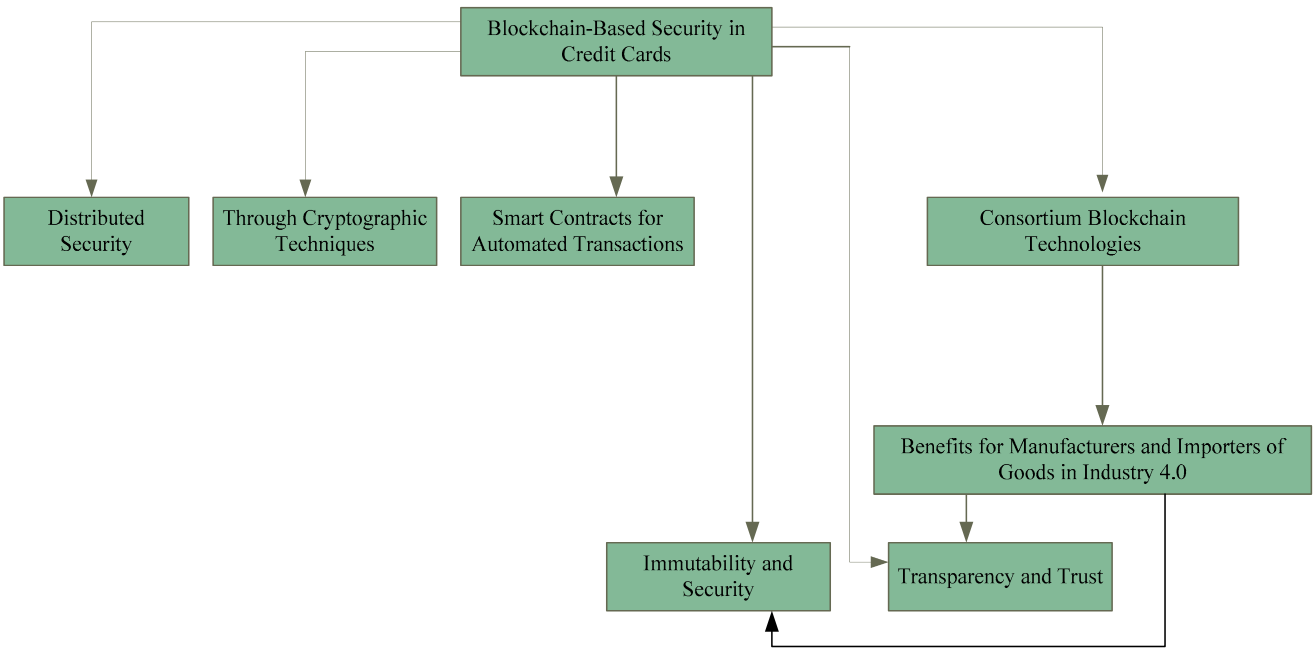


Figure 4. Enhancing credit card security with blockchain.

Algorithm 1: Securing commodities using consortium blockchain technology

1. **Initialization** {Im: Importers; Mf: Manufacturer; B_{cn}: Consortium blockchain; Ser: Secure request; O: Order; Cm: commodities; R: Request; γ: Secure}
2. **Input {}**
3. **Output{}**
4. Im sends $Ser \rightarrow B_{cn}$
5. **Set** $Mf \stackrel{m}{=} B_{cn}$
6. $B_{cn} \leftrightarrow Mf$
7. Mf accepts O and respond B_{cn} and $B_{cn} \rightrightarrows Im$
8. Get $Im \leftarrow Ser(Cm)$
9. If $Im(R) \equiv Ser(Cm)$ then
10. **Do** $Cm \cong \gamma$
11. **Else If** $Im(R) \neq Ser(Cm)$ then
12. **Do** $Cm \nexists \gamma$
13. **End-else**
14. **End-if**

Algorithm 1 secures commodities by utilizing consortium blockchain technology. Step 1 defines the variables that will be used in the algorithm. Input and output are provided in Steps 2–3. Step 4 depicts the behavior of importers who make secure queries via blockchain. Steps 5–6 verify that the manufacturers are likewise linked to the consortium blockchain technology. Steps 7–8 depict the order acceptance process and its response to the consortium blockchain, after which the blockchain transmits the order acceptance process to importers. Steps 9–10 validate that if the importer's request matches the secure commodities request, the commodities are considered secure. Steps 11–12 show that if the importer's request does not match the secure request for commodities, the commodities are unsecured.

The incorporation of AI and machine learning into credit assessment processes marks a profound shift in how creditworthiness is evaluated for manufacturers and importers.

Figure 5 demonstrates the AI-driven credit assessment process, providing a concise overview of how artificial intelligence and machine learning are applied in evaluating creditworthiness for manufacturers and importers. The process initiates with data collection, where relevant data sources are gathered. These data then undergo data preprocessing to ensure their quality and readiness for analysis. Subsequently, "feature engineering" involves selecting and constructing meaningful variables for predictive modeling. The pivotal step occurs in the machine learning model, where predictive analytics and machine learning algorithms are employed to assess credit risk. The risk assessment phase evaluates the creditworthiness of the entity under consideration. Decision-making follows, where informed decisions are based on the risk assessment outcomes. Finally, the credit decision step determines whether credit is extended. This succinctly encapsulates the sequential stages of AI-driven credit assessment, showcasing the process's logical progression from data collection to the final credit decision. Moreover, AI and machine learning play a pivotal role in revolutionizing credit assessment for manufacturers and importers. These technologies introduce several key advancements, such as AI algorithms, which are capable of analyzing vast datasets that encompass financial histories, market trends, economic indicators, and even non-traditional data sources [47–52]. The blockchain's immutable ledger can be leveraged to create an unalterable record of data access and modifications, thus providing transparency and aiding in the detection of unauthorized changes. Data minimization practices, where only the necessary data are collected and retained, help reduce the potential impact of a breach [53].

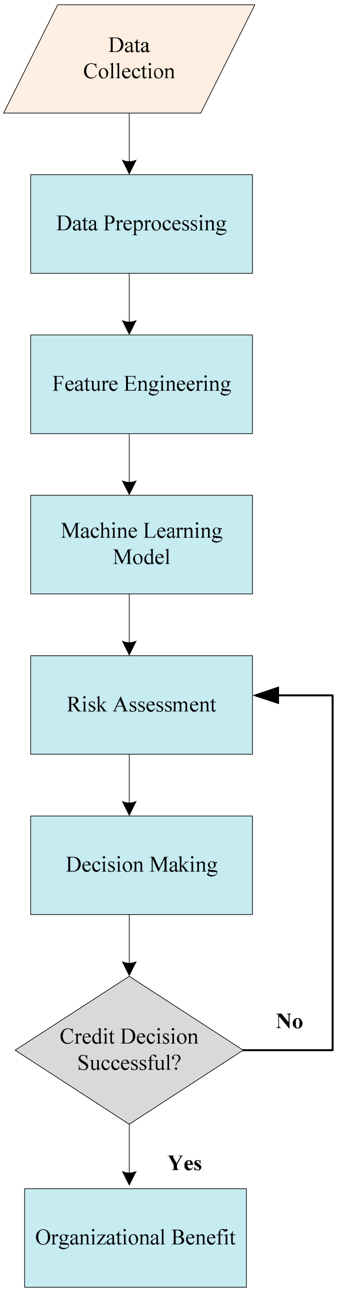


Figure 5. AI-powered credit evaluation process.

5. Testing Process with Experimental Setup and Results

This section provides the testomg process, including the experimental setup and results.

5.1. Testing Process

This process involves categorizing the participants by their industry affiliations. It demonstrates the number of participants in each industry category, providing a clear overview of the distribution across manufacturing, importing, IT, and retail and the total number of participants. The data reveal a diverse representation among the survey respondents, with participants spanning various sectors, thus enriching the study's insights with a broad spectrum of perspectives and experiences. Figure 6 shows the numbers of the participants.

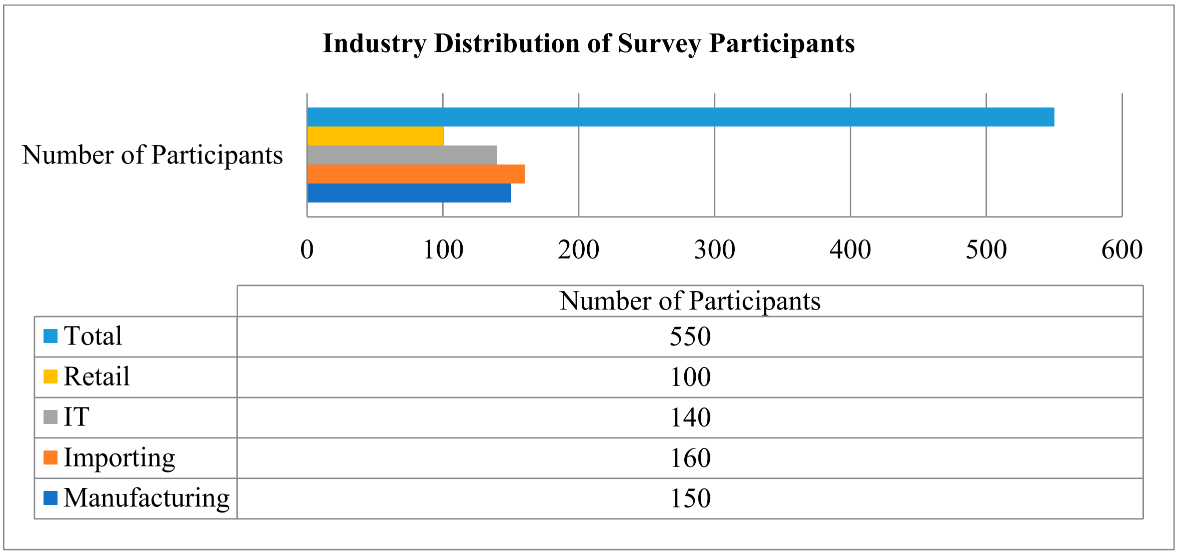


Figure 6. Industry distribution of survey participants.

The manufacturing and importing sectors should provide feedback on the current credit card systems. Thus, the perceptions come from the individuals listed in Table 2. A summary of the responses from the participants regarding the limitations and challenges of the traditional credit card systems is given. Particularly, the majority of respondents expressed concerns about security, high transaction fees, and limited transparency. Furthermore, to scale the willingness of manufacturers, importers, and financial professionals to adopt the intelligent credit card system, we asked respondents about their intentions regarding the issues they encounter with a credit card system.

Table 2. Perceived limitations of current credit card systems.

Limitations	**Concerns of Participants**
Security concerns	78%
High transaction fees	78%
Limited transaction transparency	56%
Lengthy payment processing	42%
Complex credit assessment	36%

In our study, a key focus was to gauge the willingness of survey participants to adopt the intelligent credit card system. To this end, we specifically included a set of questions in our survey designed to measure this willingness. It is important to clarify that all survey participants who were part of our study responded to these specific questions regarding their adoption intentions. The survey participants comprised manufacturers, importers, and financial professionals, each playing a critical role in the credit card system ecosystem. Their responses to the adoption intention questions were crucial in understanding the market readiness and potential challenges in implementing the intelligent credit card system. The results, as depicted in Table 3, show a diverse range of attitudes towards adoption. A notable 42% of participants expressed strong willingness, while 32% were somewhat willing to adopt the system. Meanwhile, 16% of participants remained undecided, and a smaller percentage (10%) were not willing to adopt the system. This varied response is indicative of the different levels of readiness and acceptance among potential users, providing valuable insights for planning implementation strategies and addressing concerns or reservations about the new system. In conclusion, the inclusion of adoption intention questions in our survey and the participation of all survey respondents in answering these questions allowed us to gather comprehensive insights into the willingness of industry stakeholders to embrace this innovative technology. Understanding these adoption intentions is critical for developing effective strategies to encourage widespread acceptance and successful integration of the intelligent credit card system in the manufacturing and importing sectors.

Table 3. Adoption intentions of survey participants.

Type of Participants	Adoption Intention (%)
Non-willing participants	10%
Strongly willing participants	42%
Undecided participants	16%
Somewhat willing participants	32%

5.2. Experimental Setup

In the experimental setup of our research, a meticulous and comprehensive approach was adopted to collect, process, and analyze data related to the intelligent credit card system for manufacturers and importers of goods in Industry 4.0. The data collection process involved both quantitative and qualitative methods. Structured surveys were conducted through online platforms like SurveyMonkey and Qualtrics to gather quantitative data regarding credit card system preferences and challenges. In parallel, qualitative data were obtained through in-depth interviews with industry experts and stakeholders, and these interviews were subsequently transcribed and analyzed using software tools such as NVivo 14 and Dedoose 9.0. Additionally, archival data from financial records and transaction histories were incorporated to enrich the dataset. When required, randomization was executed using specialized software to ensure unbiased group assignment. The subsequent data analysis phase encompassed statistical techniques, including regression analysis, t-tests, and ANOVA, implemented with the help of software R and Python for the quantitative data. The qualitative data from interviews were scrutinized for thematic patterns by using NVivo 14 and Dedoose 9.0. Ethical considerations were strictly adhered to, with informed consent obtained from participants to guarantee voluntary involvement and data confidentiality. The adoption of data visualization tools like Tableau facilitated the presentation of key findings with clarity. In summary, this robust experimental setup ensures that both quantitative and qualitative data are effectively collected and analyzed, leading to a comprehensive exploration of the research problem in the context of intelligent credit card systems for both segments of the industry.

5.3. Results

In this section, we present the key findings and results of our study, shedding light on the effectiveness and potential of the intelligent credit card system for the manufacturers and importers of goods in Industry 4.0 with Blockchain and AI Integration. We present the key findings and outcomes of our study on the intelligent credit card system's implementation. Through comprehensive analyses and assessments, we examine the system's impact on various financial performance metrics. These results illuminate the potential of cutting-edge technologies like blockchain and AI in revolutionizing financial services, emphasizing the system's role in enhancing efficiency, security, and user experience. Based on the results, we determined the following metrics.

- Predicative credit risk forecasting;
- Fraud detection;
- Credit assessment accuracy;
- Loan approval rate comparison;
- Default rate reduction;
- Monthly revenue growth trend.

5.3.1. Predictive Credit Risk Forecasting

We present a visual representation of credit risk forecasting over a time span of five months in Figure 7a. It illustrates changes in 'Risk Score' along the y-axis, with 'Time (months)' represented on the x-axis. Initially, we observe a gradual decrease in the 'Risk Score' over the first three months, indicating a lower perceived credit risk. However, in subsequent months, the 'Risk Score' begins to rise slightly, suggesting a potential reassessment of credit risk. This predictive assessment holds significance in our paper, highlighting the role of predictive analytics in credit assessment. It demonstrates how financial institutions utilize data-driven insights to monitor and anticipate shifts in credit risk, enabling proactive risk management strategies. This parameter aligns with the broader theme of our paper, emphasizing the transformative impact of AI and machine learning in enhancing risk assessment processes for manufacturers and importers.

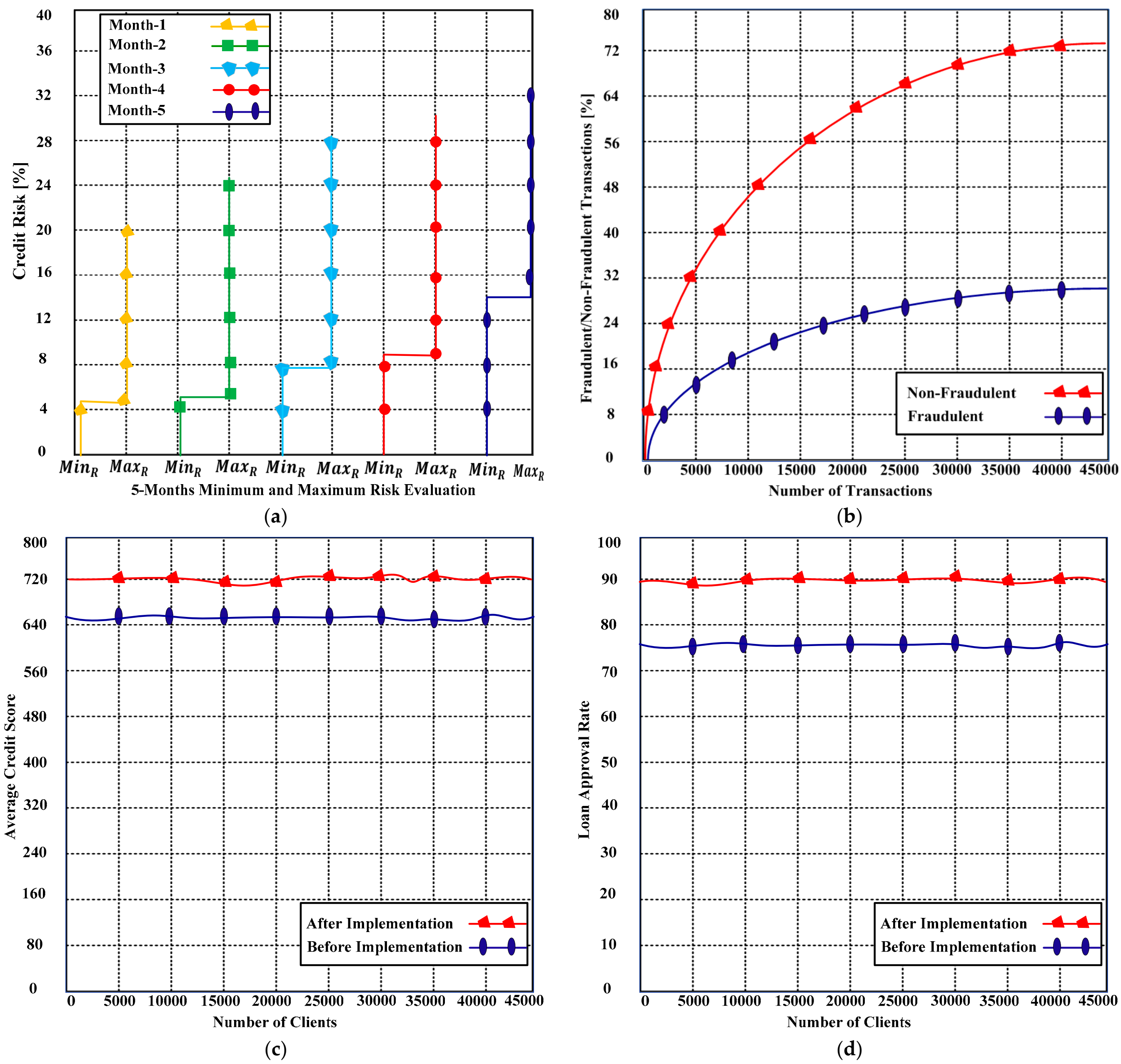


Figure 7. (**a**) Predicative credit risk forecast over time. (**b**) Distribution of outcomes in fraud detection. (**c**) Improvement in credit assessment accuracy. (**d**) Loan approval rate comparison.

5.3.2. Fraud Detection

In Figure 7b, we visually represent the distribution of outcomes in fraud detection. It is divided into two segments: 'Non-Fraudulent' and 'Fraudulent' outcomes. Each segment represents the proportion of transactions or cases falling into these respective categories.

This highlights the critical role of fraud detection in risk management. The 'Non-Fraudulent' segment illustrates the majority of cases where transactions or activities are deemed legitimate and pose no fraudulent risk, comprising 72% of the total cases. On the other hand, the 'Fraudulent' segment signifies cases where fraudulent activities have been detected, accounting for 28% of the total cases, and the distribution of outcomes depicted in Figure 7b is pivotal for risk assessment and mitigation strategies. It enables financial institutions and businesses to allocate resources effectively, focusing their efforts on addressing the relatively smaller but potentially high-impact 'Fraudulent' cases. Moreover, it underscores the significance of advanced technologies like AI and machine learning in identifying and minimizing fraudulent activities. Moreover, the integration of AI and machine learning into credit assessment processes brings about a transformative shift in the manufacturing and importing sector. These advanced technologies enable real-time adjustments of credit policies, personalized credit solutions based on behavioral analysis, and proactive fraud detection. Furthermore, they excel at identifying emerging risks, facilitating data-driven decision-making, ensuring real-time monitoring, and enabling timely risk mitigation. In summary, AI and machine learning serve as catalysts for innovation, offering a deeper understanding of creditworthiness, precise risk assessments, and personalized credit solutions. This empowers manufacturers, importers, and financial institutions to make informed decisions and proactively manage credit risks.

5.3.3. Credit Assessment Accuracy

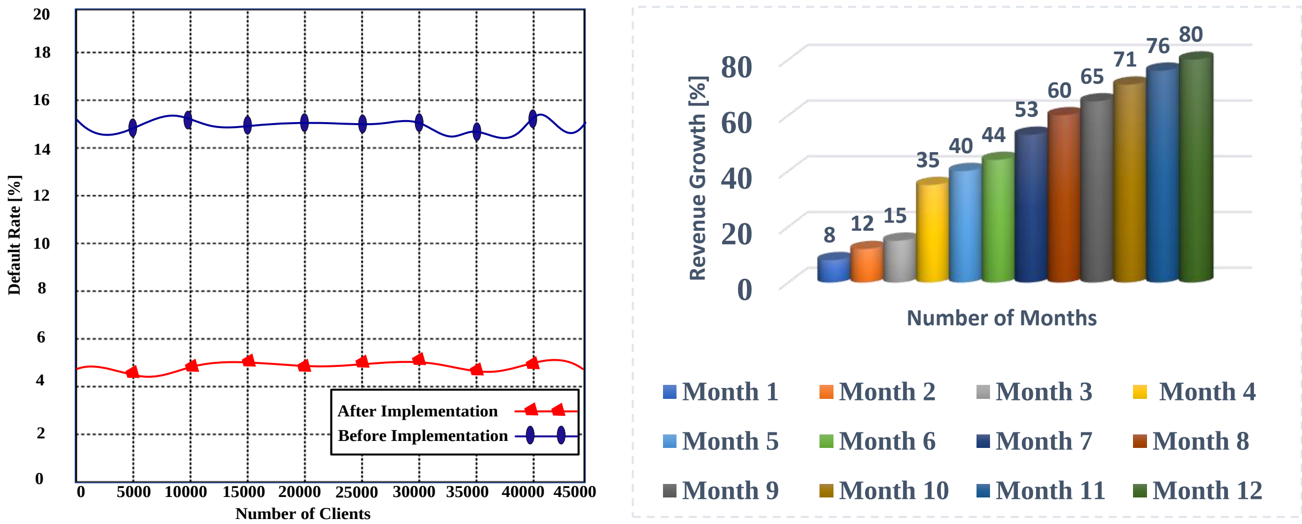
The proposed approach brings noteworthy improvement in credit assessment accuracy resulting from the implementation of the intelligent credit card system. Figure 7c compares the average credit score before and after the system's deployment. Before implementation, the average credit score stood at 650, while after implementation, it saw a substantial increase to 720. This improvement reflects the system's effectiveness in enhancing the precision of credit assessments, a pivotal aspect of our study's findings. It underscores how advanced technologies, such as blockchain and AI, contribute to elevating credit assessment outcomes in the financial sector, benefiting both the importer and manufacturer.

5.3.4. Loan Approval Rate Comparison

A comparison of loan approval rates before and after the implementation of the intelligent credit card system is presented. Figure 7d provides valuable insights into the system's impact on the efficiency of loan approval processes. Before implementation, the loan approval rate was 75%; and after implementation, it significantly improved to 90%. This substantial increase in loan approval rates highlights the positive influence of advanced technologies like blockchain and AI on the credit assessment and approval workflows. Importers and manufacturers can benefit from expedited and more efficient loan approval processes, ultimately enhancing their financial operations and business growth prospects.

5.3.5. Default Rate Reduction

Figure 8a visually depicts the reduction in default rates achieved following the implementation of the intelligent credit card system. We compare the default rates before and after the system's deployment. Before implementation, the default rate was 15%, and after implementation, it experienced a significant reduction to 5%. This reduction signifies the system's effectiveness in mitigating default risks and enhancing the overall credit risk management process. For manufacturers and importers, lower default rates translate to reduced financial losses and improved stability in their credit operations, contributing to long-term financial health.



(**a**) (**b**)

Figure 8. (**a**) Default rate reduction. (**b**) Monthly revenue growth trend.

5.3.6. Monthly Revenue Growth Trend

Figure 8b provides a comprehensive visual representation of the revenue growth trend over the course of a year, following the implementation of the intelligent credit card system. It spans 12 months, with each data point reflecting the monthly revenue growth percentages. The chart reveals a compelling story of financial success and growth. It begins with an 8% increase in revenue in the first month and steadily progresses from there. Notably, in Month 4, there is a substantial spike, with a remarkable 35% growth rate, indicating a significant boost in revenue during that period. This surge is followed by consistent and impressive growth, with revenue growth rates reaching 80% by Month 12.

This substantial growth can be attributed to several key factors. Firstly, by the fourth month, the system's AI-driven credit assessment algorithms had accumulated enough data to provide more precise and tailored credit decisions. This improvement in credit assessment accuracy led to an increase in loan approvals for credible borrowers, thereby boosting financial transactions and revenue for the company. Secondly, the enhanced security and transparency features provided by the blockchain integration began to yield tangible results. These features increased trust among our clients, attracting new customers and retaining existing ones, which, in turn, led to higher transaction volumes. Additionally, the operational efficiencies gained from the system, such as reduced processing times and automated risk assessments, resulted in a more streamlined financial operation. This efficiency allowed for quicker turnaround times on customer transactions, leading to increased customer satisfaction and repeat business. Moreover, the fourth month marked the beginning of a strategic marketing campaign aimed at promoting the new and improved services enabled by the intelligent credit card system. This campaign effectively increased market awareness and attracted a larger customer base, further contributing to the revenue spike. In summary, the significant increase in revenue growth during the fourth month can be attributed to the cumulative effect of improved credit assessment accuracy, enhanced security and trust, operational efficiencies, and successful marketing efforts. These factors combined to create a substantial positive impact on the company's financial performance, as evidenced by the notable growth in revenue.

Overall, this is the positive impact of implementing advanced technologies such as blockchain and AI on the financial performance of manufacturers and importers. The consistent upward trajectory in revenue growth demonstrates the system's effectiveness in driving financial prosperity and highlights its potential as a valuable tool for enhancing business operations and financial outcomes for both segments of the industry.

6. Summary

This section summarizes the entire paper and provides a future research direction, research limitations, and implications for both Industry 4.0 manufacturers and importers.

6.1. Conclusions

The intelligent credit card system has been introduced for manufacturers and importers of goods in Industry 4.0. The proposed ICCS integrates the features of artificial intelligence and blockchain technology. The proposed ICCS improves security, transparency, and efficiency, which has a profound transformative impact on financial operations within the context of Industry 4.0. The findings illustrate a remarkable improvement in predictive credit risk forecasting, fraud detection, and credit assessment accuracy. The significant increase in loan approval rates and the significant reduction in default rates post-implementation highlight the ICCS's efficacy in optimizing credit operations. Blockchain technology's decentralized and immutable ledger significantly reduces the likelihood of fraudulent activity while simultaneously providing real-time transaction recording. However, there are hurdles to implementing such a sophisticated system. Our research recognizes these challenges, which range from integration issues with existing systems to scalability and regulatory compliance. The decentralized feature of blockchain technology improves multi-party computing, and quantum-safe mechanisms are used to improve the proposed credit system. The proposed ICCS is implemented using R and Python languages. Based on the findings, the proposed ICCS provides better predictive credit risk forecasting, fraud detection, credit assessment accuracy, default rate reduction, and revenue growth trends. In the future, the cyber threats will be tested on the proposed ICCS to determine the operational efficiency in the manufacturing and importing sectors.

6.2. Future Research Direction

In the ever-evolving landscape of blockchain and artificial intelligence, several emerging trends hold promise for further enhancing credit card systems tailored to the unique needs of manufacturers and importers. Table 4 summarizes key emerging directions in credit card systems for manufacturers and importers. It provides insights into the adoption rates and potential benefits of each trend, highlighting their significance for the financial sector. Decentralized Finance (DeFi) has ushered in a new era of credit systems with the emergence of decentralized credit networks. These networks facilitate peer-to-peer lending and borrowing, eliminating the need for traditional financial intermediaries. Manufacturers and importers stand to benefit from these innovative platforms, gaining access to a wider array of credit options with the potential for lower interest rates. In an era of evolving threats, the financial industry is exploring cutting-edge security solutions. Multi-party computation (MPC) is a promising privacy technology that enables secure joint computations while keeping sensitive data inputs confidential. Meanwhile, the advancements in quantum computing are raising concerns about traditional cryptographic systems' vulnerability. To counter this, future credit card systems are expected to incorporate quantum-safe cryptographic algorithms to ensure the long-term security of critical data. The fusion of AI and machine learning is leading to the development of hyper-personalized credit solutions. These next-generation credit card systems have the capacity to tailor credit options based on an individual's unique financial behavior and requirements. Additionally, advanced predictive analytics driven by AI empower real-time insights into financial trends, enabling proactive decision-making in credit management and risk mitigation. As financial regulations evolve, RegTech solutions leveraging AI and blockchain are automating compliance processes. This automation not only reduces administrative burdens on businesses but also ensures that they remain aligned with the ever-changing compliance requirements. The future holds the promise of seamless cross-blockchain integration in credit card systems. Such integration is poised to revolutionize cross-border transactions, offering enhanced liquidity for manufacturers and importers. Additionally, with the advent of CBDCs, novel payment and credit card systems could harness digital currencies, simplifying cross-border trade and transactions. The ecological impact of blockchain technologies is receiving heightened attention. Future credit card systems may prioritize sustainable blockchain solutions, including the adoption of proof-of-stake (PoS) consensus mechanisms, to minimize environmental footprints. Moreover, ethical concerns are at the forefront of AI integration, emphasizing the importance of credit card systems that adhere to ethical guidelines, guaranteeing equitable and unbiased credit assessments.

Table 4. Predictive trends in intelligent credit card system.

Research Directions/Trends	Key Data
Decentralized credit networks	Access to diverse credit options; lower interest rates
Multi-Party Computation (MPC)	Enhanced privacy for credit assessments
Quantum-Safe Cryptography	Ensuring long-term data security
Hyper-Personalized Credit Solutions	Tailored credit options based on behavior
Predictive Financial Analytics	Real-time insights into financial trends
Regulatory Technology (RegTech)	Automated compliance with financial regulations
Cross-Blockchain Integration	Seamless integration for cross-border transactions
Central Bank Digital Currencies (CBDCs)	Simplifying cross-border trade and transactions
Sustainable Blockchain	Environmentally friendly blockchain solutions
Ethical AI	Fair and unbiased credit assessments

6.3. Research Limitations and Challenges

This section discusses the implementation issues and future trends that will face Industry 4.0. The successful implementation of an intelligent credit card system tailored to the needs of manufacturers and importers presents various challenges that need to be carefully addressed to ensure a smooth transition and adoption. Table 5 shows the implementation of an intelligent credit card system incorporating blockchain and AI technologies presents several challenges. Integrating with existing legacy systems may pose compatibility issues and necessitate complex data migration processes. User adoption is critical, and it requires effective change management, training, and a user-friendly interface. Ensuring security and compliance is an ongoing concern, as evolving regulations and emerging security risks demand constant attention. Scalability challenges may arise with increased system usage, and managing initial investments within budget is vital. To address these challenges, a comprehensive planning approach is essential, focusing on integration, data migration, and change management. Prioritizing a user-centric design, employing continuous user training, and adopting an agile development approach can enhance user adoption. Implementing robust data security measures, including encryption and access controls, while ensuring regulatory compliance, should be a priority throughout the implementation process. Establish a dedicated team or partner with experts to monitor and ensure compliance with evolving regulations. Staying ahead of compliance requirements reduces the risk of non-compliance. In summary, while implementing an intelligent credit card system for manufacturers and importers presents several challenges, strategic planning, user-centric design, and a commitment to security and compliance can pave the way for successful implementation and widespread adoption. The intelligent credit card system for manufacturers and importers presents several challenges, so strategic planning, user-centric design, and a commitment to security and compliance can pave the way for successful implementation and widespread adoption.

Table 5. Implementation challenges in intelligent credit card system integration.

Category	Challenges
Integration with existing system	Legacy systems compatibility Data migration
User adoption	Change management Training and education User experience
Security and compliance	Regulatory compliance Security risks
Scalability	Handling increased volume
Cost management	Initial investment

6.4. Research Implications

Prior to implementing an intelligent credit card system, manufacturers and importers should conduct a comprehensive evaluation of their specific financial requirements, including credit assessment needs, payment processing efficiency, and data security concerns unique to their businesses. It is crucial to ensure that the chosen system seamlessly integrates with their existing financial infrastructure, such as Enterprise Resource Planning (ERP) systems, to facilitate a smooth transition and uninterrupted operations. To maximize the system's success, allocate resources for comprehensive training programs for staff and partners, recognizing the pivotal role of user adoption. Additionally, place paramount importance on data security by implementing robust measures to safeguard sensitive financial information and ensure compliance with data protection regulations. Stay vigilant about emerging trends and advancements in blockchain and AI technologies, continuously assessing their potential to enhance and align with evolving financial operations. Tailor intelligent credit card systems to cater to the unique needs of manufacturers, importers, and other niche sectors through customization, enhancing client satisfaction, and strengthening competitive advantage. Design systems with scalability in mind to ensure that they can seamlessly grow and adapt to accommodate expanding client requirements, a key factor in long-term viability. Provide dedicated support and maintenance services to assist clients in optimizing system utilization, promptly addressing queries and concerns for sustained client satisfaction. Foster collaborative relationships with regulatory authorities to ensure ongoing compliance with evolving financial regulations, promoting trust and confidence among users. Allocate resources for ongoing research and development efforts to stay at the forefront of technological innovation, offering cutting-edge solutions and maintaining a competitive edge. Embrace and enforce ethical AI practices to ensure fair and unbiased credit assessments, fostering transparency and trust among users. Be mindful of the environmental impact of blockchain technology, opting for sustainable solutions to minimize the ecological footprint. Maintain agility in adapting to technological advancements and remain open to innovations that optimize financial operations. Foster collaborative partnerships with technology providers, financial institutions, and regulatory bodies to facilitate innovation and a seamless transition to intelligent credit card systems. By adhering to these recommendations, manufacturers, importers, and financial institutions can confidently navigate the implementation of intelligent credit card systems, optimizing their financial operations and securing a competitive advantage in the ever-evolving financial landscape.

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Abbreviations

Acronyms	**Full Form**
ICCS	intelligent credit card system
VAE	variational automatic coding
AI	artificial intelligence
ML	machine learning
UI	user interface
DPO	data protection officer
GDPR	general data protection regulation
CCPA	California Consumer Privacy Act
EEA	European Economic Area
DeFi	Decentralized Finance
RegTech	regulatory technology
CBDCs	central bank digital currencies
ERP	Enterprise Resource Planning

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