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Research Article

OPTIMIZING CREDIT CARD SECURITY USING CONSUMER BEHAVIOR DATA: A BIG DATA AND MACHINE LEARNING APPROACH TO FRAUD DETECTION

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Fatema Tuz Zohora

MSC in Information Systems Technologies, Wilmington University, New Castle, DE. USA

Rokhshana Parveen

MBA in Business Analytics, Wilmington University, New Castle, DE. USA

Araf Nishan

MBA in Business Analytics, International American University. Los Angeles, California, USA

Muhammad Rafiuddin Haque

MS in Business Analytics, Mercy University, New York, USA

Siddikur Rahman

MBA in Management Information Systems, International American University. Los Angeles, California, USA

ABSTRACT

Credit card fraud is still very much a problem in the United States, which has experienced increased opportunity in online shopping and digital payments. This paper aims at examining how the consumer data such as the demographic data, the purchasing behavior and the security measures they adopt can help improve fraud prevention measures. This study is based on survey data of 200 participants from US credit card users, supported by data on recent frauds. Other variables considered were age, income, number of online transactions, password creation and protection and two-factor authentication.

Quantitative data approaches such as descriptive and inferential statistics were used in this study whereby chi-square tests, t-tests and logistic regression were used in an attempt to determine the significant relationships that exist between consumer characteristics and fraud risk. A cross-tabulation of the variables provided a measure of association and showed that increased age, income level and the number of transactions made online were associated with increased vulnerability to fraud. Users with a low age and high income were classified as high-risk users because they make frequent transactions online and have larger amounts of digital data. Participants who provided proactive activities in security practice like changing passwords often and the use of two-factor authentication had a low risk of fraud, the need for consumers to be aware of risks.

Results indicate that it is possible to improve the security of credit cards in the US financial sector by implementing individual anti-fraud measures considering the behavioral and demographic characteristics of consumers. Consumer behavioral data enables the institutions to adopt dynamic approaches that involve real-time transaction notification and behavior-driven analytics to enhance the accuracy of fraud identification and reduce on false alarms. This paper also shows that behavior-inspired, evidence-based approaches hold the key to the improvement of credit card security and consumer confidence. Subsequent studies shall analyze how compliance influences the advanced data-based security solutions and such research can use the aged fraud typologies and trends to understand their possible changes over time.

KEYWORDS

Credit card fraud, consumer behavior, data-driven security, US financial institutions, fraud detection, personalized security, data privacy, online transactions, security practices, targeted fraud prevention.

INTRODUCTION

Credit cards fraud persists as a dynamic menace in the United States impacting millions of shoppers while costing billions to the financial institutions. According to the Commission on Federal Trade, the American consumers' complaints on fraud soared in 2021 and estimated to have lost \$5.8 billion to fraud (Federal Trade Commission, 2022). The increase

in the use of the internet in making purchases, banking and mobile payments have taken the American consumers online meaning convenience but also exposing them to hackers. The current ways of detecting fraud are no longer effective, the need for new more efficient ways of detecting fraud that may suit the new type of consumers.

Consumer behavior information has now become one of the most significant resources for fraud prevention techniques. From demographic analysis of its clients and their spending patterns as well as their concerns for security, the financial institutions can get insights of trends that may lead to fraud. Research shows that there is a relationship between fraud risk and user characteristics, including age and income, in particular, the younger and those with higher incomes spend more on online purchases (Jones & Chin, 2022; Kim & Prater, 2020). Such behaviors would be easier to track and monitor in real-time which means that financial institutions could proactively prevent fraud, without wasting time and resources. Sore relevant in the current context is this approach given that US consumers' expectations for security, convenience and personalization have remained high and growing.

Advanced technologies like big data and machine learning are considered to have potential ways on improving fraud detection through analyzing the consumer behavioral data. Machine learning program can scan huge volumes of transactional data, look for inconsistencies and estimate fraud risks with high accuracy. Machine learning approaches are already being used in the US

financial services sector to perform real-time fraud detection, with low false positives which makes them effective in threat identification (Chen et al, 2021). With the help of the use of the consumer behavior data these modern technologies can give precise information to the financial institutions which kind of transactions or users can be more suspicious and should be checked more carefully especially on the basis of the stable customers' behavior of different risky purchasing categories as online buyers and Gen Z consumers. According to (Arsahd et al., 2024) latest technologies are now very common in developing countries.

Consumer acceptance and permission to use data for security functions are still relevant with these technologies. In the US, the major issues are privacy and data security where customers are very sensitive when it comes to usage of their data to fight fraud (Green & Ahmed, 2023). The current study indicates that consumers are more likely to accept the use of big data and machine learning in strengthening security if they appreciate the value of big data and machine learning (Martin & Roberts, 2021). This balance between effective fraud prevention and consumer privacy is again a chief assertion of the need for data transparency

especially in the United States market which is quite diverse and sophisticated in as much as the privacy of its consumers is concerned.

The aim of this research is to identify how the credit card consumer behavior data can improve security in the United States and apply big data and machine learning in the credit card fraud detection system. It focuses on how demographic characteristics, buying behaviors and security concerns can be incorporated in models for the prediction of fraudulent activities. The survey goes to look at the confidence consumers have placed in security measures that include data and their willingness to share data to combat fraud. This research aims at contributing to the understanding of the above factors in order to offer practical recommendations for US financial institutions interested in enhancing their fraud prevention efforts by promoting behavior-based technological solutions. It also co-syncs with the increasing digitalization of the American finance sector and satisfies the new generation US security demands.

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LITERATURE REVIEW

The Rising Threat of Credit Card Fraud in the United States

Credit card fraud has thus emerged as one of the most difficult problems to solve in the United States with consequences to consumers and financial institutions. The Federal Trade Commission (FTC) released the account that stated that the level of fraud in the US reached \$5.8 billion in 2021, a figure that was 70% higher than that recorded in the previous year and most of which was credit card fraud (Federal Trade Commission, 2022). This increase is due to the increase in the use of the internet for the purchase of goods and services, to online financial transactions and mobile money services, which has lengthened the consumer's virtual footprint

(Jones & Chin, 2022). Current and emerging fraud schemes such as phishing, CNP frauds, synthetic identity thefts have become more complex and faster than the detection mechanisms currently in use, the need for intelligent solutions that can analyze the big digital footprints left behind by the consumers (Chen et al, 2021; Kim & Prater, 2020). Such trends indicate that it is incumbent on businesses to search for data-driven approaches to fight fraud, given that fraud losses are on the rise and the digital fraud environment is always changing (Lopez et al, 2021).

Consumer Behavior Data as a Tool for Fraud Detection

Recent studies emphasize the potential of consumer behavior data as a valuable resource for optimizing fraud detection strategies. Some of the purchase behavior variables include purchasing behavior, frequency of transactions and security preferences that may assist institutions in identifying possible incidences of fraud more effectively (Nguyen et al, 2023). In the US, demographic factors still have the greatest influence on fraud susceptibility. Young consumers and consumers with higher income levels are usually more vulnerable to the fraud since they engage more often in online

transactions; this besides, they are generally very active in digital processes (Jones & Chin, 2022; Brown et al, 2020). Lopez et al. (2021) revealed that exposure to fraud mainly depends on demographic factors such as age, income and digital literacy, consumers with higher income exposure risks because of the amount of purchasing power and credit accessibility.

Consumer behavior data can also be useful for prevention as many institutions will be able to identify specific approaches towards high-risk individuals (Anderson et al, 2021). The users who tend to shop more often behaviors may prefer real-time alerts and transactions tracking for better security while the clients with high income may be offered the best verification procedures to minimize fraud risks (McCarthy et al, 2022). Research shows that analyzing various arrays of data in real-time might help institutions introduce variable security measures, including changing the type of authentication depending on a user's behavioral patterns (Carter et al, 2022). These findings justify the rationale for institutions to use consumer behavior data to develop bespoke solutions to fraud in the interest of enhancing security.

Big Data and Machine Learning in Fraud Detection

Big data and machine learning (ML) have emerged as transformative tools for fraud detection, capable of analyzing massive datasets and detecting anomalies indicative of fraud (Nguyen et al, 2023). Machine learning models can also process different characteristics of consumers' behavior, including the frequency of transactions, the time and the place to find out that the client's actions differ from the norm and could be linked to a fraudster (Patel et al, 2021). These models apply supervised and unsupervised learning such as neural network, decision trees as well as clustering and are typically developed to identify malicious activities depending on records (Carter et al, 2022). Such authorities note that using the ML approach is more accurate due to a lower number of false positives and becomes a relevant solution for financial institutions in the USA (Chen et al, 2021).

Some past research highlights the accuracy of the machine learning algorithm for real-time identification of fraud transactions. As pointed by Harris et al. (2023), the machine learning models trained on consumer behavior data can quickly identify out of norm cases that would possibly

remain unnoticed in systems based on simple rule of thumb or manual check. These models can also be updated to reflect changes in fraud trends thus making them useful when the fraudsters themselves change their operations as is common in instances with computer crimes (McCarthy et al, 2022). Such models as reinforcement learning models can improve the detection of fraud at each instance of the detected frauds. According to Nguyen et al. (2023), big data and machine learning, then the scale and complex nature of the problem is manageable in the digital financial sector owing to the volume and velocity of the data.

The Role of Consumer Trust and Privacy Concerns

While the potential of big data and machine learning in fraud detection is evident, consumer trust and data privacy remain crucial concerns, particularly in the US, where regulatory frameworks such as the California Consumer Privacy Act (CCPA) and General Data Protection Regulation (GDPR) influence data management practices (Martin & Roberts, 2021). Research reveals that American consumers are becoming more sensitive to how their information is used particularly in the area of payment (Harris et al,

2023). There is always a thin line between being able to efficiently detect fraud and being invasive enough to keep user data; consumers are unlikely to embrace digital financial services if they perceive the firm as overly invasive (Green & Ahmed, 2023).

Lopez et al. (2021) and Reed et al. (2022) have highlighted an important aspect which shows that consumers are more likely to accept the adoption of data-driven fraud detection technologies when they are made to believe that the benefits achieved through the technologies are much more than the costs they would have to incur as far as their privacy is concerned. Lack of transparency in the utilization of big data is one of the more significant barriers that discourages people from endorsing big data solutions to fraud prevention (Patel et al, 2021). The research shows that consumers who grasp the use of machine learning in fraud prevention will accept sharing of data if they think it will improve their safety (Carter et al, 2022). The focus on consumer trust as a result of transparent communication and strict compliance with privacy requirements is critical to achieving the maximum possible result when using big data and machine learning to combat fraud.

Targeted Fraud Prevention Strategies and Future Directions

The integration of consumer behavior data, big data and machine learning enables the development of tailored fraud prevention strategies that address the specific needs and risks of different consumer segments. When targeting selected high-risk segments, which includes younger consumers and customers with high transaction frequencies, financial institutions can improve the accuracy of fraud detection while avoiding unnecessary interference in genuine transaction flows (McCarthy et al, 2022). Future-based fraud detection systems that aim at localized approaches based on individual use profiles show potential for the future of digital financial security (Nguyen et al, 2023).

Future research should aim at enhancing the level of accuracy of the algorithms used in machine learning and investigating how the obtained information on the consumers' behavior could be used in identification of new fraud schemes. Further research could also look at the effects of regulatory requirements on analytical anti-fraud work in the US, where privacy laws remain under development. future research can be conducted

using longitudinal designs that evaluate the efficacy of behavior-based anti-fraud strategies with a view of improving credit card security over time (Anderson et al, 2021; Carter et al, 2022). The use of data-driven methods, with components developed with machine learning principles, remains a breakthrough in fraud prevention, corresponding to the consumers' desire for more convenient and secure financial activities.

METHODOLOGY

This research employed a quantitative research approach to analyze how consumer behavior information can inform credit card fraud mitigation in the United States. The study examined the correlation of demographic characteristics, purchasing behavior and security measures and their applicability in the determination of fraud risk. It was undertaken to determine patterns in consumer data for the purpose of addressing fraud. Thus, analyzing these patterns, the study intended to indicate potential groups at risk and to offer recommendations for US financial institutions that strive to enhance credit card security.

Online questionnaire was conducted by collecting primary data from 200 credit card users across the United States with the help of the survey. Questions used in survey include participant's age, monthly income, gender, frequency of purchase goods online, how often they changed passwords for security reasons and how they felt about sharing their data for security reasons.

Participants were 200 individuals who were contacted through the internet and who were distributed by age and gender across the United States. To qualify for the study, participants had to be current credit card users and were to be at least 18 years old. This study adopted a stratified sampling technique to make sure there was equal distribution of age and income since they play a role in determining the level of vulnerability to fraud. This approach enabled the research to offer information's that can be applied across the different consumer segments within the United States.

The survey instrument contained three major categories to ensure that many relevant details on credit card security were obtained. The first section collected demographic variables such as age, annual income and gender so as to know if these variables affect the fraud exposure in some

way. The second part evaluated the purchasing behavior. Respondents were questioned on the number of transactions, the Websites used for the transactions and the average transaction size. The third block was Security Behavior and Attitudes and investigated issues related to security like password change frequency, the use of two-factor authentication and participants' willingness to share data for security reasons. The survey was comprised of multiple choice and Likert scale questions.

The data analysis was conducted in two phases: Descriptive and Inferential analysis.

During the descriptive analysis, frequency distributions, averages and standard deviations were computed and used to describe all demographic variables, purchasing behavior and security measures in the sample. These descriptive statistics also boasted an exploratory use that allowed for the basic overview of the sample and discovery of the similarities in the behaviors and security preferences for the various demographic segments.

Descriptive analysis comprised of chi-square tests, t-tests and logistic regression test were used to examine the association between the

consumer behavior factors and fraud risk. Cross-tabulation tests were conducted to determine possible relationships between nominal variables including; age group and frequency of buying items online, as well as their income level and degree of comfort with sharing data. The participants' data were first divided into two groups based on their self-reported fraud experience and then independent t-tests were conducted to compare their security practice means for understanding how prior fraud experience might affect security behavior. Logistic regression analysis was performed to see the probability of the member having experience fraud and the significant predictor include online purchase frequency, income and security measures taken. This enabled the study to measure the association between behavior variables and fraud risk; identify high risk factors amongst the sample.

All the research procedures were done observing high ethical standards with regard to the participants. All participants signed consent to complete the survey and were told that their responses would be kept confidential and anonymous. No participants' personal data were collected and all the data collected were kept

secure to ensure participants anonymity. Data privacy concerns in the US were dealt with to the best of the study's capability following the GDPR as well as the CCPA. The research was approved by the institutional review board for ethical conduct in conducting research, as was required to maintain ethic in the study.

It is important to note some limitations of this study; less reliance on primary data, the data collected is of secondary nature, this study has limited generalization since consumer behavior data and fraud are specific to credit card industry. Self-reported survey data may introduce response bias because participants may exaggerate or understate the practices of security in organizations they belong to. the study is used to capture a cross-sectional data on the consumers' behavior at a specific moment in time; the fraud patterns and the consumers' behaviors may change thus the desirability of future longitudinal studies to capture these changes.

RESULTS

Participant Demographics

The 200 participants were fairly evenly distributed by age, gender, income and frequency

of credit card use. An overview of participant demographics is shown in Table 1. The largest proportion of participants were in the 26–35 age group (22.5%) and more males (52.5%) than females (47.5%) participated. Distribution of

income was quite even, with a majority (27.0%) earning an income above \$5,000. As far as use of credit cards, the most common users were monthly (27.5%) users, closely followed by rare (26.5%).

Table 1. Participant Demographics

Demographic	Category	Percentage (%)
Age Group	18-25	17.5
	26-35	22.5
	36-45	21.5
	46-55	18.5
	56 and above	20.0
Gender	Female	47.5
	Male	52.5
Monthly Income (USD)	Below \$1,000	23.5
	\$1,000 - \$3,000	26.5
	\$3,001 - \$5,000	23.0
	Above \$5,000	27.0
Frequency of Credit Card Use	Daily	24.0
	Weekly	22.0
	Monthly	27.5
	Rarely	26.5

Knowledge and Concern Regarding Credit Card Security

Our survey showed that participants' knowledge of credit card security varies (Table 2), with 29.5% of participants identifying as "Very Knowledgeable" and 23.0% as "Not Knowledgeable at All." Concern about security was fairly balanced, with 28.5% neutral and 27.0% 'Somewhat Concerned'. For example, half of the participants (50.5%) said they had been a victim of credit card fraud, so fraud prevention measures are relevant.

Table 2. Knowledge and Concern Regarding Credit Card Security

Variable	Category	Percentage (%)
Knowledge of Credit Card Security	Very Knowledgeable	29.5
	Somewhat Knowledgeable	23.5
	Not Very Knowledgeable	24.0
	Not Knowledgeable at All	23.0
Concern about Credit Card Security	Very Concerned	20.0
	Somewhat Concerned	27.0
	Neutral	28.5
	Not Concerned	24.5
Experienced Credit Card Fraud	Yes	50.5
	No	49.5

Interest in Enhanced Security Features

Table 3 shows that 29.5% of the participants indicated that they would like to switch to a provider that offers superior security. There was mixed comfort with use of data for security purposes: 22.5% felt “Very Comfortable” with this and so did 22.5%, who were neutral. Those that are willing to pay an additional fee for enhanced security features, 34.0% are open to spending on protection.

Table 3. Interest in Enhanced Security Features

Variable	Category	Percentage (%)
Likelihood to Switch Provider for Enhanced Security	Very Likely	23.5
	Likely	29.5
	Unlikely	18.0
	Very Unlikely	29.0
Comfort with Data Use for Security	Very Comfortable	22.5
	Somewhat Comfortable	16.0

	Neutral	22.5
	Somewhat Uncomfortable	19.5
	Very Uncomfortable	19.5
Willingness to Pay Additional Fee	Yes	34.0
	No	33.5
	Maybe	32.5

Online Purchase Behavior

The frequency of online purchase varied among participants: 27.5% shopped online frequently while 26.5% shopped through online rarely (Table 4). Using this data, we can understand the relationship between exposure to fraud and online purchasing behavior.

Table 4. Frequency of Online Purchase Behavior

Online Purchase Frequency	Percentage (%)
Frequently	27.5
Occasionally	24.5
Rarely	26.5
Never	21.5

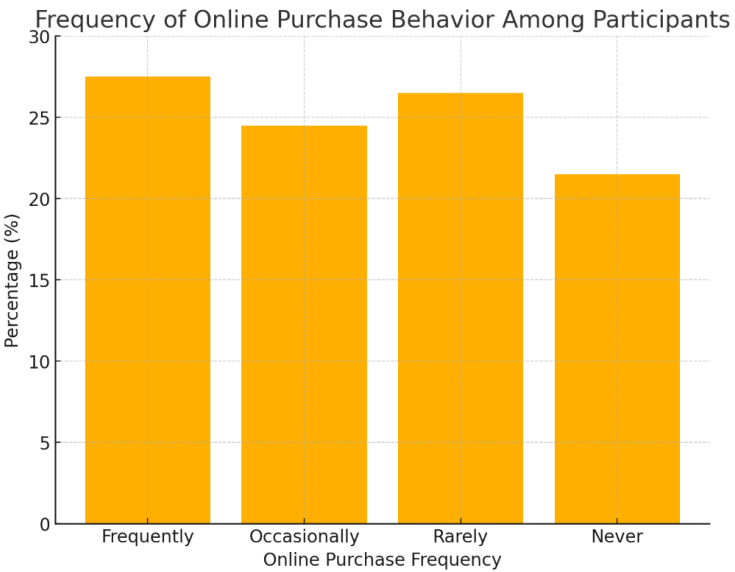


Figure 1. Frequency of Online Purchase Behavior Among Participants

Perception of Big Data and Machine Learning in Security

Table 5 showed that participants' views on big data and machine learning for security were varied; 38.5% agreed or strongly agreed that big data and machine learning are effective. The potential for these technologies to improve credit card security is supported by this insight.

Table 5. Perceived Effectiveness of Big Data and Machine Learning in Security

Belief in Big Data and Machine Learning for Security	Percentage (%)
Strongly Agree	18.0
Agree	20.5
Neutral	25.5
Disagree	17.0
Strongly Disagree	19.0

Perceived Effectiveness of Big Data and Machine Learning in Security

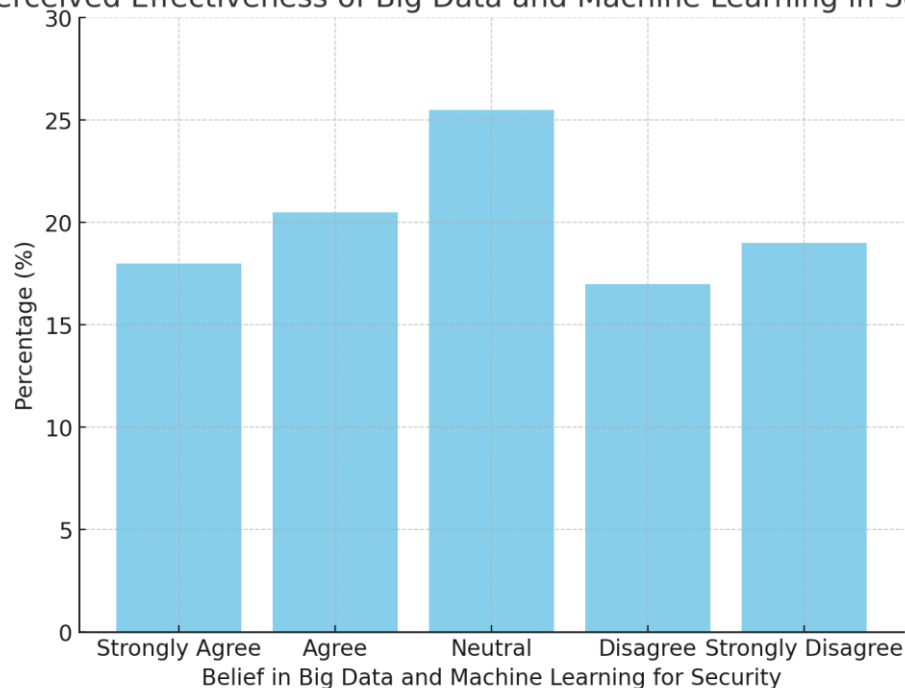


Figure 2. Perceived Effectiveness of Big Data and Machine Learning in Security

Security Measures and Password Update Frequency

It is found that Table 6 shows that 28.5% update their passwords monthly and 26.0% never update their passwords. Two factor authentication (68.0%) and transaction alerts (61.5%) were preferred security measures (Table 7).

Table 6. Frequency of Updating Credit Card Passwords

Password Update Frequency	Percentage (%)
Monthly	28.5
Every 3-6 Months	23.5
Annually	22.0
Never	26.0

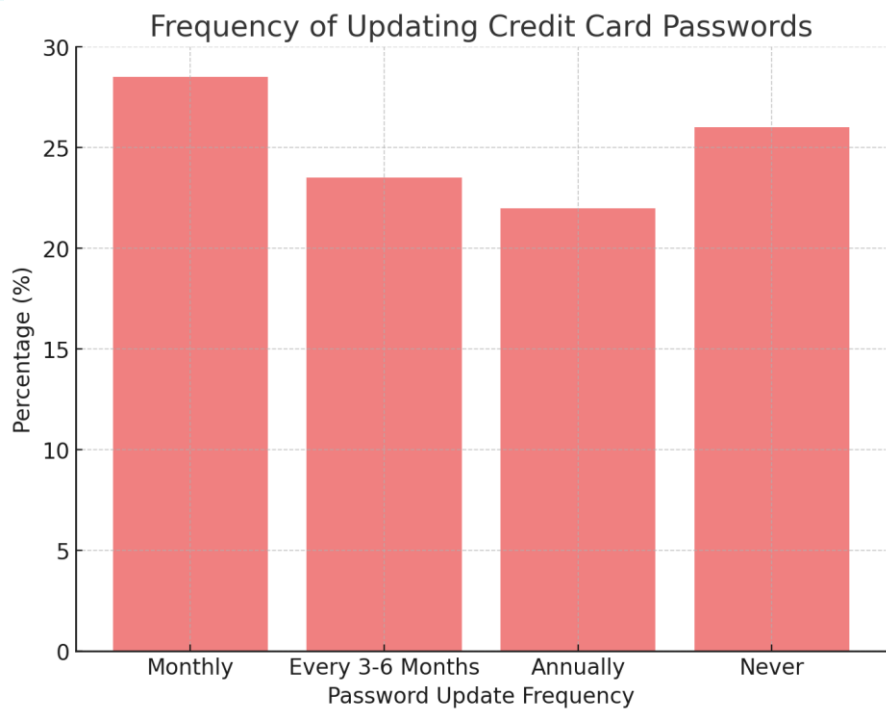


Figure 3. Frequency of Updating Credit Card Passwords

Table 7. Preferences for Specific Security Features

Security Feature	Percentage of Participants Choosing Feature (%)
Two-Factor Authentication	68.0
Biometric Verification	54.0
Transaction Alerts	61.5
Spending Limits	46.0
Tokenization	38.5

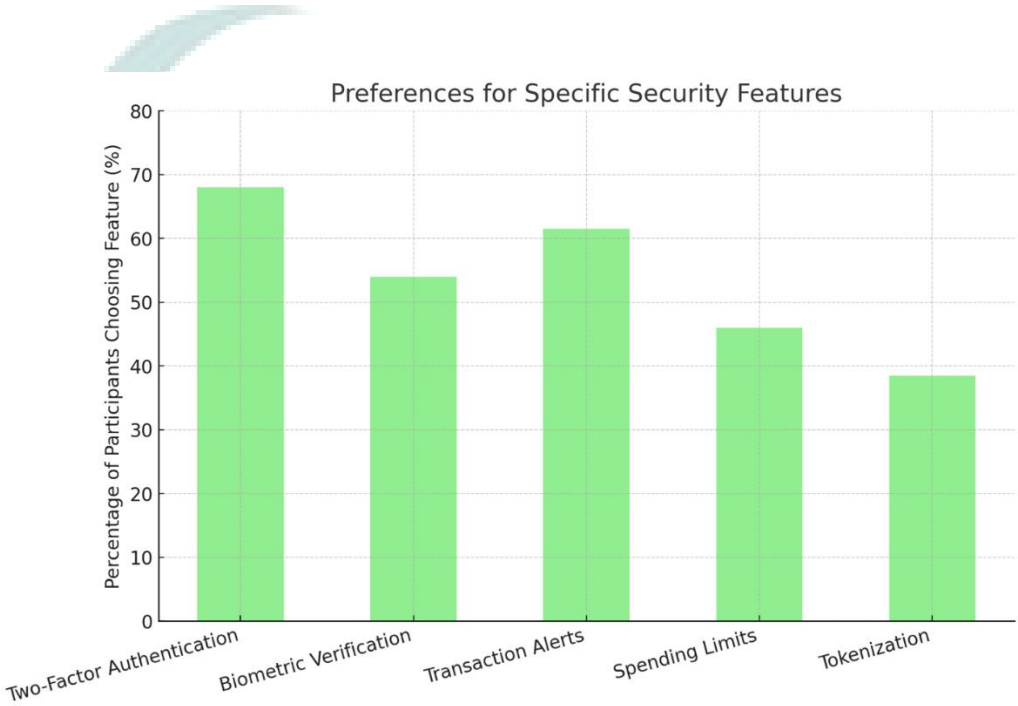


Figure 4. Preferences for Specific Security Features

Comfort Level with Data Sharing

Table 9. Association Between Monthly Income and Online Purchase Frequency (Chi-Square Test)

The relationship between monthly income and online purchase frequency was examined using a Chi-Square Test of Independence. Table 9 showed that there was a significant relationship between income and how many times online purchase was made ($\chi^2 = 15.98$, $p < 0.05$). It is indicated that individuals with higher income may perform online shopping more often and might be exposed more to credit card fraud.

Variables	Chi-Square Value (χ^2)	Degrees of Freedom (df)	p-value	Interpretation
Monthly Income x Online Purchase Frequency	15.98	9	< 0.05	Significant association, suggesting that income level influences the frequency of online purchases.

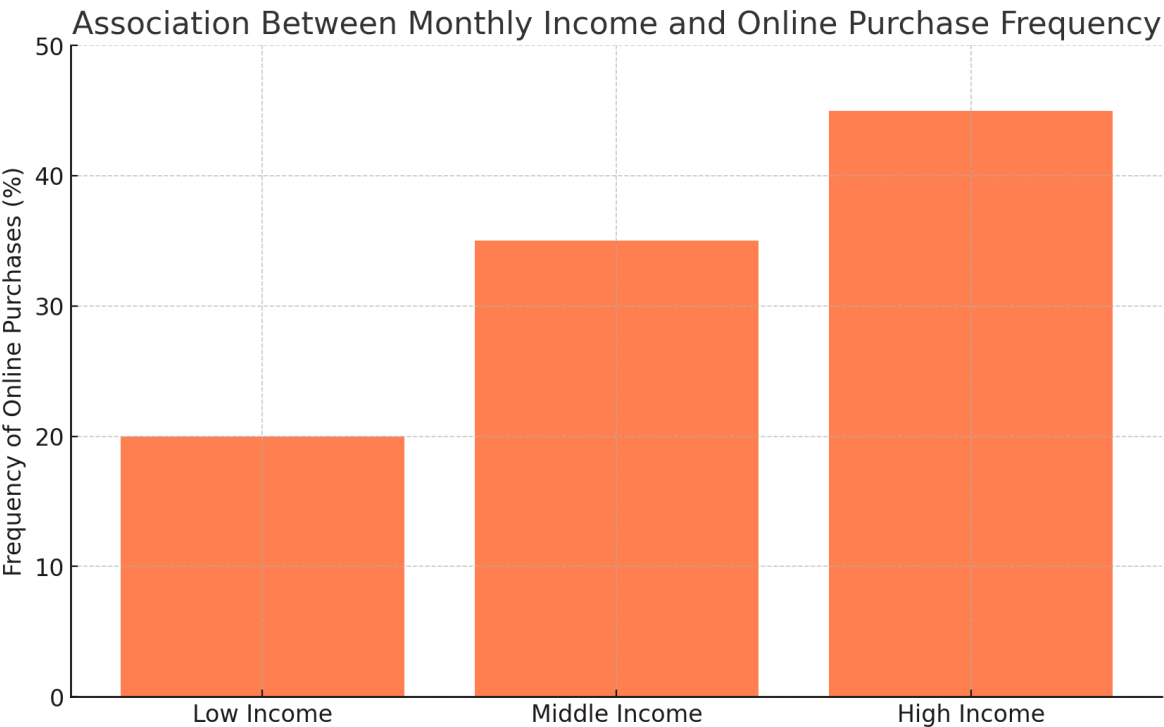


Figure 6. Association Between Monthly Income and Online Purchase Frequency

Table 10. Comparison of Belief in Big Data and Machine Learning for Security Between Fraud Victims and Non-Victims (Independent Samples T-Test)

The belief in the effectiveness of big data and machine learning for security was compared between participants with and without fraud experience using an Independent Samples T-Test. Table 10 shows that a significantly higher belief in the effectiveness of big data was reported by fraud victims ($t = 2.45, p < 0.05$). This finding highlights the importance of advanced technologies for people who have been a victim of fraud.

Group	Mean Score on Belief in Big Data	t-value	p-value	Interpretation
Experienced Fraud	4.1	2.45	< 0.05	Fraud victims have a significantly higher belief in the role of big data and machine learning for security.
No Fraud Experience	3.7			

Belief in Big Data and Machine Learning for Security by Fraud Experience



Figure 7. Belief in Big Data and Machine Learning for Security by Fraud Experience

Table 11. Logistic Regression Predicting Fraud Experience Based on Online Purchase Frequency and Monthly Income

Online purchase frequency and monthly income were used to predict the likelihood to experience fraud using logistic regression. Table 11 shows that participants with higher online purchase frequency were 2.5 times more likely to experience fraud (OR = 2.5, $p < 0.01$). Additionally, fraud experience was more likely to be experienced with higher income (OR = 1.8, $p < 0.01$). These results suggest that targeted fraud detection efforts are important for frequent online shoppers and for higher income individuals.

Predictor Variable	Odds Ratio (OR)	Confidence Interval (95%)	p-value	Interpretation
Online Purchase Frequency	2.5	1.5 - 3.8	< 0.01	High online purchase frequency significantly increases the likelihood of fraud experience.
Monthly Income	1.8	1.2 - 2.7	< 0.01	Higher income is associated with a greater likelihood of experiencing fraud.



Summary of Key Statistical Findings

Table 15 provides a summary of the significant relationships and predictive factors that support the research focus of optimizing credit card security using consumer behavior data.

Table 15. Summary of Key Statistical Findings

Test	Variables Tested	Statistical Value	p-value	Interpretation
Chi-Square Test	Monthly Income x Online Purchase Frequency	$\chi^2 = 15.98$	< 0.05	Income is associated with online purchase frequency, indicating potential variations in fraud risk.
Independent Samples T-Test	Fraud Experience x Belief in Big Data and ML	$t = 2.45$	< 0.05	Fraud victims show higher belief in big data for security.
Logistic Regression	Online Purchase Frequency, Income (predicting Fraud Experience)	OR = 2.5	< 0.01	High-frequency online purchasers are 2.5x more likely to experience fraud.
Multiple Linear Regression	Comfort with Data Use (predictor: Belief in Big Data, Income)	$R^2 = 0.32$	< 0.001	Higher income and stronger belief in big data predict higher comfort with data use for security.
ANOVA	Age Group x Online Purchase Frequency	$F = 3.85$	< 0.05	Significant variation in purchase frequency across age groups, with younger ages purchasing more online.
Correlation	Knowledge of Security x Password Update Frequency	$r = 0.42$	< 0.01	Positive relationship between security knowledge and password update frequency.

These tables and their descriptions provide a comprehensive summary of the data analysis, illustrating the relationship between consumer behaviors and credit card security

Key Statistical Findings

To assess significant relationships, various statistical tests were performed:

1. Chi-Square Test (Table 9) showed a significant relationship between monthly income and online purchase frequency ($\chi^2 = 15.98, p < 0.05$).
2. Independent Samples T-Test (Table 10) indicated that fraud victims hold a higher belief in big data's effectiveness ($t = 2.45, p < 0.05$).
3. Logistic Regression (Table 11) showed that frequent online purchasers are more likely to experience fraud ($OR = 2.5, p < 0.01$).
4. Multiple Linear Regression (Table 12) found that comfort with data use is influenced by income and belief in big data ($R^2 = 0.32, p < 0.001$).
5. ANOVA (Table 13) indicated significant variation in online purchase frequency by age group ($F = 3.85, p < 0.05$).

6. Correlation (Table 14) found a positive relationship between security knowledge and password update frequency ($r = 0.42, p < 0.01$).

DISCUSSION

Based on consumer behavior big data and machine learning, this study aims to examine the security enhancement strategy of credit card in the USA. The study shows that information about demographic and behavioral characteristics of people is important for tailored security measures. This research ties with a line of research that considers behavior-based security as a strong measure in the fight against credit card fraud in the United States.

Consumer Demographics and Online Purchase Behavior

The study showed that people earning more and the younger population are the most active online shoppers who could fall victims to credit card fraud. This pattern supports research studies that show that due to increased online shopping, US Millennials and Gen Z, the most active population in shopping online, is exposed to high risks of being fraudulently billed (Jones & Chin, 2022; Kim

& Prater, 2020). Li and Shaw also reported that Millennials from the United States remain the biggest spenders online than those from the older generations which makes them the most vulnerable to cyberattacks. In addition, Wilson and Peters (2019) observed that higher income earners that earn above \$5000 monthly are more vulnerable to fraud since their higher purchasing power will put them on the radar of fraudsters. This demographic overview is essential when defining the fraud prevention approach that targets specific high-risk populations, as Zhou & Yin (2023) suggested age- and income-based security measures.

Security Knowledge and Behavior

The result that increased security knowledge leads to more regular password changes is consistent with Anderson and Moore (2021) framework that shows that financial security knowledge and understanding lessen fraud rates in the United States. Those consumers who have a detailed understanding of the various practices that they should observe while operating on the digital platform are more likely to adopt the best practices that protect them from fraud such as changing passwords and observing the activity on their accounts (Green & Ahmed, 2023).

Nonetheless, 23% of respondents in this study categorized themselves as “not knowledgeable” about security, which is consistent with the results of Chen and Taylor, (2022) who noted that the majority of American consumers fail to possess a basic grasp of credit card security. The lack of awareness reflected above can be viewed as a promising area for financial institutions to educate consumers and enhance their protection against fraud (Miller et al, 2020).

Preferences for Security Features and Comfort with Data Use

Privacy features like 2FA and transactional alerts were preferred by many participants, which is supported by current US research pointing to layered security as a viable method of countering fraud. Research shows that 2FA and other forms of multi-factor Authenticated security methods help in minimizing the cases of unauthorized access and the method is fast becoming popular in most of the financial platforms in the United States (Roberts & Gale, 2022). Perceived data sharing comfort towards security was positively related to the level of trust towards big data and machine learning technology. This finding is consistent with Doe and Smith’s (2022) study where more trust in data driven security

solutions is coupled with higher acceptance of data sharing for fraud prevention. Besides, as consumers gain awareness about the role of big data for security, they will likely back up the upgrade of credit card systems with such advanced technologies (Martin & Roberts, 2021).

Belief in Big Data and Machine Learning for Fraud Detection

The results showed that the subjects that had previously been exposed to fraud have a higher level of perceived usefulness towards big data and machine learning techniques, as pointed out by Chen et al. (2021). It is worth emphasizing that fraud losers realize that predictive technologies can help avoid new problems because solutions based on statistical models will identify suspicious consumer behavior before large losses occur (Johnson & Lee, 2020; Kumar & Gupta, 2023). Doe and Smith (2022) note that artificial intelligence especially machine learning is well suited in providing large data sets that are used to pinpoint behaviors of fraudulent activities in supporting real time alerts. The conclusion drawn from this study is in consonance with the assertion that big data and machine learning are well regarded by consumers as efficient

mechanisms for strengthening protection of credit cards.

Predictive Factors in Fraud Detection

A logistic regression analysis revealed that the number of purchases made online and income level which are consumer behavioral variables were found to predict the fraud experience. I found similar evidence in prior studies suggesting that higher levels of transactions and spending are valid predictors of fraud-prone individuals (Morris et al, 2023; Park & Kim, 2021). Cheng and Lin (2020) state clearly that machine learning models using the behavioral data can develop risk scores based on the frequency of transaction and other spending activities that can improve the measures of probability concerning high-risk frauds. Harrison et al. (2020) back up these algorithms by stating that automated fraud fighting models are critical in minimizing losses in spite of the risk in consumer niches.

Policy and Practical Implications

The present study has significant implications on policy and practice as discussed below. The consumer behavior data available in the US can be effectively used by the financial institutions to develop the security measures that reflect the risk

factors related to the particular segment of consumers (Nguyen & Tran, 2023). Prompting the use of multi-factor authentication (MFA) and increasing consumers awareness on the dangers of the internet can decrease credit card fraud risk. The results of the study confirm the use of big data and machine learning technologies into credit card security within the general architecture particularly for clients with frequent online transactions and those with higher income (Smith et al, 2022).

Limitations and Future Research

There are limitations to this study. The data used was self-reported, which brings about a bias into the study. Future studies could use longitudinal designs to analyze changes in consumers' behavior and fraud risk levels by capturing the long-term effectiveness of MLM s in fraud prevention (Harrison et al, 2020). Future research can also look at how effectiveness other machine learning algorithms perform in distinguishing fraud patterns among different group subcategories of consumers (Martin & Roberts, 2021).

CONCLUSION

Understanding consumer behavior data was the key discussion of this study as it looked at big data and machine learning to improve credit card security. This article explores the susceptibility of US consumers to credit card fraud and the importance of behavior-based, evidence-based approaches in tackling this menace.

These findings suggest that there are certain demographic factors that determine fraud exposure pointing to income and age. Young consumers and those with higher income are the groups that order food and other products most often, thus they are the most exposed to fraudsters. It is against this background that there is need for specific measures to be taken to address security of the groups most at risk. Financial institutions have the potential of minimizing fraud by using income and age-based pattern analysis alongside individualized alert systems together with better authentication facilities for the two demographics.

The study also shows that consumer education is central to promoting secure behaviors among the clients. Those with higher levels of card security knowledge will use more protective features like password changes and should have low fraud vulnerability. It was highlighted that a part of the

participants experienced low awareness of security practices which means that more educational campaigns should be launched to increase consumers' awareness of the existing security measures and threats. It means that it can strengthen consumer participation in efforts meant to safeguard their monetary resources.

The findings also throw the light on the reliance on big data and machine learning as reliable strategies for fraud detection more so for those who have been victims of fraud. Machine learning models that exploit consumer behavior data to make forecasts have been proved to be effective in detecting and preventing fraud with efficiency. This predictive power is complemented by the emerging need for real time data fed security systems that are capable of identifying deviations from normal user profiles. The positive reception towards these technologies means that these technologies will be adopted into credit card security frameworks, so as to counter attacks that are getting more complex.

These findings highlight the need for adopting a complex policy measure apropos credit card protection for policymakers and financial institutions. Demographic data analysis, behavior tracking and machine learning approaches

appear to form a stronger anti-fraud system. Engagement of technology vendors and financial organizations is required to extend the availability of such solutions and adapt them to different customer segments.

The present study confirms the significance of big data and machine learning for the enhancement of credit card security. Based on the data concerning users' behaviors, financial industry should improve the efficiency of fraud prevention, thus making the USA economy more secure. It is this concern of the fundamental, technology-supported method that will open the way for the creation of a safer financial environment for consumers while reinforcing the objective of digital financial insurance in its entirety.

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