Routine Activity Theory and Predictors of Interpersonal Fraud

By

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Abstract

This study explores what victim, offender, and crime characteristics affect property value loss or likelihood of arrest for credit card fraud. The theoretical foundation for this study comes from routine activity theory, which proposes that routine activities can increase or decrease the chances of victimization. Data from the 2016 National Incident-Based Reporting System was used to test how victim and offender characteristics, used as proxy variables, affect credit card fraud. The results of this study suggest that the older the victim is, the older the offender is, if the victim is male, and if the victim is Black, there will be a higher average property loss value for credit card fraud. When it comes to arrest, the findings suggest that when the victim is Black or male, it is less likely that the offender for credit card fraud will be arrested. The results of this study could be used for crime prevention, victim outreach, and a basis for further research.

Keywords: routine activity theory, credit card fraud, arrest, property value loss, fraud, white-collar crime, victim characteristics, offender characteristics

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Routine Activity Theory and Predictors of Interpersonal Fraud

The focus of this study is on one of the many crimes that falls under the umbrella of white-collar and fraud crimes. The purpose of this study is to use various victim, offender, and crime characteristics to determine the dollar value of loss from credit card fraud or if the offender was arrested. This study explores the best model for determining loss and whether there was an arrest using the characteristics described. The study begins with a brief history of how the definitions of fraud and white-collar crimes have changed and ends with how this study can inform future research.

The crime of fraud can be traced back to the earliest civilizations with Aristotle recounting a story of financial fraud in sixth-century B.C. (Gong et al., 2016). The term fraud has been used to describe various behaviors that have also been referred to as white-collar crimes (Rorie, 2019). When Edward Sutherland wrote about white-collar crime and the high status of those who commit it back in 1949, he was providing a unique outlook at a time when crime was deemed to be associated with the working class (Michel et al., 2016).

Sutherland defined white-collar crimes as “a crime committed by a person of high social status and respectability in the course of his occupation” (1949, p. 9). While Sutherland’s definition at the time was innovative, it has since been criticized due to the definition’s lack of focus on the act, the nuances of business versus interpersonal fraud, and the fact that individuals from all income levels commit fraud crimes (Michel et al., 2016). Although Sutherland tried to highlight the need for a greater focus on white-collar crime, it did not become a mainstream area of study compared to traditional or street crime. In addition, it has been argued that it is more beneficial to understand the situations in which crime occurs as opposed to the differences between those who commit crime and those who do not (Weisburd et al., 2001).

In addition to Sutherland's original definition, other widely used and important definitions include Edelhertz's definition where white-collar crime is described as "an illegal act or series of illegal acts committed by nonphysical means and by concealment or guile, to obtain money or property, to avoid the payment or loss of money or property, or to obtain business or personal advantage" (1970, p. 3). This definition was further revised by Wheeler et al. (1982, p. 642), who classified white-collar crimes as "economic offenses committed through the use of some combination of fraud, deception, or collusion." Unlike Sutherland, neither of these definitions focus on the social status of those who commit the crime and instead highlight the acts that fall within white-collar crime, which could be committed by someone of any status.

More recently, the term white-collar crime was further redefined by Felson and Boba (2010) as a crime of specialized access that was categorized as "a criminal act committed by abusing one's job or profession to gain specific access to a crime target" (p. 119). This definition highlights that legal work can create opportunities for crime. It is important to understand that white-collar crimes can be committed against anyone or by anyone and therefore it is necessary to study all aspects of these crimes.

One of the many crimes that falls under the definition of white-collar crime is credit card fraud. When it comes to reporting statistics and information on white-collar crimes, National Incident-Based Reporting System (NIBRS) has a subsection of fraud crimes, with credit card fraud being one of them. NIBRS defines what is considered a fraud crime and then further defines how each of those crimes is defined.

The white-collar crime discussed for the purposes of this paper is a fraud crime as defined by the NIBRS. The definition of fraud according to NIBRS is "the intentional perversion of the truth for the purpose of inducing another person or other entity in reliance upon it to part with some thing of value or to surrender a legal right" (UCR FBI, 2017). Specifically, this study focuses on card/automatic teller machine fraud, which is defined by NIBRS as "the unlawful use of a credit (or debit) card or automatic teller machine for fraudulent purposes" (National Archive of Criminal Justice Data, 2016, p. 356).

Credit card fraud is a crime that has multiple victims, including the individual whose credit card was fraudulently used, credit card companies, and merchants who sell items to fraudsters using the card. Offenders can commit credit card fraud in numerous ways, including the least complex method of using a credit card that was misplaced or taken. Non-receipt fraud is another type of credit card fraud that occurs when a new card gets intercepted before it gets to the victim. A more sophisticated type of credit card fraud called occurs when the information from an existing card is copied onto a new card for fraudulent use. Credit card fraud that occurs using email is called phishing and is perpetrated through sending out links through emails that direct victims to a fake website where they are asked to enter in credit card information that is then stolen (Barker et al., 2008).

When it comes to financial fraud research, more attention has been given to studying financial fraud against businesses and governments. According to Deevy et al. (2012), interpersonal fraud research has been neglected. It has also been argued that there is more research on fraud against businesses and governments as opposed to individuals because the amount lost is less for individuals (Deevy et al., 2012). Overall, it appears that nonviolent crimes do not receive the attention they warrant with violent and drug crimes receiving more dedication from the criminal justice system. One of the reasons for this is that white-collar crimes such as identity theft are complex and when there is a conviction in these cases, the punishments are light compared to violent or drug crimes (Allison et al., 2005). Due to the lack of research on fraud crimes in general, the research discussed includes research on financial fraud, internet fraud, and crimes similar to credit card fraud.

While interpersonal fraud has been neglected in the research, it is important to study because of the financial and emotional costs it has on their victims. According to the Federal Bureau of Investigation's (FBI) Internet Crime Center (IC3), the center received 301,580 complaints from victims of internet crime in 2017 totaling $1.4 billion in total losses with the numbers increasing to 351,937 complaints totaling $2.7 billion in losses for 2018 (IC3, 2018, p. 5). Victims of credit card fraud alone accounted for 15,210 complaints totaling $88,991,436 in losses for 2018 (IC3, 2018, p. 5). The large increase in losses will only continue to grow. More effective strategies need to be implemented to reverse the upward trend in fraud losses.

When it comes to the psychological costs of fraud, victims of credit card fraud can experience work, school, family, and friend problems as a result of victimization, as well as mild to severe emotional distress (Harrell, 2019). Stopping fraud victimization before it occurs can help prevent not only the financial costs but the social and emotional costs as well. One of the ways to prevent fraud victimization would be to understand who has the greatest probability of being victimized and looking at what makes them a higher risk, such as their age (Shao et al., 2019). Age is just one factor that can increase the risk of fraud victimization and the more risk factors that are identified, the better law enforcement can be equipped to help protect vulnerable individuals.

It is difficult to be completely protected from fraud, but it is important to build a profile of who is victimized in order to give government the ability to seek out those who are most susceptible and efficiently use resources to protect the most likely victims (Deevy et al., 2012). For example, prior research on telemarketing fraud and previously victimized seniors found that providing prior victims with warnings about fraud schemes could protect them against future fraud attempts (Scheibe et al., 2014). By using what is known about victim characteristics, new strategies to prevent fraud can focus on those who are most susceptible.

In addition, while there is no standard offender for every case, understanding offender traits can assist merchants in stopping fraud before it happens (Barker et al., 2008). For example, creating a profile for those who perpetrate fraud is difficult because a great deal of the current research aligns with the stereotype of fraudsters being White, young or middle aged, but this profile could be inaccurate and further research is warranted (Deevy et al., 2012).

Due to the nature of the credit card fraud and the ability of offenders to victimize online, it is important to understand how potential targets can be educated to prevent victimization. With widespread access to computers, the accessibility of information that can be used to commit white-collar crimes has been expanded for many people (Weisburd et al., 2001). By applying routine activities theory to explain these crimes, potential victims can be informed on how their online use can increase or decrease the chances of them becoming a victim of fraud. In addition to potential victims, those who conduct business online and internet service industries can help to make potential victims more difficult targets, which could lower the number of chances offenders have to commit these crimes (Pratt et al., 2010).

When it comes to sophisticated fraud crimes, there needs to be a greater focus in the research because of the effects these crimes have on victims and to gain a better understanding for prevention efforts (Allison et al., 2005). While it may appear on the surface that there is a limitless number of potential victims for economic crime, research on fraud crimes has shown that offenders specifically target who they should victimize, where the crime will take place, and when. By narrowing down how fraudsters think and choose a target, this information could be used to proactively identify crimes before they happen (Powell et al., 2019). Aside from identification, it has been argued that there is an underlying sentiment that economic crimes are insignificant and the penalties for these crimes is lower. In order to combat these crimes, it may be beneficial to put a greater emphasis on informing individuals about the punishments for these crimes. In addition to deterring potential offenders, if victims are educated on the harm caused by these crimes, they could take more steps to protect themselves from victimization (Powell et al., 2019). The purpose of this research is to add to the current knowledge on fraud and provide a basis for prevention efforts and education.

Consequently, this study is an examination of credit card fraud, to determine what offender and victim characteristics affect harm to victims or are predictive of an arrest. The findings can inform crime prevention efforts, victim assistance, and provide a direction for future research. The goal of this study is to help fill a gap in the current research on interpersonal fraud crime and victim, offender, and arrestee characteristics. This study is unique for the characteristics analyzed and the way the dependent variables are used. It is important to understand what crime characteristics can lead to more or less harm and chances for offender arrest.

This paper contains four additional chapters including the theoretical foundations and literature review, research data and methodology, analytical results, and discussion and conclusions. The theoretical framework and the literature review examine the current research on the topic ending with the research questions, and the research methodology show the data and approach for answering the proposed research questions. The analytical results highlight the statistical results with interpretations, and the discussion, implications, limitations, and conclusion chapter describes what the findings could be used for and how this study was limited.

Literature Review

This chapter gives the underlying theoretical foundations and research to provide a framework for this study and an overview of the relevant research completed on credit card fraud. The theoretical foundations section of this chapter focuses on routine activities theory and how it explains credit card fraud. The review of the literature covers what research has already been done on this topic and how it applies to the current study. Based on the current research, the next section highlights gaps in the research that lead to the research questions for this study.

Theoretical Foundations

The theoretical foundation of this study comes from routine activities theory and provides the basis for understanding interpersonal fraud crime and how victim and offender characteristics can affect property loss value. The difference between routine activities theory and many other criminological theories is that routine activities theory does not focus on what makes the offender commit crimes but focuses on how routine behavior of individuals creates opportunities that allow for crimes to happen (Cohen & Felson, 1979). Prior research has shown that most white-collar criminals live very normal lives and so trying to distinguish between offenders and non-offenders based on background is not possible (Weisburd et al., 2001). This is important because it means that white-collar criminals cannot be limited to one section of society but could come from any background. Therefore, it is important to understand what characteristics do affect specific crimes to help inform research and prevention efforts.

In routine activities theory, routine activities are things that an individual commonly does to satisfy their needs and these routine activities can include things like going to a place of employment, grocery shopping, and socializing with others (Cohen & Felson, 1979). The argument proposed in the routine activities theory is that crime can come from structural modifications that affect the convergence of people who are willing to commit a crime (motivated offenders) coming into contact with someone who can be victimized (suitable target) without anyone who can stop the potential offender (no capable guardians against a violation). This theory further proposes that crime can be prevented if just one of the three conditions mentioned previously is not present (Cohen & Felson, 1979).

The original three conditions coming together in time and space necessary for a crime or crime triangle states that there needed to be a motivated offender, suitable target, and no capable guardian for a crime (Cohen & Felson, 1979, p. 589).

Figure 1

The Revised Crime Triangle

Note. Source: Eck (2003, p. 89).

This triangle was revised as shown by Figure 1 with the three essential components for a crime, including an offender, place, and target or victim. In addition to the three components on the inside of the crime triangle, there is a second triangle showing how managers can keep an eye on places, handlers can keep track of offenders, and guardians can protect targets or victims. All the additional controllers can assist in preventing or lowering the chances of a criminal event (Hollis et al., 2013).

An example of two structural changes that increased opportunities for white-collar crime include the invention of computers that hold a great deal of information and could be used to commit white-collar crime, and the increase in the size of state governments giving people access to large amounts of money they would have never had access to otherwise. Age has also been found to increase opportunities for white-collar crime with more opportunities for someone to commit crime as someone ages (Weisburd et al., 2001). These examples can be applied to credit card fraud specifically because it is a crime that can be committed over the internet and younger individuals have a better understanding of how to use technology, which makes older individuals more susceptible to crime (Stamatel & Mastrocinque, 2011).

When applying routine activities theory to property loss value, it can be argued that both victim and offender characteristics can affect how much money is taken based on victim or offender characteristics. For example, older individuals living a more isolated lifestyle and having greater wealth can make them more susceptible to fraud crimes and could allow offenders to take more money from them (DeLiema, 2018).

Based on the different behaviors of individuals with varying characteristics, routine activities theory, when applied to fraud, can provide a framework for understanding why victim and offender characteristics affect credit card fraud. Specifically, this study proposes that victim characteristics such as age and sex will affect perceived or actual risks associated with committing interpersonal fraud. The routine activities of individuals are different overall based on various demographics and those different behaviors increase or decrease how the offender perceives the potential victim.

While routine activities theory has traditionally been used to explain crimes where a victim and offender come into contact in a physical space, it can also be applied to crimes that are perpetrated online. For example, research on identity theft in Britain found that credit card fraud, which can be perpetrated online, was the most common form of identity theft and that victim characteristics were predictive of fraud victimization (Reyns, 2013). Prior research has also shown that characteristics such as sex, how old an individual is, and race are related to the amount of time people spend online. With more time spent online, there are more opportunities for victimization; therefore, time online was predictive of falling victim to fraud (Reyns, 2013). While routine activities theory proposed that individuals are more likely to become victims of certain crimes such as burglary while they are not in their residence, when it comes to fraud, the opposite can be true, and shopping at home over the internet can lead to victimization (Pratt et al., 2010).

When it comes to research on violent crime looking at routine activities theory, emphasis has been put on the criminal activities that potential victims engage in that could increase their chances of victimization (Schreck et al., 2006). In addition to violent crime, routine activities theory has also been used to explain financial crimes (DeLiema, 2018). However, when it comes to consumer fraud, this becomes more difficult because of the non-criminal nature of activities that can lead to consumer fraud victimization. For example, normal and legal activities, such as buying items online from the comfort of one's home, can increase the chances of victimization by creating opportunities for victimization (Pratt et al., 2010).

This study proposes that routine activities affect opportunities for crime and individuals have different routines overall based on demographic characteristics. Due to the nature of credit card fraud and the ability of victimization to occur online and in person, routines discussed include but are not limited to online routines. For example, prior research found that when compared to women, men do more and dedicate greater amounts of time on the internet (Donner, 2016). When it comes to race, the research has shown that Black individuals spent less time online, which could create fewer opportunities for credit card fraud victimization since that is one of the places where this fraud occurs (Reyns, 2013).

When it comes to the amount that could be taken using a credit card, research has shown that White individuals are given higher credit limits (Freeman, 2017); therefore, it could be argued that when White individuals are victimized, more could be taken. In addition, Black individuals have lower rates of credit card ownership (Freeman, 2017), and so there could be fewer opportunities to victimize Black individuals using a credit card. Finally, when it comes to age, the research on elder fraud has highlighted that the isolated lifestyle and wealth of older individuals can make them an easier target for fraud crimes (DeLiema, 2018).

These characteristics of potential victims and where they spend their time can increase the chances of them becoming a victim. These characteristics, such as age, race, and sex, can increase chances of victimization since differing groups participate in unique routine activities that could lead to a greater or lesser chance of victimization. This study applies routine activities theory to credit card/automated teller machine fraud and how victim and offender characteristics can affect seriousness or chances of an arrest.

The next section covers the research on victimization and offending of credit card fraud/automated teller fraud by demographic categories to determine what is already known and identify the gaps to inform the research questions and hypotheses for this study.

Review of the Research

The review of the research highlights what research has already been completed on similar topics, explores what characteristics can be used as a proxy for types of behavior, and shows where the research is lacking. The demographic characteristics covered include sex, race, ethnicity, and age. All the characteristics outlined below in the research highlight the differences that can increase or decrease the likelihood of victimization, offending, and arrest.

Sex

The research on sex differences at it relates to credit card fraud shows that there are important variations when it comes to victims and offenders. The 2016 Identity Theft Supplement (ITS) from the National Crime Victimization Survey (NCVS) showed more male victims than females for the crime of misuse of existing credit card, and while this survey did not show a property loss value by sex, males could have a higher loss value based on their higher victimization rates (Harrell, 2019).

Prior research has also shown that males spend more time online, which is one of the places credit card fraud can occur, and females were less likely to become victims of identity theft, with credit card fraud being the largest form of identity theft in the study (Reyns, 2013). When looking at opportunities for victimization based on behaviors, people who buy things on the internet, those who have more money, and individuals who are male were more likely to be targeted for internet fraud (Pratt et al., 2010).

Looking at offending, the research on cybercrime hacking, which includes credit card fraud, found that overall men were more likely to commit hacking crimes compared to women (Donner, 2016). Increased amounts of time on the internet was also associated with more offending due to the potential offenders being able to connect with others and enhance their abilities online. This research also found that men use the internet to do more, devote greater amounts of time on the internet, and use the internet more often when compared to women (Donner, 2016). Based on the behaviors and characteristics of offenders and victims, it can be argued that property loss for credit card fraud will be higher when the victim and offender are male. In addition, prior research on arrestees for credit card/ATM fraud has found that males had a higher median value of property compared to females (Steffensmeier et al., 2015).

When looking at sex of the offender and likelihood of arrest, the research appears mixed. The research on identity theft, which includes credit card fraud, found there were more female offenders and more male victims (Allison et al., 2005). Research on computer assisted fraud, which included credit card fraud, found a significant correlation for gender and arrests, with females having a greater likelihood of being arrested. This research proposed that the reason for this was due to the higher representation of females committing property crimes overall (Liao et al., 2017). Other research that used NIBRS data and had a large sample size found that there were more male arrestees as opposed to females (Steffensmeier et al., 2015). While the research appears mixed, it can be argued that when it comes to sex, males will have a higher likelihood of being arrested for credit card fraud.

Race and Ethnicity

Research has also found important differences when it comes to race and ethnicity. Looking at the 2016 ITS from the NCVS, there were more White victims for misuse of existing credit card than any other race. The number of victims who were White individuals was 10,661,500, with Black individuals accounting for 756,100 victims (Harrell, 2019). The population of White individuals living in the United States in 2016 was approximately 248.5 million, while Black individuals accounted for approximately 43 million (Duffin, 2019). Comparing the numbers based on population, 4.3% of White individuals were victimized and only 1.8% of Black individuals were victimized. While this survey did not show a property loss value by race, individuals who are White could have a higher loss value based on their higher victimization.

When it comes to time spent online, prior research has also shown that Black individuals spend less time online, where credit card fraud can occur, which could mean less opportunity for victimization (Reyns, 2013). Research on internet use has also shown time spent on the internet and the amount of time spent online was correlated with being targets for internet fraud (Pratt et al., 2010). The research highlighted previously could suggest that White offenders victimizing White victims would result in a greater financial loss.

When it comes to seriousness or property value loss, research has shown that White individuals receive higher credit card limits (Freeman, 2017) and so it could be argued that White victims could have more stolen from credit card fraud. Prior research has also shown that Black individuals possess credit cards at lower rates (Freeman, 2017). Further research on financial exploitation, which includes credit card fraud, has shown that in about three out of every four cases, the offender was White (Stamatel & Mastrocinque, 2011). It can also be argued that based on most offenders being White, they would also have more experience committing credit card fraud and gaining more money from each crime. White individuals possessing more credit cards and having higher limits could also lead to them being perceived as higher value targets and enable offenders to take more money.

The research on identity theft, which includes credit card fraud, found that Black offenders were overrepresented as offenders compared with the study population (Allison et al., 2005). The research on computer assisted fraud, which includes credit card fraud, found that even though there were fewer Black than White individuals in the study population, Black individuals were more likely to be arrested. While the study did not propose a reason for this finding, it did propose this as an area that could be researched further (Liao et al., 2017). Based on the overrepresentation as offenders and arrestees in prior research, it could be argued that non-White offenders have a higher chance of being arrested when compared to White individuals.

In addition to race, the research has shown that there are important differences when it comes to interpersonal fraud crime and ethnicity. The 2016 ITS from the NCVS showed fewer Hispanic victims for misuse of existing credit cards. The number of victims for non-Hispanic individuals was over 10,661,500 with only 1,026,200 Hispanic victims (Harrell, 2019, p. 4). While this survey did not show a property loss value by ethnicity, individuals who are Hispanic could have a lower property loss value based on their lower victimization.

The research on income and credit card use has shown that Hispanic households have lower income levels compared to white households and white households use credit cards more when compared to Hispanic households (Fisher, 2016). Based on income and credit card use, it can be argued that when victims are Hispanic, the value of credit card fraud will be lower since non-Hispanic individuals could be perceived as better targets.

When it comes to offenders, research on identity theft has shown that the most common form of identity theft involves credit card fraud and over half of the offenders of identity theft are Black, with Hispanic individuals accounting for less than 1% (Copes & Vieraitis, 2009). Hispanic income levels being lower could also make them a less suitable target and Black individuals making up most of the offenders could make them a group of more effective offenders for this crime. Based on the income levels, credit card ownership rates, and most offenders being non-Hispanic, it can be argued that when the offender is non-Hispanic, the property loss value will be higher.

The research looking at identity theft including credit card fraud shows that there were very few Hispanic offenders and victims for this crime. This research also highlighted that Black individuals had the highest offender rates (Allison et al., 2005). Based on the underrepresentation of Hispanics as offenders and the overrepresentation of Black individuals, it can be argued that when the offender is non-Hispanic, it is likelier that there will be an arrest.

Age

The research has shown that in addition to sex, race, and ethnicity, victim and offender age can make a difference when it comes to interpersonal fraud crimes. While the 2018 Internet Crime Report (IC3, 2018) did not look at victims and total loss by age for credit card/automatic teller machine fraud by itself, it did break out victims and total loss by age for all internet crimes, which includes credit card fraud. The report found that for all the age groupings, the total loss and victimization was greater the older the victim age group was, with individuals over 60 years of age accounting for the highest total loss and victimization, and individuals under 20 years of age representing the least total loss and victimization (IC3, 2018, p. 16).

The 2016 ITS from the NCVS showed increases in the number of victims for misuse of existing credit cards in all age groups except individuals 65 and older (Harrell, 2019). Prior research on elder fraud has suggested that offenders commit fraud crimes against older victims at higher rates because of a perception that they have more to take, they have a more isolated lifestyle, and they may have physical or mental impairments that make them an easier target (DeLiema, 2018). The older potential victims can also be more susceptible to fraud because their family, friends, or capable guardians may not know they need protecting, or they may be the ones victimizing if they are the ones with special access to victims' financials (DeLiema, 2018). Prior research using NIBRS data looking at credit card/automatic teller machine fraud specifically found that individuals under 65 had a lower average value of property lost than individuals over 65 (Stamatel & Mastrocinque, 2011).

When it comes to offenders, the research covering elder financial exploitation showed that most of the offenders were the victim's children. In addition to children offenders, financial crimes such as credit card fraud have also been moving to the internet and older individuals could be easier targets since they do not understand the new technology as well as younger individuals. Older individuals could also be perceived as better targets because of their better monetary situation and their deteriorating mental health over time (Stamatel & Mastrocinque, 2011). Based on younger individuals' greater familiarity with technology compared to older individuals and older individuals' better financial position, it could be argued that the younger the offender and the older the victim is, the greater the property loss is.

The research on elder abuse has shown that for financial exploitation, which includes credit card/automatic teller machine fraud, the majority of the perpetrators of this fraud were the children of those victimized (Stamatel & Mastrocinque, 2011). Prior research on identity theft, which includes credit card fraud, found that most of the victims and offenders did not know each other (Allison et al., 2005). Based on the prior research, it could be argued that when the offender and victim do know each other, there is a greater likelihood of arrest since the victim can help the police find the offender once the offender's identity is known. Since the research also showed that the majority of the offenders for elder financial exploitation were the children of those victimized, it could be argued that with younger offenders, it would be more likely that they know the victim and therefore it would be more likely they would be arrested.

Property Value Loss

The information on how individuals investigating fraud make decisions or whether to investigate a fraud crime and what cases they will work first highlighted that investigators will look at the amount of loss from the fraud in making their decision (Wilhelm, 2004). This research also argued that the higher the loss to fraud was, the greater the chances of an investigation would be (Wilhelm, 2004). Based on this information, it can be argued that the higher the loss amount is, the more willing law enforcement will be to use limited resources to investigate and the likelier there will be an arrest made.

When it comes to credit card fraud, the Fair Credit Billing Act (FCBA) protects credit cardholders if their credit card is fraudulently used. According to FCBA, the maximum amount cardholders will have to pay is $50 if their credit card is used when they did not approve the purchase (Federal Trade Commission, 2019). However, even though victims will likely get their money back, there can be a temporary loss of funds and mental costs associated with the crime and process of recovering funds. Prior research has found that those who were victimized for credit card fraud suffered mild to severe emotional distress and reported work, school, and family issues (Harrell, 2019).

Consequently, this study argues that when offenders decide whether or not to commit a crime, they weigh what they believe to be the risks of committing the crime against what they believe they will gain (Drawve et al., 2014). When it comes to credit card fraud, the higher the property loss value is, the greater an offender could perceive the rewards and his or her willingness to commit the crime. Due to the financial nature of this crime, it can also be argued that the greater the financial loss is, the more harm is caused by this crime.

Gaps in the Research

There has been a great deal of research on different aspects of interpersonal fraud as highlighted previously. However, research in many different areas could benefit from a similar study and there are gaps that could be filled. The research using the theoretical foundations of routine activities theory and NIBRS data has focused on violent crimes, but propose that further research in this area is warranted and different approaches should be used to apply routine activities theory in different ways (Drawve et al., 2014). When it comes to financial fraud research in general, there has been a greater emphasis on crimes against companies and governments at the same time as the research on interpersonal fraud has been neglected (Deevy et al., 2012).

Research using NIBRS data, multivariate regression, and bivariate analyses to predict arrest has been used in prior research, but the focus of this research was on offender characteristics on violent crime (D’Alessio & Stolzenberg, 2003). The research on predicting arrests based on offender characteristics has highlighted gender, race, and age impacting likelihood of arrest for credit card fraud, but has not looked at the impact of property loss value and ethnicity as predictors of arrest (Liao et al., 2017).

There appears to be extensive research on credit card/automatic teller machine fraud with routine activities theory being applied in some studies. Research on credit card fraud has used a routine activities theory to explain this crime, but the focus was on elder fraud specifically and had a small sample size (DeLiema, 2018). Other research using routine activities theory to explain identity theft listed credit card fraud as the most common form of identity theft studied, but this research did not look at whether victim characteristics affected the amount of money each victim lost, and looked at Britain and not the United States (Reyns, 2013).

The research using NIBRS data and looking at victim characteristics for the crimes outlined in this study did look at age and average property loss value. However, this research did not look at property loss for any other characteristic of victims, split the victims into two age groups, and did not cover arrestee data (Stamatel & Mastrocinque, 2011).

While there is some research that has used NIBRS data to look at fraud, applied routine activities theory to various fraud crimes, and looked at victim, offender, and arrestee characteristics, this study is unique. Prior research has not used the recently available 2016 NIBRS data to look at victim, offender, and arrestee characteristics as it relates to seriousness or likelihood of arrest. This study uses a unique approach by applying the routine activities theory as a framework for better understanding the widespread and harmful crime of credit card/automated teller machine fraud.

Research Questions and Hypotheses

The information highlighted previously shows that while there is a great deal of information on fraud in general, there are some significant gaps in the research that are worth exploring. The gaps in the research that this study helps to fill cover important topics and have implications for assisting law enforcement in helping individuals at risk of victimization prevent themselves from becoming victims of fraud. This area of research was also chosen in part because of the enormous financial losses, physical costs, and mental harms these crimes can cause, as well as to inform future research.

Research Question 1: How are victim characteristics predictive of the seriousness of credit card/automatic teller machine fraud?

The question of seriousness is important to understand when looking at fraud crimes for many reasons. Based on the seriousness of these crimes, the harm caused could go from a minor inconvenience to life altering. Since this study is focused on a white-collar crime, seriousness is defined by property value lost as a result of the fraud crimes.

This is an important question because when it comes to credit card fraud specifically, not only do victims suffer direct and indirect financial losses, but this crime also causes work problems, school problems, family problems, friend problems, and mild to severe emotional distress (Harrell, 2019). When it comes to consumer fraud, the financial losses can be difficult to get back especially if those victims are no longer working; they may also lose their independence and the money they were going to leave for others, as well as experience mental anguish due to fraud (Deevy et al., 2012).

The hypotheses propose the victim characteristics that will increase harm for credit card/automatic teller machine fraud. As prior research has shown, victim characteristics such as sex (Donner, 2016), race (Freeman, 2017; Reyns, 2013), ethnicity (Fisher, 2016), and age (DeLiema, 2018) can affect routine activities that can increase or decrease the risk of fraud victimization.

Hypothesis 1.1: When controlling for other variables, the younger the victims are, the lower the value of property loss for credit card/automatic teller machine fraud will be.

Hypothesis 1.2: When controlling for the other variables, if the victims are female, the value of property loss for credit card/automatic teller machine fraud will be lower.

Hypothesis 1.3: When controlling for the other variables, if the victim is Black, the value of property loss for credit card/automatic teller machine fraud will be lower.

Hypothesis 1.4: When controlling for the other variables, if the victim is Hispanic, the value of property loss for credit card/automatic teller machine fraud will be lower.

Research Question 2: How are offender characteristics predictive of the seriousness of credit card/automatic teller machine fraud?

Research Question 1 highlighted victim characteristics, but it is also important to understand how offender characteristics affect the seriousness of the fraud. Research Question 2 goes one step further than Research Question 1 and focuses on a smaller group of crimes where the offender is known and explores how offender characteristics are related to the seriousness of the crimes. In order to combat fraud crimes, it is important to understand who is committing the crimes and even though offenders will not always be the same, understanding their traits can assist in preventing fraud (Barker et al., 2008).

Looking at prior research, younger individuals have a greater understanding of technology, which can be used to commit financial fraud. This research also found that elder financial exploitation was committed by the victim’s children (Stamatel & Mastrocinque, 2011). Based on younger individuals’ understanding of technology and access to parents’ finances, it could be argued that younger offenders could cause more harm for credit card fraud.

When examining offender sex differences, research on cybercrime hacking, which includes credit card fraud, found that men were more likely to be offenders as opposed to women (Donner, 2016). This research also highlighted that time spent on the internet was correlated with offending and that men spent more time online compared to women (Donner, 2016). Based on this information, it can be argued that when the offender is a man, the harm will be greater.

Race and ethnicity also appear to be associated with financial fraud offending. Research on financial exploitation found that most of the offenders were White, with another study on identity theft finding that less than 1% of offenders were Hispanic (Copes & Vieraitis, 2009). Hispanic offenders representing a very small amount of the overall offender population could mean that when the offender is Hispanic, the property value loss could be less.

Hypothesis 2.1: When controlling for other variables, the older the offender is, the value of property loss for credit card/automatic teller machine fraud will be lower.

Hypothesis 2.2: When controlling for other variables, if the offender is female, the value of property loss for credit card/automatic teller machine fraud will be lower.

Hypothesis 2.3: When controlling for other variables, if the offender is Black, the value of property loss for credit card/automatic teller machine fraud will be lower.

Hypothesis 2.4: When controlling for other variables, if the offender is Hispanic, the value of property loss for credit card/automatic teller machine fraud will be lower.

Research Question 3: How are crime characteristics, offender characteristics, and victim characteristics predictive of an arrest for credit card/automatic teller machine fraud?

The previous two research questions highlighted victim and offender characteristics as it relates to the seriousness of the crimes measured by property value loss. Research Question 3 uses a different dependent variable and looks at all incidents (similar to Research Question 1) to examine what offender or crime characteristics are predictive of whether an arrest was made for credit card fraud. This is a valuable question to ask since prior research has shown that the best ways to anticipate the likelihood of an arrest comes from victim and offender characteristics such as how old someone is, his or her race, and if he or she male or female (Drawve et al., 2014). The research looking at the likelihood for arrests focused on violent crime and found that an arrest was more likely if the offender is female, White, and younger (Drawve at al., 2014). While violent crime and financial crimes are different, prior research has found many similarities between white-collar and street crime offenders (Weisburd, Waring, & Chayet, 2001).

Hypothesis 3.1: When controlling for other variables, the younger the offender is, the more likely there is an arrest for credit card/automatic teller machine fraud.

Hypothesis 3.2: When controlling for other variables, if the offender is male, the more likely there is an arrest made for credit card/automatic teller machine fraud.

Hypothesis 3.3: When controlling for other variables, if the offender is Black, the more likely there is an arrest made for credit card/automatic teller machine fraud.

Hypothesis 3.4: When controlling for other variables, if the offender is non-Hispanic, the more likely there is an arrest made for credit card/automatic teller machine fraud.

Hypothesis 3.5: When controlling for other variables, the higher the value of property loss is, the more likely there is an arrest made for credit card/automatic teller machine fraud.

Hypothesis 3.6: When controlling for other variables, the younger the victim is, the more likely there is an arrest for credit card/automatic teller machine fraud.

Hypothesis 3.7: When controlling for other variables, if the victim is male, the more likely there is an arrest made for credit card/automatic teller machine fraud.

Hypothesis 3.8: When controlling for other variables, if the victim is White, the more likely there is an arrest made for credit card/automatic teller machine fraud.

Hypothesis 3.9: When controlling for other variables, if the victim is non-Hispanic, the more likely there is an arrest made for credit card/automatic teller machine fraud.

Methodology

The present study utilizes secondary 2016 NIBRS data to help fill a gap in the research concerning interpersonal fraud crimes and the characteristics of victims, offenders, and arrestees, as well as how these characteristics affect the seriousness of the crimes or likelihood of arrest. NIBRS data has been used by others to study fraud crimes, including the fraud crime outlined for this study (Gong, et al., 2016). Crime measures such as NIBRS can assist with assessing the effectiveness of protocols, understanding where investments are needed using limited funds, and examining theories. While NIBRS data is not representative of the United States or crime, the detailed information allows for analysis of incident specific crime information. Studies of crimes using NIBRS data have focused on violent crime, white-collar crime, adult offenders, juvenile offenders, gender characteristics of offenders, and more (Pattavina et al., 2017).

The present study focuses on a fraud crime where the victim is listed as an individual as opposed to a business, financial institution, government, religious organization, other, or not listed. The crime analyzed for this study is credit card/automatic teller machine fraud. The definition of fraud for the purposes of this study comes from the Federal Bureau of Investigation's (FBI) NIBRS, which is a part of the Uniform Crime Reporting Program (UCR). According to NIBRS, fraud offenses are defined as "the intentional perversion of the truth for the purpose of inducing another person or other entity in reliance upon it to part with some thing of value or to surrender a legal right" (UCR FBI, 2017). The fraud crime selected for this study is credit card/automatic teller machine fraud, which will be defined as "the unlawful use of a credit (or debit) card or automatic teller machine for fraudulent purposes" (National Archive of Criminal Justice Data, 2016, p. 356). The seriousness of these crimes for the purposes of this study is defined by the value of the property loss for the property crimes.

The research design for this study is a correlational analysis to determine if the variables described in the hypotheses are related at one point in time. A correlation analysis is “a standardized statistical technique that summarizes the strength of a relationship between two quantitative variables in terms of its adherence to a linear pattern” (Bachman & Schutt, 2020, p. 523). An independent samples t-test is used for determining differences in the means of two independent groups (Weisburd & Britt, 2014). For example, this study uses an independent samples t-test to determine if there is a difference in the means for property value between males and females.

Pearson’s correlation coefficient is used to test bivariate relationships because it is a popular research method used to determine the associations between the variables. More specifically, looking at Pearson’s correlation coefficient, this study will determine if the relationships are positive or negative and whether they are statistically significant (Weisburd & Britt, 2014). The correlation coefficient will be used to determine the strength of the association ranging from a perfect negative or positive to no relationship at all (Bachman & Schutt, 2020). Chi-square will also be used to determine whether any of the positive or negative associations are statistically significant. Using chi-square, the associations with a $p < .05$ or 95% confidence level demonstrate that the association was not a chance association and is statistically significant (Bachman & Schutt, 2020).

Multiple linear regression is used for testing the first two research questions to show how the independent variables, victim and offender characteristics, are correlated with the dependent variable, property value loss. A multiple linear regression allows for each additional independent variable to be tested for its effect on the dependent variable, while controlling for the other variables in the model (Bachman & Schutt, 2020).

Research Question 3 has a binary categorical dependent variable and therefore cannot be analyzed using multiple linear regression. The assumption in a linear regression is that the dependent variable has no limit, but when working with a dichotomous dependent variable, the value of the dependent variable will either be 0 or 1. Logistic regression also fits the data along a curve instead of a straight line used for linear regression. The output from a logistic regression provides an odds ratio, which explains the odds of the dependent variable being 1 (Weisburd & Britt, 2014). In this study, that describes how the independent variables increase or decrease the likelihood of an offender being arrested. The following sections describe how the dependent and independent variables are defined and measured for these analyses.

Data

Specifically, 2016 NIBRS extract files from the University of Michigan's Inter-university Consortium for Political and Social Research is used for the analysis. These extract files were created in order to make it easier to use the NIBRS data and overcome issues including utilizing merged data from different segment levels (National Archive of Criminal Justice Data, 2016). In 2016, 34 states were certified to submit crime data using NIBRS, with 16 of those states' agencies submitting all crime data and the other 18 states having a combination of agencies using NIBRS to submit their data and others using the summary reporting system (UCR FBI, 2017).

There was a total of 5,293,536 incidents in the 2016 NIBRS data including violent and property crime. Based on the topic of this study being credit card fraud, the analysis was limited to cases with one offense code, with the offense code being credit card fraud, limiting the pool of cases to 84,796. Since the focus of the study is on consumer fraud, cases were only included if the victim was listed as an individual as opposed to a business, government, or other entity. The study was further limited to include only cases with one victim, one offender, the victim was at least 18, the offender was at least 18, a 5% trimmed mean for property value loss was completed by removing the highest and lowest 5% of cases in order to eliminate outliers, deleted cases that had a missing value for property values loss, only included cases where the property description was money, eliminated cases missing a victim sex or race, and eliminated cases without an offender's sex or race.

The data was limited to ensure that the focus was on credit card fraud and outliers or probable data entry errors would not affect the analysis. The target population for this study was limited to cases where an offender could be matched against a victim to determine property loss value based on all the characteristics described. Limiting the data and excluding outliers created a final dataset consisting of 4,862 cases.

Dependent Variables

The two dependent variables for this study are 1) seriousness of the crime, which is measured as the amount of property loss value, and 2) whether there was an arrest for the crime. Property loss is a ratio variable and arrest is a dummy variable. Arrest is coded with 0 being not arrested and 1 meaning arrest. While FCBA protects credit card holders from more than a $50 liability when their credit card is used without their permission, there can be an initial loss of funds and other issues (Federal Trade Commission, 2019). The research has shown that in addition to the financial loss, there can be emotional problems victims can suffer due to the fraud (Harrell, 2019). Credit card fraud is a financial crime and the greater the financial loss is, it can be argued that the more harm the crime has caused.

The descriptive statistics and frequencies are broken out for credit card/automated teller machine fraud. The property value for credit card/automated teller fraud showed 4,862 incidents where there was a property value listed with the minimum being $1 and a maximum of $2,152 with a mean of $392.93 and standard deviation of $449.23. The number of incidents where there was no arrest was 3,879 (79.8%) and there were 983 (20.2%) incidents where one individual was arrested.

Independent Variables

The independent variables used for this study include race, ethnicity, age, and sex of victims, offenders, and arrestees. There are more offenders than arrestees in the data since not all offenders were arrested for credit card fraud and there are arrestees that were not previously identified as offenders. The categorical variables will be coded with White being 0 and Black as 1, ethnicity will be coded with Hispanic or Latino being 0 and not Hispanic or Latino being 1, and for sex, female will be coded as 0 and male being 1. Age is the only ratio variable that is an independent variable.

Analytical Results

The following sections show the results of the statistical analysis and an interpretation of what they mean. Research Questions 1 and 2 will include the results of the tests on victim and offender characteristics with the dependent variable being property value loss. Research Question 3 will also test victim and offender characteristics, but with arrest as the dependent variable.

In order to test Research Questions 1 and 2, a Pearson correlation coefficient analysis is used to determine the strength, direction, and significance of the bi-variate relationships and test the stated hypotheses. In addition, a backward linear regression was used to determine the best model that explains these relationships while controlling for the other factors considered in the research question.

Research Question 3 will be tested using Chi Square and t-tests to determine if there is a statistically significant relationship between the bivariate variables. Following that, a logistic regression model is used to determine the likelihood of arrest due to the dependent variable being dichotomous. The logistic regression will show how much of the variance in arrest the independent variable accounts for as well as the likelihood based on each variable.

Descriptive Statistics

The following tables break down each category for victim, offender, and arrestee characteristics. The percentages shown are compared with population data to highlight over or underrepresentation of individuals in various categories.

Table 1

Descriptive Statistics of Categorical Data

Characteristic		N	%
Sex of the Victim	Female	2,967	61.0%
	Male	1,895	39.0%
Race of Victim	White	4,000	82.3%
	Black or African American	862	17.7%
Ethnicity of Victim	Not Hispanic or Latino	3,952	81.3%
	Hispanic or Latino	136	2.8%
Sex of the Offender	Female	2,167	44.6%
	Male	2,695	55.4%
Race of Offender	White	3,543	72.9%
	Black or African American	1,319	27.1%
Ethnicity of Offender	Not Hispanic or Latino	1,462	30.1%
	Hispanic or Latino	67	1.4%
Sex of the Arrestee	Female	425	8.7%
	Male	558	11.5%
Race of Arrestee	White	760	15.6%
	Black or African American	223	4.6%
Ethnicity of Arrestee	Not Hispanic or Latino	854	17.6%
	Hispanic or Latino	33	.7%

The descriptive statistics show some numbers that conform to what prior research has found and some numbers appear to be a deviation from what others have found. When it comes to the race of the offender, prior research showed an overrepresentation of Black offenders, which also appears to be the case in this data set (Allison et al., 2005). Prior fraud research also found that for ethnicity, Hispanics made up a very small portion of offenders and victims, which is also the case for this study population (Allison et al., 2005). When looking at arrestees, previous fraud research showed that there were more White individuals in the study population, but more Black arrestees; however, this study population shows more White than Black arrestees (Liao et al., 2017). Using this study population, this study will highlight whether prior research mirrors this study or if there are new findings based on this dataset. The following section will highlight the descriptive statistics for the count data.

Table 2

Descriptive Statistics for Count Data

Characteristic	N	Minimum	Maximum	Mean	SD
Age of Victim	4,862	18	95	47.05	17.61
Age of Offender	4558	18	99	33.10	11.06
Age of Arrestee	974	18	65	32.31	9.48

The age of the study population shows that the average age of the victims in this study population is over 10 years older than the offenders and arrestees. The standard deviation is also over 5 more years of age for victim age than offender or arrestee age.

According to the U.S. Census Bureau (2019), females account for approximately 51% of the U.S. population, White individuals account for slightly more than 76% of the population, Black or African Americans account for almost 13.5% of the population, and 18.5% of the population is Hispanic or Latino. Based on the database, there are more female victims, slightly more Black and White victims, and a lot fewer Hispanic or Latino victims compared to the general population. There are more male offenders, Black offenders, and fewer Hispanic or Latino offenders compared to the general population. NIBRS data is not representative of the U.S. population, this dataset is not in line with general population estimates, and this study should not be taken as representative of the U.S.

Bi-variate results: Correlation and T-Tests

Research Question 1 looks at the victim characteristics that could affect property value loss. Specifically, age, sex, race, and ethnicity are tested as predictors of property value loss. Correlation and t-tests are used to determine the strength, significance, and direction of the relationships.

The correlation results show that age of the victim and value of property from credit card fraud has a positive statistically significant relationship (Pearson's $r = .138$) at the $p < .01$ level. That is, the older the victim is, the higher the value of property loss is. However, the relationship is considered weak based on social science standards with values of positive or negative .1 to .3 are deemed a weak correlation, positive or negative .4 to .6 are viewed as moderate, and positive or negative .7 is seen as a strong correlation (Bachman & Schutt, 2020).

An independent samples t-test was run to determine whether there is a statistically significant difference in the means between females and males for property value loss. Using Levene's test for equality of variances shows that equal variances cannot be assumed since Levene's test for equality of variances is significant at the $p < .01$ level. The variances between men and women for value of property are significantly different.

The results of the t-test show that there is a significant difference in average property loss value for females, \$368.38 (SD = 433.35), and males, \$431.37 (SD = 470.57). Based on the t-test, the results, t(3791.18) = -4.69, p < .01, suggest that there is a difference between property loss for male and female victims of credit card fraud with females having a lower average property loss value.

An independent samples t-test was run to determine whether there is a statistically significant difference in the means between Black and White victims for property value loss. Using Levene's test for equality of variances shows that equal variances cannot be assumed since Levene's test for equality of variances is significant at the p < .01 level. The variances between Black and White victims for value of property are significantly different.

The results of the t-test show that there is not a significant difference at conventional levels in average property loss value for White victims, $397.98 (SD = 456.07), and Black victims, $369.47 (SD = 415.43). The t-test results, t(3791.18) = 1.795, p = .073, indicate that there is a difference between White and Black victims of credit card fraud with Black victims having a lower property value. While not significant at the .05 level, 0.1 is considered one of the significance limits presented in statistics literature (Figueiredo Filho et al., 2013).

Using Levene's test for equality of variances shows that equal variances can be assumed since Levene's test for equality of variances are not significant, p = .472. The variances between Hispanic and non-Hispanic victims of credit card fraud for value of property are not significantly different.

The results of the t-test illustrate that there is not a significant difference in property value for non-Hispanic individuals, $382.99 (SD = 443.52), and Hispanic individuals, $376.71 (SD = 437.93). Based on the results, t(4086)= .162, p=.871, there is not a statistically significant difference in property loss value by ethnicity for victims of credit card fraud.

Research Question 2 looks at the offender characteristics that could affect property value loss. In particular, age, sex, race, and ethnicity are tested as predictors of property value loss. A combination of t-tests and correlation tests are used to determine the strength and significance of the relationships outlined below.

The results show that age of the offender and value of property from credit card fraud has a positive statistically significant relationship (Pearson's $r = .06$) at the $p < .01$ level. That is, the older the offender is, the higher the value of property loss is. However, the relationship is considered weak based on social science standards with r values of positive or negative .1 to .3 viewed as weak correlations (Bachman & Schutt, 2020).

An independent samples t-test was run to determine whether there is a statistically significant difference in the means between female and male offenders for property value loss. Using Levene's test for equality of variances shows that equal variances cannot be assumed since Levene's test for equality of variances is significant at the $p < .01$ level. The variances between male and female offenders for value of property are significantly different.

The results of the t-test illustrate that there is not a significant difference at the conventional level in average property value for females, \$406.58 ($SD = 461.83$), and males, \$381.95 ($SD = 438.60$). Based on the t-test, the results, $t(4530.89) = 1.89$, $p = .059$, suggest that there is not a statistically significant difference in property value loss based on offender sex at conventional levels. While not significant at the .05 level, 0.1 is considered one of the significance cutoff levels presented in statistics literature (Figueiredo Filho et al., 2013).

An independent samples t-test was run to determine whether there is a statistically significant difference in the means between Black and White offenders for property value loss. Using Levene's test for equality of variances shows that equal variances cannot be assumed since

Levene's test for equality of variances is significant at the $p < .01$ level. The variances between White and Black offenders for value of property are significantly different.

The results of the t-test show that there is a significant difference in property value for White offenders, \$401.85 ($SD = 460.74$), and Black offenders, \$368.96 ($SD = 415.96$). Based on the t-test, the results, $t(2595.47) = 2.380$, $p < .05$, suggest that there is a statistically significant difference between property loss for White and Black offenders of credit card fraud. Cases with Black offenders have a lower average property loss value, meaning that Black offenders steal less compared to White offenders.

Using Levene's test for equality of variances shows that equal variances can be assumed since Levene's test for equality of variances not significant, $p = .636$. The variances between Hispanic and non-Hispanic offenders of credit card fraud for value of property are not significantly different.

The results of the t-test suggest that there is not a significant difference in property value for non-Hispanic individuals, \$391.61 ($SD = 441.84$), and Hispanic individuals, \$475.07 ($SD = 411.44$). Based on the t-test, the results, $t(1527) = -1.516$, $p=.130$, suggest that there is not a statistically significant difference between property loss for non-Hispanic and Hispanic offenders of credit card fraud. This means that non-Hispanic offenders do to not steal significantly more or less than Hispanic offenders.

Multivariate results: Multiple Regression

A Backward Stepwise Ordinary Least Squares regression was run to answer Research Questions 1 and 2 determining how victim and offender characteristics are predictive of the seriousness of credit card/automatic teller machine fraud. The models were initially separated for victim and offender characteristics, but it was revealed that when combined, the model was stronger. The separate models were too low and R^2 for each model separately explained less than 1% of the variance in property value loss. Once the models were combined and the final dataset was established to only focus on cases where money was taken, the results explained over four times as much of the variance in property value loss. Tables 3 and 4 outline the results of the backward stepwise regression and how each model differs until the final model that shows the most efficient model for predicting property value loss using victim and offender characteristics.

Table 3

Backward Stepwise Regression

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
1	.216[a]	.047	.041	432.38
2	.216[b]	.047	.042	432.23
3	.216[c]	.047	.043	432.11
4	.215[d]	.046	.043	432.08
5	.213[e]	.045	.042	432.14

a. Predictors: (Constant), Offender Ethnicity, Offender Age, Offender Sex, Victim Race, Victim Sex, Victim Age, Victim Ethnicity, Offender Race

b. Predictors: (Constant), Offender Ethnicity, Offender Age, Offender Sex, Victim Race, Victim Sex, Victim Age, Victim Ethnicity

c. Predictors: (Constant), Offender Ethnicity, Offender Age, Offender Sex, Victim Race, Victim Sex, Victim Age

d. Predictors: (Constant), Offender Ethnicity, Offender Age, Victim Race, Victim Sex, Victim Age

e. Predictors: (Constant), Offender Age, Victim Race, Victim Sex, Victim Age

Table 4

(N = 1,386)

Backward Multiple Regression Analysis Models 1, 2, 3, 4, 5

Variable/Model	B	SEB	β	Significance	R^2
Model 1					**.047**
Victim Age	4.438	.678	.181	.000****	
Victim Sex	47.251	24.745	.051	.056*	
Victim Race	65.789	39.366	.056	.095*	

Victim Ethnicity	36.009	72.121	.014	.618	
Offender Age	2.314	1.139	.055	.042**	
Offender Sex	-20.386	23.923	-.023	.394	
Offender Race	5.178	34.004	.005	.879	
Offender Ethnicity	61.799	67.893	.026	.363	
Model 2					**.047**
Victim Age	4.436	.678	.181	.000****	
Victim Sex	47.320	24.732	.051	.056*	
Victim Race	69.442	31.204	.060	.026**	
Victim Ethnicity	36.503	72.023	.015	.612	
Offender Age	2.315	1.138	.055	.042**	
Offender Sex	-20.054	23.815	-.023	.400	
Offender Ethnicity	60.566	67.384	.026	.369	
Model 3					**.047**
Victim Age	4.405	.675	.180	.000****	
Victim Sex	48.003	24.688	.052	.052*	
Victim Race	68.431	31.132	.059	.028**	
Offender Age	2.327	1.138	.056	.041**	
Offender Sex	-20.920	23.747	-.024	.379	
Offender Ethnicity	74.111	61.841	.032	.231	
Model 4					**.046**
Victim Age	4.447	.673	.181	.000 ****	
Victim Sex	51.510	24.363	.056	.035**	
Victim Race	69.388	31.110	.060	.026**	
Offender Age	2.335	1.137	.056	.040**	
Offender Ethnicity	72.975	61.822	.031	.238	
Model 5					**.045**
Victim Age	4.441	.673	.18	.000****	
Victim Sex	50.705	24.357	.055	.038**	
Victim Race	67.388	31.068	.058	.030**	
Offender Age	2.333	1.138	.056	.040**	

Note. *p < .1, **p < .05, ***p < .01, ****p < .001

The first model in the Backward Stepwise Ordinary Least Squares regression included all the independent variables. The independent variables included in the beginning model were age of victim, sex of victim, race of victim, ethnicity of victim, age of offender, sex of offender, race of offender, and ethnicity of the offender. The first model has an R^2 of .047 and accounts for 4.7% of the variance in property value loss using eight variables.

In the second model, the race of the offender was excluded showing an R^2 of .047 with seven variables accounting for 4.7% of the variance in the dependent variable. Model three removed the ethnicity of the victim and was the last model with an R^2 of .047 to explain 4.7% of the variance in property value loss using six predictor variables. The fourth model had an R^2 of .046, which explained slightly less (4.6%) of the variance in the dependent variable, but only uses five predictor variables and does not include the sex of the offender as a predictor variable.

The fifth and final model removed the ethnicity of the offender as a predictor. The model produced $R^2 = .045$, $F(4,12196881.17) = 16.33$, $p < .01$, indicating that 4.5% of the variance in property value loss can be explained by the variance in the age of the offender, age of the victim, sex of the victim, and race of the victim. Comparing the results of the fifth model against the hypotheses, four of the hypotheses were significant predictors of property value loss for credit card fraud.

The results show that every year increase in the age of the victim resulted in a $4.44 increase in the average property value loss for credit card fraud, which supports hypothesis 1.1. Hypothesis 1.2 was also supported since a male victim resulted in $50.70 more in average property value loss than if the victim is female. The final victim hypothesis 1.3 was significant with an average increase of $67.39 in property value loss if the victim is Black as opposed to a White victim. While significant, the results were the opposite of what was predicted since a Black victim resulted in more and not less property value loss. Lastly, hypothesis 2.1 was supported with every year increase in the age of the offender, there is a $2.33 increase in the average property value loss for credit card fraud. All the relationships are statistically significant at the $p < .05$ level except for the age of the victim, which is significant at the $p < .001$ level.

Research Question 3

Research Question 3 looks at the victim, offender, and crime characteristics that could affect whether the offender was arrested. Specifically, victim and offender age, sex, race, ethnicity, and property value loss are tested as predictors of arrest for credit card fraud. Due to the dependent variable being categorical, chi-square and t-tests were used to determine the significance and strength of the relationships.

Bi-variate results: Chi-Square and t-test

An independent samples t-test was run to determine whether there is a statistically significant difference in the means for age of offender between offenders who were arrested and offenders who were not arrested. Using Levene's test for equality of variances shows that equal variances cannot be assumed since Levene's test for equality of variances is significant at the $p < .01$ level. The variances in the means for offender age between offenders who were arrested and offenders who were not arrested for credit card fraud are significantly different.

The results of the t-test show that there is a significant difference in offender age for offenders who were not arrested, \$33.32 (SD = 11.42), and offenders who were arrested, \$32.30 (SD = 9.595). Based on the t-test, the results, $t(1816.37) = 2.836$, $p < .01$, suggest that there is a statistically significant difference between offender age for offenders who were arrested and offenders who were not arrested for credit card fraud. Offenders who were arrested were younger compared to offenders who were not arrested.

Due to the variables being both being categorical, a chi-square test of independence was run to determine if there was a statistically significant relationship between the reported sex of the offender and if that offender was arrested. The results of the chi-square test indicate that there is not a significant relationship between offender gender and arrest, X^2 (1, N = 4,862) = 1.03, $p = .31$.

A chi-square test of independence was run to determine if there was a statistically significant relationship between the reported race of the offender and if that offender was arrested. The results of the chi-square test indicate that there is a significant relationship between offender race and arrest, X^2 (1, N = 4,862) = 11.75, $p < .01$.

A chi-square test of independence was also run to determine if there was a statistically significant relationship between the reported ethnicity of the offender and if that offender was arrested. The results of the chi-square test indicate that there is not a significant relationship between offender ethnicity and arrest, X^2(1, N = 1,529) = 3.09, p = .079.

An independent samples t-test was run to determine whether there is a statistically significant difference in the means for average property value loss between offenders who were arrested and offenders who were not arrested. Using Levene's test for equality of variances shows that equal variances can be assumed since Levene's test for equality of variances is not significant at p = .068. The variances in the means for property value loss between offenders who were arrested and offenders who were not arrested for credit card fraud are not significantly different.

The results of the t-test show that there is a significant difference in average property value for offenders who were not arrested, $400.25 (SD = 452.78), and offenders who were arrested, $364.03 (SD = 433.94). Based on the t-test, the results, t(4530.89) = 2.259, $p < .05$, suggest that there is a statistically significant difference between property loss for offenders who were arrested and offenders who were not arrested for credit card fraud. Offenders who were arrested had a lower property value loss compared to offenders who were not arrested.

An independent samples t-test was run to determine whether there is a statistically significant difference in the means for age of victim between offenders who were arrested and offenders who were not arrested. Using Levene's test for equality of variances shows that equal variances can be assumed since Levene's test for equality of variances is not significant at p =

.881. The variances in the means for age of the victim between offenders who were arrested and offenders who were not arrested for credit card fraud are not significantly different.

The results of the t-test show that there is not a statistically significant difference in the average victim age for offenders who were not arrested, 47.16 years old (SD = 17.65), and offenders who were arrested, 46.62 years old (SD = 17.48). Based on the t-test, the results, $t(4860) = .853$, $p = .394$, suggest that there is not a statistically significant difference between victim age for offenders who were arrested and offenders who were not arrested for credit card fraud.

Since the variables are both categorical, a chi-square test of independence was run to determine if there was a statistically significant relationship between the reported sex of the offender and if that offender was arrested. The results of the chi-square test indicate that there is a significant relationship between offender gender and arrest, X^2 (1, N = 4,862) = 15.71, $p < .01$.

A chi-square test of independence was run to determine if there was a statistically significant relationship between the reported race of the victim and if the offender was arrested. The results of the chi-square test indicate that there is a significant relationship between offender race and arrest, X^2 (1, N = 4,862) = 13.49, $p < .01$.

A chi-square test of independence was also run to determine if there was a statistically significant relationship between the reported ethnicity of the victim and if that offender was arrested. The results of the chi-square test indicate that there is a significant relationship between victim ethnicity and arrest, X^2(1, N = 4,088) = 7.74, $p < .01$.

Multivariate results: Logistic Regression

A Binary Logistic Regression was run to determine if the age of victim, sex of victim, race of victim, ethnicity of victim, age of offender, sex of offender, race of offender, ethnicity of the offender, and value of property loss influenced whether the offenders were arrested. The results showed that the model was statistically significant, $\chi^2(9, N = 1{,}386) = 45.1, p < .001$. Based on the Nagelkerke R Square test, this model describes 4.7% of the variance in arrest and correctly classified 73.1% of cases.

Table 5

Logistic Regression Analysis: Likelihood of Arrest

Variable	B	S.E.	Wald	df	Sig.	Exp(B)
Property Value	.000	.000	3.43	1	.064*	1.000
Victim Age	.004	.004	1.35	1	.245	1.004
Victim Sex	-.396	.136	8.55	1	.003***	.673
Victim Race	-1.02	.236	18.7	1	.000****	.361
Victim Ethnicity	-.431	.426	1.02	1	.312	.650
Offender Age	-.006	.006	1.01	1	.316	.994
Offender Sex	.010	.127	.006	1	.937	1.01
Offender Race	.195	.178	1.19	1	.275	1.22
Offender Ethnicity	-.327	.388	.711	1	.399	.721

Note. *p < .1, **p < .05, ***p < .01, ****p < .001

The results show that sex of the victim ($p < .01$) and race of the victim ($p < .01$) were statistically significant predictors of arrest. While not statistically significant at the $p < .05$ level, value of property had a $p = .064$, which is within the $p < .1$ significance cutoff levels presented in statistics literature (Figueiredo Filho et al., 2013).

The lower the property value loss is, if the victim is male, and if the victim is Black, it is less likely there will be an arrest for credit card fraud. If the victim is male, it is .673 times less likely that the offender for credit card fraud will be arrested. When the victim is Black, it is .361 times less likely that the offender will be arrested. The value of property loss, age of the victim, ethnicity of the victim, age of the offender, sex of the offender, race of the offender, and ethnicity of the offender were not statistically significant predictors at conventional levels of whether an offender was arrested for credit card fraud.

Discussion, Implications, Limitations, Future Research, and Conclusion

The following sections include a discussion of the results of the analysis, the implications the findings have on various areas in research and practice, the limitations of the current study, and a conclusion. These sections cover what this study means for future research, how the study could be used to prevent credit card fraud, and how the study increases the current knowledge on credit card fraud, including filling gaps in the current research.

Discussion

The overall focus of this study is to determine what offender and victim characteristics affect harm to victims or are predictive of an arrest for credit card fraud. This study included three research questions seeking to determine how victim characteristics are predictive of the seriousness of credit card/automatic teller machine fraud, how offender characteristics are predictive of the seriousness of credit card/automatic teller machine fraud, and how crime characteristics, offender characteristics, and victim characteristics are predictive of an arrest for credit card/automatic teller machine fraud. The hypotheses and results of the analysis are described below.

Research Question 1

The first research question sought to determine how victim characteristics are predictive of the seriousness of credit card/automatic teller machine fraud. The following section outlines all the hypotheses under Research Question 1 and the results of the analyses.

Hypothesis 1.1: When controlling for other variables, the younger the victims are, the lower the value of property loss for credit card/automatic teller machine fraud will be. Hypothesis 1.1 was supported with the correlation results, which shows that age of the victim and value of property from credit card fraud has a positive statistically significant relationship (Pearson's $r = .138$) at the $p < .01$ level. That is, the older the victim is, the higher the value of property loss is. While the relationship is statistically significant, it is considered weak based on social science standards with values of positive or negative .1 to .3 are deemed a weak correlation (Bachman & Schutt, 2020). This was also supported when controlling for other variables in the multivariate analysis. Specifically, the multivariate analysis showed that as the age of the victim increased, there was increase in the average property value loss of $4.41 for credit card fraud.

Hypothesis 1.2: When controlling for the other variables, if the victims are female, the value of property loss for credit card/automatic teller machine fraud will be lower. Hypothesis 1.2 was supported with the correlation results, which showed that there is a significant difference in average property loss value for females, $368.38, and males, $431.37, $p < .01$. The results suggest that there is a difference between property loss for male and female victims of credit card fraud with female victims having a lower average property loss value compared to male victims. This was also supported when controlling for other variables in the multivariate analysis. If the victim is male, there was average of $50.70 more in property value loss than if the victim is female.

Hypothesis 1.3: When controlling for the other variables, if the victim is Black, the value of property loss for credit card/automatic teller machine fraud will be lower. Hypothesis 1.3 was supported with the correlation results, which showed that there is a significant difference in average property loss value for White victims, \$397.98, and Black victims, \$369.47, $p = .073$. A $p = .073$ is not significant at the .05 level, but 0.1 is considered one of the significance limits presented in statistics literature (Figueiredo Filho et al., 2013). While not significant at the $p < .05$ level using a bivariate correlation, when controlling for other variables in the multivariate analysis, there was a statistically significant relationship at the $p < .05$ level. The direction of the relationship did not support the hypothesis since a Black victim resulted in an average increase of \$67.39 in property value loss as opposed to a White victim.

Hypothesis 1.4: When controlling for the other variables, if the victim is Hispanic, the value of property loss for credit card/automatic teller machine fraud will be lower. Hypothesis 1.4 was not supported with the correlation results, which showed that there is not a significant difference in average property value for non-Hispanic individuals, \$382.99, and Hispanic individuals, \$376.71, $p = .871$. This was also not supported when controlling for other variables with model two showing a $p = .612$.

Research Question 1 inspects what victim characteristics affect property value loss for credit card fraud. The results of the bivariate and multivariate analyses confirmed that some victim characteristics affect property value loss, while others do not. Specifically, victim age, sex, and race affected property value loss, while victim ethnicity did not.

Research Question 2

The second research question sought to determine how offender characteristics are predictive of the seriousness of credit card/automatic teller machine fraud. Research Question 2 continues to look at the characteristics that affect property value loss but uses offender instead of victim characteristics. The following section outlines all the hypotheses under Research Question 2 and the results of the analyses.

Hypothesis 2.1: When controlling for other variables, the older the offender is, the value of property loss for credit card/automatic teller machine fraud will be lower. Hypothesis 2.1 was supported with the correlation results, which show that age of the offender and value of property from credit card fraud has a positive statistically significant relationship (Pearson's $r = .06$) at the $p < .01$ level. The older the offender is, the higher the value of property loss is. This was also supported when controlling for other variables in the multivariate analysis. Specifically, the multivariate analysis showed that for every year increase in the age of the offender, there is a $2.33 increase in property value loss for credit card fraud.

Hypothesis 2.2: When controlling for other variables, if the offender is female, the value of property loss for credit card/automatic teller machine fraud will be lower. Hypothesis 2.2 was supported with the correlation results, which showed that there is a significant difference in property value for females, $406.58, and males, $381.95, $p = .059$. While not significant at the .05 level, 0.1 is considered one of the significance cutoff levels presented in statistics literature (Figueiredo Filho et al., 2013). The results suggest that there is a difference between property loss for male and female offenders of credit card fraud with female offenders having a higher average property loss value compared to male offenders. However, this was not supported when controlling for other variables with model three showing a $p = .379$.

Hypothesis 2.3: When controlling for other variables, if the offender is Black, the value of property loss for credit card/automatic teller machine fraud will be lower. Hypothesis 2.3 was supported with the correlation results, which showed that there is a significant difference in property value for White offenders, $401.85, and Black offenders, $368.96, $p < .05$. Based on the t-test, the results suggest that there is a statistically significant difference between property loss for White and Black offenders of credit card fraud. Cases with Black offenders had a lower average property loss value, meaning less was stolen by Black offenders compared to White offenders. However, this was not supported when controlling for other variables with model one showing a $p = .879$.

Hypothesis 2.4: When controlling for other variables, if the offender is Hispanic, the value of property loss for credit card/automatic teller machine fraud will be lower. Hypothesis 2.4 was not supported with the correlation results, which showed that there is not a significant difference in property value for non-Hispanic individuals ($M = 391.61$, $SD = 441.840$) and Hispanic individuals ($M = 475.07$, $SD = 411.435$); $t(1527) = -1.516$, $p = .130$. Based on the t-test, the results suggest that there is not a statistically significant difference between property loss for non-Hispanic and Hispanic offenders of credit card fraud. This was also not supported when controlling for other variables with model four showing a $p = .238$.

Research Question 3

Research Question 3 looks at how crime characteristics, offender characteristics, and victim characteristics are predictive of an arrest for credit card/automatic teller machine fraud. The first two research questions look at victim and offender characteristics, but instead of property loss value, Research Question 3 examines likelihood of arrest for credit card fraud.

Hypothesis 3.1: When controlling for other variables, the younger the offender is, the more likely there is an arrest for credit card/automatic teller machine fraud. Hypothesis 3.1 was supported with the t-test results, which showed that there is a significant difference in offender age for offenders who were not arrested, 33.32 years old, and offenders who were arrested, 32.30 years old, $p < .01$. Offenders who were arrested were younger compared to offenders who were not arrested. However, this was not supported when controlling for other variables showing a $p =$

.316. Overall, the hypothesis is not be supported due to the logistic regression not showing a statistically significant result.

Hypothesis 3.2: When controlling for other variables, if the offender is male, the more likely there is an arrest made for credit card/automatic teller machine fraud. Hypothesis 3.2 was not supported with the results of the chi-square test indicating that there is not a significant relationship between offender gender and arrest, X^2 (1, N = 4,862) = 1.030, p = .31. This was also not supported when controlling for other variables showing a p = .937.

Hypothesis 3.3: When controlling for other variables, if the offender is Black, the more likely there is an arrest made for credit card/automatic teller machine fraud. Hypothesis 3.3 was supported with the chi-square test indicating that there is a significant relationship between offender race and arrest, X^2 (1, N = 4,862) = 11.747, p < .01. However, this was not supported when controlling for other variables showing a p = .275. Overall, the hypothesis is not supported due to the logistic regression not showing a statistically significant result.

Hypothesis 3.4: When controlling for other variables, if the offender is non-Hispanic, the more likely there is an arrest made for credit card/automatic teller machine fraud. Hypothesis 3.4 was supported with the chi-square test indicating that there is a significant relationship between offender ethnicity and arrest, X^2(1,N = 1,529) = 3.085, p = .079. While not statistically significant at the p < .05 level, a p = .079 within the p < .1 significance cutoff levels presented in statistics literature (Figueiredo Filho et al., 2013). However, this was not supported when controlling for other variables showing a p = .399. Overall, the hypothesis is not supported due to the logistic regression not showing a statistically significant result.

Hypothesis 3.5: When controlling for other variables, the higher the value of property loss is, the more likely there is an arrest made for credit card/automatic teller machine fraud.

Hypothesis 3.5 was supported with the correlation results, which showed that there is a significant difference in average property value loss for offenders who were not arrested, $400.25, and offenders who were arrested, $364.03, p,<,.05. This was also supported when controlling for other variables showing a $p = .064$. While not statistically significant at the $p < .05$ level, value of property had a $p = .064$, which is within the $p < .1$ significance cutoff levels presented in statistics literature (Figueiredo Filho et al., 2013).

Hypothesis 3.6: When controlling for other variables, the younger the victim is, the more likely there is an arrest for credit card/automatic teller machine fraud. Hypothesis 3.6 was not supported with the correlation results, which showed that there is not a statistically significant difference in victim age for offenders who were not arrested and offenders who were arrested, $p = .394$. This was also not supported when controlling for other variables showing a $p = .245$.

Hypothesis 3.7: When controlling for other variables, if the victim is male, the more likely there is an arrest made for credit card/automatic teller machine fraud. Hypothesis 3.7 was supported with chi-square test indicating that there is a significant relationship between offender gender and arrest, X^2 (1, N = 4,862) = 15.709, $p < .01$. This was also supported when controlling for other variables at the $p < .01$ level. The analysis also showed that if the victim is male, it is .673 times less likely that the offender of the crime will be arrested.

Hypothesis 3.8: When controlling for other variables, if the victim is White, the more likely there is an arrest made for credit card/automatic teller machine fraud. Hypothesis 3.8 was supported with the chi-square test indicating that there is a significant relationship between offender race and arrest, X^2 (1, N = 4,862) = 13.488, $p < .01$. This was also supported when controlling for other variables at the $p < .001$ level. When the victim is Black, it is .361 times less likely that the offender will be arrested.

Hypothesis 3.9: When controlling for other variables, if the victim is non-Hispanic, the more likely there is an arrest made for credit card/automatic teller machine fraud. Hypothesis 3.9 was supported with the chi-square test indicating that there is a significant relationship between victim ethnicity and arrest, $X^2(1, N = 4{,}088) = 7.737$, $p < .01$. However, this was not supported when controlling for other variables showing a $p = .312$. Overall, the hypothesis is not be supported due to the logistic regression not showing a statistically significant result.

Research Question 1 and 2 examined what victim and offender characteristics affect property value loss for credit card fraud. Research Question 3 took those same characteristics and property value loss to predict the likelihood of arrest. The results of the bivariate and multivariate analyses confirmed that some offender, victim, and crime characteristics affected likelihood of arrest, while others do not. The value of property loss, sex of the victim, and race of the victim affected likelihood of arrest, while all of the offender characteristics, age of the victim, and ethnicity of the victim did not in a multivariate analysis controlling for other variables.

Specifically, the multivariate analysis showed that as the age of the victim increased, there was increase in the average property value loss of $4.41 for credit card fraud. If the victim is male, there was average of $50.70 more in property value loss than if the victim is female. When it comes to race, a Black victim resulted in an average increase of $67.39 in property value loss as opposed to a White victim. Looking at offender characteristics, the multivariate analysis showed that for every year increase in the age of the offender, there is a $2.33 increase in property value. Looking at arrest, the logistic regression showed two statistically significant relationships. Black victim cases had an arrest .361 times less likely and if the victim is male; it is .673 times less likely that the offender of the crime will be arrested. The other relationships were not statistically significant at conventional levels.

Implications

The results of this study suggest that certain victim and offender characteristics are predictive of harm or arrest. In line with other research using NIBRS data to better understand financial fraud, this study can be used to stop future crime before it occurs and assist with current cases (Stamatel & Mastrocinque, 2011). For example, if law enforcement practitioners focus on victims who are more likely to suffer the greatest harm, they can prevent the greatest losses. Crime prevention based on the information in this study could not only prevent financial costs, but the mental costs associated with fraud crimes. It has also been argued that understanding victim characteristics and why certain victims are at a greater risk for victimization can assist with prevention (Shao et al., 2019). In addition, if government entities can isolate those who are most likely to be victimized, finite recourses can be used efficiently to target those most in need of protection (Deevy et al., 2012).

While there were several statistically significant results for victim and offender characteristics affecting property value loss or likelihood of arrest, the results are not as strong as anticipated. Model 5 predicted only 4.5% of the variance in property value loss while the logistic regression model explained 4.7% of the variation in likelihood of arrest. Since these models only explain about 5% of the variance in the dependent variable, there could be other variables that would be stronger predictors. These results also indicate that the proxy variables used may not explain differences in behavior. Additional research is needed to determine how more of the variance in property value loss and likelihood of arrest could be explained.

Specifically, the current study aligned with prior knowledge when it comes to age of the victim and the amount that was taken through fraud. This study showed a $4.41 average increase in property value loss for each year increase in victim age. Prior research aligned with this finding showing a total loss for internet crimes including credit card fraud was greater with older age groups (IC3, 2018). The results of this study also showed there was an average of $50.70 more in property value loss if the victim was male. These results support research on targets of internet, which showed that males were more likely targeted along with individuals with more money, which could explain the higher property loss (Pratt et al., 2010).

Looking at race, the results of victim race and property value loss were significant and showed that if the victim was Black, there was an average of $67.39 more in property value loss as opposed to a White victim. These results are surprising when looking at the research showing that White individuals receive higher credit card limits and possess credit cards at greater rates when compared to Black individuals (Freeman, 2017). This could be explained by the differences in types of credit card fraud and their costs. Prior research looking at existing account fraud, new credit card fraud, and existing credit card fraud found differences by race. While White victims were more likely to be victims of existing credit card fraud, Black victims were more likely to be victims of new credit card fraud and existing account fraud, which are the types of fraud that result in more money taken (Copes et al., 2010). This could explain the unexpected results since NIBRS data does not differentiate between new and existing credit card fraud.

Finally, the results indicate that for every year increase in the age of the offender, there is a $2.33 increase in average property value loss for credit card fraud. The results of this study do not align with what was hypothesized but are not surprising. The research on financial exploitation among older adults showed that most of the offenders were the children of the victim and the victims could be perceived as easier targets because of their mental state and better financial state (Stamatel & Mastrocinque, 2011). However, it could be argued that older offenders would have more experience committing these crimes and are able to steal more with each offense.

The results of the study on predicting arrest show that it is less likely there will be an arrest if the victim is Black and if the victim is male. These results could be explained by the research showing that non-White victims of fraud and female victims of conventional crime are more likely to report their victimization, which could explain the disparity in arrest (Schoepfer & Piquero, 2009).

When it comes to offenders, this study could also be used to recognize offender characteristics and use that information to determine who is most likely to commit credit card fraud. This information could also be used for prevention efforts to stop credit card fraud before it happens (Barker et al., 2008).

Limitations

While this study is unique in several respects and can be used to inform other research and practice, it is not without limitations or results that did not meet what was expected. This study is limited in applying routine activities theory since this study used secondary data so offender and victim routine activities were not reported, and proxy measures were used to assess what could have affected the crime. The data used is not representative of the United States and only includes crimes reported to law enforcement, leaving out a large segment of unreported crime. Additionally, when it comes to the crimes being reported, the reported race or ethnicity of the victim or offender could be inaccurate. If the victim incorrectly identified the offender, if an officer did not ask the victim his or her race to ensure accuracy, or if an offender is known and the offender is not asked for this information, there could be data issues.

There are limitations to NIBRS data when it comes to participation as well. While participation is increasing, not all law enforcement agencies participate in NIBRS and so the data is limited only to those agencies who report to NIBRS (Stamatel & Mastrocinque, 2011). The data could also be biased toward areas with less crime and areas with fewer law enforcement officers since those places have higher NIBRS participation (Tillyer & Tillyer, 2019).

When it comes to reported data, property crimes also are often missing offender information and in this study cases that were missing offender sex, limited the study to cases that listed either a Black or White offender, and only included adult offenders (Tillyer & Tillyer, 2019). The data was also limited to incidents with one reported offense, there was only one victim, one offender, and crimes where the victim is a person. Limiting the analysis provides a clear research goal but could affect the overall results had the additional data been included.

Future Research

The current study fills several gaps in the research by taking a unique approach at trying to determine what characteristics are predictive of harm and likelihood of arrest for credit card fraud. While other studies have used NIBRS data, this study presents a unique set of independent and dependent variable to better understand credit card fraud.

While this study was unique and fills current gaps in the research, there are still areas that this study did not seek to fill. Similar research could use updated NIBRS data or date across multiple years to determine if the findings of the current study hold true or changed based on new data. Researchers seeking to use NIBRS data could also look at a different dependent variable than property value loss or arrest. For example, additional research using the same dataset could look at differences when there is a White offender and Black victim or vice versa or other victim-offender interactions using gender and ethnicity. Additional predictor variables could be included such as location, population, or resident status. Including additional predictor variable could help increase R^2 for stronger findings. Different crimes could also be added into the analysis and may include additional fraud crimes or violent crimes as a comparison group.

This study also used secondary data, so future research could gather more specific information on offender motivation through interviews, or victim surveys could provide more information on victims' routine activities. Overall, while this study provided a unique outlook on credit card fraud, there are many areas for further research based on the findings of this study.

Conclusions

The review of the research in this study showed that while the number of white-collar crimes and harm caused by them is increasing, financial fraud is a neglected area of research. This study provides a unique perspective on credit card fraud and showed that victim and offender characteristics do affect property value loss and likelihood of arrest. While this study added to the current research, there is a great deal of information that can still be learned about this important area of research. The results of this study could be used for crime prevention, victim outreach, and a basis for further research.

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