# THE UNIQUE CONTRIBUTION OF CREDIT INFORMATION IN THE SELECTION PROCESS

by

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## ABSTRACT

The purpose of this study was to determine if credit information provided a unique contribution beyond the other selection predictors, such as criminal records, education, previous experience, or background checks. Ordinal logistic regression analyses were performed to compare two models: one without credit information (Model 1) and one with credit information (Model 2). Through likelihood ratio tests comparing both models, Model 2 was consistently found to be significant. Pseudo r-squared comparisons between the models showed that the Model 2 consistently explained more of the variability than Model 1. Significance tests with regression coefficient estimates showed the higher number of overdue accounts an applicant had, and the longer those accounts were past due, the lower the rating an applicant received in the selection process.

# TABLE OF CONTENTS

# LIST OF TABLES

# CHAPTER I: INTRODUCTION AND LITERATURE REVIEW

Using credit information for employee selection began around 1988, after polygraph tests for such purposes were banned for most organizations. Only a few organizations, mainly government, are still legally able to use polygraphs in their selection process. In order to find an alternative to polygraphs, organizations sought other methods that predicted employees' behavior and gave insight into their honesty, responsibility, and integrity. Since the early 1990s, the influence of credit information on hiring decisions has increased significantly. As of 2010, forty-seven percent of organizations use credit reports for specific jobs, and 13% use them for all jobs (Bryan & Palmer, 2012). The U.S. Equal Employment Opportunity Commission (EEOC) reported that organizations screen for negative credit histories and use that information to impact their hiring decisions (Bryan & Palmer, 2012).

## Face Validity

Many organizations anecdotally believe credit information indicates whether a person has characteristics of responsibility, honesty and accountability. This belief has been advocated as particularly face valid in the financial industry's selection system for two reasons: 1) financial history relates to an ability to handle financial accounts, and 2) the opportunity to steal is greater at financial institutions (Nielson & Kuhn, 2009). While there may be face validity in the financial industry, most industries are relying on credit information to measure candidates' conscientiousness and honesty. The assumption is that low credit scores imply financial irresponsibility, which could indicate the potential for dishonesty or fraud (Bryan & Palmer, 2012). Additionally, credit agencies often advertise that credit reports can help organizations gain insight into employee integrity. Experian claimed to “provide credit information that would normally not appear on an application but may have an impact on job performance” (Nielson & Kuhn, 2009, p. 117). However, as credit report usage expands, its job relevance is less evident (Nielson & Kuhn, 2009).

**Fraud Prevention**

Organizations use credit information to predict job performance under the anecdotal belief that good employees have good credit histories. U.S. organizations lose around five percent of revenue to fraud, totaling approximately $650 billion in losses annually (Brody, 2010). While fraud prevails at all organizational levels, fraud at executive and upper management levels can put an organization out of business. Protecting assets and selecting honest employees is pertinent to an organization’s survival.

John Neilson defrauded Phillip Crosby Associates Inc. (PCA) of $961,000 before he was caught. The company hired Mr. Neilson as director of finance. Mr. Neilson had excellent references and credentials. PCA was unaware that his actual name was Robert Liszewski, who served time in prison for embezzling $400,000 from a previous employer. Most organizations settle these cases privately for fear of reputational damage (Brody, 2010), and stolen funds are rarely recovered in full (ACFE, 2006).

The average loss per fraud increases with the employee’s level of responsibility. According to Brody (2010), the median fraud loss is five times higher in schemes by owners/executives than by managers/supervisors. It was over 13 times higher for owners/executives than for employees. Despite the Sarbanes-Oxley Act of 2002, which requires management of publicly traded organizations to “take responsibility for 'establishing and maintaining internal controls' and to certify that they 'have designed such internal controls to ensure that material information relating to the company and its consolidated subsidiaries is made known to such officers by others within those entities', controls may still be ineffective in detecting fraud cases committed by owners or senior executives, given the level of authority they have to override such controls" (Brody, 2010, p. 212). In a 2010 study published by the Association of Certified Fraud Examiners (ACFE), employees from the following departments were found to have committed more than 80% of fraud: accounting, operations, sales, executive/upper level management, customer service, or purchasing (Brown, 2011).

Additionally, organizations can be liable for negligent hiring when it experiences significant fraud by an employee. To increase legal defensibility against this liability, organizations need to run a ten-year background search of a candidate's employment, criminal record, addresses, and persons with whom he or she lived during that time (Brody, 2010). However, completing a thorough background check can be difficult. There are no nation-wide criminal databases. To ensure a complete background check is assessed for each applicant, organizations would have to request one from every state in the country, and from every county and city near the current and past places that each applicant has lived. This can be costly and time-consuming. Organizations have to rely on the honesty of applicants to declare where they have previously lived.

Organizations should go beyond simple background checks, and also use integrity interviews and honesty tests which have (mostly) proven valid for highlighting candidates' viability (Brody, 2010). The best fraud prevention is hiring the right employees at all organizational levels (Brody, 2010). With so much responsibility weighing on organizations about their employment decisions, credit information may be an important aid in choosing the best job candidate.

Certain criteria within a person's credit information are believed to predict an employee's potential for fraud. The top two criteria are living above one's means and financial hardship. Because most fraud goes unreported, credit information may help organizations identify warning signs and reduce their risk of damages. "To the employer, creditworthiness is potentially as important to the hiring decision as it would be to the lender considering a loan application. While a bad loan can result in direct and immediate financial losses to the lender, a dishonest or unproductive employee can likewise cause an enormous expense to the unsuspecting employer" (Brown, 2011, p. 3). Employers attempt to mitigate the potential of hiring dishonest employees through checking their references and backgrounds. However, applicants may falsify information in their résumé and an in-depth background check can be tedious and expensive. Due to the challenges of verifying information on résumés and running background checks, credit information can be used to assess a potential employee's financial situation. Yet, organizations can have difficulty getting information about a potential employee. Laws limit organizations from accessing an applicant's credit information without first obtaining written permission from the applicant. Full access to credit information during the hiring process could help an organization avoid serious and potentially devastating damages, if assumptions about its value for predicting harmful employee behaviors become validated by research.

**Inaccuracies**

Credit information is considered a more objective part of the selection processes. However, employee advocates claim that creditworthiness does not necessarily reflect job performance. They stipulate that many factors influence creditworthiness such as a poor economy, personal hardships, unemployment, unforeseen medical expenses or a spouse's poor spending habits. Using credit information to measure trustworthiness may be problematic when looking at applicants with no credit history, such as young adults.

Credit information frequently contain errors. The National Association of State Public Interest Research Groups found that 79% of credit reports have errors, whereby 25% of the errors are serious enough for a credit denial (Brown, 2011). In a study by the Consumer Federation of America, some credit reports had a range of 500 points or more between agencies for a single person (Gallagher, 2006). Credit reports were also found to omit positive accounts 78% of the time (Gallagher, 2006). In 29% of the credit reports sampled, errors were extreme enough for a credit denial (Gallagher, 2006). When reporting court cases, credit agencies often do not stipulate whether the individual was the plaintiff or defendant (Gallagher, 2006). These errors may negatively impact a person's credit information and prevent them from job candidacy, and removing incorrect information is difficult without unequivocal proof of its inaccuracy.

While some evidence exists that shows credit information is a valid predictor for insurance and lending purposes, no empirical evidence exists of their validity for employment purposes (Nielson & Kuhn, 2009). Bryan and Palmer (2012) studied the validity of credit reports in predicting performance appraisal ratings and termination. They found no correlation between credit history and performance ratings. Gallager

(2006) points out that the empirical relationship between credit information and work performance is "dubious" (pg 1595). Palmer and Koppes (2004) found that no aspect the credit information assessed in their study predicted the performance evaluations or terminations of the 178 financial services employees. However, Oppler et al. (2004) found a link between federal employees who had a "bankruptcy, judgment against them for unpaid debt, or loan delinquency of more than 180 days were significantly more likely to participate in counterproductive citizenship behaviors (CWBs)" (pg 117). This information was not ascertained through credit information, but through a survey employees were expected to participate in when hired and then once every five years after (Nielson & Kuhn, 2009). With little to no empirical evidence that credit information is valid for selection purposes, no concrete link to job performance exists.

Using credit information as a means for selection could have harmful effects for both organizations and potential employees. An organization must let job candidates know if their credit information impacted a hiring decision. The potential employee can access his or her report and refute any errors that may have contributed to that decision. However, refuting errors can be a lengthy process that may not resolve before the position is filled. Credit agencies must employ "reasonable procedures" to maintain accuracy of credit reports, but the "technical accurate defense" has allowed them to escape liability for the inaccuracies often found (Gallagher, 2006). This technical accurate defense allows credit agencies to give inaccurate information to organizations, which can then be used to make employee selection choices. Because organizations can condition employment upon access to job candidates' credit reports, the right to refuse access is nullified.

**Adverse Impact**

Adverse impact is a concern when using credit reports for selection. Minorities have been found to have lower credit scores. Minorities with equal qualifications are twice as likely to be denied credit than the majority (i.e., whites) (Gallagher, 2006). A study by the State of Missouri Department of Insurance found that neighborhoods with high minority populations within a specific postal code had significantly lower credit scores, (Kabler, 2004) even after controlling for all other socio-economic factors (Gallagher, 2006). If minorities are denied credit based on race, improving or increasing their credit standing becomes difficult. Organizations enact a vicious cycle if they refuse to hire minorities based on low credit scores. If minorities are denied employment based on credit reports that are lower due to adverse impact, then using credit reports to make selection decisions may have an adverse impact.

Courts have separate frameworks for "disparate impact" and "disparate treatment", and minorities may more easily claim racial discrimination from employment rejection based on credit reports. In Griggs vs. Duke Power (1971), the U.S. Supreme Court concluded employment practices that have not been proven to be job relevant and which discriminate against members of a certain race are not allowed, and the intent of the organization is not pertinent. (Gallagher, 2006). This decision was later amended to require organizations to show that the discrimination was job-relevant and "consistent with business necessity" (Gallagher, 2006, p. 1612). "If the use of credit reports in hiring decisions has the same disparate impact in disqualifying minorities from employment as does using criminal histories as a hiring factor, it likely also violates Title VII" (Gallagher, 2006, p. 1612).

Gallagher (2006) stipulates that employee protection is insufficient from the Financial Credit Reporting Act, Title VII, tort law and state statutes from “probing employers”. In this article, she notes that while many employees believe only their basic demographics and credit score are being given for employment purposes, often times organizations are being given access to the employees’ complete credit history. There are no privacy laws for employees when allowing potential employers to access their credit information. This means that employers have access to credit information that is not job relevant and may be using it to make hiring decisions. Gallagher believes that Congress should enact legislation that requires organizations to show credit history correlates with job performance. She suggests this will justify the use of credit information for selection purposes and on the basis of adverse impact, as it will show whether using credit information for selection purposes has job relevance. If validity is found, then organizations could discriminate during the selection process based on credit history. Gallagher points out that without understanding credit scores and reports’ direct impact on employee productivity and performance, the use of credit information for selection purposes harms employees more than benefits organizations. In fact, organizations may be harmed if selection errors increase from false assumptions of validity.

Employers are required to obtain permission from job candidates before running a credit check. However, employers often make chedit checks a condition of employment, which doesn’t give the candidate the option of declining a credit check if they want to work for said employer. Organizations are often advised by human resources experts to find out if negative credit information was caused by a health issue or divorce which candidates may not want to dicuss with a potential employer (Nielson & Kuhn, 2009).

Candidates may not get the chance to discuss their credit information with potential employers because they are simply told that they were not a “good fit” or that the organization decided to go with a “more qualified candidate” (Nielson & Kuhn, 2009). As credit checks do not allow the candidates to demonstrate their knowledge, skills, and abilities as they apply to the job, candidates may be selected out of the process before they have an opportunity to show how they could be an asset to the organization.

**Employee Reactions**

Perceptions of using credit reports in the selection process can impact an organization’s reputation. Organizations should be concerned with applicants’ perception of using credit information in the selection process. Unfavorably viewing the process can impact organizations’ reputation and the type of potential employee attracted to them (Nielson & Kuhn, 2009). Nielson and Kuhn (2009) argue that organizational justice theory impacts the attitudes of potential employees regarding the use of credit checks. This involves three aspects: 1) the formal characteristics of the test – job relatedness, consistency of administration; 2) explanation – feedback, honesty of treatment; and 3) interpersonal treatment received by applicant – propriety of questions, interpersonal effectiveness of administrator.

Credit checks do not allow potential candidates to show their knowledge, skills, and abilities (KSAs) to the organization. Regarding the fairness perceived by applicants, an opportunity to show their ability to perform the job is an important selection predictor (Nielson & Kuhn, 2009). There is also a lot of variation in how credit information is used by the organization as a whole, and by different departments within the organization in the selection process (Nielson & Kuhn, 2009). The main factor in perceptions of fairness is thought to be job-relatedness (Nielson & Kuhn, 2009).

Applicants may find the use of credit information to be an invasion of their privacy. A more transparent procedure can help reduce the perception of invasiveness: The applicant knows which parts of the report are being reviewed and how those parts are measured. Another concern is the extent to which applicants view the accuracy of the credit information being used to determine selection. This is highly relevant and has a great impact on applicants' perceptions of the selection process: The less accurate credit reports are perceived to be, the lower the perceptions of their usage will be. A study conducted by Nielson and Kuhn (2009) on undergraduate business majors found that attitudes towards credit checks in selection processes were relatively negative. However, those who had been through the process previously seemed more confident than those who had not been through it. About half of the participants (51%) believed their credit information made them more attractive to an organization. Forty-five percent had no expectation of their credit information's effect on their employability, and 3% thought they would be less attractive to an organization. Yet, their findings may underestimate the population's concerns, since undergraduates are often young adults who have only begun to assemble a credit history. As people age beyond young adulthood, debts may escalate along with related concerns.

**Personality Assessment Findings**

Integrity and personality tests are often used as alternatives or supplements to credit information in predicting job performance. Researchers are increasingly interested in personality measures as a performance indicator, particularly in the area of Person-

Organization fit. Due to globalization and downsizing, organizations expect more from their employees. This emphasizes a greater reliance on selection to ensure hired employees are a good fit for the organization, not just the position. Much research focuses on the Big Five personality traits of conscientiousness, extroversion, openness to experience, emotional stability and agreeableness to determine any linkage between personality and job performance. Dependability was shown to predict performance in the contextual dimension of personal discipline (Borman, Hanson, & Hedge, 1997). A more "fine-grained" look at nine dimensions of personality, instead of the Big Five, showed that achievement had an even stronger correlation with overall job performance than did conscientiousness (Borman, Hanson, & Hedge, 1997). Many studies show a correlation between conscientiousness and job performance. In one meta-analysis by Barrick and Mount (1991), conscientiousness was consistently found as a valid predictor for all occupational groups and criteria. They found that extraversion was a valid predictor of performance specifically in sales and management positions, and openness to experience was a valid predictor for training proficiency, but not job proficiency. They found little to no correlation for emotional stability or agreeableness and job performance. Bernerth, Taylor, Walker & Whitman (2012) found that conscientiousness was positively related to credit scores, but they found no correlation between counterproductive work behaviors (CWBs) and credit scores. This finding may indicate that, while higher credit scores indicate conscientiousness, lower credit scores do not necessarily indicate poor job performance.

However, evidence is growing that personality can predict job performance, mainly on the contextual level (Borman, Hanson, & Hedge, 1997). Using compound-trait constructs may be more useful than the Big Five alone (Borman, Hanson, & Hedge, 1997). To understand the CWB antecedents, research has been done on personal variables – individual characteristics that may indicate a person's likelihood of CWBs (Fine, Horowitz, Weigler, & Basis, 2010). CWBs can fall into three areas: 1) individual factors (personality), 2) social and interpersonal factors (reaction to unfair treatment), and 3) organizational factors (reaction to problems with the job) (Fine, Horowitz, Weigler, & Basis, 2010). Certain personality traits and attitudes have been found to have an empirical relationship with CWBs (Fine, Horowitz, Weigler, & Basis, 2010). Integrity tests tend to have higher predictive validity than using any one the Big Five traits alone, but disagreement exists about whether using more specific constructs to determine integrity or applying broader constructs are more predictive (Borman, Hanson, & Hedge, 1997).

While personality tests are broader, for instance extending into social conformity (thrill-seeking, trouble with authority, hostility, conscientiousness, dependability, etc.), integrity tests attempt to detect dishonesty without a polygraph. They have also been found to predict job performance (Berry, Sackett, & Wiemann, 2007). Integrity tests were found to be consistently correlated with conscientiousness, agreeableness and emotional stability, though these traits do not explain all the variance in integrity tests, and even less variance in CWBs or job performance (Berry, Sackett, & Wiemann, 2007). Integrity tests are appropriate for job selection due to stability across time and situations (Fine, Horowitz, Weigler, & Basis, 2010). Integrity tests are widely used to predict potential CWBs, with over five million administered in the early 1990s in the U.S. alone (Fine, Horowitz, Weigler, & Basis, 2010). Two types of test are used: 1) overt – those who fantasize about CWBs are more likely to commit them; and 2) personality-based – looking at broad personality traits that may link to CWBs, such as conscientiousness. Integrity tests have been shown to have no adverse impact towards minorities of race, gender, or age (Fine, Horowitz, Weigler, & Basis, 2010).

Congress began looking into the validity of integrity tests after the removal of polygraphs from the selection process. In 1989, the American Psychological Association (APA) also began researching integrity test validity, as many researchers agreed that evidence largely lacked in this area. The APA and the U.S. Office of Technology Assessment (OTA) differed in their focus of study. This included the purpose of the study, the evidentiary bases, and the conclusions determined. The OTA's report was written to guide Congress in making a determination on integrity tests, if needed. It focused on public policy. The APA looked at the scientific and technical issues of integrity tests. It took an indirect look at policy.

The OTA only included five predictive validity studies in their research and dismissed any that included contrast groups, self-reports of theft, CWBs, and shrinkage studies. The studies that they did use were investigated for methodological flaws often found in solitary studies. It reported that the investigation was inconclusive (Palmer & Koppes, 2004).

The APA looked at over 300 studies from a variety of validity designs. While it admitted that methodological errors could be found, due to the nature of applied research, the pattern of evidence it found was consistent over a large number of independent validation studies and different designs that would have compensated for the methodological flaws. It found that unstructured interviews tended have lower validity than integrity tests (Palmer & Koppes, 2004).

OTA and APA agree somewhat on the definition of integrity. They both reported that test users may not be qualified to interpret the integrity tests' data. They also agree that publishers need to open their development processes to the research process to fully determine the tests' validity. Both the APA and OTA found issues with organizations wanting to use cut off scores, and publishers of the integrity tests are accommodating these organizations. Publishers have developed cut-off scores and 'pass or fail' categories based on the scoring categories of hire/not hire (Palmer & Koppes, 2004). Psychologists are not allowed to encourage unqualified persons to use integrity tests independently. Using these tests requires knowledge of statistical analyses and assessments, and many individuals who are expected to administer these tests lack this knowledge. Publishers have developed proprietary and non-proprietary tests for different groups. Non-proprietary tests are given to clients qualified to interpret statistical data. Proprietary packages are given to clients without such interpretation skills, and the publisher receives and interprets the results for the client.

**Lack of Validity of Credit Checks**

There is a lack of established criterion validity for the use of credit information in the selection process (Nielson & Kuhn, 2009). Additionally, there is a lack of evidence showing performance validity for the use of credit information in the selection process (Bryan & Palmer, 2012). While organizational use of credit information in selection procedures has increased over the past several decades, the determination of validity is still not known. Aside from Bryan and Palmer (2012), little research has been done into whether credit information can predict the job performance of a potential employee.

Additionally, the use of credit information as a selection tool varies greatly and lacks consistency, not only between organizations, but often within an organization. As the impact of credit information on employment increases, the need to understand their applicability increases. This study attempted to determine the relevance of credit information in the selection process.

**Purpose of the Present Study**

Before determining the validity of credit information usage in predicting job performance or potential fraud risks, it is beneficial to know whether or not credit information provides a unique contribution to the rating of applicants in the selection process: In particular, does using the information provided in a credit report reveal information that could not be discovered through education, criminal checks, social media, military background, etc.? If credit information provides a unique contribution that cannot be attained through other selection methods, then there may be added value of using credit reports in the selection process, if that information is a valid indicator of subsequent job performance.

This study examined the impact of credit information on the selection decision process, though did not extend into longitudinal post-selection performance. This study looked at whether or not credit information provided a unique contribution to the summary ratings of applicants in the selection process when compared with other selection criteria: social media, criminal records, education, military background, and child support/alimony obligations. These variables were used as predictors in the selection process. These predictors were considered when qualitative judgments were made of an applicant's overall rating, called the Final Report Card (FRC). There were three types of FRC ratings: Green, Yellow, and Red. Green FRCs indicated that no concerns in regard to hiring the applicant were raised in the application process. Yellow FRCs indicated that there were some concerns raised in the application process, but further consideration was required in regard to whether or not the applicant would be considered for hire. Red FRCs indicated that serious concerns were raised in the application process and the applicant would not be considered for hire.

## Hypotheses

**Hypothesis 1a**. Credit information (number of accounts overdue) is related to the FRC rating.

**Hypothesis 1b**. Credit information (number of accounts overdue), social media, criminal record, child support/alimony obligation, education, and military background are related to the FRC rating.

**Hypothesis 2a**. Credit information (number of accounts overdue 120+ days) is related to the FRC rating.

**Hypothesis 2b**. Credit information (number of accounts overdue 120+ days), social media, criminal records, child support/alimony obligation, education, and military background are related to the FRC rating.

# CHAPTER II: METHOD

## Participants

The participants for this study were from a large law enforcement agency in the state of Tennessee. These participants were applicants who desired to work at this organization. All personal information was redacted. Selection information for a total of 921 de-identified applicants was analyzed. All eligible applicants were required to pass a physical abilities test and an interview before arriving at this stage of the selection process. Three years of data were analyzed: 2017, $N$ = 367; 2018, $N$ = 300; 2019, $N$ = 254.

## Procedure

This study utilized archival data that was collected during the selection process of a large law enforcement agency in the state of Tennessee. The law enforcement data collected includes the applicants' credit information, social media, criminal records, education, and child support/alimony obligation. The data was analyzed in accordance with how the data was used to make selection decisions. The data was qualitative, and therefore needed to be content-coded into quantitative measures for analysis. The independent variables were coded into ordinal variables due to the organization ranking each applicant on a "good – bad" scale based on the applicants' assessment on each variable. The measures section provides more detailed coding information within its descriptions of each of the variables.

## Measures

### Dependent Variable.

***Final report card (FRC) rating.*** The independent variables that were cumulatively considered for the FRC rating were credit score, criminal records, social media, child support and alimony obligations, education, previous employment, personal declarations of alcohol or drug use, bankruptcy, personal references, military service, preferred assignment location, and ability to relocate if needed. The organization used a subjective scale when considering all of the independent variables, and made a collective determinant of "red", "yellow" or "green" based on the information found on each of the variables:

- 1: Red: Problematic background – was not considered for selection
- 2: Yellow: There were some concerns in the background, but more information was needed – may or may not have been considered based on the additional information gathered.
- 3: Green: No problems in the background – was considered for selection.

### Independent Variables.

The independent variables in this study were the credit information, social media, criminal records, military background, education, and child support/alimony obligation of the candidates. The independent variables were analyzed to see how well they predicted judgment in the selection process. Independent variables and how they were measured in this study are listed below:

***Credit information.*** The applicants' actual credit score was not considered in this process. The organization looked at the credit information regarding how much debt is past due, if any, and what type(s) of debt obligation(s) the candidate had. Credit information was scored on a 12-point scale:

- 0: Blank, no credit information was entered
- 1: Bankruptcy
- 2: Collections: This is when the debt has been written off as "bad debt" and the creditor has given up any collection efforts. It has been turned over to a collection agency.
- 3: 120+ days late
- 4: 90-120 days late
- 5: 60-90 days late
- 6: 30-60 days late
- 7: On schedule
- 8: No credit
- Additional considerations for credit information:
    - 66: Medical
    - 77: Other - Foreclosure, deferred student debt, identity theft, legal debt
    - 99: Credit has not been run

The credit information took into consideration the number of accounts the applicant had against the length of time the account had been overdue. Medical debt was not as weighted against the applicant as discretionary debt. If there was any medical debt, proof of a payment plan was preferred.

This variable required content coding for analysis purposes. The values for this variable were coded into twelve groups, as indicated above. If the data stipulated that the applicant has no credit, the value was coded as an 8. If the data stated that the applicant had accounts that were current, or paid as agreed, that value was coded as a 7. This included if the data stated that the applicant had "good credit". In these instances, a one was coded "On Schedule", as that is the minimum about of information that could be determined from the data. If the data stated any accounts that were 30-60 days past due, that value was coded as a 6. If the data stated that the applicant had "poor credit", or "past due accounts" without specifying the amount or lateness of the accounts, the data was coded as a one or a two (depending on if the data was indicated as singular or plural) in this category. This was because 30-60 days late is the minimum amount of information that could be determined from the data. If the data stated that any accounts were 60-90 days past due, that value was coded as a 5. If the data stated that any accounts were 90-120 days past due, that value was coded as a 4. If the data stated that any accounts were 120+ days past due, that value was coded as a 3. If the data stated that any accounts were in collections, that value was coded as a 2. If the data stated that the applicant had "bad debt", this was coded as a 2. If the data did not stipulate the amount of bad debt accounts, this was coded as a one in the collections category. If the data stated that the applicant had filed bankruptcy, that value was coded as a 1. If the data stated that the applicant had outstanding "medical" debt, that value was coded as a 66. If the data stated that the applicant had debt that did not fall into the above categories, it was coded as a 77 for "other". Examples of "Other" debt would be foreclosures, identity theft, deferred student debt, and legal debt. If the data stated that no credit check was run for the applicant, the value was coded as a 99. These values were potentially cumulative, as applicants could have credit information in multiple categories. When applicants had values in multiple fields, it was recorded in all of the applicable fields.

For analysis purposes, credit data that was coded as “blank” or “not ran” were treated as missing from this study. Credit data coded as “blank” were treated as missing because there were only eight “blanks” with $N = 921$, seven of which were in 2017. Credit data coded as “not ran” were treated as missing because there were 143 “not ran” with $N = 921$, all of which were in 2017. To reduce the influence that “not ran” and “blanks” had on the results of 2017, as well as cumulative year analyses, these items were excluded.

Hypothesis 1a: Credit information (number of accounts overdue) is related to the FRC rating included all past due credit accounts when be analyzed for this study. Hypothesis 2a: Credit information (number of accounts overdue 120+ days) is related to the FRC rating included accounts 120+ days overdue, and also considered credit accounts that extended beyond being overdue: collections and bankruptcy.

***Social media.*** Social media is a subjective consideration as a selection predictor. The organization looked at the social media sites that applicants had access to, such as Twitter, Facebook, Pinterest, Snap Chat, and Instagram. Applicants had to grant access to their social media accounts to the organization. The organization was looking for any “red flags”. This may have included derogatory or racist language, any anti-government posts, and/or associations with groups that management felt were inappropriate representations of their organization. Social media was rated on the following factors. Social media was scored on a 3-point scale.

- 1: Offensive materials were found in the social media accounts.

- 2: No offensive materials were found in the social media accounts.
- 3: Has no social media accounts.

This variable required content coding for analysis purposes. The values for this variable were coded into three groups, as indicated above. If the data stated that offensive material was found, the value was coded with a 1. This included statements that social media was “negative”, “offensive”, “derogatory”, etc. If the data stated that there were no offensive materials found in the social media account(s), then the value was coded as a 2. This also included statements that social media was “good”, “no problems found”, “nothing offensive found”, etc. When the data stated that the applicant had no social media accounts, the value was coded as a 3.

***Criminal records.*** Criminal records were reviewed to determine if the applicant had a history of breaking the law. If there were any criminal records, the applicant was required to explain the situation. The applicant was automatically flagged for having a criminal record, but the organization would consider the reasons when considering the applicant for hiring. Criminal records were reviewed for felonies, misdemeanors, or other types of criminal activity that may impact an applicant’s ability to be hired. The criminal records data was scored on an 8-point scale:

- 0: No criminal history order
- 1: Felony
- 2: Misdemeanor
- 3: Expunged
- 4: Charges were dropped
- 5: No criminal history

- 77: Other
- 99: Blank – no data was entered for applicant's criminal history

This variable required content coding. The variable was coded into eight groups, as indicated above. If the data stated that no criminal records check had be run on the applicant, the value was coded as a 0. If the data stated that the charges against the applicant are currently considered a felony under current Tennessee state law, the value was coded as a 1. If the data stated a criminal charge that is currently considered a misdemeanor under Tennessee state law, the value was coded as a 2. If the data stated that the charges against the applicant were expunged from the record, the value was coded as a 3. If the data stated that the charges against the applicant were dropped, the value was coded as a 4. If the applicant had no record of criminal history, the value was coded as a 5. Any data recorded in criminal records that did not fall under the above categories was coded as a 77 under "Other". Examples of data that were considered in the "Other" category would be protective orders, driving citations, revoked driver's license, underage consumption or other juvenile records. When the data record was left blank and contained no information, the value was coded as a 99. Applicants were scored by the lowest rating they had in their criminal record.

For analysis purposes, data that was coded as "no criminal history order" and "blank" were treated as missing from this study. Criminal records coded as "no criminal history order" were treated as missing because there were 139 "no criminal history order" with $N = 921$, all of which were in 2017. Criminal records coded as "blank" were treated as missing because there were 78 "blanks" with $N = 921$, 70 of which were in 2018. To reduce the influence that "no criminal history order" and "blanks" had on the results of

2017 and 2018 independently, as well as cumulative year analyses, these items were excluded.

***Education.*** Education was a selection predictor. For this organization, it was required to have a high school diploma or an equivalent. Higher education was taken into consideration as well. The higher education was considered as part of the whole rating scale, not necessarily carrying any merit on its own. Education was scored on an 8-point scale:

- 0: No high school diploma/GED
- 1: Has a high school diploma/GED
- 2: Some college
- 3: Technical/ vocational school
- 4: Associate's degree
- 5: Bachelor's degree
- 6: Graduate degree
- 99: Blank, no information about the applicant's education was provided

This variable required content coding. The variable was coded into 8 groups, as indicated above. If the data stated the applicant did not have a high school diploma or a GED, the value was coded as a 0. If the data stated the applicant had a high school diploma or a GED, the value was coded as a 1. This included when the data stated that the applicant graduated from a specific high school, and/or gave the name of the high school and a date. If the data stated that the applicant had college hours but did not stipulate a graduation date or a degree, the value was coded as a 2. This included when data stated "college transcripts enclosed" but did not specify a type of degree that was received. If the data stated the applicant received a degree from a technical or vocational school, the value was coded as a 3. If the data stated the applicant attended a police academy or received certifications for EMT, this value was also coded as a 3. If the data stated that the applicant received an associate's degree, the value was coded as a 4. If the data stated that the applicant received a "degree", or a bachelor's degree, the value was coded as a 5. If the data stated that the applicant received a graduate degree, the value was coded as a 6. Applicants were scored by the highest rating they had in their education data.

For analysis purposes, blanks were coded as missing data from the study. In 2017, there were 11 blanks, in 2018 there was one blank, and there were no blanks in 2019 with $N$ = 921. To reduce the influence these blanks had on the independent and cumulative analyses, these items were excluded.

***Child support and alimony obligation.*** Child support and alimony obligations are considered. This was considered in order to determine if there was any past due obligations that the organization needed to take into consideration. Having a child support or alimony obligation was not counted against any applicant. Child support and alimony obligations were scored on a 2-point scale:

- 1: Has child support/alimony in arrears.
- 2: Has no arrears on child support/alimony.

This variable required content coding. The variable was coded into two groups, as indicated above. If the data stated that the applicant did have child support/alimony obligations and was in arrears with their payments, the value was coded as a 1. If the data stated that the applicant did not have child support/alimony obligations, and/or was current with their payments, the value was coded as a 2.

***Military background information*.** Whether or not the applicants had previous military experience, and how they were discharged was considered. Military background was scored on a 3-point scale.

- 1: Dishonorable discharge
- 2: No military service
- 3: Active/honorable discharge/retired

This variable required content coding. The variable was coded into three groups, as indicated above. If the data stated the applicant had a dishonorable discharge, the value was coded as a 1. If the data stated that the applicant had no military experience, the value was coded as a 2. If the data stated that the applicants was retired, honorably discharged or active in the military, including the National Guard or the Reserves, the value was coded as a 1.

***Rater training***. The first coder was the primary author of the thesis, an MTSU graduate student, and the second coder was an MTSU undergraduate student. After determining the above-mentioned coding system, the primary author met with the second coder and explained the specific codes for each variable. The coding information was also sent as a reference guide, via email, to the second coder. If the second coder had questions about information that needed to be coded, questions would be sent to the primary author, and the primary author would respond on how that information would be coded. After both coders finished coding, they came together and went over the data to come to a consensus.

## Data Analysis

**Ordinal logistic regression.** Ordinal logistic regression was used to determine strength of the contribution each of the independent variables makes to the dependent variable of FRC rating. Odds ratio analyses and likelihood ratio tests were performed, and the pseudo r-squared between the models were compared to determine if credit information made a unique contribution to the FRC rating above that of the non-credit independent variables.

***Model 1.*** An ordinal logistic regression analysis of the independent variables, excluding credit information, was run to determine the amount of contribution these independent variables made to the FRC rating.

$$Model\ 1: FCR = \beta_0 + \beta_{ChildSupport} + \beta_{CriminalRecords} + \beta_{Education} + \beta_{Military} + \beta_{SocialMedia}$$

***Model 2.*** An ordinal Logistics regression analysis of all independent variables, including credit information, was run to determine the amount of contribution credit information added to the FRC rating.

$$Model\ 2: FCR = \beta_0 + \beta_{ChildSupport} + \beta_{CriminalRecords} + \beta_{Education} + \beta_{Military} + \beta_{SocialMedia} + \beta_{NoCredit} + B_{OnSchedule} + \beta_{30-60} + \beta_{60-90} + \beta_{90-120} + \beta_{120+} + B_{Collections} + \beta_{Medical} + \beta_{Bankruptcy} + \beta_{Other}$$

# CHAPTER III: RESULTS

Analyses of the selection variables excluding credit information variables (Model 1) were conducted in SPSS using ordinal logistic regression to determine the covariate estimates, odds ratios and pseudo r-squared for individual years of data: 2017, 2018, 2019. Then a cumulative analysis of Model 1 was conducted in SPSS of all three years combined. Model 2 added the credit information variables to the selection variables in Model 1.

Model 2 analyses were conducted to determine the covariate estimates, odds ratios and pseudo r-squared for individual years of data: 2017, 2018, 2019. Cumulative analyses of Model 2 were also conducted in SPSS on all three years combined. Odds ratio analyses were computed from the regression coefficients of both models to determine the predictive strength of each independent variable on the FRC dependent variable. Tables 1-4 show a comparison of the regression coefficient estimates, odds ratios and the significance levels of the variables in each of the models across all three years and cumulative years. Likelihood ratio tests were performed on the differences between the models for each individual year and the cumulative years. Table 5 compares the differences between the models' pseudo r-squared and the likelihood ratio tests .

Table 1.
*2017 Model Comparison of Odds Ratios and Significance Levels*

| | | | | | | | Odds Ratios | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | 95% C.I. | |
| Model | Variable | Estimate | Standard Error | Wald | Df | P-value | Odds Ratio | Lower Bound | Upper Bound |
| 1 | Child Support | 14.59 | 0.00 | 2.99 | 1 | | 0.00 | 216948.20 | 216948.20 |
| | Criminal Records | 0.08 | 0.05 | 4.31 | 1 | 0.08 | 0.93 | 0.99 | 1.18 |
| | Education | 0.18 | 0.09 | 2.05 | 1 | 0.04 | 0.84 | 1.01 | 1.41 |
| | Military | -0.37 | 0.26 | 0.35 | 1 | 0.15 | 1.44 | 0.42 | 1.15 |
| | Social Media | 0.66 | 1.10 | 2.99 | 1 | 0.55 | 0.52 | 0.22 | 16.78 |
| 2 | Child Support | 13.73 | | | 1 | | 0.00 | 919881.38 | 919881.38 |
| | Criminal Records | 0.21 | 0.05 | 14.61 | 1 | 0.00 | 0.81 | 1.11 | 1.37 |
| | Education | 0.14 | 0.09 | 2.40 | 1 | 0.12 | 0.87 | 0.96 | 1.38 |
| | Military | -0.45 | 0.28 | 2.55 | 1 | 0.11 | 1.57 | 0.369 | 1.11 |
| | Social Media | 0.15 | 1.20 | 0.02 | 1 | 0.90 | 0.86 | 0.11 | 12.21 |
| | No Credit History | -0.01 | 1.14 | 0.00 | 1 | 0.99 | 1.00 | 0.11 | 9.28 |
| | On Schedule | -0.01 | 0.01 | 0.23 | 1 | 0.63 | 1.01 | 0.97 | 1.02 |
| | 30-60* | -0.16 | 0.18 | 0.85 | 1 | 0.36 | 1.18 | 0.60 | 1.21 |
| | 60-90* | -0.10 | 0.47 | 0.05 | 1 | 0.83 | 1.10 | 0.36 | 2.26 |
| | 90-120* | -0.32 | 0.38 | 0.69 | 1 | 0.41 | 1.37 | 0.35 | 1.53 |
| | 120+* | -0.13 | 0.06 | 3.96 | 1 | **0.05 | 1.14 | 0.78 | 1.00 |
| | Collections | -0.38 | 0.12 | 9.68 | 1 | 0.00 | 1.46 | 0.52 | 0.87 |
| | Medical | -0.37 | 0.12 | 9.03 | 1 | 0.00 | 1.44 | 0.54 | 0.88 |
| | Bankruptcy | -0.96 | 0.38 | 6.40 | 1 | 0.01 | 2.61 | 0.18 | 0.81 |
| | Other | 0.25 | 0.21 | 1.48 | 1 | 0.22 | 0.78 | 0.86 | 1.92 |

*Note:* * = number of days late; ** = actual p = 0.047

Table 2.

*2018 Model Comparison of Odds Ratios and Significance Levels*

| | | | | | | | Odds Ratios | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | 95% Confidence Intervals | | |
| Model | Variable | Estimate | Standard Error | Wald | Df | P-value. | Odds Ratio | Lower Bound | Upper Bound |
| 1 | Child Support | $0^{\alpha}$ | | | 0 | | | | |
| | Criminal Records | 0.59 | 0.10 | 33.73 | 1 | 0.00 | 0.56 | 1.47 | 2.170 |
| | Education | 0.19 | 0.10 | 3.74 | 1 | 0.05 | 0.83 | 1.00 | 1.47 |
| | Military | 0.29 | 0.28 | 1.08 | 1 | 0.30 | 0.75 | 0.77 | 2.32 |
| | Social Media | 15.28 | 0.00 | | 1 | | 0.00 | 4329386.33 | 4329386.33 |
| 2 | Child Support | $0^{\alpha}$ | | | 0 | | | | |
| | Criminal Records | 0.60 | 0.11 | 29.00 | 1 | 0.00 | 0.55 | 1.46 | 2.26 |
| | Education | 0.14 | 0.11 | 1.62 | 1 | 0.20 | 0.87 | 0.93 | 1.44 |
| | Military | 0.55 | 0.32 | 2.95 | 1 | 0.09 | 0.58 | 0.93 | 3.26 |
| | Social Media | 15.11 | 0.00 | | 1 | | 0.00 | 3639581.07 | 3639581.07 |
| | No Credit History | 0.82 | 1.06 | 0.60 | 1 | 0.44 | 0.44 | 0.28 | 17.97 |
| | On Schedule | -0.00 | 0.02 | 0.00 | 1 | 0.97 | 1.00 | 0.97 | 1.032 |
| | 30-60* | -0.51 | 0.14 | 12.81 | 1 | 0.00 | 1.66 | 0.46 | 0.80 |
| | 60-90* | 0.20 | 0.52 | 0.16 | 1 | 0.70 | 0.82 | 0.44 | 3.38 |
| | 90-120* | -0.31 | 0.26 | 1.36 | 1 | 0.24 | 1.36 | 0.44 | 1.23 |
| | 120+* | -0.38 | 0.15 | 6.32 | 1 | 0.01 | 1.46 | 0.51 | 0.92 |
| | Collections | -0.42 | 0.13 | 10.61 | 1 | 0.00 | 1.52 | 0.51 | 0.85 |
| | Medical | -0.78 | 0.36 | 4.86 | 1 | 0.03 | 2.19 | 0.23 | 0.92 |
| | Bankruptcy | -0.75 | 0.78 | 0.92 | 1 | 0.34 | 2.11 | 0.10 | 2.17 |
| | Other | -0.35 | 0.27 | 1.68 | 1 | 0.20 | 1.42 | 0.41 | 1.197 |

*Note:* * = number of days late

Table 3.
*2019 Model Comparison of Odds Ratios and Significance Levels*

| | | | | | | | Odds Ratios | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | 95% Confidence Intervals | | |
| Model | Variable | Estimate | Standard Error | Wald | Df | P-value | Odds Ratio | Lower Bound | Upper Bound |
| 1 | Child Support | 0.33 | 0.97 | .116 | 1 | .73 | 0.72 | 0.21 | 9.19 |
| | Criminal Records | 0.82 | 0.11 | 59.37 | 1 | 0.00 | 0.44 | 1.85 | 2.81 |
| | Education | 0.15 | 0.09 | 2.92 | 1 | 0.09 | 0.87 | 0.98 | 1.36 |
| | Military | 0.09 | 0.29 | 0.10 | 1 | 0.75 | 0.91 | 0.62 | 1.93 |
| | Social Media | $0^{\alpha}$ | | | 0 | | | | |
| 2 | Child Support | -0.33 | 1.18 | 0.08 | 1 | 0.77 | 1.40 | 0.07 | 7.17 |
| | Criminal Records | 0.86 | 0.12 | 54.33 | 1 | 0.00 | 0.42 | 1.88 | 2.97 |
| | Education | 0.07 | 0.09 | 0.48 | 1 | 0.49 | 0.94 | 0.89 | 1.28 |
| | Military | 0.15 | 0.32 | 0.21 | 1 | 0.65 | 0.86 | 0.62 | 2.17 |
| | Social Media | $0^{\alpha}$ | | | 0 | | | | |
| | No Credit History | -0.49 | 1.25 | 0.15 | 1 | 0.70 | 1.63 | 0.05 | 7.16 |
| | On Schedule | -0.01 | 0.02 | 0.23 | 1 | 0.63 | 1.01 | 0.96 | 1.02 |
| | 30-60* | -0.27 | 0.24 | 1.23 | 1 | 0.27 | 1.31 | 0.48 | 1.23 |
| | 60-90* | 0.12 | 0.43 | 0.08 | 1 | 0.78 | 0.89 | 0.49 | 2.63 |
| | 90-120* | 1.00 | 0.73 | 1.85 | 1 | 0.17 | 0.37 | 0.65 | 11.37 |
| | 120+* | -0.36 | 0.16 | 5.22 | 1 | 0.02 | 1.43 | 0.52 | 0.95 |
| | Collections | -0.42 | 0.11 | 13.9 | 1 | 0.00 | 1.52 | 0.53 | 0.82 |
| | Medical | -0.68 | 0.34 | 4.01 | 1 | **0.05 | 1.97 | 0.26 | 0.99 |
| | Bankruptcy | -0.74 | 0.73 | 1.02 | 1 | 0.32 | 2.09 | 0.11 | 2.02 |
| | Other | -0.27 | 0.15 | 3.11 | 1 | 0.08 | 1.31 | 0.57 | 1.03 |

*Note:* * = number of days late; ** actual $p = 0.045$

Table 4.

*Cumulative Years Model Comparison of Odds Ratios and Significance Levels*

| | | | | | | | Odds Ratios | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | 95% Confidence Intervals | | |
| Model | Variable | Estimate | Standard Error | Wald | Df | P-value | Odds Ratio | Lower Bound | Upper Bound |
| 1 | Child Support | 1.70 | 0.81 | 4.39 | 1 | 0.04 | 0.18 | 1.12 | 26.63 |
| | Criminal Records | 0.15 | 0.03 | 23.58 | 1 | 0.00 | 0.86 | 1.09 | 1.23 |
| | Education | 0.15 | 0.05 | 9.08 | 1 | 0.00 | 0.86 | 1.05 | 1.27 |
| | Military | -0.13 | 0.15 | 0.70 | 1 | 0.40 | 1.14 | 0.65 | 1.19 |
| | Social Media | 1.66 | 0.79 | 4.45 | 1 | 0.04 | 0.19 | 1.12 | 24.71 |
| 2 | Child Support | 0.77 | 0.94 | 0.67 | 1 | 0.41 | 0.46 | 0.34 | 13.59 |
| | Criminal Records | 0.25 | 0.03 | 55.34 | 1 | 0.00 | 0.78 | 1.20 | 1.37 |
| | Education | 0.12 | 0.05 | 4.83 | 1 | 0.03 | 0.89 | 1.01 | 1.25 |
| | Military | -0.06 | 0.16 | 0.15 | 1 | 0.70 | 1.06 | 0.68 | 1.29 |
| | Social Media | 1.25 | 0.83 | 2.28 | 1 | 0.13 | 0.29 | 0.69 | 17.68 |
| | No Credit History | -0.08 | 0.58 | 0.02 | 1 | 0.89 | 1.09 | 0.30 | 2.87 |
| | On Schedule | -0.02 | 0.01 | 3.50 | 1 | 0.06 | 1.02 | 0.97 | 1.00 |
| | 30-60* | -0.36 | 0.10 | 13.91 | 1 | 0.00 | 1.44 | 0.58 | 0.84 |
| | 60-90* | 0.19 | 0.25 | 0.54 | 1 | 0.46 | 0.83 | 0.74 | 1.97 |
| | 90-120* | -0.29 | 0.15 | 3.61 | 1 | 0.06 | 1.34 | 0.55 | 1.01 |
| | 120+* | -0.16 | 0.05 | 11.78 | 1 | 0.00 | 1.17 | 0.78 | 0.934 |
| | Collections | -0.43 | 0.07 | 43.45 | 1 | 0.00 | 1.54 | 0.57 | 0.74 |
| | Medical | -0.37 | 0.11 | 12.65 | 1 | 0.00 | 1.47 | 0.55 | 0.84 |
| | Bankruptcy | -0.81 | 0.29 | 7.64 | 1 | 0.01 | 2.24 | 0.25 | 0.79 |
| | Other | -0.14 | 0.10 | 1.93 | 1 | 0.17 | 1.14 | 0.72 | 1.057 |

*Note:* * = number of days late

Table 5.
*Comparison of Likelihood Ratio and Pseudo R-Squared Tests*

| Year | Model | Likelihood Ratio Test | Pseudo R-Squared | |
|---|---|---|---|---|
| | | | Cox and Snell | 0.06 |
| | | | Nagelkerke | 0.07 |
| 2017 | 1 | | McFadden | 0.03 |
| | | | Cox and Snell | 0.20 |
| | | | Nagelkerke | 0.23 |
| 2017 | 2 | $\chi^2(10) = 195.76$, $p < .001$ | McFadden | 0.12 |
| | | | Cox and Snell | 0.21 |
| | | | Nagelkerke | .024 |
| 2018 | 1 | | McFadden | .011 |
| | | | Cox and Snell | .041 |
| | | | Nagelkerke | .047 |
| 2018 | 2 | $\chi^2(10) = 206.67$, $p < .001$ | McFadden | .025 |
| | | | Cox and Snell | 0.27 |
| | | | Nagelkerke | 0.31 |
| 2019 | 1 | | McFadden | 0.16 |
| | | | Cox and Snell | 0.41 |
| | | | Nagelkerke | 0.47 |
| 2019 | 2 | $\chi^2(10) = 197.71$, $p < .001$ | McFadden | 0.26 |
| | | | Cox and Snell | 0.07 |
| | | | Nagelkerke | 0.08 |
| Cumulative | 1 | | McFadden | 0.03 |
| | | | Cox and Snell | 0.25 |
| | | | Nagelkerke | 0.29 |
| Cumulative | 2 | $\chi^2(10) = 710.22$, $p < .001$ | McFadden | 0.14 |

**Regression Coefficient Estimates**

Tables 1-4 show the regression coefficient estimates of each independent variable in relation the FRC rating. Negative coefficient estimates in the tables show a negative correlation between those independent variables and the dependent variable. All significant credit information variables in Model 2 across all years (Tables 1-4) have negative coefficients estimates.

Having no credit did not have any significant influence on the FRC rating, nor did having accounts paid on time. Neither of these variables were significant predictors for any year (2017, 2018, or 2019) nor cumulative years as shown in Tables 1-4. In 2018 (Table 2) and cumulatively (Table 4) , having accounts 30-60 days late did have a stronger influence on the FRC rating, as there was a statistically meaningful negative relationship between the two. However, across all years, individually and cumulatively, having accounts 60-90 days late and 90-120 days late did not have a statistically meaningful relationship with the FRC rating. Therefore having accounts 60-90 days late and/or accounts 90-120 days late did not influence the FRC rating.

When looking at credit accounts that are overdue 120+ days, we find that across all years, a fairly consistent pattern emerges: accounts 120+ days late, accounts in collections, medical debt, and bankruptcy show as significant, $p < .05$, in influencing the outcome of the FRC rating. There was a negative relationship between the regression coefficient estimates of the credit information variables and the FRC rating. This indicated that the longer overdue the accounts were, the lower the FRC rating they received.

Criminal records weres shown to have a consistent significantly meaningful relationship with FRC ratings through across all years (Tables 1-4), with the exception of 2017 where credit information was excluded (Table 1, Model 1). As this data was from an agency that is tasked with helping society adhere to the established laws, it is not surprising to find that having a history of criminal activity would negatively impact an applicant’s FRC rating.

Child support/alimony obligations and social media were not found to have a significantly meaningful relationship with FRC ratings in any of the analyses, with the exception of Table 4, Model 1, where the years were combined into a cumulative analysis and credit information was excluded. This indicated that neither of these variables influence the FRC rating. Education was found to have a significantly meaningful relationship with FRC ratings in 2017 when credit information was not included (Table 1, Model 1), and again when cumulative years were analyzed (Table 4, Model 1 and 2). This indicated that education had an influence on FRC ratings when considered across the years as a whole, but did not influence FRC ratings in any of the full model analyses (Model 2) for any of the individual years. Military background was consistently found to not have an influence on FRC ratings across all years.

This supported Hypothesis 2a: Credit information (number of accounts overdue 120+ days) is related to FRC ratings. This indicated that those with more accounts overdue 120+ days received lower FRC ratings. Partial support for Hypothesis 2b was found: Credit information (number of accounts overdue 120+ days) social media, criminal records, child support/alimony obligation, education, and military background are related to the FRC rating. Specifically supported hypothesis 2a by showing that credit information for accounts overdue 120+ days and the criminal records were statistically meaningful in their relationship to the FRC rating, but the remaining variables in this hypothesis were not. Additionally, bankruptcy had a statistically meaningful relationship with the FRC, which is an extension of credit accounts overdue 120+ days. Medical debt, though not part of the hypotheses, also had a statistically meaningful relationship with the FRC.

**Odds Ratios**

Odds ratios were calculated for each of the variables based on the regression coefficient estimates. $1/(e^{\beta)})$. Across Tables 1-4, bankruptcy, medical debt, collections, and 120+ days late had the highest influence on FRC rating.

- Bankruptcy (OR: 2.09 – 2.61)
- Medical (OR: 1.44 – 2.19)
- Collections (OR: 1.46 – 1.54)
- 120+ Days Late (OR: 1.17 – 1.46)

Independent variables that had a significance level of $p < .05$ and an OR > 1 were the variables that related to credit information. Independent variables that were not related to credit information, with a significance level of $p < .05$, had an OR < 1. Odds Ratio analyses supported Hypothesis 2a: Credit information (number of accounts overdue 120+ days) is related to the FRC rating. The credit information selection variables showed a general increase in odds of having a negative relationship with the FRC rating as credit accounts became increasingly late. Not only were accounts overdue 120+ days found to have high odds ratios, but having bankruptcy collections, or medical debt had higher odds ratios. This indicated that having collections, medical debt, or bankruptcy would increase the odds of getting a lower FRC rating up to twice as much in comparison to the other independent variables. Overall, the longer an account was overdue, or a bankruptcy was filed, the higher the odds that the FRC rating was lower.

The odds ratio for criminal records, the only non-credit independent variable that had an influence on FRC ratings across all years and cumulative years (Tables 1-4) was less than one (OR: 0.93 – 0.44). This indicated that the credit information variables had a stronger influence on the FRC rating than the selection variables that were not credit information related.

**Likelihood Ratio Test**

Table 5 shows a comparison of the likelihood ratio tests between Model 1 and Model 2 across each year as well as the cumulative years. Likelihood ratio tests were performed to determine if adding credit information to the other selection variables (Model 2) contributed unique information beyond that of the other selection variables (Model 1) for predicting FRC ratings. Each likelihood ratio test was found to be significant, which indicated the credit information contributes unique information above and beyond other independent variables. This supported Hypothesis 1a: Credit information (number of accounts overdue) is related to the FRC rating. This also supported Hypothesis 2a: Credit information (number of accounts overdue 120+ days) is related to the FRC rating.

**Pseudo R-Squared Test**

Table 5 shows a comparison of the pseudo r-squared of both models for each year as well as for cumulative years. For each year, Model 2 pseudo r-squared was higher than Model 1. A comparison the pseudo r-squared of each model for each year, and then for cumulative years showed that including credit information (Model 2) consistently explained more variance than excluding credit information (Model 1) across all years. This indicated that the credit information variables in Model 2 did make a unique contribution beyond that of the non credit information selection variables in Model 1. This supported Hypothesis 1a: Credit information (number of accounts overdue) was related to the FRC rating.  This also supported Hypothesis 2a:  Credit information (number of accounts overdue 120+ days) is related to the FRC rating.

**Frequency Distribution of Accounts**

A table is provided in the appendices showing a breakdown of the frequency distribution of credit accounts that were analyzed in this study.

# CHAPTER IV: DISCUSSION

This study looks at the potential contribution credit information had in one Tennessee law enforcement agency's selection process. The use of credit information as a selection predictor is a topic with heated discussion on both sides. There are reasons why a company would prefer to run a credit check on potential employees, especially when the position involves access to large amounts of money. On the other side, using credit information for selection purposes has been shown to lead to adverse impact concerns. While credit information has been validated for use when determining loan eligibility, Palmer and Koppes (2004), Gallager (2006), and Bryan and Palmer (2012) point out in their research that it has not been shown to predict employee performance.

## Hypothesis 1a

The analyses provided partial support for Hypothesis 1a: Credit information (number of accounts overdue) was related to the Final Report Card (FRC) rating. Accounts 30-60 days late were found to have a significant influence on the FRC rating. However, accounts 60-90 days late and accounts 90-120 days late were not found to be significant. Both the likelihood ratios tests and the pseudo r-squared tests show that adding credit information into the model adds unique information to the model and explains more variance than other selection variables alone.

## Hypothesis 2a

The analyses provided support for Hypothesis 2a: Credit information (number of accounts overdue 120+ days) was related to the FRC rating. Results indicated that credit information that included 1) accounts overdue 120+ days, 2) collections, 3) bankruptcy, or 4) medical debt had a stronger influence on FRC ratings than other non-credit information selection variables, with the exception of criminal records. Applicants who had accounts 120+ days late, collections, bankruptcy, or a criminal record were more likely to receive a lower FRC rating.

Hypothesis 2a was also supported in the odds ratio analyses. Accounts overdue 120+ days late had an OR: 1.17 – 1.46, which would indicate that having accounts overdue 120+ days would increase the likelihood of receiving a negative FRC rating by up to 1.46. Outside of 120+ days, medical debt, collections, and bankruptcy all of the significant variables had relatively lower odds of influencing the outcome of the FRC rating. Results indicated that an applicant's odds of receiving a low FRC rating increased significantly the later the credit accounts were, as well as if they had collection accounts, bankruptcy, or medical debt.

**Hypothesis 2b**

Hypothesis 2b looked at how credit information (number of accounts overdue 120+ days), social media, criminal records, child support/alimony obligations, education and military background related to the FRC rating. The analyses provided partial support for Hypothesis 2b. Accounts 120+ days late and criminal records had a statistically significant relationship with the FRC rating across all years and in both models. The remaining selection predictors of child support/ alimony obligations, social media, education, and military background were not found to have a statistically meaningful relationship with FRC ratings across all years and models.

**Implications of the Results**

Support and partial support were found for all hypotheses in this study. This indicated that credit information had a significant influence on the FRC rating. This suggests that using credit information as a selection predictor had an effect on the organization's selection decisions. The analyses across models and across years indicated that using credit information as a selection predictor for the law enforcement agency from which the data was received does provide a unique contribution to above and beyond the non credit information variables. Also, the credit information variables did influence the FRC ratings. The move overdue an applicant's credit accounts were, the lower the FRC rating they would receive.

The odds ratios show that credit information selection variables have higher odds of impacting the FRC rating than other non-credit information selection variables. The odds of an applicant getting a low FRC rating increased the more overdue their accounts were. The likelihood ratio tests showed that including credit information (Model 2), across all years, independent and cumulative, provided unique information beyond that of non credit information variables (Model 1). The pseudo r-squared test showed that, across all years, independent and cumulative, Model 2 explained more of the variance in the analyses than Model 1. Regression coefficient estimates showed that having accounts past 120+ past due, collections, medical debt, and bankruptcy negatively influences the relationship with the FRC rating.

One surprising finding was that even though criminal records was significant across both models in all years, the odds ratios of criminal records were consistently less than one. This could be due to the organization giving consideration to the extenuating circumstances around the criminal record and not just considering the criminal record in and of itself.

**Limitations and Future Research**

While there is predictive validity of credit scores for loan and auto insurance purposes, employers do not look solely at an applicant's singlular credit score. Nor do employers use a uniformed systematic process of determining how credit information will be applied to the selection process. This is true not only across organizations, but within them (Nielson & Kuhn, 2009). Literature on the validity of applying credit information to the selection process is minimal (Bryan and Palmer, 2012), and/or "dubious" (Gallager, 2006, pg 1595). Nielson & Kuhn (2009) were unble to find any published studies that determined the validity of using credit information for selection purposes.

The results of this study indicated that credit information does have an influence on the decision making process. Whether that influence improves the validity of predictive performance or not, or if it adds error, is unclear at this point. Ideally, a longitudinal study would be needed to try and ascertain how performance information correlates with using credit information as a selection predictor.

Before credit information can be established as a valid predictor of performance, reliability of credit information usage needs to be established. If there is no reliability in the way credit information is used, there will not be any validity in using credit information as a selection predictor. Future studies are recommended in to look at the reliability of using credit information as a selection predictor and determine whether or not reliability is setting an upper limit on validity.

This study cannot determine the validity of using credit information as a selection predictor, as data on employee performance was not included in this study. Future studies are recommended to look at how using credit information as a selection predictor may impact performance or fraud and whether credit information is a valid predictor of future job performance or risk of fraud.

Due to the information in this study coming from one source, a government agency in Tennessee, this study is limited to the way the agency has decided to utilize the information collected for selection purposes.

**Conclusion**

This study was not able to determine performance validity, however it does bring up the question of whether credit information is a valid predictor of selection. Predictive validity enables an organization to accurately assess whether a selection process is reliable (Ekuma, 2012). If credit reports are influencing the selection decisions of organizations, determining the predictive validity of credit information is important. Advocates of using credit information in the selection process often assume the predictive validity found in the financial arena correlates with job performance in the work arena (Nielson & Kuhn, 2009).

From the perspective of content relevance, the law enforcement organization’s process (whose data was used for this study) has established job-relatedness for using credit information as a variable by going with the general assumption that character is related to the job and credit information is an indicator of character. To understand the extent to which these assumptions are true, more analyses would need to be done to determine whether or not credit information is an actual predictor. The law enforcement organization has content justification of believing that credit information is adding value to the selection decision process, but it is possible that bias, or error, or both could be introduced instead.  Regardless of whether the contribution of credit information is good or bad, there is a unique contribution.

This study has found that credit information does contribute unique information above and beyond the other non credit information variables.  It has also found that credit information did have an influence on FRC ratings.  Whether that influence improves the prediction of determining who will be better for the job is still unknown.  It is possible that the influence credit information has on FRC ratings could be introducing bias or error.  While it is the belief of the authors that it may improve the prediction of who will be better for the job, research is still limited.

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# APPENDICES

# APPENDIX A: IRB Approval Letter

**IRB**
**INSTITUTIONAL REVIEW BOARD**
Office of Research Compliance,
010A Sam Ingram Building,
2269 Middle Tennessee Blvd
Murfreesboro, TN 37129

MIDDLE TENNESSEE STATE UNIVERSITY

## IRBN007 – EXEMPTION DETERMINATION NOTICE

Wednesday, May 15, 2019

| | |
|---|---|
| Principal Investigator | **Mandy Matsumoto** (Student) |
| Faculty Advisor | Patrick McCarthy |
| Co-Investigators | Mark Frame and Amanda Terry |
| Investigator Email(s) | *mmm9y@mtmail.mtsu.edu; patrick.mccarthy@mtsu.edu; mark.frame@mtsu.edu* |
| Department | Psychology |
| Protocol Title | ***The unique contribution of credit information in the selection process*** |
| Protocol ID | **19-1249** |

Dear Investigator(s),

The above identified research proposal has been reviewed by the MTSU Institutional Review Board (IRB) through the **EXEMPT** review mechanism under 45 CFR 46.101(b)(2) within the research category *(4) Study involving existing data* A summary of the IRB action and other particulars in regard to this protocol application is tabulated as shown below:

| IRB Action | **EXEMPT from furhter IRB review***** | Date | **5/15/19** |
|---|---|---|---|
| Date of Expiration | NOT APPLICABLE | | |
| Sample Size | 2,000 (TWO THOUSAND) applicants' records | | |
| Participant Pool | **Data previously collected from Healthy Adults (18 or older) - applicants for the position of Tennessee Highway Patrol Officer** | | |
| Exceptions | NONE | | |
| Mandatory Restrictions | 1. Participants must be 18 years or older<br>2. Informed consent must be obtained from the participants<br>3. Identifying information must not be collected | | |
| Restrictions | **1. All restrictions for exemption apply.**<br>**2. Not approved for new data collection: analysis of data collected through the application process of the THP Officer position.** | | |
| Comments | NONE | | |

***This exemption determination only allows above defined protocol from further IRB review such as continuing review. However, the following post-approval requirements still apply:

- Addition/removal of subject population should not be implemented without IRB approval
- Change in investigators must be notified and approved
- Modifications to procedures must be clearly articulated in an addendum request and the proposed changes must not be incorporated without an approval

- Be advised that the proposed change must comply within the requirements for exemption
- Changes to the research location must be approved – appropriate permission letter(s) from external institutions must accompany the addendum request form
- Changes to funding source must be notified via email (irb_submissions@mtsu.edu)
- The exemption does not expire as long as the protocol is in good standing
- Project completion must be reported via email (irb_submissions@mtsu.edu)
- Research-related injuries to the participants and other events must be reported within 48 hours of such events to compliance@mtsu.edu

**Post-approval Protocol Amendments:**

The current MTSU IRB policies allow the investigators to make the following types of changes to this protocol without the need to report to the Office of Compliance, as long as the proposed changes do not result in the cancellation of the protocols eligibility for exemption:

- Editorial and minor administrative revisions to the consent form or other study documents
- Increasing/decreasing the participant size

***Only THREE procedural amendment requests will be entertained per year. This amendment restriction does not apply to minor changes such as language usage and addition/removal of research personnel.***

| Date | Amendment(s) | IRB Comments |
|---|---|---|
| NONE | NONE. | NONE |

The investigator(s) indicated in this notification should read and abide by all applicable post-approval conditions imposed with this approval. Refer to the post-approval guidelines posted in the MTSU IRB's website. Any unanticipated harms to participants or adverse events must be reported to the Office of Compliance at (615) 494-8918 within 48 hours of the incident.

All of the research-related records, which include signed consent forms, current & past investigator information, training certificates, survey instruments and other documents related to the study, must be retained by the PI or the faculty advisor (if the PI is a student) at the sacure location mentioned in the protocol application. The data storage must be maintained for at least three (3) years after study completion. Subsequently, the researcher may destroy the data in a manner that maintains confidentiality and anonymity. IRB reserves the right to modify, change or cancel the terms of this letter without prior notice. Be advised that IRB also reserves the right to inspect or audit your records if needed.

Sincerely,

Institutional Review Board
Middle Tennessee State University

Quick Links:

Click here for a detailed list of the post-approval responsibilities.
More information on exmpt procedures can be found here.

## APPENDIX B: Frequency Distribution of Credit Accounts

*Frequency Distribution of Credit Accounts Across Years*

| | Frequency of Accounts by Year | | | |
|---|---|---|---|---|
| Credit Account Timeframe | 2017 | 2018 | 2019 | Cumulative |
| No Credit | 366 | 300 | 254 | 920 |
| On Schedule | 2,276 | 3,158 | 2,392 | 7,826 |
| 30-60 Days Late | 43 | 92 | 48 | 183 |
| 60-90 Days Late | 13 | 16 | 20 | 49 |
| 90-120 Days Late | 12 | 41 | 8 | 61 |
| 120+ Days Late | 142 | 201 | 145 | 488 |
| Collections | 149 | 243 | 183 | 575 |
| Medical | 367 | 300 | 254 | 921 |
| Bankruptcy | 19 | 12 | 8 | 39 |
| Other | 31 | 69 | 41 | 141 |