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# Relationship Between Multiple Train Derailment Causal Factors and the Occurrence of Train Derailment

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has been found to be complete and satisfactory in all respects,
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Abstract

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by

Samantha Cooper

MS, American Military University, 2017

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Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Business Administration

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Abstract

Train derailments can result in loss of life, interruption of services, and destruction of the environment. Understanding the correlates of train derailments can help railway managers and safety managers reduce the occurrences of train derailments. Grounded in the Swiss cheese model, the purpose of this quantitative correlational study was to examine the relationship between train derailment causal factors, visibility, weather, number of crew members, crew members' length of time on duty, and the occurrence of a train derailment. Data were collected from secondary data on 1,396 Class I and Class II railroad accidents during the 2019 calendar year. The results of the binomial logistic regression were statistically significant, $X^2(12, N = 1396) = 114.265$, $p < .001$. Nonoperator causal factors and the number of crew members on duty were statistically significant predictors of the occurrence of a train derailment. A key recommendation for railway managers is to adjust preventative maintenance measures and increase the number of crew members on duty. The implications for positive social change include potentially reducing the frequency of train derailments and saving lives.

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# Dedication

I would like to dedicate this study to my late mother and father, Colleen M Cooper and Ralph W Cooper. I know they are both looking down on this accomplishment and have been encouraging me the whole time. Also, I would like to thank Zachary Green for supporting me through this journey and just telling me how huge this accomplishment is. It has been a rewarding journey to not only fuel my passion for learning and researching but to also look outside the box.

Acknowledgments

I want to thank my committee chair, Dr. Meridith Wentz. Your guidance and support along this journey have been nothing short of amazing. I appreciate the time you spent going through corrections and ensuring that what I was looking to achieve was attainable. I also want to acknowledge and thank Dr. Lisa Pearo, my second committee member. Both of your contributions to my doctoral study are indispensable; thank you for sharing your time and expertise. I could not have the growth and development during this process without the two of you.

I also would like to say thank you to all my Walden classmates. I have made friends through encouraging one another and cheering each other on throughout our doctoral journey. While at residency I have made great friends and it was amazing to have their support throughout this doctoral journey. This journey cannot be completed alone; classmates are what help to encourage each other to reach for the next step in the doctoral journey and encourage others that are one step behind. I would like to thank all my classmates and lifelong friends for their encouragement on this doctoral journey.

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# Section 1: Foundation of the Study

Human factors can have major contributions to accidents across various industries including railway, aviation, maritime, and mining (Li et al., 2019). Human factors and nonhuman factors are causes of train derailment (Liu et al., 2013). Though these errors can cause catastrophic outcomes, understanding the causes of error can provide the knowledge to help eliminate these errors (Underwood & Waterson, 2013). For example, when snowy and icy weather occurs, the likelihood of accident occurrence is four times higher (Malin et al., 2019). The objective of this study was to help railway managers understand the relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment.

## Background of the Problem

Train derailments can result in the loss of life or property, interruption of services, and destruction of the environment (Liu et al., 2013). They are the most frequent kind of Federal Railroad Administration (FRA) reportable mainline train accident in the United States (Barkan, et al., 2003). There are four main causes for train derailment: (a) operations and human mistakes, (b) track failures, (c) factors regarding to rolling stock and (d) environmental and natural catastrophes (Mohammadzadeh & Ghahremani, 2012). In the FRA Safety Office of Safety Analysis database, the train accident codes can be further broken down into specific causes that influenced the occurrence of train derailments.

Train derailment severity is a key factor in understanding the outcome of a train derailment and its impact (Martey & Attoh-Okine, 2019). Derailment severity has been influenced by multiple causal factors, which include car mass, derailment speed, residual train length, derailment cause, ground friction, proportion of loaded railcars in the train, and train power distribution (Zakar & Mueller, 2016). Train derailment severity can also be impacted by visibility, weather, number of crew on duty, and crew member length of time on duty, which were researched in this study. The topic of train derailment is important because the findings may allow management and employees in the railroad industry to understand the relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment. Knowing this information can help management and safety managers understand how to reduce occurrences of train derailments.

## Problem Statement

Since 2016, there have been over 4,000 train derailments in the United States, resulting in over 248 million dollars' worth of loss (FRA, 2019). Train derailments have decreased by 5.9% each year but continue to have impact on the on-track equipment, signals, track, track structures, supply chain, employees, and railbed (Liu et al., 2017). The general business problem is that train derailments, sometimes the results of operator error, have an impact on community safety, transportation efficiency, and organizational cost. The specific business problem is that some railway managers do not understand the relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment.

## Purpose Statement

The purpose of this quantitative correlational study was to examine the relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment. The independent variables were train derailment causal factors, visibility, weather, number of crew members, and crew members length of time on duty. The dependent variable was the occurrence of train derailment, represented as a dichotomous variable. The targeted sample population consisted of Class I and Class II rail lines in the railroad industry across the United States. Data collection was completed through the FRA Office of Safety Analysis, which is a publicly available database. All derailment safety reports are reported and complied on this site. The implications for social change include the potential to reduce the frequency of train derailment occurrences in the railroad industry and save lives.

## Nature of the Study

I used the quantitative method to examine the relationship between the identified independent and dependent variables. Quantitative researchers identify changes in numerical characteristics of the population being studied and examine statistical relationships between variables (Paul & Garg, 2014), which was the purpose of this study. In contrast, by using the qualitative approach, researchers usually derive themes from the subjective answers of the research participants (Yin, 2018). A mixed methods study contains the attributes of both quantitative and qualitative methods (Guetterman et al., 2015). Since the intent of my study was to identify the relationship between variables, the qualitative and mixed-method approaches were not appropriate.

I used the quantitative method with a correlational design to investigate the relationship between five independent variables and one dependent variable. Using the correlational design approach, researchers can examine the direction and strength of the relationship between the predictor/independent variables and criterion/dependent variables (Curtis et al., 2015). Experimental design includes many of the same elements of a quasi-experimental design, but with quasi-experimental design there is no random selection of the secondary participants for control or experimental groups (Jaffee et al., 2012). The quasi-experimental or experimental research design is used when identifying and assessing the causes that influence outcomes (Creswell, 2009). For this study, my objective was to examine the relationship between variables within the real world without controls. Therefore, the experimental and quasi-experimental designs were not appropriate for my study.

## Research Question

What is the relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment?

$H_0$: There is no statistically significant relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment.

$H_a$: There is a statistically significant relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment.

**Theoretical Framework**

James Reason's (1990) Swiss cheese model suggests that longstanding organizational deficiencies can create the necessary conditions for a frontline active failure to trigger an accident (Underwood & Waterson, 2014). Layers of defense are like a slice of Swiss cheese with the potential to have holes or weaknesses (Olson & Raz, 2021). When the holes in a system's defenses align, an accident trajectory can pass through the defensive layers and result in a hazard causing harm to people, assets, and the environment (Reason, 2008). Holes in a single slice or defense will not normally cause a bad outcome, but when all the holes momentarily align, that is when a failure has a clear path through the system, resulting in a catastrophic accident (Reason, 1997). These holes are also changing in sizes and location at any given time. Additionally, these holes can be looked at as latent and active errors. Latent errors are the results of organizational system or design failures that will allow active errors to happen and cause harm (Collins et al., 2014). Active errors are the results of an individual's failure and occur at the point of contact between a human and an aspect of a larger system (Collins et al., 2014). Both latent and active errors impact the chances of an accident to occur and are both equally important when understanding what caused an accident to occur.

The variables in this study were train derailment causal factors, visibility, weather, number of crew members, and crew members length of time on duty. Each of these variables can be looked at as a slice of cheese. Further, Reason looked at four levels that are present within sociotechnical systems: unsafe acts, preconditions for unsafe acts, supervisory factors, and organizational influences. Each variable in this study can fall into one of these categories as they all have impact on the likelihood of an accident to occur. With this study, the goal was to determine the relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment.

## Operational Definitions

*Class I railroad:* A Class I railroad is based on the annual operation revenue and has a threshold of revenue greater than $250 million (Code of Federal Regulation [CFR], 2018).

*Class II railroad:* A Class II railroad is based on the annual operational revenue and has a threshold of revenue less than $250 million but in excess of $20 million (CFR, 2018).

*Federal Railroad Administration (FRA):* The FRA compiles all train derailment reports received from around the United States that exceed a monetary threshold of damage costs and include items such as total damage costs, number of cars derailed, track type, train length, derailment speed, and other impacting variables (Liu et al., 2013).

*Nonoperator causal factors:* Nonoperator causal factors could include (a) track, roadbed, and structure (roadbed, track geometry, rail joint bar and rail anchoring, frog, switches and track appliances, other way and structure), (b) signal and communication (signal and communication codes), (c) mechanical and electrical failures (brakes, trailer or container on flatcar, body, coupler and draft system, track components, axles and journal bearings, wheels, locomotives, doors, general mechanical electrical failures), (d) miscellaneous causes not otherwise listed (environmental conditions, loading procedures, high-way grade crossing accidents, unusual operational situations, and other miscellaneous; FRA, 2019).

*Operator causal factors:* Operator causal factors are train operation human factors, which can include (a) use of brakes, (b) employee physical condition, (c) hand and radio signals, (d) general switching rules, (e) main track authority, (f) train handling/train make-up, (g) speed, (h) use of switch, (i) cab signals, and (j) other miscellaneous codes (FRA, 2019).

## Assumptions, Limitations, and Delimitations

### Assumptions

Assumptions are unverified opinions that researchers hold while conducting their study (Roy & Pacuit, 2012). The first assumption in this study was that railroads are reporting all train derailments according to their rail class and including the necessary details within each report. Each accident report should include over 50 different variables with each providing different input into the railroad train derailment report analysis (Liu et al., 2017). The second assumption was that all information within the FRA of Safety Analysis Office database can be broken down into the correct causal code for the train derailment. The final assumption was that all information entered in the database on weather, visibility, number of crew members, and crew members length of time on duty was entered correctly by the accident recorder.

## Limitations

Limitations refer to potential weaknesses of the study that are not within the control of the research but can be further researched by others once the limitations are identified within the study (Simon, 2011). One limitation in the database was that there are only two sections for causal code entry and there might be more than just the primary causal code and contributing causal code that made the train derailment occur. The second limitation was that there are potentially additional causes that are not adequately captured by the list of options within the database. The final limitation was that each independent variable (train derailment causal factors (human or nonhuman), visibility, weather, number of crew members, crew members length of time on duty) in the FRA database is entered by the accident recorder, and there could be incorrect information recorded.

## Delimitations

Delimitations refer to the bounds or scope of the study that are within the control of the researchers (Patton, 2014). One delimitation was my focus on Class I and Class II railroads. This was a delimitation because within the CFRs 49, Title 49, Part 1201 there are other classes of railroad Class III–Class VIIII, which each fall into different annual operation revenue thresholds (CFR, 2018). The second delimitation was the selection of the United States as the area of data collection for train derailment analysis.

## Significance of the Study

### Contribution to Business Practice

One common metric for assessing rail safety is accident rate, which can be defined as the number of train accidents normalized by traffic exposure, such as train miles, car miles, gross ton-miles, or passenger miles (Liu, 2015). Derailments are the most common type of train accident in the United States and can cause damage to infrastructure, rolling stock, and lading; disrupt service; and have the potential to cause casualties and harm to the environment (Liu et al., 2017). The findings from this study will provide information to railway managers to help to better understand and prevent train derailments, because they will understand the relative importance of the different factors on the potential outcomes. Finally, for the nonoperator causal factors, for instance with weather, informed decisions can be made on resource allocation to prevent potential issues.

### Implications for Social Change

The impacts for positive social change include giving management the understanding of the relative importance of the elements of operator causal and nonoperator causal factors. There is also the potential for managers to understand the unforeseen accident causal factors for train derailments. Improving operator and managers awareness of train derailment causal factors can help to improve the safety measures occurring during and after a train derailment. Finally, management will be able to analyze causal factors for information disseminate to the community on train derailment safety precautions, which in turn may increase public awareness on disaster prevention.

**A Review of the Professional and Academic Literature**

The purpose of this quantitative correlation study was to examine the relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment. The theoretical framework for this study was James Reason's (1990) Swiss cheese model. For the literature review, I searched EBSCO host, ProQuest, Thoreau multidata base, and Google Scholar for all articles related in the topic areas of *aviation accidents, aviation accident by human error, maritime accidents, human error maritime, train accident human error, accidents in aviation, accidents in maritime, accidents in railway, accidents in oil field, aviation accident causes, maritime accident causes, railway accident causes, nonhuman error in organizational accidents, medical accidents, human error in accidents, accident occurrence through error, train derailment, train safety, causal factors, operator error, risk management, organizational accident, accident causation, the swiss cheese model, man-machine-environment, 3M model, 5M model, hot cheese model, linkage to swiss cheese model, updated swiss cheese model, accidents in multiple sectors, common occurrences in accidents, derailment causes, weather, weather accidents, visibility, crew members, accident factors, human error causes for accidents, nonhuman accident causes,* and *industry accident causes.* I also obtained data from the FRA Safety of Safety Analysis database pertaining to the occurrence of train derailments and the causes of those train derailments. The review of literature includes 141 references. Eighty-three percent of the references were published within the past 5 years (2017–2021), and 90% are peer-reviewed.

In this literature review, I first discuss organizational accidents, including accident occurrence in multiple industries and accident causation. Next, I discuss the theoretical framework for this study, including the origins of the Swiss cheese model, the development and the evolution of this model, and the model's components followed by supporting and contrasting theories. Additionally, I review the literature related to accidents within the aviation, maritime, and railroad industry. Finally, I conclude the literature review with an analysis of the implications of this study for business practice related to train derailments.

## Organizational Accidents

### *Accident Occurrence Across Industries*

In a number of industries, the occurrence of accidents is high when dealing with human error or nonhuman errors (Erjavac et al., 2018). Currently, an estimated 60% to 80% of system failures from aviation, railway, and maritime areas are attributable to human performance (Erjavac et al., 2018). In each industry, researchers are looking to further understand the role of employees in complying with safety standards and also ensure that employees have the decision-making skills to handle sudden situations that could create an accident.

Across sectors, there are a number of areas where human error can come into play when an accident occurs. Human error within the aviation field means actions associated with the pilots, cabin crew members, navigators, meteorologists, mechanics, and constructors (Ding et al., 2019). In the maritime sector, human error often includes navigator error or inappropriate behaviors (Youn et al., 2018). Finally, in the railway sector, human error often includes accidents that occurred due to operator error (Sun et al., 2020). Besides the human element, there is also the chance of nonhuman occurrences such as those caused by glitches within the system (Strauss, 2017). Across sectors, human error can encompass intentional or unintentional violation of procedures, or organizational influences from a managerial level (Kelly & Efthymiou, 2019).

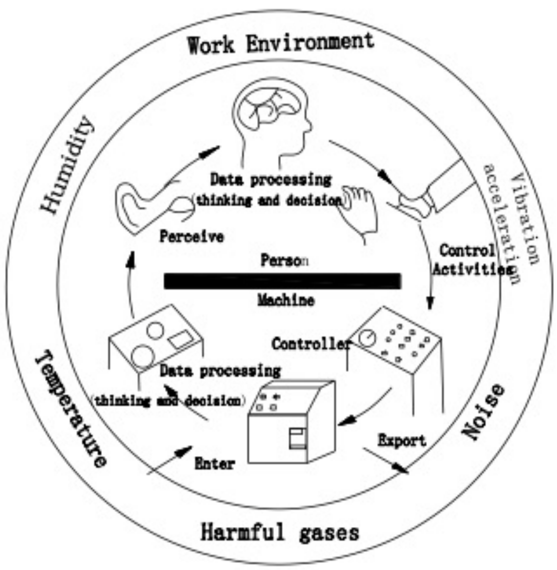
### *Accident Causation*

When an accident occurs in a system, one way to discover the causes is to complete an analysis using accident causation theories and models (Li et al., 2017). Accident causation analysis can help companies find the common patterns within the failures to help reduce or sometimes prevent the occurrence of the accident happening again. Over time, numerous methods have been developed, but structural decomposition and functional abstraction are the two most viable for understanding accident causation. Structural decomposition takes a system, breaks it down into objects, and explains the causal factors for the object’s failure (Li et al., 2017). This method is most commonly used to analyze and break into categories the failures that occurred within a system. Functional abstraction deals with analyzing the functional relationships within a system to understand the behaviors that occur within the system.

When discussing accident causation models and theories, two models (3M and 5M) are used to further analyze the system safety factors, which deal with man, machine, and environment. The first adopted version of the man, machine, and environment model, referred to as the 3M model, created by Professor Long in 1981, was used to show that there is not a single causal factor when dealing with equipment failure (Guo et al., 2019). The 3M model can be seen in Figure 1, but it has been updated over time to include more factors that could be causing frequent accidents to occur.

**Figure 1**

*Man-Machine-Environment (3M) Model*




*Note.* From “Application of Man-Machine-Environment System Engineering in Coal Mines Safety Management,” by S. Xiaoyan, and X. Zhongpeng, 2014, *Procedia Engineering, 84,* p. 88 (https://doi.org/10.1016/j.proeng.2014.10.413).

Both the 3M and 5M model help to first create a picture of the potential reasons for the accident to occur (Xiaoyan & Zhongpeng, 2014). The first step in accident causation analysis is to understand the different variables that can have an impact of the potential outcome for an accident to occur. Over time, the 3M was expanded to include variables that were not thought of when the model was first created. To expand on the 3M model, the 5M model was created, which includes the following variables: man, machine, media, management, and mission. Expansion of the 3M to the 5M helped to show other areas that need to be understood on the impact they have to the creation of accidents in multiple environments. With each iteration of the models the figure changes to streamline the overall impact of the creation of the new model.

There is an overlap within the 5M model that includes mission and management, which is depicted in Figure 2. The 5M and 3M models are important to help accident research analyst understand the potential factors that had an impact on the occurrences of accidents across multiple industries. Researchers have also proposed another version of the 5M model that evaluated the impact of human, process, and technology factors on system failures (Irani et al., 2017). The variables were expanded to include other variables that have a key role in the accident causation that occurs after a failure in a system. Although all factors might not act together, more than one factor can be causing the accident or failure within a system.

**Figure 2**

*5M Model*

*Note.* From "An Accident Causation Analysis and Taxonomy (ACAT) Model of Complex Industrial System from Both System Safety and Control Theory Perspectives," by W. Li, L. Zhang and W. Liang, 2017, *Safety Science, 92,* p. 97 (https://doi.org/10.1016/j.ssci.2016.10.001).

Although the 3M and 5M model help to show how each safety factor can create the perfect opportunity for accidents to occur within a system, the Swiss cheese model is still one of the leading models used when looking at accident causation. Accident causation is a factor in understanding how Reason came to develop the Swiss cheese model (Liu et al., 2017). Reason was more focused on the latent, active, and defenses that exist within a system to cause an accident to occur.

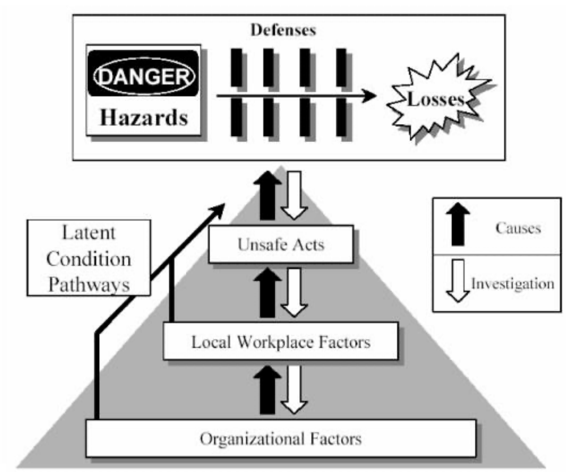
## The Swiss Cheese Model

### *Creating the Swiss Cheese Model*

Reason (1997) created the Swiss cheese model after placing cat food into a teapot instead of the cat bowl, which led to modeling organizational accidents and the foundation to the Swiss cheese model (see Figure 3). The question was raised as to which defenses failed, how did they fail, and why did they fail, defenses, barriers, and safeguards (Peltomaa, 2012). In this model, Reason was looking to understand how organizational factors, local workplace factors, and unsafe acts impact the defenses that are currently in place within an organization. The defenses that are in place need to be strong enough to withstand the factors that could come to break down the efficiency in an organization and to create a layered effect to the defensive layer in a system (Bode & Vraga, 2021).

**Figure 3**

*Model of Organizational Accidents*

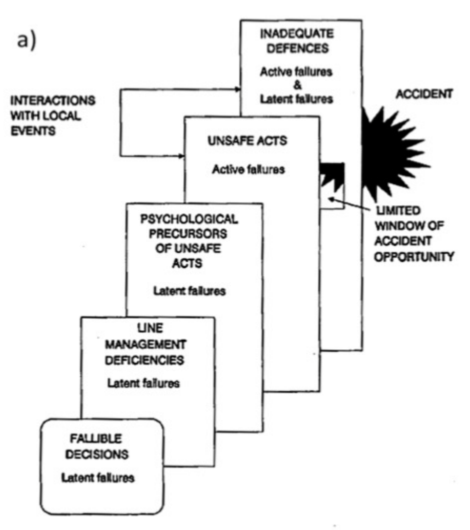



*Note.* From *Managing the Risks of Organizational Accidents*, by J. Reason, 1997, Ashgate Publishing.

Figure 4 shows the early edition of Reason's Swiss cheese model, which focused on decision makers, line management, preconditions, productive activities, and defenses. The Swiss cheese model was established as a reference model in the causation, investigation, and understanding, and prevention of organization accidents (Larouzee & Le Coze, 2020).

**Figure 4**

*Early Edition of James Reason's Model*




*Note.* From "Good and Bad Reason: The Swiss Cheese Model and Its Critics," by J. Larouzee, and J. C. Le Coze, 2020, *Safety Science, 126,* p. 5 (https://doi.org/10.1016/j.ssci.2020.104660).

The Swiss cheese model also includes active failures, latent failures, and defenses. Active failures are looked at as unsafe acts by front-end operators, which includes errors, mistakes, and violations. Latent failures are gaps or weaknesses in the system safety defenses that were implemented into the creation of the system. Latent failures, unlike active failures, can lay dormant or undetected for hours, days, weeks, or even longer, until one day they adversely affect the system, which creates the failure (Wiegmann et al, 2021). The layers of defense can be looked at as the holes in Swiss cheese that can be the weaknesses within the system. Holes or weaknesses in a single slice or defense do not normally result in a catastrophic outcome, but when all the holes align, any failure has a clear path through the system, with the potential to result in a catastrophic accident (Reason, 1997).

Since the creation of the Swiss cheese model, it has been adopted by many industries including aviation, nursing, health care and medical, nuclear, chemical processing, oil and gas, and rail. The most widely used theory for accident causation in various industries is the Swiss cheese model (Waterson et al., 2017). The Swiss cheese model is used in risk analysis and risk management, including aviation safety, engineering, health care, and emergency organization, and as the principle behind layered security (Karimi et al., 2021).

In the aviation sector, the Swiss cheese model has been used to help identify the human and organizational factors that contributed to the occurrence of a general aviation accident (Xue & Fu, 2018). For instance, 70–80% of civil and military aviation accidents are caused by human error (Shappelll & Wiegmann, 2001). The Swiss cheese model can be used in the aviation sector to help understand the potential unsafe acts, unsafe conditions, preconditions for unsafe acts and unsafe conditions, deficiencies in the general aviation safety management, and deficiencies in safety culture (Xue & Fu, 2018). The variables in this model are taken from the Swiss cheese model and are used to understand how human and organizational factors impact the likelihood of an accident to be caused.

The health care industry has used the Swiss cheese model to mold the model to a specific accident that occurred and connect the holes to show how it created the perfect alignment for an accident to occur (Seshia et al., 2017). For example, a surgical error may occur due to the following factors that created the perfect alignment for the accident to occur: incorrect site on consent, first day at the new hospital, new equipment never inserviced, band used instead of marking, video transition down had to use pheon, family does not speak English, history and physical examination not verified with consent, which resulted in the wrong site surgery. Each of these factors represent the holes that created the failures in the barriers (Seshia et al., 2017). Though the Swiss cheese model has a simplified version, in the health care industry this model can be tailored to show where there were holes in the barrier, creating an increased likelihood for an accident to occur. The Swiss cheese model can help health care professionals understand the safety measures that need to be put into place (Wiegmann et al., 2021).

The Swiss cheese model has also been used within the railroad industry to understand how inadequate defenses, unsafe acts, psychological precursors of unsafe acts, line management deficiencies, and fallible decisions can have an impact on the occurrence of a train accident (Suryoputro et al., 2015). Within each variable, there could be issues that occurred and created the perfect alignment of the hole to cause the accident to occur. For instance, psychological precursors of unsafe acts could include poorly coordinated communication, physical and mental fatigue, and feeling unwell. When one factor within each layer of the Swiss cheese model fails, it creates the perfect opening for a train accident to occur.

Human error is inevitable, and it is impossible for humans to fully eliminate error (Reason, 1995). Because errors occur, there is a need for systems to be able to handle the potential error. Human error can be looked at as a potential consequence rather than a cause and blaming operators for the occurrence of the error or accident does not improve safety prevention. Looking at the traditional model for accident causation that focused on active failures (human errors and mistakes) and single causes is inadequate (Xia et al., 2018). When creating the organizational accident theory, Reason focused on how organizational accidents are catastrophic events that occur in complex systems that involve many people at different levels (Reason, 1997). The Swiss cheese model was classified as an epidemiological model because of the suggestion that standing defects within a system can create the ideal conditions for active failures to trigger an accident to occur (Underwood & Waterson, 2014).

***Evolution of the Swiss Cheese Model***

The Swiss cheese model was first introduced in 1987 when Reason was exploring human error. From this, Reason published the seminal book, *Human Error* (Reason, 1990). While researching human error, Reason was able to find the differences between active errors and latent errors. Reason (1990) concluded that active errors, which are performed by operators, can be influenced by the conditions that exist within the organization, which are known as latent errors. Latent errors can be looked at as dormant errors that can be active when combined with other factors creating a breach in the defenses and resulting in the occurrence of an accident.

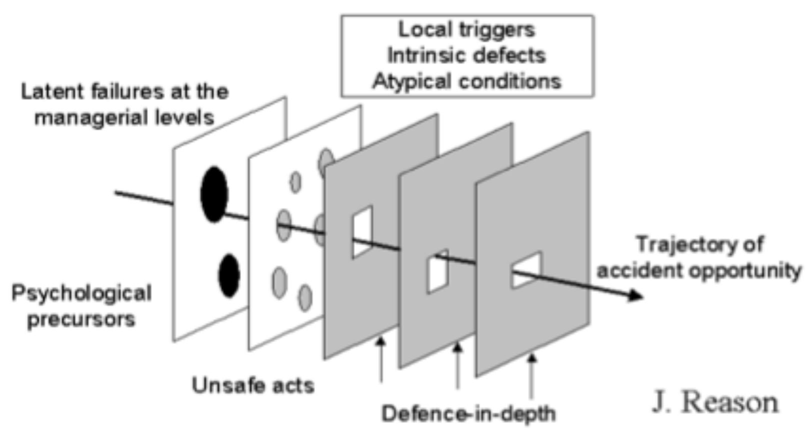
Perrow (2004) developed the normal accident theory which describes how normal accidents or system accidents occur due to multiple failures that are not in direct operational sequence. The Swiss cheese model helps to expand on how active errors and latent errors have an impact on the occurrence on an accident (Grant et al., 2018).

Accident pathogens are adverse latent or preexisting conditions, passive or with no impact on the system until triggered by other adverse events (Gnoni & Saleh, 2017).

When by chance all holes are aligned, the hazard reaches perfect alignment creating the potential error or accident to occur (Perneger, 2005). One main point within this model was the focus on human error and how each focused area can fall into latent failures, active failure or active and latent failures (Reason, 1990). Figure 5 shows updated version of the model which incorporated the defense-in-depth concept into the model (Reason, 1990).

**Figure 5**

*Updated Reason Model*

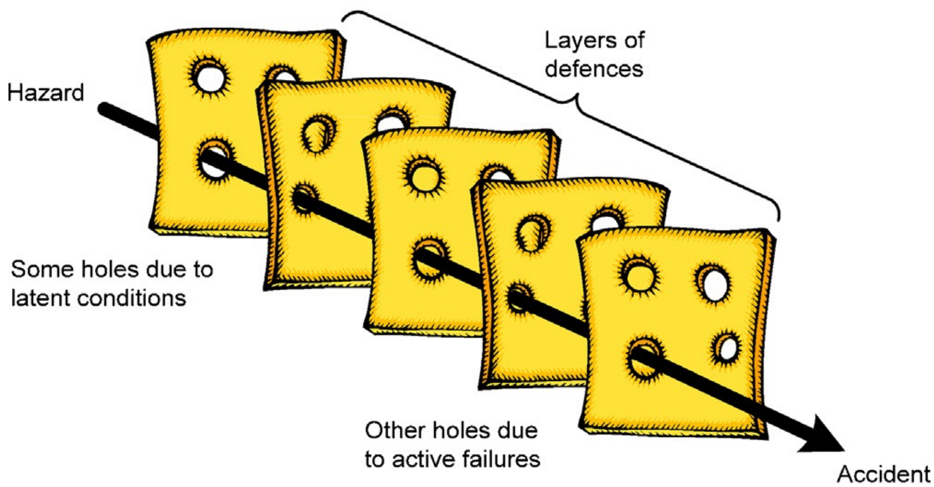



*Note.* From *Human Error*, by J. Reason, 1990, Cambridge University Press.

While the model was updated in 1995, latent errors were later renamed to latent failures because Reason realized that effective decisions at one point in time may have unintended negative outcomes at another time in the system (Larouzee & Le Coze, 2020). Further improvements were made to the model by Reason to illustrate that the holes will always be moved, changing in shape and size as a reaction of the acts from operator and local demands (Suryoputro et al., 2015). Figure 6 shows the most current version of the Swiss cheese model which has not been updated since 2000.

**Figure 6**

*Current Version of Swiss Cheese Model*




*Note.* From "Systems Thinking, The Swiss Cheese Model and Accident Analysis: A Comparative Systemic Analysis of the Grayrigg train derailment Using ATSB, AcciMap and STAMP models," by P. Underwood, and P. Waterson, 2014, *Accident Analysis and Prevention, 68,* p. 76 (https://doi.org/10.1016/j.aap.2013.07.027).

***Swiss Cheese Model Components***

The Swiss cheese model consists of different components each having a different effect on the potential occurrence of human error or accidents. The independent variables in this study are train derailment causal factors, visibility, weather, number of crew members, and crew members length of time on duty. Each of the independent variables in this study can be looked at as holes that occur in the slice of cheese to increase the chance of accidents to occur (Reason, 2016). The holes will create faults in the defense layer, which in turn will increase the likelihood of accident occurrence (Peltomaa, 2012). The Swiss cheese model explains the failure of numerous system barriers or safeguards to block errors, each represented by holes in cheese slices that allow errors to pass through and harm occur (Stein & Heiss, 2015). The first two components are active failures and latent conditions which can occur either singly or in diabolical combination creating a gap in the defenses (Reason, 2016). Finally, the third component is the defense that is currently in place that was ineffective, failed or unavailable during the time of error. Next, these components will be explained in more detail.

**Active Failures.** Active failures are unsafe acts, errors or procedural violations on the part of those in direct contact with the system (Reason, 2016). Active failures can be created by the operators which in turn create a weakness within the defensive layers in the system. Also, active failures can create long lasting effects on the defenses or protective layers that are currently available on the system. Reason (2000) stated that almost all legal approaches seek an individual to blame for unsafe acts but almost all such acts have a causal history that dates back in time or up through the levels of the system. Active failures can also have direct impact on the safety of the system and because of this create an environment for adverse effects to happen (Reason, 1997).

**Latent Conditions.** Latent conditions can be looked at as poor design, gaps in supervision, undetected manufacturing defects or maintenance failures, unworkable procedures, clumsy automation, shortfalls in training, less than adequate tools and equipment and can go undetected in a system for years before they are combined with local circumstances and active failures to penetrate the many layers of defense (Reason, 1997). Latent conditions are present within the system before the operator interacts with the system. Latent conditions are weaknesses or gaps in the defenses that were unknowingly created by the engineers, designers, builders or stakeholders who were there in the beginning creation of the system.

Every system has the possibility to have latent conditions as no system is built perfect. The key importance with latent conditions is to identify them before they cause harm to the system. Reason (2000) provided a great analogy on active and latent failures: active failures are like mosquitos because they can be swatted one-by-one, but they keep coming back. The best medicine is to create more effective defenses and to drain the swamp where the mosquitos are bred. In this case, the swamps are the latent conditions within the system.

**Defenses.** Defenses, barriers, or safeguards are put into place to protect the people and assets that are within the local area of the hazard and could be exposed to potential harm if an accident were to occur. Defenses can be categorized both according to the various functions they serve and by the way the functions are achieved (Reason, 1997). Defenses are created for more than one purpose but are in place to protect people and local hazards. When creating defenses, Reason (1997) stated that creating defenses-in-depth provide successful layers of protection, one behind the other, each guarding against the possible breakdown of the one in front. Defenses should include a variety of functions so if one fails the others have a chance to alarm when an accident is occurring before it becomes too late to act. Another strategy for creating the defensive layers is to have mutually supporting defenses that protect against a single failure, either human or technical.

These defenses are how the Swiss cheese model got its name because of the holes like a piece of swiss cheese. The holes within the slice of cheese are dynamic, always opening and closing, growing or shrinking, and shifting from one location to another. Due to the nature of the holes in a single slice or defense it does not normally cause a bad outcome but, if the error trajectory has a clear path through the system when all the holes align momentarily, this can create the catastrophic accident to occur (Reason, 2016).

### *Comparing the Swiss Cheese Model to Other Models*

The Swiss cheese model has been analyzed multiple times against other models to see the links or disconnects. From the Swiss cheese model other researchers created their own adaptation adding in additional variables that they felt were necessary to expand the gap areas in the Swiss cheese model. For instance, the Human Factors Analysis and Classification System (HFACS) expanded the Swiss cheese model to explain the different levels to human factors in accident occurrences (Underwood & Waterson, 2014). Leveson (2012) also adapted the System-Theoretic Accident Model and Processes which focused mainly on safety as a control problem. Each model is created from the knowledge from the researcher and the context the application will be applied to. While many researchers stated that the Swiss cheese model is still the most popular model used (Underwood & Waterson, 2013), there could be further updates to the model on how the holes line up to create the perfect line to create failure within the system.

Variations of the Swiss cheese model have also been used to better understand train accidents. Specifically, Underwood and Waterson (2014) conducted an analysis on Grayrigg train derailment using the Australian Transport Safety Bureau (ATSB), AcciMap, and systems theoretic accident modeling and processes (STAMP) model. The ATSB was created from the Swiss cheese model and the modifications represent the operation of a system via five levels of 'safety factors', where a safety factor is an event or condition that increases safety risk (Underwood & Waterson, 2014). The ATSB model used the Swiss cheese model for investigation and reporting within an accident, while research and academic applications of accident analysis often were looked at using the AcciMap and STAMP models (Underwood & Waterson, 2014).

Both AcciMap and STAMP are additional examples of models that are aligned with the Swiss cheese model that have been applied to the train industry. The AcciMap was developed by Rasmussen (1997) as a means of analyzing the series of interacting events and decision-making processes which occurred throughout a socio-technical system and resulted in a loss of control. This model was a combination of the cause-consequence chat and the Risk Management Framework which deals with the socio-technical systems over six organizational levels. Underwood and Waterson (2014) used this framework in their study because it pulled off the Swiss cheese model and also has been used previously for analysis on train accidents. The STAMP model was based on system and control theory, which focused on safety as a control problem. This model looks at three basic constructs (safety constraints, hierarchical safety control, and process models) to determine why control was ineffective and resulted in an accident. Safety constraints in this model can be looked at as passive or active and this is pulled from the Swiss cheese model.

Underwood and Waterson (2014) sought to understand how the ATSB, AcciMap, and STAMP differ from the Swiss cheese model but overall, how the Swiss cheese model still preforms analysis from a system thinking approach. Although the ATSB, AcciMap, and STAMP models each pull different aspects from the Swiss cheese model they still all point back to the Swiss cheese model being an appropriate model to analyze system thinking accidents.

Shappell and Wiegmann (2001) used the Swiss cheese model to further focus on the latent and active failures to create the HFACS. The HFACS framework creation helped to bridge the gap between theory and practice by providing investigators with a comprehensive, user-friendly tool for identifying and classifying the human causes (Shappell & Wiegmann, 2001). The creation of the HFACS model was the most successful adaptation from the Swiss cheese model that is used within the industry today. There are two causal factors explained in this model symptomatic causal factors which are direct or active causes; the initiating events that lead to system failure and latent causal factors which are both spatially and temporally disparate from the system failure; the factors that increase the potential for systematic causal factors (Erjavac et al., 2018).

HFACS models help to understand the human factors that can contribute to the occurrence of accidents within different industries. The main focus within the HFACS system is that human errors can happen at four levels: organizational influences, unsafe supervision, preconditions for unsafe acts, and the unsafe acts of operators. The model shows that there latent and active failures but there is an increase focus on human aspect of these failures. The HFACS model is useful to identify the organizational and systemic weakness rather than focusing on blaming the individual for the accident (Theophilus et al., 2017).

Other versions of the Swiss cheese model have been created to further define some of the areas that other researchers have criticized because of the lack of detail. Some criticism that is seen around the use of the Swiss cheese model could come from the misuse within certain industries. For example, Collins et al. (2014) analyzed use in the medical field to understand the active failures. While active failures are an important part of the Swiss cheese model there is still the need to look at all aspects of the model because this will have an overall impact on the conclusions found within the study. The latest Swiss cheese model was updated in 2000.

Many researchers since then have created other models to attempt to address the criticisms of the current Swiss cheese model. Li and Thimbleby (2014) developed the hot cheese model which went into a more complex version of the Swiss cheese model where there are eight different ‘types’ of cheese layers. The development of this model came from Li and Thimbleby who found that the Swiss cheese model didn’t display the situations and interactions between the layers also felt that the categorization with the unsafe acts of error, violations, and reckless behaviors were not transparent in the model. While Li and Thimbleby were trying to achieve a more detailed explanation on the Swiss cheese model it got flooded with the creation of the eight layers of cheese. Another issue that might have led to the development of a further defined model is the lack of understanding within the layers that were defined in the Swiss cheese model. The hot cheese model has not successfully superseded the Swiss cheese model and other authors have not regularly referred to it within researcher articles. Although the researchers had a goal for the creation of this method, the expansion of the layers has caused issues with other researchers using it within their field (Li & Thimbleby, 2014).

Within this section, I provided a detailed analysis on the Swiss cheese model which is the theoretical framework in this study. This analysis included the organizational accidents and accident causation, Swiss cheese model, the evolution of the Swiss cheese model, Swiss cheese model components and comparing the Swiss cheese model to other models. I provided detailed information on why the Swiss cheese model was the best choice for the theoretical framework. The next section of this literature review will be on accidents across industries, train derailments and the impact they have on the research to be conducted in this doctoral study.

**Causes of Accidents**

Throughout multiple industries there is the chance for accidents to occur by human or nonhuman errors. Human errors include personality, attitude toward road safety, attention, concentration, and memory (Santoso & Maulina, 2019). Human error can also be related to environmental interfaces, organizational and technical factors or even the personal like of the employees (Rong et al., 2016; Tripathy & Ala, 2018). Non-human errors include visibility, weather, number of crew members, crew members length of time on duty and road conditions. It is important to understand how these factors impact the likelihood of accident occurrence. There is variation across each system domain but 60% to 80% of system failures are, to a certain extent, attributable to human performance (Erjavac et al., 2018). Human errors, technical failures, and mechanical failures make up the majority factors that occur when an accident happens in industry accidents.

Weather can have an impact on the visibility and increase accident risk. Accident risk is significantly heightened during snowy and icy road conditions (Malin et al., 2019). For snowy and icy road conditions, Salli et al. (2008) found that accidents were more than four times higher compared to bare roads and slushy roads were fivefold for causing fatal accidents. In windy conditions, there is an increase in the frequency of rollovers and sideslip and spin accident occurrences (Zou et al., 2021). Weather can have an impact on occurrences of accidents because response time can be limited for the operator.

Time of duty has been shown to impact accident occurrences due to the connection to fatigue. Worker fatigue can be caused by no limit on employee weekly or monthly work hours, irregularity or unpredictability of on-call work schedules, mandatory commuting distances without compensatory time off (Coplen & Sussman, 2000). Within each industry there are different standards to the limitation on how many hours workers can work in one day but there are not the same standards established across all industries. Since there are not limitations on workdays, excess time on duty can cause workers to become tired because they are wanted to complete the task within the day. Within the North American Rail Alertness Partnership there are eight key components for an effective fatigue countermeasure program education and training, employee scheduling practices, emergency response requirements, alertness strategies, evaluation of policies and procedures, adequate rest environments, work environment, and implementation strategies (Coplen & Sussman, 2000). Crew members that have been on duty for extended periods of time are more likely to have poor or reduced alertness, poor psychometric conditions, and impairs the overall health of workers which can have impacts of accident occurrences (Peng et al., 2020).

The number of crew members on duty also has an impact on the occurrences of accidents. With more crew members on duty there are more eyes on the train tracks to help detect potential situations that can cause train accidents. Crew members within the railroad can consist of engineers/operators, firemen, conductors, and brakemen (FRA, 2021). Each crew member has an important role on the operation of the train engine and the rail cars that are pulled along with the train. If the train members are limited there is a chance for members to be distracted and accidents to occur (Coplen & Sussman, 2000). There is a need for more research to fully understand the impact that number of crew members has on the occurrence of train derailments. In this study, I aimed to understand the relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and occurrence of train derailment.

The focus in this literature review is on aviation accidents, maritime accidents, and railroad accidents. Within each sector, the factors impacting accident occurrence will be discussed along with what researchers are currently still looking to understand. Train derailments will also be covered, including the causes of train derailments. This information is important because the focus of this study was to understand the factors that have an impact on the occurrence of train derailment. Information on factors that impact the occurrence of accident will be helpful to inform management within each sector on how employees and crew members can help to decrease the likelihood of an accident to occur (Reason, 1995).

### *Aviation Accidents*

The aviation sector includes general aviation and air carriers. General aviation is air travel that is apart from scheduled air carriers. General aviation accounts for more than 85% of all aviation fatalities and over 95% of all fatal accidents even though flight hours between general aviation and air carrier operations are similar (Fuller & Hook, 2020). In the aviation field, pilot error is attributed to 75% of all aviation accidents (Gramopadhye & Drury, 2000). The overall aviation accident rate has declined since World War II; however, the incidence of human error has not improved and remains the primary flight safety risk (Erjavac et al., 2018). Looking at the potential for human error, it is known that within a complex system there is no way to avoid human influence on accidents (Reason, 1995). Human error can account for intentional or unintentional violations of procedures or from organizational influences from management that causes effects on flights (Kelly & Efthymiou, 2019).

The top two causes of aircraft accidents are loss of control in-flight and controlled flight into terrain. The main difference between the two is that controlled flight into terrain is an in-flight collision or near collision with terrain, water, or obstacle without indication of loss of control (Kelly & Efthymiou, 2019). Accidents within the aviation industry can also be caused due to the pilot and crew losing the sense of situational awareness. Loss of situation awareness can be seen when pilots and air crew forget to ensure pre-flight planning is completed, improving manual flight skills, and maintaining a high-level of specific aircraft mechanical and avionics knowledge (IATA, 2014).

Shappell and Wiegmann (2000) used the Swiss cheese model to create the HFACS which helped to further break down what factors impact the occurrence of aviation accidents. At a top level in HFACS there is unsafe acts which are classified into two categories: errors and violations. Figure 7 was created from their analysis, which explains the unsafe acts of pilot operators. These acts can be broken down from errors into skill-based errors, decision errors, and perceptual errors. Acts can include human and nonhuman errors. The violations can then be broken down into multiple causes that can impact the occurrence of an aviation accident occurrence.

**Figure 7**

*Unsafe Acts of Pilot Operators*

**TABLE 1**. Selected examples of Unsafe Acts of Pilot Operators (Note: This is not a complete listing)

| ERRORS | VIOLATIONS |
|---|---|
| **Skill-based Errors** | Failed to adhere to brief |
| Breakdown in visual scan | Failed to use the radar altimeter |
| Failed to prioritize attention | Flew an unauthorized approach |
| Inadvertent use of flight controls | Violated training rules |
| Omitted step in procedure | Flew an overaggressive maneuver |
| Omitted checklist item | Failed to properly prepare for the flight |
| Poor technique | Briefed unauthorized flight |
| Over-controlled the aircraft | Not current/qualified for the mission |
| **Decision Errors** | Intentionally exceeded the limits of the aircraft |
| Improper procedure | Continued low-altitude flight in VMC |
| Misdiagnosed emergency | Unauthorized low-altitude canyon running |
| Wrong response to emergency | |
| Exceeded ability | |
| Inappropriate maneuver | |
| Poor decision | |
| **Perceptual Errors (due to)** | |
| Misjudged distance/altitude/airspeed | |
| Spatial disorientation | |
| Visual illusion | |

*Note.* From “The Human Factors Analysis and Classification System-HFACS,” by S. Shappell, and D. Wiegmann, 2000, *ResearchGate.* (https://commons.erau.edu/publication/737).

Just like unsafe acts of the pilots, there can also be unsafe acts from the air crew. These can include human and nonhuman influence factors. At the top level, the air crew could be dealing with adverse mental states which could affect their performance when under pressure. Another potential area for the aircrew to deal with would be physiological states which could include fatigue and medical illness. Other areas of impact to the aircrew could be physical/mental limitations, crew resource management, and personal readiness. Each of these categories can be further expanded as shown in Figure 8 below. These factors are important to understand when safety officers are analyzing what factors caused an aviation accident to occur.

**Figure 8**

*Unsafe Aircrew Conditions*

**TABLE 2**. Selected examples of Unsafe Aircrew Conditions (Note: This is not a complete listing)

| SUBSTANDARD CONDITIONS OF OPERATORS | SUBSTANDARD PRACTICE OF OPERATORS |
|---|---|
| **Adverse Mental States** | **Crew Resource Management** |
| Channelized attention | Failed to back-up |
| Complacency | Failed to communicate/coordinate |
| Distraction | Failed to conduct adequate brief |
| Mental fatigue | Failed to use all available resources |
| Get-home-itis | Failure of leadership |
| Haste | Misinterpretation of traffic calls |
| Loss of situational awareness | **Personal Readiness** |
| Misplaced motivation | Excessive physical training |
| Task saturation | Self-medicating |
| **Adverse Physiological States** | Violation of crew rest requirement |
| Impaired physiological state | Violation of bottle-to-throttle requirement |
| Medical illness | |
| Physiological incapacitation | |
| Physical fatigue | |
| **Physical/Mental Limitation** | |
| Insufficient reaction time | |
| Visual limitation | |
| Incompatible intelligence/aptitude | |
| Incompatible physical capability | |

*Note.* From "The Human Factors Analysis and Classification System-HFACS," by S. Shappell, and D. Wiegmann, 2000, *ResearchGate.* (https://commons.erau.edu/publication/737).

According to the IATA (2014) there are other factors that can impact the potential occurrence of aviation accidents. These other factors are noncompliance with established standard operating procedures, inadequate flight path management, lack of vertical and/or horizontal position awareness in relation to terrain, un-stabilized approached, failure to initiate a go-around when required, conducting operations in poor weather conditions, incorrect action/response by flight crew, and failure in crew resource management such as cross-checking, communications, coordination, and leadership. All of these factors plus human error can increase the chances of an inflight accident to occur within the aviation industry.

Researchers are still conducting analyses to understand how upgrading the technology and training for pilots can help to limit the occurrence of an aviation accident to occur (Kelly & Efthymiou, 2019). While there will never be a 100% elimination of the factors that can cause an aviation accident to occur advancements in technology could help pilots and flight crew to identify when an accident will occur and the proper precautions to take before the situation escalates into the loss of life (IATA, 2014). More pilots are being trained through simulation on procedures to complete when an accident is occurring. Flight simulators are used extensively for training procedures as they permit more in-depth, safer, and more flexible instruction that is possible with real flight (Koglbauer, 2016).

***Maritime Accidents***

Over the years, there has been an increase in the number of items being transported via maritime way. Researchers identified that 65% of the 74 Greek maritime accidents analyzed from 1992 to 2005 each accident had more than one causal factor, but most accidents were caused by human error, 76% of these were due to negligence on the bridge of the ship, 17% to human error in the engine room and the remaining 7% elsewhere on board (Antao & Soares, 2019). Some of the most common reasons for accidents within the maritime sector are grounding, ship sinking, fire, collision, contact damage, dragging, wind damage and human factors (Xue et al., 2020).

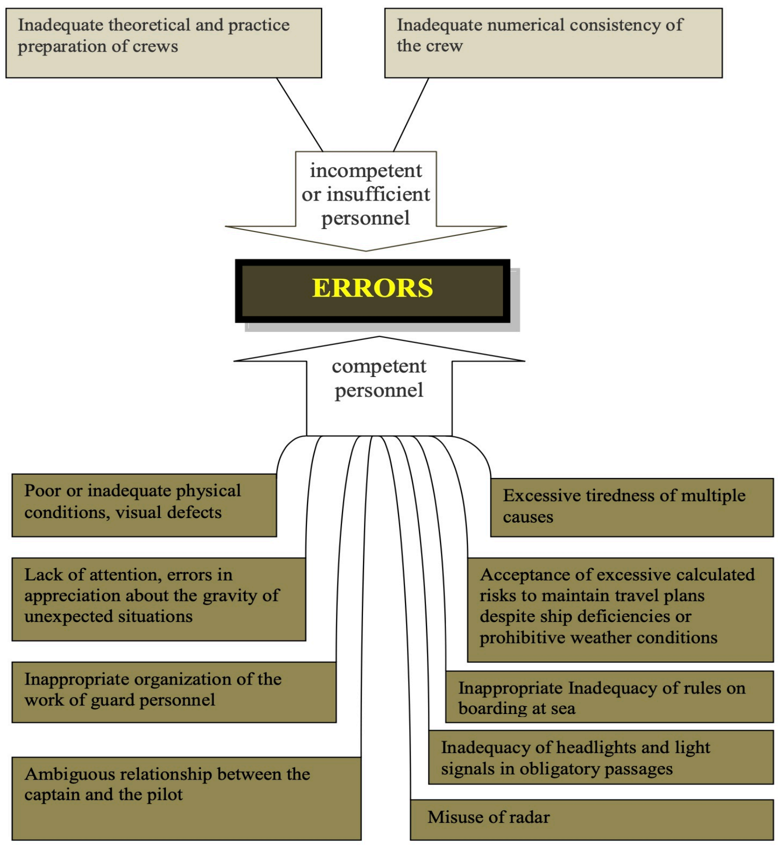
Different weather conditions can also affect the situational awareness of the crew on the ship and make the changes of accident occurrence higher. When weather occurs, it can have an effect on the decision-making ability of the crew and can have lasting effect on the ship (Antao & Soares, 2019). Other factors that impact the occurrence of accidents are organization are fatigue, training, and other external factors.

When conducting analysis on maritime accidents, researchers identified a need to understand how incompetent or insufficient personnel and competent personnel can contribute to the occurrences of accidents (see Figure 9). The errors that occur in both of these groups can be broken down into insufficiencies, inequities, ambiguities, and excess (Apostol-Mates & Barbu, 2019). One important factor that researchers sought to understand further is the impact of fatigue on the overall operation of the crew. Fatigue can decrease the operator's work performance, by manifestations like slowing down physical and mental reflexes and cutbacks in making rational evaluations (Apostol-Mates

& Barbu, 2019). Fatigue can have a big impact on the occurrences of accidents and a decrease in the security levels that are normal in place when operators are at their full potential. Apostol-Mates and Barbu (2019) noted that as the total work hours per week, hours of work per day, and number of consecutive night duties per week increased, there was decreased output from the crew. The same can be said when the hours of rest between duty periods and number of short breaks within duty periods decreased, accidents were more likely to occur.

**Figure 9**

*Errors in Maritime Accidents*




*Note.* From “Fatigue leading to human error: A study based on marine accidents,” by R. Apostol-Mates, and A. Barbu, 2019, *Scientific Bulletin of Naval Academy.* (https://doi.org/10.21279/1454-864X-19-12-013).

While modern ships have been updated to include advanced technologies such as navigation technology, onboard information, and bridge resource management systems, human factors are still present in the majority of accidents (Fan et al., 2020). All accidents within the maritime sector have some contributions from human or nonhuman causal factors. Nonhuman factors may include weather, visibility, number of crew members on duty, and length of time on duty for the crew members. Since the weather patterns can be spatial in different oceans around the world this can cause a challenge for the crew when responding to weather changes, visibility limitations, and length of time on duty for the crew (Zhang et al., 2021). However, researchers have stated that human elements account for 75%-96% of maritime casualties within accidents that occur in the modern ships and has not changed over time (Fan et al., 2020). Human factors can be broken down into workplace conditions, physical and natural environment, procedures, technology, training, organization, management, fatigue, task load, and mental state.

A majority of the accidents have more than one contributing factor. A combination of factors may create the perfect holes in the defenses to cause an accident. Some of the factors that work together are poor crew competence, fatigue, lack of communication, lack of proper maintenance, lack of application of safety culture and protocols or other procedures, inadequate training, poor situational assessment, and stress (Fan et al., 2018). Safety analysis can be completed on maritime accidents to fully understand what occurred when the accident happened. From this research, procedures and protocols can be updated so management and crew members can help to limit the occur of accidents. Updating research procedures and protocols can help to ensure that crew members and management are aware of some of the precursors that lead to accident occurrence (Xue et al., 2020).

***Railway Accidents***

Within the railroad industry, accidents can be broken down into derailment, head on collision, rear end collision, side collision, raking collision, broken train collision, highway-rail crossing, railroad grade crossing, obstruction, explosion-detonation, fire/violent rupture, and other impacts (FRA, 2021). The railroad sector is broken down into freight and passenger trains. Freight is moving railcars with different consumer items and passenger trains more people from one location to another. Also, within the railroad sector, there are different classes of railroad depending on the yearly profit from that company. There are multiple factors within the railroad sector that have an impact on the occurrence of an accident to occur.

Within the railroad industry, there are multiple commodities that can be moved, including hazardous material, fuel, oil, grains, stones, ice salt, and multiple other items. There are multiple ways a train accident could happen which include improper track conditions, weather, visibility, time on duty, operator error, and other impending factors. Researchers have looked to understand the relation between train accident causes and the narrative that is included within the accident report (Heidarysafa et al., 2018). Since only the primary and secondary codes are recorded within the FRA accident reporting sheet, the narrative could help to explain other important factors that contributed to the occurrence of the train accident. This narrative also helps to explain if there were circumstances that were outside the control of the conductor and engineer on the train.

Studies have shown that changes to the technical condition of railroad tracks, railroad bridges, tunnels, crossings, individual cars, and the entire rolling stock, may enhance the safety of rail transport (Aliev et al., 2019). This information is important in areas around the world that have seismic activity where the integrity of the track equipment can be altered. In other areas around the world, it is important to ensure that track maintenance is conducted because the track can be worn out over time. One important issue that is new with little research is the upgrade to Positive Train Control brake system since the current brakes have been used since the civil war era (Schouten, 2016). One issue with the old brake system is that the hardware could be broken down and increase the chances of derailment occurrence. This breakdown has been seen multiple times with oil lines which caused concern from lawmakers (Schouten, 2016).

In the railroad sector, once an accident occurs, crew members are required to complete a form to detail what occurred and the factors that contributed to the train accident. There are only two fields where crew members can list the causal code for the derailment, and this is their primary and contributing factor to the train accident occurrence. Crew members give a detailed encounter of the train accident which helps safety officials determine what happened and how to correct this within the industry to it does not occur again (Heidarysafa et al., 2018).

The occurrence of train derailments can be attributed to human operator and nonhuman operator causal factors. Outside of human and nonhuman errors other factors can have an impact on the occurrences of train derailments such as, weather, visibility, number of crew members on duty, and crew members length of time on duty. There is still much analysis to be completed on this field to fully understand how multiple factors can feed into the overall occurrences of train derailments.

***Train Derailment***

All railroad employees have the responsibility to report accidents when they occur and ensure that the information recorded is accurate. Derailments are the most common type of train accident accounting for more than 70% of incidents that occurred between a fifteen-year period 2001-2015 with a total of 27,014 incidents (Li et al., 2018). With respect to Class I and Class II railroads they accounted for 20,249 derailments (Li et al., 2018). Within the accident causal codes during this fifteen-year period, there were 7,753 derailments from operator causal factors and 19,261 derailments from nonoperator causal factors. I will focus on derailments for my study due to the high percentage of accidents that are caused by derailments. The accident reports include important information to understand how multiple factors impact the occurrence of train derailments. This information can help railway managers to understand the relationship that multiple factors have with the occurrence of train derailments and how this information might help to eliminate the occurrences of derailments within the railroad industry. The causal codes in the accident reports can help to minimize the occurrence of train derailments by further understanding how the causal codes once broken down into operator and nonoperator, have an impact on the number of train derailments.

Train derailments can cause huge financial impacts to the company over time if they occur multiple times throughout the year and cause lasting effects on the operations within the company. The derailments during a fifteen-year period 2001-2015 had a financial impact of more than $30.7 million on railroad companies. Costs from train derailments can further be broken down into how much operator causal factors and nonoperator causal factors each cost the rail lines when the derailment occurs. Researchers have argued that train derailment risk management should be further examined such as human factors, rail parts failure, semaphore and control systems, vehicle-track interaction, and other contributing factors to train derailments (Zhang & Sun, 2019).

Track maintenance needs to be completed at highest efficiency because this can help to prevent the train derailments. Currently it is estimated that track maintenance accounted for 30-40% of the total operating cost (Miwa & Oyama, 2018). Ensuring that track maintenance is completed before the issue is serious will help to mitigate the occurrence of train derailments due to lack of maintenance on the rail lines.

There has been further analysis completed on train derailments and the lasting effects that they can have on employees and the likelihood of train derailments to occur from the employee again. Holmes and Rahe (1967) are American psychologists that suggest certain situations cause change in human behavior, making it necessary for adjustments so we can deal with those events. These events have been known as life events and they can create high-stress levels for the individuals that experienced the event (Floris et al., 2021). Stress can be looked at as an advanced state of homeostasis, in which individuals reach behaviorally, physiologically and psychologically, in an attempt to return to normal homeostasis (Paluch et al., 2018). When looking at life events and the stress that can occur from such events, each individual has a different response mechanism if the life event was the occur again (Floris et al., 2021).

While working on the railroad, there is a chance for employees to experience a traumatic event. Most of the time this traumatic event is related to individuals committing suicide and running in front of the train or jumping from bridges (Li et al., 2018). When these incidents occur, employees are required to pull the train brake and stop the train to report what happened to the local authority. When this occurs, this can cause a train derailment as the employee pulls the brake too fast and other factors play into what occurred when the train was stopped. From these traumatic incidents, employees might be on edge or experiencing post-traumatic stress disorder.

When an incident occurs, there are multiple forms that need to be completed and recorded within the FRA safety website. All information included within the form will help others to understand what occurred when the derailment happened. Included within the form is the causal code for the derailment and whether it was an operator or nonoperator causal factors. Next, I will provide a detailed analysis on the train derailment reporting process and the causes for train derailments.

**Train Derailment Causes.** The FRA complies the accident reports submitted into the rail equipment accident database, which contains information about the accident location, speed, consist type, and damage cost, along with other important information (Liu et al., 2017). The causal factors for each derailment are included within the accident/incident report. The FRA has more than 350 codes used for the causal factors of train derailments. Causal codes are broken down into main level headings and then further detailed into the applicable codes that are used when reporting on the Form FRA

F 6180.97. Within the FRA accident database, the causal codes are not broken down into operator causal codes and nonoperator causal codes.

Operator causal factors, within the FRA Guide for Preparing Accident/Incident Reports (2021), include (a) brakes, use of, (b) employee physical condition, (c) flagging, fixed, hand and radio signals, (d) general switching rules, (e) main track authority, (f) train handling/train makeup, (g) speed, (h) switches, use of, (i) cab signals, and (j) miscellaneous (see Appendix B, Table 1). Operator causal factors are important to understand because this can help understand the factors human have impact on when a train derailment occurs. Within the list of operator causal factors there are many important safety factors that need to be understood by employees or train derailments may happen. The physical condition of the employee is also included within the causal codes. Included within this area is the impairment, incapacitation, restriction in work, employee asleep and employee physical condition. If one of these causal codes is listed on the accident report, it could cause further investigation into the employee and what occurred on the train.

Operator causal factors, within the FRA Guide for Preparing Accident/Incident Reports (2021), include (a) track, roadbed, and structures, (b) signal and communication, and (c) mechanical and electronic failures (see Appendix B, Table 2). Nonoperator causal factors are the factors that humans do not have control over. Primarily these deal with the mechanical aspect of the tracks or rail car that the employees do not have the ability to stop before it occurs. There have been many articles published on the need to ensure that maintenance is completed on the tracks and ensuring that during times of extreme weather precautions are taken before trains get onto the tracks (Miwa & Oyama, 2018). Completing the maintenance beforehand can help to limit the number of train derailments that occur. All employees need to understand the track and when there are issues during the extreme weather that might occur in that region. Contracted personnel need to ensure that shortcuts are not taken when performing the maintenance and if anything were to occur the day of maintenance this would be on management to get with the contracted company to see what was performed or what might have been missed.

**Research on Train Derailments**

There has been no research conducted on the relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment. In contrast, there were multiple studies on the causes of train derailment or the after effect of a train derailment and how to improve the occurrence of train derailments occurring (Hunter-Zaworski, 2017; Underwood & Waterson, 2014; Zhang & Sun, 2019).

Underwood and Waterson (2014) completed an analysis on the Greyrigg train derailment using the Swiss cheese model to see if the train accident occurred from a system thinking approach. The researchers included different elements from the Swiss cheese model or expanded on the model completely. Underwood and Waterson (2014) completed the analysis on a single train derailment to fully understand the best model when looking at the accident causation models currently available for use in analysis on train derailments. They determined that the Swiss cheese model was still a viable method on analyzing train derailments. It was determined that the Greyrigg train derailment had multiple factors that caused the derailment to occur which are an incomplete understanding within Network Rail of points maintenance requirements which caused an absence of clear, properly briefed standard for maintenance (Underwood & Waterson, 2014).

Hunter-Zaworski (2017) completed an analysis on passenger incident data from five rail transit systems in the United States and Canada. The researcher wanted to understand the injury incident data to help improve safety at rail transit platform/train and platform/guideway interfaces. Since this research was on transit trains, Hunter-Zaworski was looking to understand the platforms where passengers entered the car. There was also analysis completed on the platform/guideway interfaces to see where the issues were occurring with the train cars. From the analysis, the researcher was able to understand the issues that were occurring for passengers to report injury while boarding trains at platform locations. The results gave safety officers and managers ideas on how to help passengers and also ensure that maintenance was being completed to limit the occurrences of derailment with passenger railcars.

Zhang and Sun (2019) completed an analysis on how the multicriteria decision-making model can be used to help with train derailment risk response strategies that can help limit the occurrences of train derailments. Both researchers found that train derailments can result in interruptions within train operations and can cause serious delays. The researchers acknowledge that there should be increased attention on derailments risk management, such as human factors, rail parts failure, semaphore and control systems, and so many more areas. Zhang and Sun's primary focus was to help the

Huangyangcheng station located in Shemu City, Shaanxi. Information within this article could be expanded to other locations to see the potential impact that it has on other railroad stations around the world.

Researchers have looked at safety within the railroad industry and how this can further be improved by the implementation of new processes or more strict safety procedures on the trains (Hunter-Zaworski, 2017). For researchers to better understand the train safety and risk analysis associated with train derailments, the derailment rates need to be accurately estimated through the train derailment rate.

Liu et al. (2017) found that higher FRA track classes had lower derailments rates, varying by more than an order of magnitude. This came as no surprise because higher FRA track classes are intended to ensure safe operations when operating at a higher speed which requires a more robust maintenance schedule for these tracks. There is still a need to understand the causal factors whether operator or nonoperator and the number of train derailments. The findings within this proposed study may help to management understand the causal factors for train derailments and how to improve risk management.

Lui et al,'s (2017) findings in this study have the potential to improve business practice because they can help railroad managers increase their knowledge on operator causal factors, nonoperator causal factors, and their interaction influence train derailments. Understanding the relationship can help railroad management update current procedures and policies to help crew members be prepared for the common causal factors that impact train derailment occurrences. The relationship can also help management understand the potential impacts that weather, visibility, number of crew on duty and crew members length of time on duty have on the occurrences of train derailments. Management can understand how over exerting employees can have catastrophic impact on train derailment occurrences.

## Transition

The purpose of this study was to examine the relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment. In Section 1, I discussed the background of the study, problem statement, purpose statement, nature of the study, research question, hypotheses, theoretical framework, operational definitions, assumptions, limitations, and delimitations, significance of the study, and review of the professional and academic literature. The literature review consisted of the theoretical framework the Swiss cheese model which further looked at organizational accidents and accident causation, Swiss cheese model, the evolution of the Swiss cheese model, Swiss cheese models components, and comparing the Swiss cheese model to other models. Next, I addressed accident occurrences in other industries which includes aviation accidents, maritime accidents, railway accidents, train derailments, and train derailment causes. Finally, there was a discussion on research on train derailments which included current research conducted on train derailments and their occurrences.

In Section 2, I restate the restatement of the purpose statement, role of the researchers, participants, research method, research design, population and sampling, ethical research, data collection, data analysis, and study validity. In Section 3, I include a presentation of findings, application to professional practice, implications for social change, recommendations for action, recommendations for further research, reflection, and conclusion.

# Section 2: The Project

Section 2 describes the research project by including the purpose statement and describing the role of the researcher, participants, research method, and research design. Also included in this section is a detailed discussion on the population and sampling, ethical research, data collection, and data analysis. Section 2 concludes with addressing study validity and reliability followed by a conclusion and transition into Section 3.

## Purpose Statement

The purpose of this quantitative correlational study was to examine the relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment. The independent variables were train derailment causal factors, visibility, weather, number of crew members, and crew members length of time on duty. The dependent variable was the occurrence of train derailment, represented as a dichotomous variable. The targeted sample population consisted of Class I and Class II rail lines in the railroad industry across the United States. Data collection was completed through the FRA Office of Safety Analysis, which is a publicly available database. All derailment safety reports are reported and complied on this site. The implications for social change include the potential to reduce the frequency of train derailment occurrences in the railroad industry and save lives.

## Role of the Researcher

The role of the researcher in the data collection and analysis process in a quantitative study is to ensure that the sample size is adequate, that there is consistency, reliability, and validity in the data, and that data analysis is completed (Kyvik, 2013). Though I have not worked in the railroad industry, I have multiple family members who have worked in the railroad industry for more than 28 years. My role in this data collection and analysis for this study was to pull the data from the FRA safety database website, which was filtered down by the railroad class to Class I and Class II railroads in the United States. From the information pulled in the FRA safety site, I analyzed the train derailment causal factors, visibility, weather, number of crew members, and crew members length of time on duty. This information was coded according to the list included in Appendix C.

The *Belmont Report* (2003) was created to provide principles when dealing with human subjects for biomedical and behavioral research, providing specific regulations under the common rule of fundamental principles research should follow (Metcalf, 2016). As a researcher, it is important to provide participants with a safe environment and to ensure that they are assured information received during interviews will be confidential. However, I did not use surveys, interviews, or participants for my data collection. Due to the information for this study being collected from a secondary source, with no human interaction, I did not require consent from participants for this study. The secondary source used for data collection helped to complete the statistical analysis pertaining to the topic of operator causal factors, nonoperator causal factors, and their interaction influence train derailments.

In the role of the researcher, bias should be mitigated to avoid influencing the outcome of the data (Daigneault, 2014). During data collection, I was not employed by the railroad, and I did not have direct contact to management within any railroad company. The data collected from the FRA website also followed a specific data collection and analysis protocol. Data were collected from the FRA website on Class 1 and Class II railroads, and the causal codes were further separated into operator causal factors and nonoperator causal factors.

## Participants

There were no participants in this study. No railroad companies, management, or employees were contacted for participation in this study. All information for this study was collected from the FRA safety website, which is a publicly available platform. I pulled information on Class I and Class II railroads in the United States.

## Research Method and Design

### Research Method

I selected a quantitative methodology for this study. The quantitative method is used to express the evaluation results with intuitive data, which is more objective, and the quantitative results are more scientific, rigorous, and profound (Du et al., 2019; Pickett, 2020; Teng et al., 2020). Quantitative research is also more applicable when the data are already available on a platform. For this study, all the data were pulled from a public platform and there will not be any interaction with management or personnel working within the company. Further, quantitative methods are used to find patterns, make predictions, test relationships, and to understand the research questions that are asked (Barnham, 2015; Paul & Garg, 2014). Quantitative methods are used to test a theory rather than develop a theory, as would be the case with a qualitative research method

(Barnham, 2015; Guetterman et al., 2015). In this study, variables were analyzed to assess and test their relationships.

In contrast, qualitative research methods are more applicable when the researcher wants to understand the human side of business by going into the natural setting of the company, exploring how people make sense and meaning, and their lived experience (Gergen et al., 2015). Qualitative research is more applicable when wanting to ask questions and understand the lived experience of someone. Qualitative research methods are used to answer the *why* questions dealing with the research topic. The purpose of this study was not to investigate the behaviors or experiences from workers within the railroad industry. Instead, the purpose of this study was to test the hypotheses using secondary data that is provided within the FRA safety database.

The mixed method is used when researchers want to understand aspects of qualitative and quantitative research methods and pull different factors from each method. The benefit of this method is when researchers are looking to eliminate the weakness of one research method (Afrifa, 2013; Sahin & Ozturk, 2019). However, the objective of my study was not to look at qualitative and quantitative methods; it was to understand the relationship between variables. Since I looked at exclusively variables, the mixed method was not applicable for this study.

**Research Design**

There are different research designs that can be used when conducting a quantitative study, which include experimental, quasi-experimental, and correlational design (Roberts & Povee, 2014; Wells et al., 2015). The research design for this study was a correlational design to understand the relationship without manipulating any of the independent variables. All data for this study were pulled from the FRA safety database and were not manipulated for data analysis. The goal of this study was to examine the relationship between five independent variables and one dependent variable, which aligns with a correlational design.

Experimental and quasi-experimental are two other quantitative research designs not chosen for the study. Experimental research focuses on potential causal relationships (Kuhberger et al., 2014), and manipulation is used to see how the dependent variable responds to changes in the independent variable (Andeweg et al., 2020; Geuens & De Pelsmacker, 2017). A quasi-experimental design is similar to experimental but lacks random assignment (Barrera-Osorio et al., 2018; Tavakol & Pinner, 2019). For this study, I collected data from Class I and Class II railroad in the United States; I did not put the railroads into assigned participant groups. The experimental or quasi-experimental design were not appropriate for my study because I did not manipulate the data that were pulled from the FRA database. The goal was to understand the relationship between variables, which aligned with the correlational research design. Correlational design is used to use statistical tools to assess relationships, which is then tested against the hypotheses to answer to research questions involving all the variables (Aderibigbe & Mjoli, 2019; Curtis et al., 2016; Vetter, 2017).

## Population and Sampling

### Population

Population does not always mean people but can also detail the total quantity of causes of things that are needed to research a subject (Etikan et al., 2016). The dependent variable was the occurrence of train derailment, represented as a dichotomous variable. The population consisted of all accidents for Class I and Class II railroads during the 2019 calendar year, which was collected from the FRA safety website as the most relevant and appropriate record. The FRA safety website was the most reliable source for this information because it includes all train accidents that have occurred on Class I and Class II railroads each year. Due to the data selection options in the FRA database, I decided to focus on Class I and Class II railroads.

### Sampling

A sample is a subset of the total population being studied to answer research questions. Nonprobabilistic sampling is used when elements of the population do not have a known or equal probability of being selected (Turner, 2020). Purposive sampling is used when the researcher selects subjects from the target population based on the fit with the purpose of the study and specific inclusion and exclusion criteria (Etikan et al., 2016). Purposive sampling can help with providing information on the topic on the specific research question (Turner, 2020). Sampling deals with the selection of a subset of the population within the research (Faul et al., 2009), but this study included the total population of included Class I and Class II railroads during the 2019 calendar year. Using the entire population of Class I and Class II railroads in the United States removed any sampling bias and subjectivity that can occur with sampling selection.

A power analysis was completed to show the sample size needed for the study (see Faul et al., 2009; Appendix D). There were five independent variables, three of which were recoded as dummy variables. The independent variables were train derailment causal factors (three dummy variables), visibility (four dummy variables), weather (six dummy variables), number of crew members, and crew members length of time on duty. Using G* Power version 3.1.9.6 software, a logistic regression analysis, assuming a medium effect size ($f^2$= .15), α = .05, and 15 independent variables, identified that a minimum sample size of 139 participants is required to achieve a power of .80 (see Appendix D, Figure D1). Increasing the sample size to 257 would increase power to .99 (see Appendix D, Figure D2). For this study I used the total population, which consisted of 1,396 accidents, exceeding the number of cases that were identified from the power analysis. Using the total population allowed for a more robust analysis.

## Ethical Research

I did not use participants or organizations in this study; therefore, I did not require informed consent, nor did I have a procedure for participants to withdraw from the study. The data on train accidents in Class I and Class II railroads was obtained from a public safety website managed by the FRA. The data contained the name of the railroad companies and location of the train derailments but was not included in this study. The only information that was used in this study is the accident causal code and the Class of railroad. The Walden Institutional Review Board approval number is 07-15-21-0983532.

## Instrumentation

For data collection, I used the FRA Office of Safety Analysis Query tool for accident/incident trends, which is a public database. Data entered in this database come from the FRA, consolidated reporting groups and individual railroads. Using the FRA Office of Safety Analysis Query tool was the best option because all the necessary information needed to complete the analysis in this study is included within the database.

The dependent variable came from the accident type and was coded 0 for an accident not classified as a train derailment and 1 for an accident classified as a train derailment. The dependent variable came from the type of accident/incident field reported in the FRA database: 1 = derailment, 2 = head on collision, 3 = rear end collision, 4 = side collision, 5 = raking collision, 6 = broken train collision, 7 = highway-rail crossing, 8 = railroad grade crossing, 9 = obstruction, 10 = explosion-detonation, 11 = fire/violent rupture, and 12 = other impacts. Everything coded as derailment was coded as a 1 for an accident classified as train derailment. Everything coded 2 through 13 was coded as a 0 for an accident classified not a train derailment.

The independent variables were train derailment causal factors (human or nonhuman), visibility, weather, number of crew members, and crew members length of time on duty. For the train derailment causal factors, I used the primary causal code and secondary causal code (refer to Appendix B for operator and nonoperator causal codes). Train derailment causal factors were initially be coded to operator, nonoperator, or both causal factors. Visibility and weather were initially coded 1- XX depending on how many factors are included within each category (refer to Appendix C for coding). Next, I had

SPSS convert these into dummy variables for train derailment causal factors, visibility, and weather, which coded the variables 1 for yes and 0 for no. This means that train derailment causal factors became three dummy variables, visibility became four dummy variables and weather became six dummy variables. Number of crew members and crew members length of time on duty were expressed as continuous variables and were not recoded. From the FRA Office of Safety Analysis Query tool, which outputted the Accident/Incident Trend report for Class I and Class II railroads, the data were then sorted into the applicable variable data columns and coded accordingly.

The data from the FRA website were exported into a Microsoft Excel file and stored, filtered, and processed as indicated above. No surveys, interviews, or participants were used, only the online tool populated by the FRA Office of Safety Analysis. All the variables in my study came from this database.

The FRA database has been used in multiple studies to help researchers gather the information needed for their studies. Zhang et al. (2019) used the FRA to analyze the human factors that have an impact on the occurrence of freight train accidents in the United States. From the database, they pulled information to understand how much movement is made on the railroad network each year and also the occurrence of human caused freight accidents. Analysis has also been completed on the analysis of passenger incidents within five different rail transit systems (Hunter-Zaworski, 2017). The researchers have used the FRA database to pull the injury reports that were completed when an accident occurred on a rail transit system. Further, Calabrese et al. (2017) used the FRA database to understand how many railroad accidents account for the casualties among maintenance of way employees and signalmen. The overall effort of this research was to understand the human factors that contribute to the time-of-day effects on railroad worker injury risk.

Reliability related to the consistency of a measure when using an instrument to measure different variables (Heale & Twycross, 2015). For this study, all information was gathered from the FRA Office of Safety Analysis database and was not altered other than the recode variables as described above. Each time the data was pulled from the website it was exported into the same excel sheet.

When using secondary databases for data collection, researchers need to ensure that the sources are free from material error and bias (Parker, 2012). All accident reports are completed by the railroads and then pulled into the FRA database. The records in the database go back to 1975. If the report is pulled multiple times in the FRA database information will not change, the only thing that will change is the personal selections that the researcher is looking for. I pulled data from the FRA database on Class I and Class II railroads and both reports included all the necessary information to complete the analysis for this research topic. None of the fields were filtered out of either document.

Validity refers to the extent that a concept is accurately measured in a quantitative study (Heale & Twycross, 2015). The FRA database uses a specific form to report all occurrences of train derailments within the railroad industry. Both forms used (Form FRA F 6180.54 & Form FRA F 6180.97) are the same throughout the entire railroad community. The data fields on the forms are the same for each railroad company and all companies are to fill out this form when a train derailment occurs. There data are then inputted into the database and can be exported into the excel sheet which is how I obtained the required data for this research topic.

To gain access to the data in the FRA database permission is not needed, this is a public website. The raw data for this study is attached in Appendix E to show how the data is sorted when exported from the FRA database. From the raw data, tables were populated in the study to show how it was separated into operator causal factors and nonoperator causal factors.

## Data Collection Technique

Data collection for this study was from a secondary source the FRA Office of Safety Analysis Query tool for Accident/Incident Trends database. The research question for this study was: What is the relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and train derailment? Data for this study was collected from the FRA database. Before downloading, the data was filtered into Class I and Class II railroads. For this study, the research was completed on the 2019 calendar year since all reports have already been complied for that year. I accessed this data from the FRA website and download the required information from the Query tab, specifically the FRA Accident/Incident Query.

For the train derailment causal factors, I used the primary causal code and secondary causal code (refer to Appendix B for operator and nonoperator causal codes). Train derailment causal factors were initially be coded to operator, nonoperator, or both causal factors. Visibility and weather were initially be coded 1- XX depending on how many factors are included within each category (refer to Appendix C for coding). Next, I had SPSS convert these into dummy variables for train derailment causal factors, visibility, and weather, which coded the variables 1 for yes and 0 for no resulting in three variables for train derailment causal factors, four variables for visibility, and six variables for weather. Number of crew members and crew members length of time on duty were expressed as continuous variables and will not need to be recoded. See Appendix B & C for details on how all independent variables were coded into the SPSS data file. For the dependent variable, I took the data from the accident type field in the FRA database and code each accident as derailment yes or no. Everything coded as derailment was coded as a 1 for an accident classified as train derailment. Everything coded 2 through 13 was coded as a 0 for an accident classified not a train derailment. All information that was exported from the FRA database was not altered because the query function allows for the selection of railroad class. Since I did not have to alter the data in the excel sheet this helped improve the overall validity and reliability of the mentioned instrument

I collected data from the FRA database which includes all the necessary information to complete my analysis and this data was exported into a Microsoft Excel file and then sorted according to the Class I and Class II railroads. The first step after pulling the data was to ensure that all sources contain relevant data to answer the research question in this study. The goal of the FRA database is to ensure that all train accident/incident trends are available for the public to see what accidents/train derailments occurred each year on the railroad. The data can be pulled from the system which allows for easy access to the data needed for this doctoral study. Data that are entered into this system come from the FRA forms that are completed once the train accident/incident occurs. Details are inputted within the forms which will them be updated in the system to ensure that it is easily accessible rather than having to look through paper copies of the reports. After obtaining Institutional Review Board approval, I collected data through electronic retrieval on train accidents that occurred on Class I and Class II railroads during the 2019 calendar year.

Obtaining data from a secondary source via an electronic database can have both advantages and disadvantages. Johnston (2014) stated that gathering information from a secondary source is inexpensive because researchers can bypass instrument creation and data collection stages by extracting the data from existing sources. Another advantage is the ability to have the data easily accessible and not having to wait to gather potential sensitive material. Other researchers have argued that secondary data saves time and financial resources, while minimizing the threat of bias (Johnston, 2014; Parker, 2012). Electronic forms of data can also make the data collection process easier than paper forms and improve the overall outcome to data reliability (Li et al., 2015). The final advantage is that researchers are afforded the opportunity to have data available when accessing human participants is difficult. However, secondary data does have potential limitations for the researcher. Obtaining data from achieved information may run into the potential for incomplete or missing data, which might cause gaps in the data needed to answer the research question.

## Data Analysis

RQ: What is the relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment?

Null Hypothesis ($H_0$): There is no statistically significant relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment.

Alternative Hypothesis ($H_a$): There is a statistically significant relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment.

The dependent variable in this study was the occurrence of train derailment, represented as a dichotomous variable. The independent variables were train derailment causal factors (human or nonhuman), visibility, weather, number of crew members, and crew members length of time on duty (see Appendix C for coding). The number of crew members and crew members length of time on duty were continuous variables; the total sum of each factor was entered into the SPSS database.

Correlation is a statistical measure of how closely and in what direction two variables are potentially related (Emerson, 2015), and Pearson correlations explore the linear relationship between variables (Sari et al., 2017). A correlation design allows researchers to examine the relationship between or among two or more variables (Altman & Krzywinski, 2015). Correlation designs also allow for the relationship between multiple independent variables and a dependent variable (Green & Salkind, 2017). The objective of this study was to understand the relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment. Due to the objective of this research, the correlation design was most applicable.

Regression analysis is a statistical technique that helps researchers to explore relationships between numerically measured independent and dependent variables, which can help researchers predict one variable based on the value of another variable (Hopkins & Ferguson, 2014). This type of analysis can help when the researcher is trying to understand how a change in an independent variable can have an effect on the dependent variable. When a researcher uses one dependent variable and two or more independent variable this will be called multiple regression or multilinear. The technique for analysis depends on the number of variables the research is looking to analyze and the deserved outcome from the completed analysis (Green & Salkind, 2017).

Binomial logistic regression is used to predict the probability of an observation that falls into one or two categories of a dichotomous dependent variable and one or more independent variable that is continuous or categorical (Laerd Statistics, 2017). Due to the dependent variable being dichotomous because everything coded as derailment was coded as a 1 for an accident caused by train derailment and everything coded 2 through 13 was coded as a 0 for an accident caused by something other than derailment, the binomial logistic regression was the most appropriate analysis method for my study. Train derailment causal factors, visibility, and weather are categorical nominal variables because they were coded 1- XX depending on how many factors are included within each category. Number of crew members and crew members length of time on duty were continuous variables; the total sum of each factor were entered into the SPSS database.

ANOVA is another statistical test a researcher can use to compare the difference between samples (Tarlow, 2016). The ANOVA test is more applicable when the researcher is dealing with a continuous dependent variable, while the independent variables are categorical. The purpose of the ANOVA test is to understand the interaction between the two independent variables on the dependent variable (Tarlow, 2016). The ANOVA test was not appropriate for my study because I have a dichotomous dependent variable which was coded into 0 for not classified as train derailment and 1 for classified as train derailment.

Data cleaning relies on the identification and repair of data quality problems (Prokoshyna et al., 2015). Data cleaning helps to ensure that outliers and errors are removed from the data set (Fatima et al., 2017). There are times when collecting data that the information included is incomplete or missing the details needed for the analysis. Data cleaning helps the researcher with clearing out the data that is incomplete or missing the important details related to the research topic. When I retrieved the data from the FRA database it was exported into a excel file. Additional variables were added to identify operator causal factors or nonoperator causal factors. Completing the data cleaning in excel this helped when inputting the information into the SPSS program because the data was free of error which could have an impact to the SPSS analysis.

Using Microsoft Excel can help with the data cleaning process because this can be completed by filtering the data and seeing where the incomplete fields are within the document. Data missing in the excel sheet can have an effect on the validity of the study. Ensuring that the data cleaning process is followed through will help to ensure that the validity of the study does not get affected. In this study, I removed all entries that have incomplete data and ensure that this does not affect the targeted sample size for this study.

There are seven assumptions associated with binomial logistic regression: (a) one dependent variable that is dichotomous (nominal variable with two outcomes), (b) one or more independent variables that are continuous or nominal scale, (c) independence of observations and the categories of the dichotomous dependent variable and all nominal independent variables should be mutually exclusive and exhaustive, (d) bare minimum of 15 cases per independent variable, (e) linear relationship between the continuous independent variables and the logit transformation of the dependent variable, (f) no multicollinearity, and (g) no outliers (Laerd Statistics, 2017). The first three assumptions were met because the dependent variable was dichotomous (0 – classified as not a train derailment, 1 – classified as train derailment), the independent variables are continuous and categorical.

According to the power analysis completed the recommended sample size for this study was 139 but all accidents within the calendar year 2019 for Class I and Class II railroads were used in this study. For the linear relationship between the continuous independent variables and the logit transformation of the dependent variable I used the Spearman's correlation coefficient approach, which measures the strength and direction of association that exists between two variables measured on the ordinal scale (Laerd

Statistics, 2017). Completing this test will show if there is statistical significance and if there is a concern with the linearity of the continuous variables with respect to the logit of the dependent variable. The next assumption with logistic regression is that there is no problem of multicollinearity. The absence of multicollinearity means that the independent variables included in the regression analysis do not correlate too highly to each other (Zahari et al., 2014). To assess multicollinearity, I reviewed the tolerance and variance inflation factor (VIF) statistics in the SPSS data file output and look for a tolerance level greater than .10 and a VIF less than 10 which indicates there is not multicollinearity among the independent variables (Zahari et al., 2014).

The final assumption with logistic regression is that there are no outliers in the data. Outliers are cases with extreme scores on one or more of the independent variables and this can cause distortions within the regression equation (Laerd Statistics, 2017). Within SPSS I checked the casewise list for accident incidents that were above 2.5 in deviation, which mean they are outliers and should be corrected or deleted from the data set.

For this study, SPSS version 25 was used for data analysis once the excel sheet was inputted into the software. When understanding the logistic regression analysis, the following factors were included in the analysis table (a) β, (b) SE, (c) Wald, (d) *df*, (e) *p*, (f) odds ratio (Exp B), and (g) 95% confidence interval for odds ratio. Beta (β) is the probability of making a Type II error in a hypothesis test by incorrectly concluding there is no statistical significance (Hollstein & Prokopczuk, 2016). Beta includes the values by which the researcher should multiply each independent variable to predict the dependent variable (train derailment). The independent variable that has a larger absolute beta value has a great impact on the dependent variable than does independent variables with smaller absolute variables (Hollstein & Prokopczuk, 2016).

The Standard Error are values are associated with the beta coefficients. These values describe how precisely the model estimates each coefficient's real but unknown value (Laerd Statistics, 2017). The SE can help researchers to test whether the value for each beta is significantly different than zero. Along with this the standard error can be used to for a confidence interval for the beta (Bekkar & Wansbeek, 2016). The SE can determine the likelihood that the beta falls between a specific higher or lower value.

The Wald test is used to determine statistical significance for each of the independent variables (Laerd Statistics, 2017). Wald is also the chi-square value and can be used with the *p* value to determine the likelihood that the beta coefficients differ significantly from those obtained by chance (Voinov, 2015). The *df* are the number of values in the final calculation of a statistic that are free to vary (Gherekhloo et al., 2016). There is currently a one-degree freedom for each independent variable. The more degrees of freedom in the model, the higher Wald must be to reject the null hypothesis that the true value of the associated beta coefficient is actually zero (Laerd Statistics, 2017).

The *p* value represents the statistical significance of each independent variable in the model (Stern, 2016). Along with this the *p* value can show the likelihood that the true value of the associated independent variables in the population are actually zero. A *p* value less than .05 is accepted as statistically significant (Stern, 2016) or also unlikely to have occurred by chance.

The Exp (B) is the probability and informs the researcher of the change in the odds for each increase in one unit of the independent variable (Laerd Statistics, 2017). The odds ratio is defined as when given a particular value for an independent variable that an event will occur, divided by the probability that an event will not occur (Lui, 2016). The odds ratio measures how much each independent variable increase the likelihood of an outcome, in this case it will determine train derailments. The 95% confidence interval of the odds ratio is used to determine whether the association is statistically significant (Laerd Statistics, 2017). When looking at the 95% confidence interval the odds ratio means there is a 95% likelihood that the true value of the odds ratio in the population falls between the upper and lower boundary values.

## Study Validity

Validity is the extent to which a concept is accurately measure in a quantitative study (Heale & Twycross, 2015). Validity can be broken down into internal and external. Internal validity examines whether the manner in which the study was designed, conducted, and analyzed allows for answers to be truthful when analyzing the research question within the study (Andrade, 2018). Often internal validity will be used in experimental and quasi-experimental research studies. Since this research study will not be experimental or quasi-experimental, I will not need to address the internal validity. However, external validity examines whether the findings within the study are generalized to other contexts (Andrade, 2018; Lievens et al., 2019). Data was collected according to the suggested sample size from the power analysis and then analyzed using the SPSS program; this reduced the threat of external validity.

Quantitative research designs also analyze validity through the use of statistical conclusion validity. Statistical conclusion validity holds when the conclusion of a research study is found through the use of adequate analysis of the data collected (Garcia-Perez, 2012). There are two different types of statistical conclusion validity, Type-I errors and Type-II errors. A Type-I error happens when the research accepts the alternate hypothesis and concluding that a relationship exists between variables when there is no relationship present (Ampatzoglou et al., 2019). On the reverse side, a Type-II error occurs when the research accepts the null hypothesis, which is saying no relationship exists, when in reality there is a relationship between the variables (Ampatzoglou et al., 2019).

Within this research study, I ensured that Type-I and Type-II errors do not occur by setting the alpha ($\alpha$) level, or level of statistical significance to 0.05 and the beta ($\beta$) level or statistical power between 0.80 – 0.99. I ensured that my sample size was big enough to help eliminate the possibility of Type-I or Type-II errors. The sample size in my study included Class I and Class II railroad in the United States. An *a priori* calculation of sample size required an effect size of $f = .15$, $\alpha = .05$, and power $\beta = 0.80$, which will require a minimum of 139 in the sample. If the power $\beta$ is increased to $\beta = 0.99$ the sample size would jump to a minimum sample size of 257.

## Transition and Summary

Section 2 contained a plan on conducting research pertaining to the determination of a relationship between operator causal factors, nonoperator causal factors, and the number of train derailments. In Section 2, I discussed the role of the researcher, participants, research methods and design, populations and sampling, ethical research, instrumentation, data collection and analysis, and the study validity. In Section 2, I explained why I choose the correlational research design and the binomial logistics regression analysis for this study. I explained where the data will be collected, and how I will use Microsoft Excel to download the information and complete data cleaning before inputting the data into SPSS for analysis. Section 3 will contain the presentation of the findings, application to professional practice, implications for social change, recommendations for action, recommendations for further research, reflections, and a conclusion.

# Section 3: Application to Professional Practice and Implications for Change

## Introduction

The purpose of this quantitative correlational study was to examine the relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment. I conducted a binominal logistic regression analysis and found nonoperator train derailment causal factors and number of crew members on duty were significant predictors in the occurrence of train derailment. The null hypothesis was rejected, and the alternative hypothesis was accepted. However, visibility, weather, operator causal factors, both operator and nonoperator causal factors and length of time on duty were not significant predictors in the occurrence of train derailment.

## Presentation of the Findings

In this subsection, I discuss the findings of the analyses of the collected data. I include the results of testing for statistical assumptions, descriptive analysis, and inferential analysis conducted to address the central research question and associated hypotheses. The results of the binomial logistic regression analysis procedures are included, along with the nature of the relationship between the study variables. I also present a theoretical discussion on the findings, application to professional practice, implications for social change, recommendations for actions and further research, and my reflections.

**Tests of Assumption**

There are seven assumptions associated with binomial logistic regression: (a) one dependent variable that is dichotomous (nominal variable with two outcomes), (b) one or more independent variables that are continuous or nominal scale, (c) independence of observations and the categories of the dichotomous dependent variable and all nominal independent variables should be mutually exclusive and exhaustive, (d) bare minimum of 15 cases per independent variable, (e) linear relationship between the continuous independent variables and the logit transformation of the dependent variable, (f) no multicollinearity, and (g) no outliers (Laerd Statistics, 2017).

The first three assumptions were met. The fourth assumption of minimum of 15 cases per independent variable was met in all but two instances. The dependent variable was dichotomous (0 = classified as not a train derailment, 1 = classified as train derailment). The independent variables includes both continuous and categorical variables. Number of crew members and crew members length of time on duty were continuous variables. Train derailment causal factors, visibility, and weather were categorical variables. The independence of observations assumption was met because accident cause could only fit under one category. According to the power analysis completed, the recommended sample size for this study was 139, but all accident within the calendar year 2019 for Class I and Class II railroads were used in this study, which totaled 1,396 accidents. There were two instances for sleet and snow where there were less than 15 cases per independent variable. All other independent variables had more than 15 cases.

The assumption of a linear relationship was not met, but this is likely due to the large sample size; therefore, no adjustments were needed to the study. According to Laerd (2017), a large sample size can result in a violation of this assumption, and when this occurs, no adjustments to the analysis are needed. For the assumption of linearity, the Spearman's rank-order correlations (see Table 1) were run to examine the relationship between number of crew members and length of time on duty. These were the only variables included in the linearity test because they are continuous. The correlation coefficient between number of crew members and length of time on duty this was .233 ($r_s$ = .233, $n$ = 1,396, $p$ < .001), which shows a weak relationship between the two variables.

**Table 1**

*Linear Relationship Assumption Testing Using Spearman's rho*

| | | Number of Crew Members | Length of Time on Duty |
|---|---|---|---|
| Number of Crew Members | Correlation Coefficient | 1.000 | .233 |
| | Sig. (2-tailed) | | .000 |
| | N | 1,396 | 1,396 |
| Length of Time on Duty | Correlation Coefficient | .233 | 1.000 |
| | Sig. (2-tailed) | .000 | |
| | N | 1,396 | 1,396 |

The assumption of no multicollinearity was met. Multicollinearity was evaluated by viewing the collinearity statistics of tolerance and VIF. Since all predictor variables had a tolerance level higher than .07 and VIF lower than 10 (Table 2), there was no violation of the assumption of multicollinearity. The following table shows the tolerance and VIF for each predictor variable.

**Table 2**

*Multicollinearity Assumption Testing Using Coefficients*

| | Tolerance | VIF |
|---|---|---|
| Visibility | .996 | 1.004 |
| Weather | .996 | 1.004 |
| Cause Code | .991 | 1.009 |
| Number of Crew Members | .947 | 1.056 |
| Length of Time on Duty | .954 | 1.048 |

The assumption of no outliers was met. To test for outliers, the case wise list was analyzed when the logistic regression analysis was performed, which showed all cases had a standard deviation below 2.5, meaning they were not outliers and could be included in the data set (Laerd Statistics, 2017).

## Data Cleaning and Descriptive Analysis

In total, there were 1,609 cases once filtered down to Class I and Class II railroads. Once filtered down into Class I and Class II railroads, each accident incident number was analyzed to ensure that there was not a duplicate input or missing information from the accident report. There were 213 records eliminated due to duplicate cases and missing data, resulting in 1,396 records for the analysis. To eliminate these cases from the datafile, I deleted those lines from the Excel file and did not include them in the SPSS data file.

Table 3 contains the descriptive statistics for the frequency of each variable. The model included 1,396 cases. The data showed 41.3% of the accidents reported occurred during the day and 65.2% of the accidents occurred during clear weather conditions. From all accidents reported 45.3% were caused by operator factors and 53.5% were caused by nonoperator causal factors. Additionally, the data showed that 63.7% of all accidents occurred when there were only two crew members on duty and 25.3% when there were three crew members on duty. When looking at length of time on duty, 7.8% of the time the crew was on duty 3–4 hours. Finally, from all accidents reported, 73.4% resulted in the occurrence of a train derailment which totals 1,024 cases. All 1,396 total cases all were considered 100% valid, and there were no missing data.

**Table 3**

*Descriptive Statistics—Frequencies*

| | *N* | Percentage |
|---|---|---|
| Dawn | 164 | 11.7% |
| Day | 576 | 41.3% |
| Dusk | 146 | 10.5% |
| Dark | 510 | 36.5% |
| Clear | 910 | 65.2% |
| Cloudy | 336 | 24.1% |
| Rain | 99 | 7.1% |
| Fog | 12 | .9% |
| Sleet | 5 | .4% |
| Snow | 34 | 2.4% |
| Operator Cause | 632 | 45.3% |
| Nonoperator Cause | 747 | 53.5% |
| Both | 17 | 1.2% |
| 1 Crew Member | 128 | 9.2% |
| 2 Crew Members | 889 | 63.7% |
| 3 Crew Members | 353 | 25.3% |
| 4 Crew Members | 23 | 1.6% |
| 5 Crew Members | 3 | .2% |
| 0-1 hours | 19 | 1.4% |
| 1-2 hours | 73 | 5.2% |
| 2-3 hours | 93 | 6.7% |
| 3-4 hours | 109 | 7.8% |
| 4-5 hours | 103 | 7.4% |
| 5-6 hours | 83 | 5.9% |
| 6-7 hours | 98 | 7.0% |
| 7-8 hours | 100 | 7.2% |
| 8-9 hours | 75 | 5.4% |
| 9-10 hours | 82 | 5.9% |
| 10-11 hours | 63 | 4.5% |
| 11-12 hours | 57 | 4.1% |
| 12-13 hours | 61 | 4.4% |
| 13-14 hours | 50 | 3.6% |
| 14-15 hours | 50 | 3.6% |
| 15-16 hours | 43 | 3.1% |
| 16-17 hours | 43 | 3.1% |
| 17-18 hours | 30 | 2.1% |
| 18-19 hours | 37 | 2.7% |
| 19-20 hours | 31 | 2.2% |
| 20-21 hours | 41 | 2.9% |
| 21-22 hours | 28 | 2.0% |
| 22-23 hours | 15 | 1.1% |
| 23-24 hours | 10 | 0.7% |
| 27-28 hours | 1 | 0.1% |
| 44-45 hours | 1 | 0.1% |
| Not a Train Derailment | 372 | 26.6% |
| Train Derailment | 1024 | 73.4% |
| Valid | 1,396 | 100% |
| Missing | 0 | |
| Total | 1,396 | |

**Inferential Statistics**

The analysis of the model fitting test is summarized in Table 4. The independent variables add statistically significant to the model or at least one independent variable is statistically significant. The significance value is less than .05; therefore, the null hypothesis is rejected. A statistically significant difference does exist between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment.

**Table 4**

*Model Fitting Information*

| | Chi-Square | *df* | Sig. |
|---|---|---|---|
| Step | 114.265 | 12 | .000 |
| Block | 114.265 | 12 | .000 |
| Model | 114.365 | 12 | .000 |

Table 5 includes inferential results for the hypotheses. Dummy coding allows researchers to turn categories into (1) yes or (2) no, when dealing with categorical variables with more than one level (Laerd Statistics, 2017). From the dummy coding there will be a reference category that identifies a category of comparison for the other categories. The reference category makes all interpretations in reference to that category. For example, using visibility—dawn as the dummy variable and visibility—dark as the reference, results for that variable showed visibility dark in comparison with train accidents visibility of dawn. Visibility, weather, and train derailment causal factors were dummy coded for data analysis in SPSS. For visibility, the variables included in the analysis were (a) dawn, (b) day, and (c) dusk. Dark was used as the reference category for visibility in the logistic regression analysis. Weather included (a) clear, (b) cloudy, (c) rain, (d) fog, and (e) sleet. Snow was used as the reference category for weather. Finally, train derailment causal factors were (a) operator causal factor and (b) nonoperator causal factors. Both operator causal factors and nonoperator causal factors were used as the reference category for train derailment causal factors.

**Table 5**

*Inferential Results*

| | *B* | S.E | Wald | *df* | *p* | Exp(B) | 95% CI for Odds Ratio Lower | Upper |
|---|---|---|---|---|---|---|---|---|
| Visibility | | | .168 | 3 | .983 | | | |
| Dawn | -.068 | .209 | .107 | 1 | .744 | .934 | .621 | 1.406 |
| Day | -.050 | .145 | .120 | 1 | .729 | .951 | .716 | 1.263 |
| Dusk | -0.29 | .224 | .017 | 1 | .896 | .971 | .626 | 1.506 |
| Weather | | | 3.917 | 5 | .561 | | | |
| Clear | .248 | .399 | .386 | 1 | .534 | 1.281 | .586 | 2.802 |
| Cloudy | .165 | .412 | .160 | 1 | .689 | 1.179 | .526 | 2.642 |
| Rain | -.147 | .450 | .106 | 1 | .744 | .863 | .357 | 2.086 |
| Fog | .264 | .802 | .108 | 1 | .742 | 1.302 | .270 | 6.269 |
| Sleet | -.692 | 1.033 | .448 | 1 | .503 | .501 | .066 | 3.796 |
| Cause Factors | | | 93.708 | 2 | .000 | | | |
| Operator Causal Factors | .630 | .500 | 1.592 | 1 | .207 | 1.878 | .705 | 5.001 |
| Nonoperator Causal Factors | 1.871 | .504 | 13.796 | 1 | .000 | 6.492 | 2.419 | 17.419 |
| Number of Crew Members | .416 | .107 | 15.062 | 1 | .000 | 1.516 | 1.229 | 1.870 |
| Length of Time on Duty | .005 | .011 | .179 | 1 | .672 | 1.005 | .983 | 1.027 |
| Constant | -1.291 | .681 | 3.588 | 1 | .058 | .275 | | |

*Note.* This table depicts the logistic regression analysis output.

The *p* value represents the statistical significance of each independent variable. *P* values of less than .05 are accepted as statistically significant, meaning that they are unlikely to have occurred by chance (Stern, 2016). From the *p* values in Table 5, nonoperator causal factors (< .001) and number of crew members (< .001) were statistically significant predictors for the occurrence of train derailment. All other predictor variables had *p* values above .05, which showed that they were not statistically significant predictors of the occurrence of train derailment. The Exp(B) also informs researchers of the change in the odds for each increase in one unit of the independent variable (Laerd Statistics, 2017). From the data, nonoperator causal code (6.494) and number of crew members (1.516) if increased by one unit increases the odds of a train derailment occurrence.

The null hypothesis was that there is not a statistically significant relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment. The regression results showed that two of the predictor variables, nonoperator causal factors and number of crew members on duty, were statistically significant predictors for the occurrence of train derailment. The other predictor variables, visibility, weather, operator causal factors, both operator and nonoperator causal factors and length of time on duty, were not statistically significant predictors of train derailment. Therefore, the null hypothesis was rejected, and the alternative hypothesis was accepted.

As shown in Table 6, the Pseudo $R^2$ values show the percentage of the dependent variable that can be predicated by the independent variables. The Pseudo $R^2$ values are used to understand how much variance in the dependent variable can be explained by the model. I used the Cox & Snell measure (UCLA: Statistical Consulting Group, 2021), which indicated that the model with the five independent variables explains 7.9% of the variance in the dependent variable, occurrence of train derailment. I also used Nagelkerke measure (UCLA: Statistical Consulting Group, 2021), which indicated that the model with five independent variables explains 11.5% of the variance in the dependent variable, occurrence of train derailment.

**Table 6**

*Pseudo R-Square*

| | -2 Log likelihood | Cox & Snell R Square | Nagelkerke R Square |
|---|---|---|---|
| 1 | 1504.318 | .079 | .115 |

## Summary

The purpose of this quantitative correlational study was to examine the relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment. I collected secondary data from the FRA safety database on train accidents that occurred in Class I and Class II railroads during the 2019 calendar year. I conducted a binomial logistic regression analysis using the data from 1,396 train accidents. The overall findings of this study provided evidence of a statistically significant relationship, $x^2(12) = 114.265$, $p < .001$. Of the predictor variables, nonoperator causal factors and number of crew members on duty were statistically significant predictors of the occurrence of train derailment. In the following sections, I will discuss these results in relation to existing literature, and the conclusions and recommendations based on the results.

**Theoretical Discussion of Findings**

While visibility, weather, operator causal factors, both operator factors, length of time on duty were not significant in the analysis of this study, nonoperator causal factors and number of crew members on duty were significant predictors of the occurrence of train derailment. The results of the study provided insight into the variables that have a significant impact on the occurrence of train derailments. Previous research can be used to help illuminate the results of this study. From previous research, 19,261 derailments were from nonoperator causal factors (Li et al., 2018). Nonoperator causal factors encompass things that our outside the control on the operator and are listed in Appendix B of this study. Number of crew members on duty can have impact on the ability for crew members to observe when other crew members are distracted, and an accident can occur (Coplen & Sussman, 2000).

Previous studies provided insight into the causes of train derailment or the after effect of a train derailment and how to improve the occurrence of train derailment occurring (Hunter-Zaworski, 2017; Underwood & Waterson, 2014; Zhang & Sun, 2019). Underwood and Waterson used the Swiss cheese model to analyze the Greyrigg train derailment and realized that poor maintenance along with other factors caused the derailment to occur. Hunter-Zaworski) completed an analysis on passenger accidents to understand the safety measures that needed to be in place or updated to ensure passenger safety. Zhang and Sun analyzed different train derailment risk response strategies to help limit the occurrence of train derailment occurrence. From precious research it was also found that high FRA track classes had lower derailment rates, varying by more than an order of magnitude (Liu et al., 2017).

Nonoperator causal factors and number of crew members were found to be statistically significant predictors of the occurrence of train derailment. This aligns with articles from Hunter-Zaworski, 2017, Underwood & Waterson, 2014, and Zhang & Sun, 2019. The goal was to understand the causes of train derailment or the after effect of a train derailment and how to improve the occurrence of train derailment occurring. From the analysis in this study researchers can further understand the main causal factors that have an effect on the occurrence of train derailment.

Visibility, weather, operator causal factors, both operator factors, and length of time on duty were not significant predictors in the occurrence of train derailment. This conflicts with previous research since operator causal factors were predictors in previous research (Hunter-Zaworski, 2017, Underwood & Waterson, 2014, and Zhang & Sun, 2019). In previous research both operator causal factors and nonoperator causal factors were analyzed as causes of train derailment but this doctoral study breaks each of these causal factors out for further analysis.

The theoretical framework for this study was the Swiss cheese model which helps to show where the holes are that create the scenario for a train derailment to occur (Olson & Raz, 2021). In this study, the holes that are aligning are nonoperator causal factors and number of crew members on duty, this can further be expanded if the analysis completed by Underwood and Waterson (2014). Researchers can use the Swiss cheese model to complete further analysis on nonoperator causal factors and number of crew members on duty to see how it impacted accidents that were caused by these factors.

The Swiss cheese model was created to understand the active failures, latent failures, and defenses within a system (Reason, 1997). Active failures are unsafe acts by front-end operators and latent failures are gaps or weaknesses in the system safety defense. Defenses can be looked at as layers of cheese' with holes in it and when they align it created a weakness in the system causing an accident to occur. From this study nonoperator causal factors and number of crew members are the slices of cheese that are aligning to create train derailment occurrence. Nonoperator causal factors can fall into the active or latent failure categories. They can fall into the active failure because there could be neglect on track maintenance or other organizational failures that are causing the train derailment. Nonoperator causal factors can be latent because there may be a condition not known that over time can become active and cause the train derailment to occur. The number of crew members can fall into the latent failure category because there could be an issue with scheduling on management and having a lack of personal on duty can cause issues to not be noticed and a train derailment to occur.

## Applications to Professional Practice

The general business problem in this study was that train derailments, sometimes the results of operator error, have impact on community safety, transportation efficiency, and organizational cost. The specific business problem was some railway managers do not understand the relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment. The most important outcome from this study that railway managers should deduce is nonoperator causal factors and number of crew members are important to help limit the occurrence of train derailment.

Railway managers should focus on the nonoperator causal factors that are increasing the chances for train derailment occurrence. Railway managers could consider increasing the frequency of track maintenance or switch maintenance or other variables that fall into the nonoperator causal factor table (Appendix B). Environmental conditions fall into the nonoperator causal factor area; therefore, railway managers could look at potential weather patterns and make decisions about whether to send the crew out if there will be a potential environmental issue.

Railway managers should also consider the number of crew members that are on a train at a time. The number of crew members was found to significantly impact the occurrence of train derailment. Specifically, train derailments were less likely to occur if there were a higher number of crew members, as compared to a lower number of crew members. Railway managers can investigate how crews are being managed and if there is a need to increase the crew members that are on duty. Limiting the number of crew members can cause potential causal factors to not be noticed, which could lead to derailment.

The Swiss cheese model analyzes active failures, latent failures, and defenses within a system that cause an accident to occur. Railway managers could have analyses completed to understand the specific causal factors that have a higher impact on their operations and find the potential solutions to correct the errors before another derailment occurs (Li et al., 2019). Analysis on number of crew members can help railway managers with allocation of resources to help limit the occurrence of train derailment. There could be the potential for lack of crew members available to be on duty at the time a train is moving cars, which could cause a potential train derailment. When there are fewer crew members on duty, there are things that can be missed by the crew that can help prevent train derailments from occurring. The number of crew members on duty could also be indicative of other factors causing derailment that are not mentioned in the accident reports. Expanding the content of the accident reports could lead to a better understanding of these factors. Further analysis from railway managers will help understand the active failures, latent failures, and defense.

## Implications for Social Change

This study has numerous implications for social change. This study provided an understanding of the relative importance of nonoperator causal factors and the number of crew members. Understanding the nonoperator causal factors and the number of crew members can help management to limit the occurrence of train derailment. Management can have further analysis completed to understand the overall impact that nonoperator causal factors have on their rail line. Such analyses can help management to allocate the correct resources and not limit the number of crew members that are on duty at one point in time.

These results may also help railway mangers to understand the unforeseen accident causal factors for train derailments. While there are operator and nonoperator causal factors from this study it was found that nonoperator causal factors have a significant impact on the occurrence of train derailments. Railway managers can take this information and understand how the nonoperator causal factors (a) track, roadbed, and structure, (b) signal and communication, (c) mechanical and electrical failures, (d) miscellaneous causes not otherwise listed are causing their train derailment numbers to increase. This information can also help management to understand the areas that might need improvement with track maintenance, switch maintenance, or environment condition pre planning prior to sending the team out on the tracks. These results can help management to understand how limiting the crew members can increase their chances of train derailment occurrence.

These results may also help everyone to understand the importance of train derailment causal factors which may help improve the safety measures taken during and after a train derailment. When a train derailment occurs, operators are required to complete a train accident report that details what occurred to allow the train derailment to happen. In this study, I found that nonoperator causal factors and number of crew members were significantly impacting the occurrence of train derailments. This information can help operators to understand what is causing the increased likelihood for a train derailment. Allowing operators to understand this information can help them to know the common causal factors that occur and to be aware of these before they could potentially happen to the operator. These results also allow the operator to understand the correct safety measures to take during and after the train derailment when reporting to management and the FRA through the accident report documentations.

Disbursing this information to the community will allow railway managers to analyze the causal factors for information to disseminate to the community on train derailment safety precautions. These results will allow for management to tell the community when track maintenance is being completed or when a potential derailment occurred and if anything, harmful was put out into the community. The results can also bring awareness to the areas in the community where train accidents are likely to occur. This information will also help with disaster prevention to help the community understand factors that can increase the chances of train derailment occurrence from outside causal factors.

## Recommendations for Action

Factors that impacted the occurrence of train derailments were nonoperator causal factors and number of crew members. Starting at the top level, managers need to understand within their organization how accidents are occurring and the factors that are impacting the occurrence of accidents. In this study, I found that nonoperator causal factors and number of crew members were significantly impacting the occurrence of train derailments. This information helps managers to understand what is causing an accident to occur within their organization and how to further decrease the likelihood of accident occurrence. Managers and business leaders would be wise to understand the causal factors that are causing the occurrence of train derailment to increase and also how to limit these factors, in order to decrease the number of train derailments.

I used the Cox & Snell measure (UCLA: Statistical Consulting Group, 2021), which indicated that the model with the five independent variables explains 7.9% of the variance in the dependent variable, occurrence of train derailment. I also used Nagelkerke measure (UCLA: Statistical Consulting Group, 2021), which indicated that the model with five independent variables explains 11.5% of the variance in the dependent variable, occurrence of train derailment. Further research could be done to include more independent variables, which might result in a model that has a higher $R^2$ value. There are multiple factors listed on the train accident reporting document that other researchers could select different factors on how it affects the occurrence of train derailment.

The theoretical framework for this study was the Swiss cheese model (Olson & Raz, 2021). Nonoperator causal factors and number of crew members can be looked at as a piece of cheese and when their holes align correctly, they increase the likelihood of train derailment occurrence. The Swiss cheese model helped to show how active failures, latent failures, and defenses are important for a railway manger to understand within their operations system (Seshia et al., 2017). Railway managers need to understand how nonoperator causal factors and number of crew members are the pieces of cheese that are lining up to increase their changes of train derailment occurrence on their railway.

Railway managers need to understand how these factors are impacting the occurrence of train derailment because it can decrease the stress that operators are feeling when a derailment occurs. When a derailment occurs, it can cause stress on the operator and increase their chances of repeating a train derailment. Since nonoperator causal factors and number of crew member were found statistically significant on the occurrence of train derailment, understanding the impact of these factors can also be important when railway managers are selecting crew members to ensure that everyone is safe and the chances of train derailment occurrence of decreased.

Managers may be reluctant to increase the number of crew members on duty at one time but doing so can help to decrease the occurrence of train derailment. When the crew size is increased, it may help every operator to notice potential causal factors before the train derailment can occur. Increasing the crew member size may also help to reduce the potential stress from the crew and decrease the likelihood of train derailment occurrence.

The results from this study will be distributed through the publication in the ProQuest dissertation database. I plan to reach out to railways to see if they are interested in understanding the data that was produced from this study to share this information with potential railway managers or business-related managers in the railway industry. There is the potential to also present this information at any industry conference to see if analysis can be completed in other industries.

## Recommendations for Further Research

The assumptions, limitations, and delimitations provide ample avenues to build upon the results. One limitation was that there are only two sections for causal code entry and there might be more than just primary causal code and contributing causal code that made the train derailment occur. When an accident occurs, operators are required to report this information on an accident form. When selecting the causal code for the accident the operator can select a primary and contributing causal code. Future researchers could embed themselves in a railway company and looking at the accident reports that are completed and asking the operator is there were more contributing factors than just two.

Another limitation was there are potentially additional causes that are not adequately captured by the list of options within the database. Appendix B lists all the potential operator and nonoperator causal factors that can be selected by the operators when completed the accident report. There could be potential accident causal factors not reflected. Future researchers could complete analysis on the individual factors and if there is potentially any missing that could be contributing to the accident occurrence.

The final limitation is that all independent variables for this study were entered by the accident recorder and incorrect information was not imputed. Since this information is manually inputted into the system there is a chance for the data to be incorrect which can change the outcome of a study. A future researcher could investigate the potential of an online system for accident recording where the operator will input the information and it could potentially decrease the change of incorrect data input.

There are also methodological implications for future research. As this study was quantitative, a qualitative research study could aid in understand how managers process the information from train accidents. A qualitative study could provide further insight into the variables to see if there are any outside forces that impact the occurrence of train derailment. Along with these researchers could complete this study in different industries to see how multiple variables impact the occurrence of accidents. By comparing and contrasting industries, researchers can make better recommendations for specific organizations. This study focused on train derailment causal factors, visibility, weather, number of crew members, and crew members length of time on duty results may be different if other variables are selected from the railway accident reporting record.

Lastly, there is room for theoretical improvement. I used the Swiss cheese model to show how nonoperator causal factors and number of crew members where the slice of cheese lining up to cause an increased likelihood of train derailment occurrence but there are other accident theories that could be used for this analysis. Research using other theoretical frameworks might result in a different outcome.

## Reflections

The Walden University doctoral study process had been challenging and rewarding. I learned a lot about myself throughout the whole process. Early in my journey, I was very motivated but nervous about how I would progress through the program. After my first residency I was worried that I would not know what to write about and then began thinking about passions that I had, which led me to my passion for the railroad industry. I have thoroughly enjoyed the interactions that I had with faculty, staff, and students while attending Walden University. Eventually, I began to find the balance between writing my study, personal life, and my full-time professional career. Working in the logistic field drove me to better understand how business managers have impact within their company. While in class and at residency I have found lifelong friends and motivation for completing this journey together. This doctoral study journey has helped to strengthen my research skills and to think outside the box when completing research analysis.

This journey has also allowed me to expand my knowledge on SPSS, which is one of the reasons that I completed a quantitative study. I expanded my knowledge on quantitative and qualitative research methods which will help me when wanting to complete analysis on different things in my professional career. While quantitative studies are not popular and most of my classmates were completing qualitative studies, it was the best option for me because it expanded my knowledge and expanded my experience while at Walden University. I have learned so much from my doctoral chair and second committee member during this journey and I will be grateful for this experience the rest of my life. I look forward to future researching opportunities and expanding my research articles.

## Conclusion

The general business problem was that train derailments, sometimes the results of operator error, have an impact on community safety, transportation efficiency, and organizational cost. The specific business problem was that some railway managers do not understand the relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment. To address this problem, the purpose of this quantitative correlational study was to examine the relationship between train derailment causal factors, visibility, weather, number of crew members, crew members length of time on duty, and the occurrence of train derailment. The theoretical framework for this study was James Reason's (1987) Swiss cheese model. I conducted this study to address the research question and provide practical information about how railway managers can use this information to decrease their likelihood of train derailment.

The overall findings of this study provided evidence of statistically significant relationships between nonoperator causal factors and number of crew members on the occurrence of train derailment. This study offered railway managers specific implications from variables studied and how they can use this information to better understand and prevent train derailments, because they understand the relative importance of the factors input on the potential outcomes. Lastly, there are plenty of opportunities for future research including studying other industries, using a qualitative approach, and by using other theories as the framework for a future study. Further research is important because train derailment has an impact on community safety, transportation efficiency, and organizational cost. Therefore, determining what variables increase train derailment occurrence allows railway managers to help reduce the frequency of train derailment occurrences within the railroad industry and save lives.

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# Appendix A: Train Derailment Reporting

Train derailments occur when on-track equipment depart the rail for reasons other than collision, explosion, and rail crossing impact (Federal Railroad Administration [FRA], 2019). All derailments, regardless of whether there is damage caused or not, are reported reporting on a Form FRA F 6180.97 – Initial Rail Equipment Accident/Incident Record which includes important information regarding the incident (see Figure A1).

**Figure A1**

*Form FRA F 6180.97*

**INITIAL RAIL EQUIPMENT ACCIDENT/INCIDENT RECORD**

**DEPARTMENT OF TRANSPORTATION**
FEDERAL RAILROAD ADMINISTRATION (FRA)

**OMB No. 2130-0500**

1. Date of Accident/Incident (YY/MM/DD)
2. Time of Accident/Incident AM PM
3. Name of Railroad
4. Incident Number
5. Other Railroad or Entity
6. Incident Number
7. Railroad or Other Entity Responsible for Track Maintenance
8. Incident Number
9. Type of Accident/Incident (Derailment, Collision, Obstruction, Other)
10. Number of Hazmat Cars Damaged or Derailed
11. Number of Hazmat Cars Releasing Product
12. Subdivision
13. Nearest City/Town
14. County
15. State
16. Milepost *(to nearest tenth)*
17. Specific Site
18. Speed Actual Estimated
19. Train/Job Number
20. Type of Equipment (Freight, Passenger, Yard/Switching, etc.)
21. Type of Track (Main, Yard, Siding, Industry)
22. Total Locomotive Units in Train
23. Total Locomotives Derailed
24. Total of Cars in Equipment Consist
25. Total Cars Derailed
26. Equipment Damage *(in dollars)*
27. Track, Signal, Way & Structure Damage *(in dollars)*
28. Primary Cause
29. Contributing Cause

| 30. Casualties | Nonfatal | Fatal | | Nonfatal | Fatal |
|---|---|---|---|---|---|
| Worker on duty – railroad employee | | | Worker on duty - contractor | | |
| Railroad employees not on duty | | | Contractor - other | | |
| Passengers on trains | | | Worker on duty - volunteer | | |
| Nontrespassers/on railroad property | | | Volunteer - other | | |
| Trespassers | | | Nontrespassers/off railroad property | | |

31. Narrative Description (Be specific, and continue on separate sheet if necessary)

32. Was this accident/incident reported to the FRA? Yes ☐ No ☐

33. Name of Railroad Official
34. Signature
35. Telephone Number
36. Date initially signed/completed

NOTE: This report is part of the reporting railroad's accident report pursuant to the accident reports statute and, as such shall not "be admitted as evidence or used for any purpose in any suit or action for damages growing out of any matter mentioned in said report. . . ." 49 U.S.C. 20903. See 49 C.F.R. 225.7 (b).

**This collection of information is mandatory under 49 CFR 225, and is used by FRA to monitor national rail safety. Public reporting burden is estimated to average 30 minutes per response, including the time for reviewing instructions, searching existing databases, gathering and maintaining the data needed, and completing and reviewing the collection of information. The information collected is a matter of public record, and no confidentiality is promised to any respondent. Please note that an agency may not conduct or sponsor, and a person is not required to respond to a collection of information unless it displays a currently valid OMB control number. The OMB control number for this collection is 2130-0500.**

**FORM FRA F 6180.97 (Rev. 08/10)** **OMB approval expires 02/28/2014**

*Note.* From Federal Railroad Administration, 2019.

Depending on the initial information being reported, further forms may need to be completed and attached to a more detailed report for input into the FRA safety website. If the damage occurring during the derailment is more than the current threshold for the current year, then further information is reported on Form FRA F 6180.54 – Rail Equipment Accident/Incident Report (see Figure A2). For calendar year 2017 and beyond, the threshold was set at $10,700. On this form there are 55 fields that all need to be completed each providing important details about the event that occurred. With respect to this doctoral study the most important fields are as follows: seven (Type of Accident/Incident, 18 (Visibility), 19 (Weather), 22 (FRA Track Class), 38 (Primary Cause Code), 39 (Contributing Cause Code), 40-43 (Number of Crew Members), and 44 & 45 (Length of Time on Duty).

Field 7 (Type of Accident/Incident) is important because code 1 is applicable to derailment which is the area of interest for this doctoral study. All other codes in this field will be coded for accidents other than train derailment. Also, this code will help to filter through all the accidents that are reported into the FRA Safety website and exported into an excel file for analysis. Field 18 (Visibility) will help to understand the conditions when the derailments occurred. Field 19 (Weather) will help to understand the weather that was occurring when the train derailment happened. Field 22 (FRA Track Class) will help to be able to ensure that only Class I and Class II railroad accidents are being analyzed. Field 38 (Primary Cause Code) and field 39 (Contributing Cause Code) will help with breaking the causal codes into train derailment causal codes (human or nonhuman). Field 40-43 (Number of Crew Members) will help to understand the number of crew members that were working when the train derailment occurred. Finally, field 44 and 45 (Length of Time on Duty) will show the amount of time that the crew members were on duty and the impact it have on the occurrence of train accidents.

**Figure A2**

*Form FRA F 6180.54*

DEPARTMENT OF TRANSPORTATION
FEDERAL RAILROAD ADMINISTRATION (FRA)

**RAIL EQUIPMENT ACCIDENT/INCIDENT REPORT**

**OMB No. 2130-0500**

| | | |
|---|---|---|
| 1. Name of Reporting Railroad | 1a. Alphabetic Code | 1b. Railroad Accident/Incident No. |
| 2. Name of Other Railroad or Other Entity with Consist Involved | 2a. Alphabetic Code | 2b. Railroad Accident/Incident No. |
| 3. Name of Railroad or Other Entity Responsible for Track Maintenance *(single entry)* | 3a. Alphabetic Code | 3b. Railroad Accident/Incident No. |
| 4. U.S. DOT Grade Crossing Identification Number | 5. Date of Accident/Incident month / day / year | 6. Time of Accident/Incident AM ☐ PM ☐ |

7. Type of Accident/Incident *(single entry in code box)* — 1. Derailment 2. Head on collision 3. Rear end collision 4. Side Collision 5. Raking collision 6. Broken train collision 7. Hwy-rail crossing 8. RR grade crossing 9. Obstruction 10. Explosion-detonation 11. Fire/violent rupture 12. Other impacts 13. Other *(describe in narrative)* — Code

| | | | | |
|---|---|---|---|---|
| 8. Cars Carrying HAZMAT | 9. HAZMAT Cars Damaged/Derailed | 10. Cars Releasing HAZMAT | 11. People Evacuated | 12. Subdivision |

| | | | |
|---|---|---|---|
| 13. Nearest City/Town | 14. Milepost *(to nearest tenth)* | 15. State Abbr. — Code | 16. County |

17. Temperature (F) *(Specify if minus)* °F
18. Visibility *(single entry)* 1. Dawn 2. Day 3. Dusk 4. Dark — Code
19. Weather *(single entry)* 1. Clear 2. Cloudy 3. Rain 4. Fog 5. Sleet 6. Snow — Code
20. Type of Track 1. Main 2. Yard 3. Siding 4. Industry — Code

21. Track Name/Number
22. FRA Track Class (1-9, X) — Code
23. Annual Track Density *(gross tons in millions)*
24. Time Table Direction 1. North 2. South 3. East 4. West — Code

25. Type of Equipment Consist *(single entry)* 1. Freight Train 2. Passenger Train-Pulling 3. Commuter Train-Pulling 4. Work train 5. Single Car 6. Cut of cars 7. Yard/switching 8. Light loco(s) 9. Maint./inspect. Car A. Spec. MoW Equip. B. Passenger Train-Pushing C. Commuter Train-Pushing D. EMU E. DMU — Code
26. Was Equipment Attended? 1. Yes 2. No — Code
27. Train Number/Symbol

28. Speed *(recorded speed, if available)* R - Recorded E - Estimated — MPH — Code
29. Trailing Tons *(gross tonnage, excluding power units)*

30. Type of Territory *(enter code(s) that apply)*
Signalization *(Mandatory)* 1. Signaled 2. Not Signaled ☐
Method of Operation/Authority for Movement *(Mandatory)* 1. Signal Indication 2. Direct Train Control 3. Yard/Restricted Limits 4. Block Register Territory 5. Other Than Main Track ☐
Supplemental/Adjunct Codes *(Mandatory*)* ☐ ☐ ☐
* Mandatory to the extent that all applicable codes are entered

30a. Remotely Controlled Locomotive?
0 = Not a remotely controlled operation
1 = Remote control portable transmitter
2 = Remote control tower operation
3 = Remore control portable transmitter - more than one remote control transmitter
Code

| 31. Principal Car/Unit | a. Initial and Number | b. Position in Train | c. Loaded *(yes/no)* |
|---|---|---|---|
| (1) First Involved *(derailed, struck, etc.)* | | | |
| (2) Causing *(if mechanical, cause reported)* | | | |

32. If railroad employee(s) tested for drug/alcohol use, enter the number that were positive in the appropriate box. — Alcohol | Drugs

33. Was this consist transporting passengers? *(y/n)*

| 34. Locomotive Units (Exclude EMU, DMU, and Cab Car Locomotives.) | a. Head End | Mid Train b. Manual | Mid Train c. Remote | Rear End d. Manual | Rear End e. Remote |
|---|---|---|---|---|---|
| (1) Total in Train | | | | | |
| (2) Total Derailed | | | | | |

| 35. Cars (Include EMU, DMU, and Cab Car Locomotives.) | Loaded a. Freight | Loaded b. Pass. | Empty c. Freight | Empty d. Pass. | e. Caboose |
|---|---|---|---|---|---|
| (1) Total in Equipment Consist | | | | | |
| (2) Total Derailed | | | | | |

| | | | |
|---|---|---|---|
| 36. Equipment Damage This Consist | 37. Track, Signal, Way, & Structure Damage | 38. Primary Cause Code | 39. Contributing Cause Code |

Number of Crew Members

| | | | |
|---|---|---|---|
| 40. Engineers/ Operators | 41. Firemen | 42. Conductors | 43. Brakemen |

Length of Time on Duty

| | |
|---|---|
| 44. Engineer/Operator Hrs: Mins: | 45. Conductor Hrs: Mins: |

| Casualties to: | 46. Railroad Employees | 47. Train Passengers | 48. Others | 49a. Special Study Block A | 49b. Special Study Block B |
|---|---|---|---|---|---|
| Fatal | | | | | |
| Nonfatal | | | | | |

| | |
|---|---|
| 50. Latitude | 51. Longitude |

52. Narrative Description *(Be specific, and continue on separate sheet if necessary)*

| | | |
|---|---|---|
| 53. Typed/Printed Name & Title of Preparer | 54. Signature | 55. Date |

NOTE: This report is part of the reporting railroad's accident report pursuant to the accident reports statute and, as such shall not "be admitted as evidence or used for any purpose in any suit or action for damages growing out of any matter mentioned in said report...." 49 U.S.C. 20903. See 49 C.F.R. 225.7 (b).

**This collection of information is mandatory under 49 CFR 225, and is used by FRA to monitor national rail safety. Public reporting burden is estimated to average 2 hours per response, including the time for reviewing instructions, searching existing databases, gathering and maintaining the data needed, and completing and reviewing the collection of information. The information collected is a matter of public record, and no confidentiality is promised to any respondent. Please note that an agency may not conduct or sponsor, and a person is not required to respond to a collection of information unless it displays a currently valid OMB control number. The OMB control number for this collection is 2130-0500.**

**FORM FRA F 6180.54 (Rev. 08/10)** **OMB approval expires 02/28/2014**

*Note.* From Federal Railroad Administration, 2019.

Completing these forms is important for companies because they allow management to understand what occurred at the time of the accident. When a train derailment occurs, there could be multiple things effected within the company because of the cost associated with train derailments. Along with this, depending on what the employee was hauling at the time of the derailment, local law enforcement might need to be called in if there was a hazardous material being transported. Safety measures are directly tied into these reports because the FRA safety office will use these forms to understand where the incident occurred, what occurred, and what was the contributing factor to the occurrence of the accident.

# Appendix B: Operator and Nonoperator Causal Codes

**Table B1**

*Operator Causal Factors—1 in SPSS Data File*

| | Applicable Codes |
|---|---|
| Brakes, Use of | H008, H017, H018, H019, H020, H021, H022, H025, H099 |
| Employee Physical Condition | H101, H102, H103, H104, H099 |
| Flagging, Fixed, Hand and Radio Signals | H201, H202, H205, H206, H207, H208, H209, H210, H211, H212, H217, H218, H219, H220, H221, H222, H299 |
| General Switching Rules | H301, H302, H303, H304, H305, H306, H307, H308, H309, H310, H311, H312, H313, H314, H315, H316, H317, H318, H399 |
| Main Track Authority | H401, H402, H403, H404, H405, H406, H499 |
| Train Handling/Train Makeup | H501, H502, H503, H504, H505, H506, H507, H508, H509, H510, H511, H512, H513, H514, H515, H516, H517, H518, H619, H520, H521, H522, H523, H524, H525, H526, H599 |
| Speed | H601, H602, H603, H604, H605, H606, H607, H699 |
| Switches, Use of | H701, H702, H703, H704, H705, H706, H707, H799 |
| Cab Signals | H821, H822, H823, H824, H899 |
| Miscellaneous | H991, H992, H993, H994, H99A, H99B, H99C, H99D, H99E, H995, H996, H997, H999 |

**Table B2**

*Nonoperator Causal Factors—0 in SPSS Data File*

| | Applicable Codes |
|---|---|
| Roadbed | T001, T002, T099 |
| Track Geometry | T101, T102, T03, T104, T105, T106, T107, T108, T109, T110, T111, T12, T113, T199 |
| Rail, Joint Bar and Rail Anchoring | T201, T202, T203, T204, T205, T206, T207, T208, T210, T211, T212, T213, T214, T215, T216, T217, T218, T219, T220, T221, T222, T223, T224, T299 |
| Frogs, Switches and Track Appliances | T301, T302, T303, T303, T305, T306, T307, T308, T309, T310, T311, T312, T313, T314, T315, T316, T317, T318, T319, T399 |
| Other Way and Structures | T401, T402, T403, T404, T499 |
| Signal and Communication | S001, S002, S003, S004, S005, S006, S007, S008, S009, S010, S011, S012, S013, S014, S015, S016, S099, S101, S102, S103, S104 |
| Brakes | E00C, E00L, E01C, E01L, E02C, E02L, E03C, E03L, E04C, E04L, E05C, E05L, E06C, E06L, E07C, E07L, E08C, E08L, E0HC, E0HL, E09C, E09L, E10L |
| Trailer or Container or Flatcar | E11C, E12C, E13C, E19C |
| Body | E20C, E20L, E21C, E21L, E22C, E22L, E23C, E23L, E24C, E24L, E25C, E25L, E26C, E26L, E27C, E27L, E29C, E29L |
| Coupler and Draft System | E30C, E30L, E31C, E31L, E32C, E32L, E33C, E33L, E34C, E34L, E35C, E35L, E36C, E36L, E37C, E37L, E39C, E39L |
| Truck Components | E40C, E40L, E41C, E41L, E42C, E42L, E43C, E43L, E44C, E44L, E45C, E45L, E46C, E4AC, E4BC, E46L, E47C, E47L, E48C, E48L, E4TC, E4TL, E49C |
| Axles and Journal Bearings | E51C, E51L, E52C, E52L, E53C, E53L, E54C, E54L, E55C, E55L, E59C, E59L |
| Wheels | E60C, E60L, E61C, E61L, E62C, E62L, E63C, E63L, E64C, E64L, E65C, E65L, E66C, E66L, E67C, E67L, E68C, E68L, E6AC, E6AL, E69C, E69L |
| Locomotives | E70L, E71L, E72L, E73L, E74L, E75L, E76L, E77L, E78L, E7AL, E7BL, E79L |
| Doors | E80C, E81C, E82C, E83C, E84C, E85C, E856C, E89C |
| General Mechanical and Electric Failures | E99C, E99L |
| Environmental Conditions | M101, M102, M103, M104, M105, M199 |
| Loading Procedures | M201, M202, M203, M204, M206, M207, M208, M299 |
| Unusual Operational Situations | M401, M402, M403, M404, M405, M406, M407, M408, M409, M410, M411 |
| Other Miscellaneous | M501, M502, M503, M504, M505, M506, M507, M509, M510, M599 |

Appendix C: Data Analysis Coding

| | Visibility |
|---|---|
| Dawn | 0 |
| Day | 1 |
| Dusk | 2 |
| Dark | 3 |

| | Weather |
|---|---|
| Clear | 0 |
| Cloudy | 1 |
| Rain | 2 |
| Fog | 3 |
| Sleet | 4 |
| Snow | 5 |

Appendix D: G*Power Analysis

**Figure D1**

*G*Power 80% Power Plot*

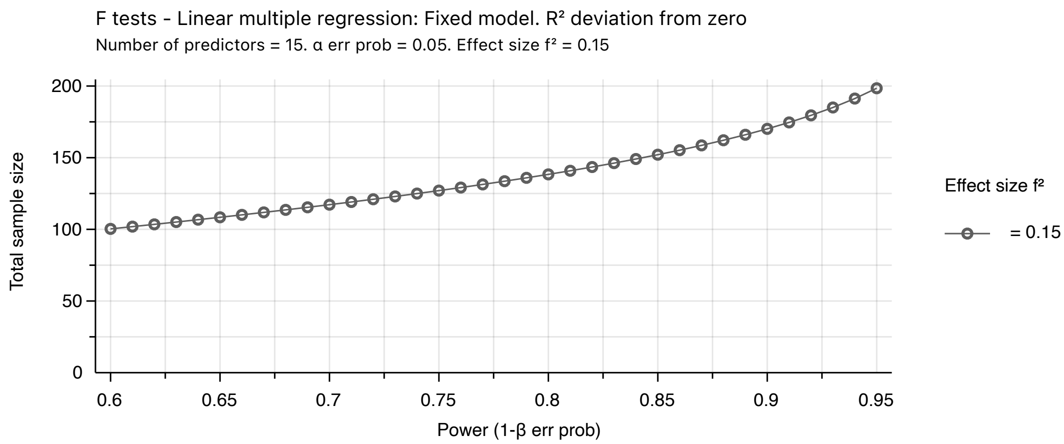
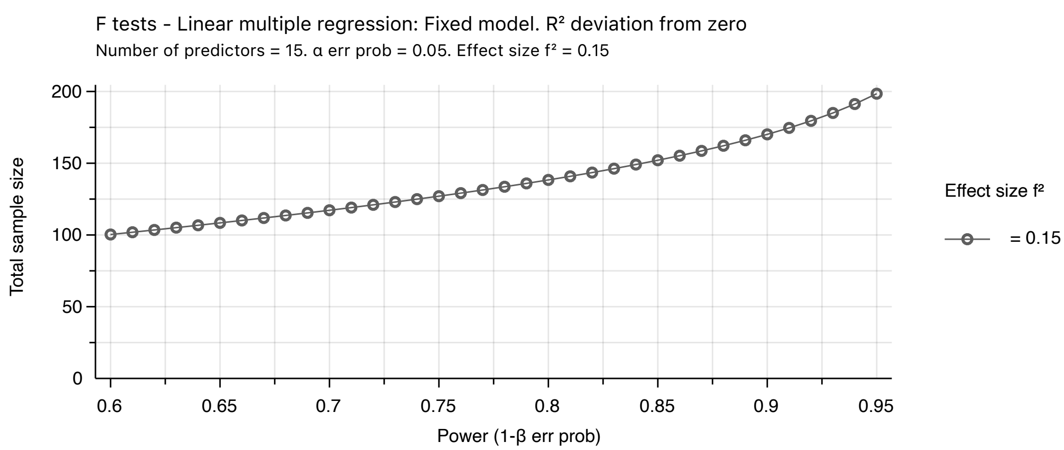



**Figure D2**

*G*Power 99% Power Plot*



# Appendix E: Data Analysis File

| TYPE | VISIBLTY | WEATHER | CAUSE | CAUSE2 | ENGRS | FIREMEN | CONDUCTR | BRAKEMEN | ENGHR | ENGMIN | CDTRHR | CDTRMIN |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 01 | 2 | 1 | T111 | | 1 | 0 | 1 | 0 | 03 | | 03 | |
| 01 | 2 | 1 | T314 | | 1 | 0 | 1 | 0 | 03 | | 03 | |
| 09 | 2 | 1 | H104 | H402 | 1 | 0 | 0 | 0 | 05 | 54 | | |
| 01 | 2 | 1 | T101 | | 1 | 0 | 1 | 0 | 07 | 10 | 07 | 10 |
| 01 | 4 | 1 | H303 | | 1 | 0 | 1 | 1 | 05 | 58 | 05 | 58 |
| 01 | 4 | 2 | H506 | | 3 | 0 | 0 | 0 | 03 | 46 | | |
| 01 | 2 | 2 | T216 | | 1 | 0 | 1 | 1 | 04 | 50 | 04 | 50 |
| 12 | 4 | 1 | S015 | | 1 | 0 | 0 | 0 | 05 | 55 | | |
| 01 | 2 | 1 | H018 | | 1 | 0 | 1 | 1 | 01 | 55 | 01 | 55 |
| 01 | 2 | 1 | T212 | | 0 | 0 | 1 | 1 | | | 06 | 51 |
| 13 | 4 | 1 | H306 | | 1 | 0 | 1 | 0 | 08 | 47 | 08 | 47 |
| 01 | 2 | 1 | M405 | | 1 | 0 | 1 | 0 | 02 | 50 | 02 | 50 |
| 12 | 4 | 1 | H312 | | 2 | 0 | 0 | 0 | 07 | 25 | | |
| 01 | 4 | 2 | E35C | | 2 | 0 | 0 | 0 | 05 | 40 | | |
| 04 | 4 | 1 | M407 | | 0 | 0 | 2 | 1 | | | 08 | |
| 01 | 2 | 1 | T207 | | 0 | 0 | 1 | 1 | | | 03 | 24 |
| 01 | 2 | 2 | T220 | | 1 | 0 | 1 | 1 | 05 | 10 | 05 | 10 |
| 12 | 3 | 1 | M407 | | 0 | 0 | 1 | 1 | | | 02 | 30 |
| 01 | 4 | 1 | H306 | | 2 | 0 | 0 | 0 | 01 | 25 | | |
| 01 | 4 | 2 | H702 | | 1 | 0 | 1 | 0 | 01 | 25 | 01 | 25 |
| 01 | 3 | 1 | H505 | H525 | 1 | 0 | 1 | 0 | 11 | | 11 | |
| 01 | 4 | 2 | T210 | | 1 | 0 | 1 | 0 | 01 | 23 | 01 | 23 |
| 12 | 2 | 1 | H999 | | 1 | 0 | 1 | 0 | 03 | 10 | 03 | 10 |
| 01 | 4 | 1 | H992 | H303 | 1 | 0 | 0 | 0 | 05 | 24 | | |
| 13 | 2 | 1 | H306 | H303 | 1 | 0 | 1 | 0 | 08 | 05 | 08 | 05 |
| 01 | 4 | 1 | T110 | | 1 | 0 | 1 | 0 | 07 | | 07 | |
| 01 | 3 | 1 | M503 | | 1 | 0 | 1 | 0 | 05 | 21 | 05 | 21 |
| 11 | 2 | 4 | T207 | | 1 | 0 | 1 | 0 | 09 | 40 | 09 | 40 |
| 01 | 2 | 6 | M101 | | 1 | 0 | 1 | 0 | 02 | 06 | 02 | 06 |
| 01 | 2 | 1 | H503 | | 1 | 0 | 1 | 0 | 04 | | 04 | |
| 01 | 2 | 1 | T199 | | 1 | 0 | 2 | 0 | 05 | 45 | 05 | 45 |
| 04 | 4 | 2 | H306 | | 1 | 0 | 0 | 0 | 03 | | | |
| 04 | 2 | 1 | H302 | | 1 | 0 | 1 | 1 | 05 | 45 | 05 | 45 |
| 01 | 2 | 6 | M101 | T402 | 1 | 0 | 1 | 0 | 05 | | 05 | |