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Walden University

College of Management and Human Potential

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Sonnie G. Bates

has been found to be complete and satisfactory in all respects,
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Walden University
2023

Abstract

Emotional Intelligence and Safety Culture in Business Aviation

by

Sonnie G. Bates

MPhil, Walden University, 2020

MSM, Minot State University, 2011

BS, Northern Kentucky University, 1986

Dissertation Submitted in Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Management

Walden University

February 2023

Abstract

With a lack of research regarding the relationship between emotional intelligence and safety culture in the aviation industry, safety professionals have inadequate information to reduce human error, the leading cause of tragic aircraft accidents. The purpose of this study was to determine the extent to which there is a relationship between emotional intelligence and safety culture in the business aviation industry. This study was grounded on Reason's theoretical model for safety culture, enhanced by Wang and Sun, and the emotional intelligence framework by Salovey and Mayer, enhanced by Jordan and Lawrence. A quantitative descriptive correlational approach was used with convenience sampling to capture data from 257 business aviation participants in the United States. The online survey consisted of 52 questions to obtain demographic data, emotional intelligence scores, and safety culture scores, integrating two established instruments—the Workgroup Emotional Intelligence Profile–Short and the Integrated Safety Culture Model. Multiple linear regression was employed to determine the relationship between the primary independent variable, emotional intelligence, and several dependent variables related to measures of safety culture. The analysis revealed that emotional intelligence is a strong predictor of safety culture. Therefore, aviation safety professionals implementing progressive measures to integrate emotional intelligence testing and training may improve safety culture and reduce human error. The results of this study can effect positive social change by reducing serious incidents and accidents in aviation, therefore improving air transportation for the general public.

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Dedication

I want to thank those who encouraged me to pursue a Ph.D. and stay the course when the goal seemed too far to reach at times. I also want to than my Walden peers worldwide, who inspired me with their friendship and dedication to excellence in scholarly research. Finally, and most importantly, I thank my family for their love and support throughout this endeavor, for this effort took much time away from being with them. However, each of them believed it was for a good cause (to affect positive change in this world), so they put up with my absence with hope for a brighter future.

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A special thanks to my Committee Chairman, Dr. Branford McAllister, for his countless insights, support, and inspiration. Through his guidance, this journey transformed me into a more capable researcher.

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Chapter 1: Introduction to the Study

Research indicates that a large majority of aviation accidents are attributable to human error (see, for example, Erjavac et al., 2018; Kelly & Efthymiou, 2019; Kharoufah et al., 2018; Shappell et al., 2007; Taneja, 2002). The International Civil Aviation Organization (ICAO; 2018), a specialized agency of the United Nations with a goal to harmonize aviation safety efforts among 193 nations, credits Dr. James Reason's theoretical model for understanding accident causation. Reason (1997) claimed, "Human errors pose the greatest single threat to hazardous technologies" (p. 124). He also asserted that a poor safety culture increases the likelihood of errors (Reason, 2017, p. 82).

Scholarly research provides evidence that emotional intelligence enhances safety culture (Rezaei & Salehi, 2018) and safety culture reduces human error (for example, Berry et al., 2020; Fox et al., 2021). Rezaei and Salehi (2018) concluded that a significant positive correlation exists between emotional intelligence and patient safety culture. Fox et al. (2021) concluded that a positive safety culture is correlated with reductions in human error in the health care industry due to increased reporting and subsequent mitigation efforts. Together, these studies indicate a link between emotional intelligence, safety culture, and error reduction in the health care industry. In my research, I hypothesized that similar results could be derived and appreciated in the aviation industry.

I conducted my study to explore the relationship between emotional intelligence and safety culture in aviation, with the intent to enhance information for safety leaders to reduce human error, thereby reducing serious incidents and accidents. In this chapter, I describe the background research that provides the logical framework to connect emotional intelligence, safety culture, and human error management. I introduce the research problem, which posits that the connection between emotional intelligence and safety culture has not been examined adequately in aviation. I conclude this chapter by describing the significance of the study (i.e., expanding and enhancing the body of scholarly knowledge to benefit aviation safety leaders worldwide). With this new knowledge, they will be better able to maintain emotionally stable teams and resilient safety cultures to reduce human error in high-risk operations.

Background of the Study

The following summaries provide evidence of the links between the social problem, emotional intelligence, safety culture, and human error. They provide a foundation that supports the merits of researching these concepts and relationships to better understand how emotional intelligence may influence safety culture in aviation.

Erjavac et al. (2018) evaluated the preconditions affecting human performance in aviation accidents. They analyzed the National Transportation Safety Board (NTSB) aviation accident database for causal factors. Their findings identify human error as a causal factor in approximately 80% of all aviation accidents for non-airline operations. Their research also applied Reason’s (1997) theoretical model that organizational factors influence human performance, including human error.

Cakıt et al. (2019) investigated the construct of perceived safety culture in Japan's petrochemical industry. They surveyed 883 employees from five companies, using a complex instrument that measured perceived safety culture, safety motivation, error behavior, and violation behavior. Their findings included evidence that perceived safety culture moderates human error behavior.

Fox et al. (2021) conducted a longitudinal study to analyze the effect of integrating training in just culture, a subculture of safety culture, according to Reason (1997), and error reporting for resident pediatric physicians at Children's Hospital of Pittsburgh, University of Pittsburgh Medical Center. Each resident physician received specialized training on identifying and reporting errors. The researchers also formally integrated error reporting as a topic in daily team discussions. Over a 4-year period, the error reporting rate improved dramatically from 3.6 to 37.8 per month, while the serious harm (or serious error) rate dropped from 15.0 to 8.1 per month. This study provides sound evidence that a positive safety culture can improve error reporting, which can reduce the error rate of an organization.

Jamshed and Majeed (2019) applied quantitative methods to investigate the correlation between team emotional intelligence and team performance in the health care industry with the goal of reducing human error. They surveyed 535 people representing 95 teams, employing an instrument for measuring team emotional intelligence and another to measure team performance. They concluded that improvements in team emotional intelligence positively influence team performance, with the assumption that this effect will lead to a reduction in human error.

Rezaei and Salehi (2018) studied the relationship between emotional intelligence and patient safety culture in the health care industry. Their research provided evidence of a positive and significant relationship between emotional intelligence and patient safety culture. Although their construct for patient safety culture differs slightly from Reason's (1997) theoretical model, the similarities between the two are significant.

Bisbey et al. (2019) studied various constructs that measure safety culture. Their findings provided evidence that psychological safety, which is a person's level of trust that they can be authentic and free to speak or act without the fear of retribution, enables a positive safety culture. Furthermore, Zhou et al. (2020) provided evidence that emotional intelligence positively influenced psychological safety. Together, these two studies make the connection between emotional intelligence and safety culture, moderated by psychological safety.

These studies provide evidence that emotional intelligence may positively influence the safety culture, and improvements in safety culture, especially in the dimensions of just and reporting cultures, can reduce human error. Although the scholarly body of knowledge is rich in information related to both emotional intelligence and safety culture, researchers are just recently beginning to explore the relationship between the two constructs. Furthermore, research on this relationship in the aviation industry is negligible in peer-reviewed journals, leaving aviation safety leaders with a lack of knowledge to effectively manage human error via enhancements in emotional intelligence and safety culture. My study was needed to provide aviation safety professionals with information related to emotional intelligence and safety culture that may reduce the likelihood of human error, incidents, and accidents.

Problem Statement

Human error is the leading cause of aircraft incidents and accidents (Erjavac et al., 2018). Scholarly research in the medical industry provides evidence that emotional intelligence improves safety culture (Rezaei & Salehi, 2018), and safety culture reduces human error (Fox et al., 2021). However, these relationships have not been explored adequately in aviation. Therefore, aviation safety managers have insufficient information to understand the relationship between emotional intelligence and safety culture in their industry and consequently lack essential knowledge to reduce human error. I addressed this gap by applying scientifically grounded methods and instruments to measure emotional intelligence and safety culture among aviation organizations and determined the degree to which meaningful relationships exist. The results may benefit the aviation industry by enhancing knowledge to improve workplace conditions and culture, reduce human error, and potentially prevent tragic accidents.

Purpose of the Study

The purpose of this quantitative descriptive correlational study was to explore the relationship between emotional intelligence, the independent variable, and safety culture, the dependent variable, among professionals in the business aviation industry. In addition to the aggregate measure of safety culture, I tested the degree to which emotional intelligence is related to each of the seven subcultures of safety culture described by Wang and Sun (2014). I also considered the moderating effect of demographic variables on the relationship between emotional intelligence and safety culture.

The primary independent variable was emotional intelligence (X_{EI}). I also examined demographic attributes as independent variables to include age (X_A), gender (X_G), job position (X_J), and how many years they have been with the company (X_Y). The influence of the primary independent variable was postulated to be moderated by demographic variables.

The primary dependent variable, safety culture (Y_{SC}), was an aggregate measure quantified by the integrated safety culture model (ISCM; Wang & Sun, 2014). Safety culture comprises seven subscales, measuring more specific attributes of safety culture that were additional dependent variables in my analysis. These included priority culture (Y_P), standardizing culture (Y_S), flexible culture (Y_F), learning culture (Y_L), teamwork culture (Y_T), reporting culture (Y_R), and just culture (Y_J). Each of these subcultures is described in detail in Chapter 2.

Research Question and Hypotheses

The research question was, To what extent is there a relationship between emotional intelligence and the safety culture in the business aviation industry? For each of the eight dependent variables (measures of safety culture), the null hypothesis was that there is no relationship between any of the independent variables (emotional intelligence and four demographic variables) and safety culture. The alternate hypothesis was that there is a relationship between at least one of the independent variables (emotional intelligence and demographic variables) and safety culture.

The null hypothesis claims that there is no relationship between any of the independent variables and the dependent variable. Said another way, if the change in the dependent variable associated with a one-unit change in the j^{th} independent variable is the regression coefficient, β_j, the hypothesis for each of the eight dependent variables is depicted mathematically as follows:

H_0: $\beta_1 = \beta_2 = \ldots = \beta_5 = 0$

H_A: at least one $\beta_j \neq 0$.

Theoretical Foundation

My study was grounded in two well-established theoretical models. Reason (1997) developed the organizational accident theoretical model. Reason hypothesized that serious incidents and accidents result from unsafe latent conditions that lie dormant in a system until an active condition, such as human error, triggers a series of events that lead to the undesired outcome. In this theoretical model, the organization's safety culture has a direct and positive influence on risk awareness and human behavior with the potential to reduce human error significantly.

Reason (1997) posited that a manager could engineer a resilient safety culture by nurturing four subcultures in their organization: *reporting culture*, *learning culture*, *flexible culture,* and *just culture*. The instrument used to measure safety culture in my research represents these subcultures plus three more, as enhanced by Wang and Sun (2014), including *teamwork culture*, *priority culture,* and *standardizing culture*. I describe the safety culture theoretical model in detail in Chapter 2.

Mayer et al. (2016) provided a theoretical model for emotional intelligence that includes four main components: perceiving emotions, facilitating thought using emotions, understanding emotions, and emotion management in oneself and others. They hypothesized that individual and team performance could be improved when people possess higher emotional intelligence levels. Furthermore, Hersing (2017) posited that emotional intelligence could reduce human error related to cognitive bias. I describe the emotional intelligence theoretical model in detail in Chapter 2.

Researchers have studied the relationship between emotional intelligence and safety culture in the health care industry (for example, du Pisanie & Dixon, 2018; Pan et al., 2018; Rezaei & Salehi, 2018). These studies provide evidence that emotional intelligence has the potential to positively influence safety culture. Furthermore, du Pisanie and Dixon (2018) provided evidence that safety culture positively correlates with human error.

Rezaei and Salehi (2018) provided evidence that teams perform better via improved team skills when they have higher levels of emotional intelligence. Furthermore, Jamshed and Majeed (2019) concluded that higher levels of emotional intelligence improved knowledge sharing (team learning) and team performance. Reason (1997) indicated that safety culture has several sub-dimensions, including a learning culture, and Wang and Sun (2014) described safety culture as having a teamwork subculture.

Nature of the Study

I employed a quantitative nonexperimental correlational approach to explore the relationship between emotional intelligence and safety culture among business aviation professionals. I applied multiple linear regression (MLR) to develop a predictive model for each dependent variable, tested the hypotheses, and addressed the research question. I tested my hypotheses with an *F* test of the regression model for the set of independent variables and a *t*-test of each independent variable. I employed other techniques to provide additional evidence, such as graphical analysis, descriptive statistics, and correlations, all of which were byproducts of my regression analysis.

I captured emotional intelligence data with the Workgroup Emotional Intelligence Profile – Short (WEIP-S; Jordan & Lawrence, 2009). The WEIP-S consists of 16 questions. I captured safety culture data via the Integrated Safety Culture Model (ISCM), which contains 32 elements. I collected the demographic data via a single online questionnaire, which incorporated the WEIP-S and ISCM. I employed MLR to explore the relationship between the primary dependent variable, aggregate measure for safety culture (Y_{SC}), and the five independent variables (X_{EI}, X_A, X_G, X_J, and X_Y). I also studied the relationship between the secondary dependent variables, sub-scales of safety culture (Y_P, Y_S, Y_F, Y_L, Y_T, Y_R, and Y_J), and the independent variables.

Definitions

Business aviation: A subset of general aviation and includes aircraft organizations that use aircraft to achieve their business objectives (National Business Aviation Association [NBAA], 2021).

Business aviation organization: Any organization that operates business aircraft and whose personnel typically include a mix of pilots, cabin crew (flight attendants), aircraft maintenance technicians, flight dispatchers/schedulers, and management personnel. These organizations operate on-demand, serving private (corporate and personal) and commercial (air charter) entities.

Emotional intelligence: The primary independent variable and measures "the ability to monitor one's own and others' feelings and emotions, to discriminate among them and to use this information to guide one's thinking and actions" (Salovey & Mayer, 1990, p. 189).

Flexible culture: A secondary dependent variable that measures the extent to which the organization is able to effectively manage safety risks during times of significant change in operations (Wang & Sun, 2014, p. 79).

General aviation: Consists of all aviation organizations other than scheduled commercial airline organizations and military flight organizations (NBAA, 2021).

International Air Transport Association (IATA): Headquartered in Montreal, Canada, it represents the airline industry worldwide. IATA members include approximately 290 airlines, which equates to roughly 82% of the global air traffic activity

(IATA, n.d.-a).

International Atomic Energy Agency (IAEA): A subsidiary of the United Nations, it is the world's principal intergovernmental council for the cooperative and peaceful use of nuclear energy.

International Business Aviation Council (IBAC): A non-profit organization that promotes business aviation around the world with 14 member associations that represent business aviation in their region of the world.

International Civil Aviation Organization (ICAO): A specialized agency under the United Nations with a mission to promote operational harmony and aviation safety around the world.

International Standard for Business Aircraft Operations (IS-BAO): An international standard for aircraft operators who operate business aircraft. An operator who conforms to this standard is eligible to be listed on IBAC's IS-BAO registry.

Just culture: A secondary dependent variable and measures the extent to which the safety management system operates "fairly for everyone . . . [and] most individuals within the organization feel satisfied about this (Wang & Sun, p. 79). It is also described as "the extent to which safe behavior and reporting of safety issues are encouraged or even rewarded, and unsafe behavior is discouraged" (Safety Management International Collaboration Group [SMICG], 2019a, p. 10).

Learning culture: A secondary dependent variable and measures the extent to which an organization exhibits "positive and supportive attitudes and behaviors to all kinds of learning, including education, training and self-learning” (Wang & Sun, 2014, p. 79).

National Business Aviation Association (NBAA): A non-profit organization with a mission to promote business aviation in the United States. The NBAA also promotes business aviation around the world by being the primary supporting member of the IBAC.

Organizational culture: It is “the reflection of shared behaviors, beliefs, attitudes and values regarding organizational goals, functions, and procedures” (Furnham & Gunter, 1993).

Priority culture: A secondary dependent variable and measures the extent to which “both organizations and individuals can consider safety issues as a priority when they make every decision and behavior in their workplace” (Wang & Sun, 2014, p. 79).

Reporting culture: A secondary dependent variable and measures the extent to which “organizations . . . actively gather and analyze all kinds of safety information and individuals . . . present a positive attitude and behavior in relation to reporting and communicating safety information (Wang & Sun, 2014, p. 79).

Safety culture: The primary dependent variable and measures an “assembly of characteristics, attitudes, and behaviors in individuals, organizations, and institutions which establishes that, as an overriding priority, protection, and safety issues receive the attention warranted by their significance (IAEA, n.d.).” Reason (1997, p.194) referred to the IAEA definition of safety culture for his research.

Safety Management International Collaboration Group (SMICG): A working group consisting of the ICAO and the national aviation authorities from the United States, Canada, Brazil, European Union, Australia, New Zealand, Singapore, Hong Kong, Japan, United Arab Emirates, and the United Kingdom. Their purpose is to promote a common understanding and facilitation of aviation safety management principles around the world.

Standardizing culture: A secondary dependent variable and measures the extent to which “organizational regulations, rules, and standards are complete, applicable and up to date; individuals also can comply with those regulations, rules, and standards completely” (Wang & Sun, 2014, p. 79).

Teamwork culture: A secondary dependent variable and measures the extent to which individuals behave with a trusting attitude and a spirit of cooperation . . . [toward] . . . their co-workers. They share knowledge and skills and [desire to] join in each other’s activities (Wang & Sun, 2014, p. 79).

Assumptions

Assumptions are aspects of my study that are believed but cannot be demonstrated to be true. Although scholarly studies provide evidence that patient safety culture reduces errors in the medical industry (Fox et al., 2021; Mardon et al., 2010), there is a lack of research that proves that a positive safety culture in aviation also produces the same benefits. Therefore, I assumed that a stronger safety culture in aviation organizations leads to less human error and fewer aircraft mishaps.

Scope and Delimitations

Many researchers have focused on safety culture for various high-reliability industries since the IAEA introduced the term following the 1986 Chernobyl accident, including nuclear power generation, health care, and aviation. But although the relationship between emotional intelligence and safety culture gains attention in the health care industry, similar exploration is relatively silent for the aviation industry, leaving aviation safety leaders with incomplete knowledge in this dimension, which is the driving force behind my study.

Reason (1997) postulated that nearly all accidents involve both the organization's influence (culture, principles, policies, processes, and procedures) and the individual's behavior (errors and violations). ICAO promotes Reason's theory, and aviation accident investigation experts worldwide identify human error as the leading root cause of most serious incidents and accidents (Erjavac et al., 2018) and often cite safety culture as contributory (Morcinek-Słota, 2019). My study focused on the error component of human performance only, reserving the opportunity to explore violation behavior in the future.

The population consists of aviation industry professionals. The target population is pilots, cabin crew (flight attendants), aircraft maintenance technicians, flight dispatchers/schedulers, and management personnel in the business aviation sector. I chose the business aviation domain for two reasons. First, this sector of aviation is under-studied compared to the scheduled airline industry. Second, due to my experience and networking, I have a robust contact list for marketing purposes, most of whom are business aviation professionals. I sampled from this target population, currently consisting of approximately 9,500 people.

I sent each contact an email that reflected the elements of the invitation letter (Appendix A). The contact list included pilots, cabin crew, aircraft maintenance technicians, flight dispatchers/schedulers, and management personnel over these functional areas. I excluded those who did not meet these criteria. The sample contact list represented professionals located in various regions around the globe. However, most contacts were in the United States, so the findings are more likely to be generalizable for business aircraft operators in the United States and in countries with national cultures similar to the United States, such as Canada and Europe. My study's results are not generalizable to military operations, scheduled airline operations, or non-Western cultures due to the potentially stark differences in managerial approaches influenced by national and corporate cultures.

Limitations

Ross and Bibler (2019) posited that many researchers slight the limitations of their study, leaving the research consumer without a complete picture of the risks related to the internal and external validity of the findings and conclusions. Therefore, the goal of describing the limitations associated with my study is to do so in such a complete way as to honor the academic community's need for full disclosure, which will aid in conveying the most accurate possible truths about the assumptions, methods, results, and the potential to generalize the findings. In the following sections, I highlight each potential weakness along with its implications. I then include alternatives to mitigate the risks related to these limitations.

Threat to Construct Validity

Scholars continue to debate both emotional intelligence and safety culture constructs. Researchers who disagree with Salovey and Mayer (1990) question the existence of emotional intelligence. Those who agree that it is a significant phenomenon disagree on its attributes and, therefore, how to measure it. Similarly, some researchers question the construct of safety culture and argue that it is merely organizational culture with features that enable behaviors that promote safety. In light of these debates, I mitigated these risks by utilizing questionnaires founded on widely respected research. Jordan and Lawrence (2009) designed the WEIP-S to reflect the theory of Salovey and Mayer (1990), as explained by Salovey (1997). Wang and Sun (2014) designed their safety culture instrument from the theory established by Dr. James Reason (1997), who is globally recognized as one of the most respected psychologists and safety theorists in the aviation community (ICAO, 2018).

Threat of Bias

I used convenience sampling (non-probability) versus probability sampling of the target population, resulting in selection bias (El-Masri, 2017). Therefore, the findings and conclusions may not represent business aircraft operators, since those who are associated with my contact list typically represent organizations that pursue and promote safety.

Self-selection bias was also a potential risk for my study. I sent the questionnaires to a wide variety of business aviation personnel. Thousands of people had the option to participate. Therefore, those who chose to participate versus those who did not may represent a proactive subculture within business aviation and not necessarily the whole. As a result, my study's findings may reflect the attitudes and culture of people who are more progressive than those who chose not to participate. To mitigate this, the questionnaires asked the participant's perceptions of their organizational (team) attitudes and behaviors versus self attributes. This approach was intended to normalize the responses to reflect the mindsets and actions of those who did not participate in the study as perceived by the participant.

Social-desirability bias may also have posed a risk for my study. This bias occurs when the participant is likely to respond to the questionnaire in a way that is, in their opinion, socially desirable versus the authentic response that should be indicated (Larson, 2018). To mitigate this risk, the WEIP-S asks the participant to provide their perspective on the team's emotional intelligence attributes versus their self-competence. The safety culture survey is designed for the participant to assess their organization versus self. Although the participant could possibly embellish their organization's actual behavior on either survey, the potential motivation to do this is much less than if they were providing an assessment of self.

Questionnaires

Another limitation of my study was that the Wang and Sun (2014) instrument is relatively new and not yet rigorously validated by other researchers. This threat was mitigated because Wang and Sun built their instrument on Reason's construct for safety culture, a paradigm that is widely promoted around the world by ICAO, third-party aviation safety audit companies, and national aviation regulatory authorities.

Other Challenges

Other challenges related to my study included the threat of not obtaining adequate questionnaire responses to ensure statistical power to support the findings and conclusions. Memon et al. (2020) provided many techniques to determine the number of participants required to ensure validity. Based on their recommendations, more than 100 participants would be required to attain sufficient statistical power. To mitigate this threat, I used G*Power (Faul et al., 2009) to calculate the minimum sample required to achieve the desired confidence, power, and effect size.

Significance of the Study

Significant to Theory

My study may uniquely contribute to aviation safety. A gap exists in the body of scholarly knowledge related to the potential influence of emotional intelligence on an aviation organization's safety culture. I explored the degree to which this relationship exists, and I hypothesized that emotional intelligence significantly influences safety culture.

Significance to Practice

My study's findings may provide aviation safety leaders with practical knowledge about the relationship between emotional intelligence and safety culture. Evidence derived from my study could be adapted to integrate emotional intelligence assessments into personnel recruitment processes. My study's findings may also improve employees' training programs to improve safety culture and human error management.

Significance to Social Change

This research may provide aviation safety managers with information to support prudent decisions related to managing human error, the primary cause of incidents and accidents in the aviation industry. As a result, this research may contribute to healthier organizational cultures, lower error rates, lower incident rates, and less risk to the general population.

Summary and Transition

I conducted this research to explore the relationship between emotional intelligence and safety culture in business aviation. Although prior research provides evidence that a positive safety culture is required to reduce human error in the medical industry (du Pisanie & Dixon, 2018), human error remains the prominent causal factor in serious aviation incidents and accidents worldwide (Kharoufah et al., 2018).

Although countless researchers have rigorously studied safety culture in the aviation industry, scholars have not sufficiently investigated the value of emotional intelligence in aviation. Furthermore, other high-reliability industries, such as health care, have studied the relationship between emotional intelligence and safety culture. Their findings indicate a direct and positive correlation between the two variables (Pan et al., 2018; Rezaei & Salehi, 2018).

Although the operational constructs of safety culture in the health care and aviation industries are different, the underlying principles are similar (i.e., managers influence organizational factors that influence human behavior). As the health care industry benefits from its increased knowledge about the relationship between these constructs, the aviation community remains uninformed about the potential relationship between emotional intelligence and safety culture.

In the following chapter, both constructs are examined thoroughly, along with their potential influence on human performance. I elaborate on Reason's (1997) theoretical model to validate the safety culture assessment design. I also describe the Salovey and Mayer (1990) theoretical model to validate the emotional intelligence questionnaire.

Chapter 2: Literature Review

The current body of knowledge provides evidence of the connections between emotional intelligence and safety culture, and the latter's positive effect on reducing human error in the medical industry (see, for example, Fox et al., 2021; Mardon et al., 2010). However, there is limited information in the body of scholarly knowledge about the relationship between emotional intelligence and safety culture in the aviation industry. The purpose of this quantitative descriptive correlational study was to explore the relationship between emotional intelligence, the independent variable, and safety culture, the dependent variable, among professionals in the business aviation industry. My research provides information to benefit aviation managers by enhancing their understanding of the relationship between emotional intelligence and safety culture in aviation, with the intent to provide safety leaders with the increased knowledge to improve effectiveness in human error management to reduce the likelihood of incidents and accidents.

In this chapter, I describe my literature search method. This strategy enabled the effective capture of pertinent peer-reviewed scholarly documents. The search also provided evidence of the gap in the scholarly body of knowledge, which provided the primary justification for my study. I then outline the theoretical foundation of safety culture, followed by a detailed and comprehensive literature review of this construct and emotional intelligence. In the conclusion of this chapter, I provide a summary that highlights the connection between these frameworks, supporting further study to fill the gap in aviation safety knowledge.

Literature Search Strategy

To ensure a thorough literature review, I searched peer-reviewed articles and seminal work on both emotional intelligence and aviation safety culture. My search of journal articles included the following terms: *emotional intelligence*, *emotional competence*, *organizational culture*, *safety culture*, *aviation*, *human performance*, *human error*, and *accident causation*. Furthermore, I used the following combinations of terms to improve the search results for articles that related to both emotional intelligence and safety culture: *emotional intelligence* and *safety culture*, or *emotional intelligence* and *organizational culture.* I used online SAGE Journals, Thoreau multi-database, and Google Scholar as primary search engines. I focused my search on the years 2016 to current, except for seminal works, which dated back to the early 20th century.

The search revealed a lack of adequate research regarding the relationship between emotional intelligence and safety culture in the field of aviation. Furthermore, although research exists in other industries to connect these two constructs, peer-reviewed information is limited and primarily exists in the health care industry. The articles provided a background on the concepts of and the relationship between emotional intelligence and safety culture. They also provided a foundation to support research to enhance the scholarly body of knowledge for the practical benefit of aviation managers who aspire to improve safety culture and reduce human error.

Theoretical Foundation

Reason (1997) posited that managers could engineer a safety culture into an organization. He theorized that safety culture consists of at least four subcultures. Of all the subcultures in his model, *just culture* appeared to be the most essential, where people can report safety issues without the fear of retribution (Provan et al., 2020, p. 6; Reason, 1997, p. 195; Wang, 2018, p. 110). Furthermore, a just culture allows people to self-report their mistakes without being punished unless their actions are proven to be a gross violation of company values or principles.

Once managers and leaders ensure a just culture, the organization can progress to the next level of safety culture, a *reporting culture*. A reporting culture promotes reporting minor errors and mistakes (Reason, 1997, p. 195; Wang, 2018, p. 106; Woodlock & Hydén, 2020, p. 58). This subculture also rewards people for reporting, underscoring the value of information to prevent human error. In this paradigm, managers passionately seek information from all employees by building flexible ways to report safety issues, leading to a *flexible culture* (Gilbert et al., 2018, p. 50; Reason, 1997, p. 213; Wang, 2018, p. 106).

Reason (1997, p. 218), along with other researchers (Gilbert et al., 2018, p. 76; Wang, 2018, p. 107), claimed that a safety culture must include a *learning culture* where all personnel can learn from lessons derived from robust reporting of safety issues, both inside and outside the organization. This part of the model assumes a transparent and effective communication system in the organization. Lastly, Reason asserted that organizations with an *informed culture* have a safety culture, which assumes that every person in the company has the knowledge they need to make prudent decisions and take effective action. In an informed culture, everyone is entirely aware of the factors that affect safety in their organization and industry.

I chose this model because it is cited by federal authorities and international associations (Air Safety Support International [ASSI], n.d.-b; Civil Aviation Navigation Services Organization, 2008; Federal Aviation Administration [FAA], 2015; IATA, n.d.-b) as the primary framework for understanding safety culture. My study builds on this theory by applying the ISCM, which adds teamwork culture, standardizing culture, and priority culture.

Literature Review

In this section, I present a critical review of previous research related to the social issue that underlies my research: Human error remains the leading cause of aviation incidents and accidents worldwide (Erjavac et al., 2018; Kelly & Efthymiou, 2019; Kharoufah et al., 2018). Although ensuring a positive safety culture can reduce human error in an organization (Cakıt et al., 2019), the way in which safety culture is analyzed and managed in aviation currently lacks emotional intelligence considerations, a variable asserted to reduce human error in aviation (Hersing, 2017) and the health care industry (Jamshed & Majeed, 2019) and improve safety culture in the health care industry (Rezaei & Salehi, 2018). Both concepts are relatively new to the world of management, with the term *safety culture* entering into academic discussions in 1991 (Hasan & Younos, 2020;

IAEA, 2016; Robertson, 2018) and emotional intelligence in 1990 (Fotopoulou et al., 2021; Kanesan & Fauzan, 2019; O'Connor et al., 2019). Since its inception, safety culture has been studied by researchers worldwide with the goal of reducing human error in high-risk industries to include nuclear energy and health care (Cakıt et al., 2019; du Pisanie & Dixon, 2018; IAEA, 2016).

Safety Culture

In this section, I present a brief history of the introduction of the concept of safety culture. I follow with insight into an ontological view of the phenomenon. I then present Reason's (1997) theoretical model, which was the first to be operationalized for the global aviation industry. I conclude this section by presenting an enhanced model of Reason's construct and supporting why I chose this model to conduct my study.

Historical Timeline for the Introduction of Safety Culture

Researchers have agreed that the IAEA first introduced and defined the concept of safety culture in the aftermath of the 1986 Chernobyl disaster (see, for example, Gilbert et al., 2018; Hasan & Younos, 2020; Lawrenson & Braithwaite, 2018). The International Nuclear Safety Advisory Group, a subgroup of the IAEA, coined safety culture in their first published summary report of the notorious nuclear accident:

> The vital conclusion drawn is the importance of placing complete authority and responsibility for the safety of the plant on a senior member of the operational staff of the plant. Formal procedures, adequately reviewed and approved, must be

supplemented by the creation and maintenance of a nuclear safety culture. (IAEA, 1986, p. 77)

In 1988, the IAEA further elaborated on the concept of safety culture in a formal report that described the basic safety principles for nuclear power plants. The agency contended, “Safety culture refers to a very general matter, the personal dedication and accountability of all individuals engaged in any activity which has a bearing on the safety of nuclear power plants” (IAEA, 1988, p. 10). However, the IAEA did not develop a formal definition until 1991, when it published a report entirely dedicated to studying safety culture. They defined the term as “that assembly of characteristics and attitudes in organizations and individuals which establishes that, as an overriding priority, nuclear plant safety issues receive the attention warranted by their significance” (IAEA, 1991, p. 4).

Since IAEA’s 1991 definition, various entities, industry leaders, and researchers re-defined and re-modeled the construct of safety culture in ways to fit their needs. After 30 years of research and practical application of safety culture, no single universal definition or model exists for this critical concept (Gilbert et al., 2018; Lawrenson & Braithwaite, 2018). Furthermore, the IAEA evolved its definition of safety culture in 2016 when it replaced the phrase “nuclear power plant safety issues” with “protection and safety issues” (IAEA, 2016, p. 7). With this change, the definition could be applied throughout the industry and likely other industries as a model, not just nuclear power plants.

When Reason (1997) developed his theoretical model of safety culture, he anchored it to the UK Health and Safety Commission's definition: "the product of individual and group values, attitudes, competencies, and patterns of behavior that determine the commitment to, and the style and proficiency of, an organization's health and safety programs" (UK Health and Safety Commission, 1993, as cited in Reason, 1997, p. 194). Reason stated that "Organizations with a positive safety culture are characterized by communications founded on mutual trust, by shared perceptions of the importance of safety, and by confidence in the efficacy of preventive measure" (p. 194).

Safety Culture: An Ontological View

To understand what safety culture is, I searched for widely accepted definitions of safety, culture, and safety culture. This effort revealed that the definition of safety varies among researchers and safety experts (Gilbert et al., 2018; Provan et al., 2020; Schulman, 2020). Likewise, researchers debate the definition of culture (Gilbert et al., 2018; Mironenko & Sorokin, 2018; Schulman, 2020). Predictably, researchers also disagree on a definition of safety culture (Bisbey et al., 2019; Schöbel et al., 2017; Schulman, 2020).

Needing to ground my research to a commonly accepted definition of safety culture in the aviation industry, I reviewed the guidance provided by the Safety Management International Collaboration Group (SMICG, a respected industry body of aviation safety representatives from ICAO and national aviation authorities worldwide, who defined safety culture as "the set of enduring values, behaviors and attitudes regarding safety, shared by every member at every level of an organization" (SMICG, 2019a, p. 9). However, even after accepting and applying a reasonable definition of safety culture, the theoretical concept remains vague and a point of contention in the scientific and scholarly community (Bisbey et al., 2019; Gilbert et al., 2018; Schöbel et al., 2017). Furthermore, many researchers consider safety culture within the broader organizational culture construct (Reason, 1997; Schulman, 2020; Silla et al., 2017; Wang, 2018), leading to the need to understand and define that concept.

Theories about organizational group norms began to appear in scientific articles circa 1920 (Schein, 1990). However, the scientific study of organizational culture was first published by Dr. Elliot Jaques in 1951 (Kassem et al., 2019, p. 119). This researcher concluded that to achieve desired individual and team performance, the social network of an organization was just as important as the organizational structure, including resources, policies, processes, and procedures (Jaques, 1951). Jaques explained that as people develop throughout their lifetime, they typically develop assumptions, values, and beliefs about the world they live in to include society and relationships with other people. He posited that if these assumptions, values, and beliefs are counter to the organization's culture (the customary way of thinking and behaving by virtually everyone in the organization), then they will need to adapt or risk poor relationships with others in the organization. Jaques asserted that the performance of the organization was highly dependent on the relationships among the people in the organization (Jaques, 1951, p. 251). Reason (1997) claimed that the discussion around organizational culture among scholars and practitioners proliferated in the 1980s after the publication of two popular books on the topic, *Corporate Culture* (Deal & Kennedy, 1982) and *In Search of Excellence* (Peters & Waterman, 1982).

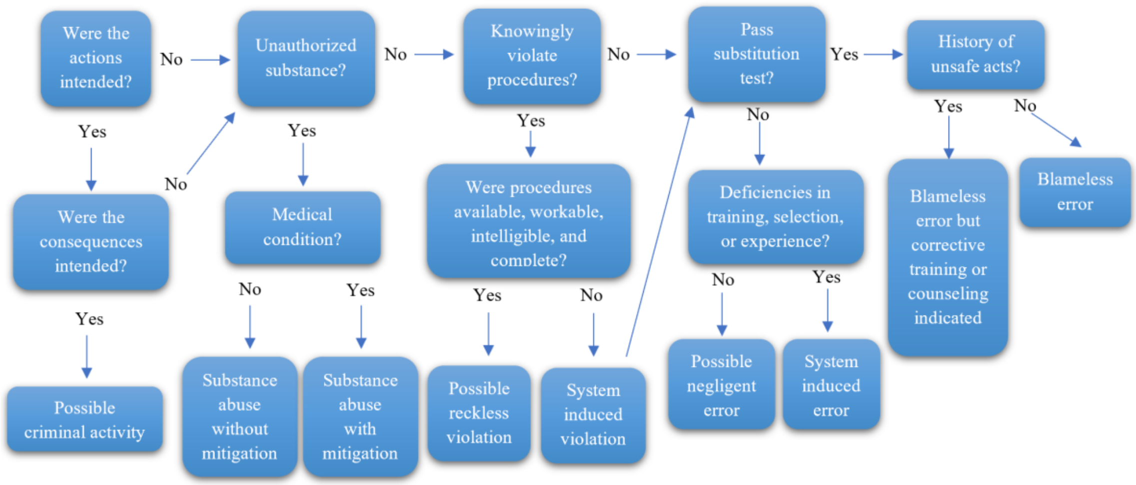
The theories and models related to organizational culture are as diverse as those for safety culture. Therefore, I do not elaborate on organizational culture as that effort does not serve the purpose of answering the research question. However, it is essential to note that Reason (1997) implied that safety culture was a type of organizational culture when he indicated that company personnel need to perceive the organizational culture as *just* (p. 212). He promoted the idea that leaders can engineer a just culture, which is a subculture of a safety culture, under his theoretical framework.

Reason's Safety Culture Model

Reason (1997) asserted that safety culture consisted of four subcultures. An organization must have a just culture to ensure company personnel feel safe to report safety issues. Under the just culture concept, the company does not seek blame for errors, violations, or unsafe events unless the person's intentions were to bring harm to the organization or their behavior exemplified a gross violation of regulations or company policy. In a just culture, the managers of the organization seek to understand why the error, violation, or unsafe event occurred and work systematically to ensure that it does not happen again. Reason provided a blueprint to engineer a just culture with a flowchart (Figure 1) that served as a decision tree for determining culpability, if any, of unsafe acts (p. 208).

Figure 1

Decision Tree to Determine the Culpability of Unsafe Acts



Note. Unsafe acts should be considered blameless errors, system-induced errors, or system-induced violations unless the evidence indicates clear negligence. Adapted from *Managing the Risks of Organizational Accidents*, by J. Reason, 1997, p. 208, Ashgate Publishing.

To have a safety culture, the organization must also have a reporting culture. The reporting culture depends on having a just culture, so people feel safe to report issues without being punished or experiencing negative outcomes to their careers or relationships with their peers. A reporting culture requires all personnel to participate in identifying not only unsafe events that have already happened but also potential unsafe acts or events that could happen based on their observations, experience, and professional judgment.

Reason (1997) also posited that a safety culture must have the characteristics of a flexible culture, which enables the organization to operate effectively while reporting unsafe acts and unsafe events in any mode of operation, including high operations tempo, low operations tempo, normal operations, even during abnormal and emergency operations. Finally, Reason (1997) asserted that an organization must develop a learning culture to ensure a safety culture. The organization must learn from lessons based on both internal reporting and information sharing as well as from outside sources such as other organizations, manufacturers, regulatory authorities, and industry associations.

Respected aviation safety agencies in the United States, Europe, Australia, Canada, and various other parts of the world refer to Reason's (1997) safety culture model in their guidance materials. For example, the ASSI is a not-for-profit subsidiary organization of the UK Civil Aviation Authority with the responsibility to manage the United Kingdom Overseas Territories (ASSI, n.d.-a). ASSI promotes Reason's safety culture model internationally among all the overseas territories they have authority over (ASSI, n.d.-b). The Australian Government Civil Aviation Authority provides training materials related to a safety culture that applies Reason's model consisting of four subcultures (Australian Government Civil Aviation Safety Authority, 2019, p. 21). The IATA also promotes safety culture among its members utilizing Reason's model with four subcultures, offering a 60-question survey that provides insight into cultural gaps compared to industry expectations (IATA, n.d.-b). The FAA implies Reason's (1997) model in their guidance to aviation safety managers on implementing a safety management system for all aviation service providers (FAA, 2015). Although the FAA does not explicitly cite Reason or follow his model rigidly, they indicate all the subcultures in various ways to represent a safety culture. Finally, the SMICG (2019a) developed a tool for evaluating safety culture. This instrument is recognized and respected worldwide by aviation safety regulators. However, the SMICG did not explicitly cite Reason in their document, nor are Reason's subcultures easily identifiable among the six characteristics of a safety culture according to the SMICG.

Although the SMICG safety culture evaluation tool is vaguely grounded in Reason's (1997) model, three documents provide evidence that they are connected. First, the 2017 SMICG pamphlet about safety culture explicitly lists Reason's (1997) subcultures next to SMICG's six characteristics (SMICG, 2017). Also, the SMICG developed an organizational culture assessment tool for regulatory agencies to assess themselves. Although this tool does not measure safety culture per se, the six characteristics in the tool to evaluate organizational culture for regulatory organizations are the same as the SMICG tool for evaluating safety cultures for aviation service providers, i.e., *commitment, justness, information, awareness, adaptability, and behavior* (SMICG, 2019a; 2019b).

Furthermore, the SMICG (2019b, p. 8) document for evaluating the organizational culture in regulatory agencies gives credit to the European Commercial Aviation Safety Team (ECAST) for the development of the six characteristics. Finally, the ECAST provides evidence of connecting their six characteristics of safety culture (used by both SMICG cultural assessment tools) to Reason's (1997) theoretical model. The ECAST guidance states, "This safety culture framework is based on a synthesis of various studies . . . inspired on the work of James Reason" (Piers et al., 2009, p. 14). Furthermore, Piers et al. (2009) connected three of ECAST's six domains (adaptability, justness, information) to Reason's model elements (just, flexible, learning, informed) to verify the connections between Reason's model and their model. Therefore, there are many nodes of connectivity between the Reason model and the present safety culture assessments.

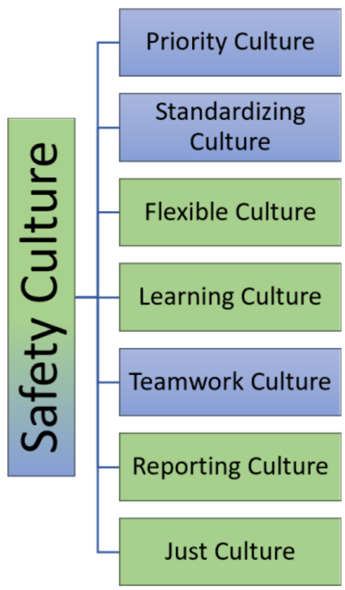
Integrated Safety Culture Model

Wang and Sun (2014) added three subcultures to Reason's model. First, they added a *priority culture,* which means that all organization personnel value safety in all their decisions. Second, they added a *standardizing culture*, which means all company instructions (policies, processes, and procedures) are up-to-date, and well-designed so every person can reasonably apply them without difficulty. This subculture also assumes that everyone competently applies all instructions every day, with only minor and reasonable deviations. Finally, Wang and Sun added the *teamwork culture,* where everyone in the organization works effectively together to achieve common goals. This last subculture assumes trust and cooperation exist among all its members. Figure 2 represents this enhanced safety culture indicating Reason's subcultures in green with Wang and Sun's blue additions.

Wang and Sun (2014) further developed the safety culture model to provide managers with a sophisticated perspective, providing a pathway for creating a safety culture that begins with a *safety philosophy*. The researchers contended that safety philosophy was a product of shared attitudes, beliefs, and values related to safety and represents the *intrinsic* attribute of safety culture.

Figure 2

Reason's Safety Culture Model Enhanced by Wang and Sun

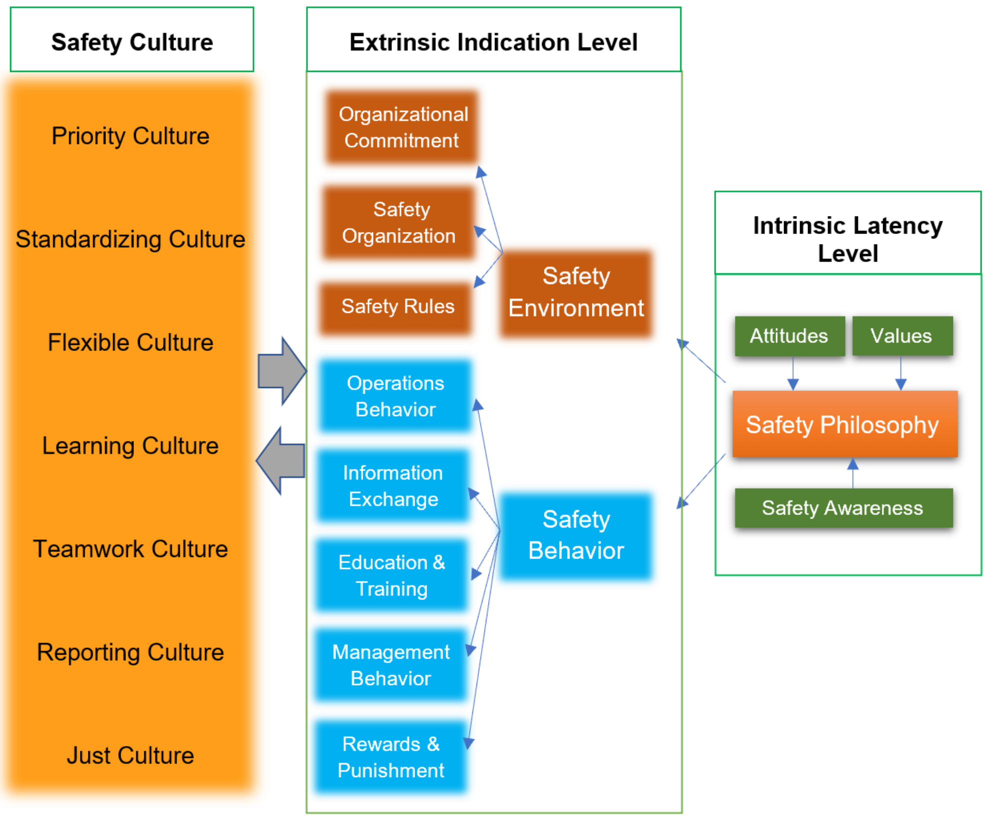


Note. Reason's (1997) safety culture elements are in green. Wang and Sun's (2014) additional elements in blue. Adapted from "A New Safety Culture Measurement Tool and its Application," by L. Wang and R. Sun, 2014, *International Journal of Safety and Security Engineering*, *4*(1), p. 79 https://doi.org/10.2495/safe-v4-n1-77-86.

Wang and Sun also reasoned that managers could develop extrinsic elements with a safety culture, including a *safety environment* and *safety behavior*. They asserted that safety behavior included operational behavior, information exchange, education, training, management behavior, rewards, and punishment. In contrast, the safety environment included leadership’s commitment, organizational structure, resources, and rules. Figure 3 depicts their comprehensive framework, the *Integrated Safety Culture Model (ISCM)*. The ISCM connects the intrinsic and extrinsic elements that make up an organization’s safety culture.

Figure 3

Integrated Safety Culture Model



Note. Adapted from "A New Safety Culture Measurement Tool and its Application," by L. Wang and R. Sun, 2014, *International Journal of Safety and Security Engineering*, *4*(1), p. 79 https://doi.org/10.2495/safe-v4-n1-77-86.

Reason for Selecting ISCM

To conduct my study, I selected the Wang and Sun (2014) ISCM for several reasons. First, they built their model on Reason's (1997) theory for safety culture, which is recognized, respected, and applied worldwide. Second, Wang and Sun (2014) added the sub-element *Teamwork*, which logically links to emotional intelligence, an essential element in effective teamwork (Jamshed & Majeed, 2019; Kanesan & Fauzan, 2019; Zhou et al., 2020). Furthermore, Wang and Sun (2014) developed an instrument to measure safety culture based on their model. This tool has only 32 elements, which is a good fit for my study. Wang and Sun administered this tool to an airline company in Europe. The outcome provided evidence of the instrument's effectiveness (Wang & Sun, 2014).

Operationalizing the ISCM

I evaluated the relationship between the aggregate scores for emotional intelligence and safety culture. Additionally, for more specific exploration, I assessed the relationship between emotional intelligence and each of the seven sub-elements of safety culture. Research indicates that enhanced emotional intelligence improves problem-solving (see, for example, Hersing, 2017; Mayer et al., 2016), as well as other research that shows a positive correlation between emotional intelligence and team success (for example, Rezvani et al., 2019; Stephens & Carmeli, 2016; Zhou et al., 2020). Wang and Sun (2014) posited that safety culture has several subcultures, including teamwork culture. My theoretical foundation connects emotional intelligence to the teamwork culture.

Emotional Intelligence

In this section, I present a brief history and introduction to the concept of emotional intelligence. I follow with insight into an ontological view of the phenomenon.

I then present Salovey and Mayer's (1990) theoretical model, widely respected as the theory's first scientific construct. I conclude this section by presenting an enhanced model of Mayer and Salovey's model and supporting why I chose this framework to conduct my study.

Historical Timeline of Emotional Intelligence

Researchers (for example, Hersing, 2017; Jan et al., 2017; Kanesan & Fauzan, 2019) connect emotional intelligence to the published work of Thorndike (1920) on the concept of *social intelligence*. Thorndike theorized that abilities to understand and manage others in human relationships (social intelligence) is just as important as cognitive intelligence. After Thorndike's publication, various researchers included social intelligence in their research (Kanesan & Fauzan, 2019; Oyewunmi, 2018). However, scholars widely credit Salovey and Mayer (1990) for developing the first theoretical model of emotional intelligence (Fotopoulou et al., 2021; Kanesan & Fauzan, 2019; Oyewunmi, 2018).

Ontological View of Emotional Intelligence

Researchers debate what emotional intelligence is, how to operationalize it, and measure it (Fotopoulou et al., 2021; Kanesan & Fauzan, 2019; Oyewunmi, 2018). This is not surprising since scholars cannot even agree upon the definitions for emotion or intelligence (Burić et al., 2017; Corazza & Lubart, 2020). Regardless of all the debate, countless researchers have studied emotional intelligence with vigor to ascertain this psychological phenomenon's theoretical and practical applications for the past three decades.

Some scholars and researchers consider emotional intelligence a useless pursuit and void of meaningful specificity beyond other psychology measures (Oyewunmi, 2018). Those who agree that it is a significant and discrete concept disagree on its fundamental perspective, i.e., trait versus ability (Fotopoulou et al., 2021).

Thorndike (1920) promoted the concept that intelligence can be measured just as we measure variables in the physical earth sciences. His works far exceeded academia's bounds and were employed in the industry, including the world of aviation, regarding his *laws of learning* (FAA, 2020; Gates, 1949). Thorndike (1920) was also the first researcher to stratify intelligence into discrete domains, including social intelligence.

Thorndike (1920) argued that each person has at least three forms of intelligence. He identified *mechanical intelligence* as a person’s ability to understand and solve problems related to the physical world, such as machines, terrain, or bodies of water. He further contended that *abstract intelligence* was a person’s ability to understand and manage ideas related to concepts and symbols such as mathematics, legal problems, and scientific laws. Finally, Thorndike asserted that a person’s *social intelligence* was their ability “to understand and manage men and women, boys and girls to act wisely in human relations” (p, 228).

Robert Thorndike, a second-generation psychologist and professor at Columbia University like his father, Edward (Cronbach, 1992), determined that there were not suitable methods to measure social intelligence (Thorndike & Stein, 1937). Furthermore, Wechsler (1943) asserted that total intelligence could not be measured until future tests included non-intellective factors. He observed certain groups of people (neurotics) who possessed relatively high intellectual scores performed poorly in managing their environment to include other people. In contrast, another group (psychopaths) possessed relatively lower intellectual scores yet skillfully managed and manipulated other people with non-intellectual skills.

Bossom and Maslow (1957) conducted a study to see if a judge's insecurity level could influence the judge's perception of another person's emotional state. They concluded that judges with higher insecurity levels perceived others as cold more often than more secure judges. Furthermore, Maslow and Mittelmann (1958) surmised that potential emotional responses could be repressed and remain in a latent state until a stimulus is encountered that sparked the repressed emotional condition. Their research supported the importance of emotional control for developing and maintaining successful relationships while suggesting that *emotional resilience could be improved*.

Gardner (1983) asserted that general intelligence was too narrow a view of the complexity of a human being and published his theory of multiple intelligences. He considered other forms of intelligence, such as linguistic and interpersonal skills, equal to scholastic intelligence.

Although Payne (1985) coined the term *emotional intelligence* in his copyrighted doctoral dissertation, Salovey and Mayer (1990) were the first to publish a peer-reviewed definition and theoretical construct of emotional intelligence (Ackley, 2016; Fotopoulou et al., 2021; Jan et al., 2017). Many researchers have investigated various ways to understand this phenomenon in the years that followed, resulting in disparate views and opposing constructs. Eventually, three primary constructs evolved, including the *ability model*, *trait model*, and *mixed model* (Fotopoulou et al., 2021; Haleem & Ur Rahman, 2018; Jan et al., 2017).

Ability Model

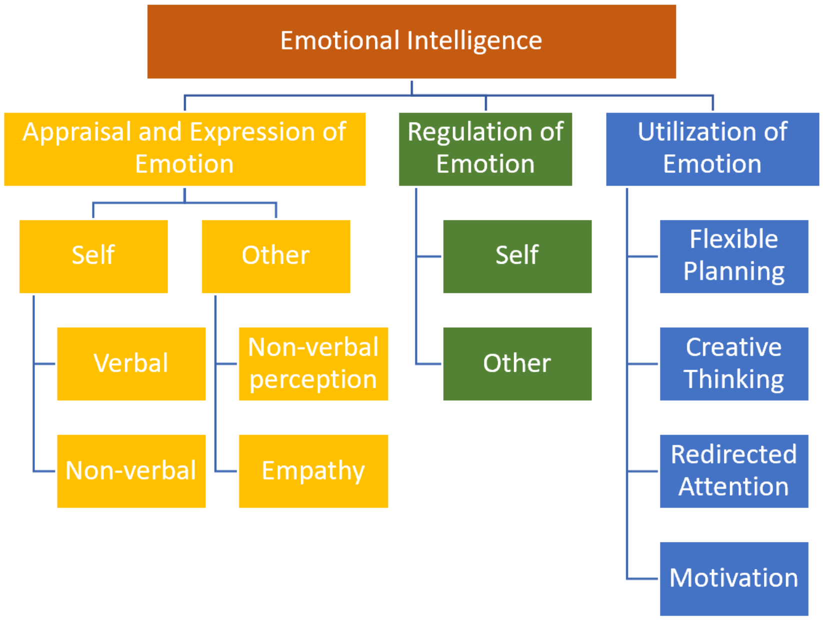
Salovey and Mayer (1990), in their seminal article, *Emotional Intelligence*, provided a historical backdrop that indicated that many researchers considered emotion as a disturbance in the human psyche that worked in opposition to intelligence. Conversely, they also provided support for a functionalist perspective of emotion (Leeper, 1948). In this view, emotion is seen as an organizing agent to motivate the human to take focused action to achieve a potentially critical objective, a possible strength for survival.

By anchoring their assumptions of emotion to Leeper's philosophy, these ground-breaking researchers defined emotion as "organized responses, crossing the boundaries of many psychological subsystems, including the physiological, cognitive, motivational, and experiential systems" (Salovey & Mayer, 1990, p. 186). Furthermore, they concurred with Wechsler's definition of intelligence as "the aggregate or global capacity of the individual to act purposefully, think rationally, and deal effectively with his environment" (Salovey & Mayer, 1990, p. 186; Wechsler, 1958, p. 7). This broad definition encompassed many of the theories related to the phenomenon: social intelligence, verbal expression, and spatial reasoning, enabling wider acceptance of Salovey and Mayer's methods and findings.

With these fundamental assumptions, Salovey and Mayer (1990) defined emotional intelligence as "the ability to monitor one's own and others' feelings and emotions, to discriminate among them, and to use this information to guide one's thinking and actions" (Salovey & Mayer, 1990, p. 189). Their initial theoretical model was built on this definition and is illustrated in Figure 4. It includes the adaptive ability of a person to appraise and express the emotional signals present in the situation, manage those emotions in oneself and others, and use these emotional states to plan, innovate, motivate, and redirect focus.

Figure 4

Early Theoretical Construct of Emotional Intelligence



Note. Adapted from "Emotional Intelligence," by P. Salovey and J.D. Mayer, 1990, *Imagination, Cognition and Personality*, *9*(3), p. 190 https://doi.org/10.2190/dugg-p24e-52wk-6cdg.

The ability model consists of four capabilities beginning from the very basic to the more sophisticated (Mayer et al., 2016). The first skill is perceiving emotions. The second level of capability deals with facilitating thought using emotions. An example of this would be when a person focuses their attention and risk analysis based on a feeling. The next level of ability relates to understanding emotions. For instance, a person with this skill can forecast an emotion under specific conditions (i.e., an emotional response to a change in work schedule that is undesirable). Finally, managing emotions deals with regulating one's own emotions and influencing others' emotions to achieve the desired outcome. People who succeed at this highest level can embrace an emotion or disengage based on its utility (Kanesan & Fauzan, 2019).

Updated Ability Model

Mayer et al. (2016) updated their theoretical model based on seven principles, the primary being that emotional intelligence is a mental ability (Mayer et al., 2016) versus a personality trait. They compared the phenomenon with social intelligence and personal intelligence, positing that all three types of intelligence deal with understanding human biosocial needs and their dealings in social settings. For this comparative endeavor, Mayer et al. provided a brief working definition of emotional intelligence as "the ability to reason validly with emotions and with emotion-related information and to use emotions to enhance thought" (p. 295). Their updated four-branch model is depicted in Table 1. I expand on each of the four branches in the following paragraphs.

Perceiving emotion consists of several capabilities. These include recognizing emotion in oneself and others. Furthermore, this skill requires the individual to perceive emotional content in the environment, such as art or music. More deft capabilities in this domain include discriminating between accurate and inaccurate emotional expressions and identifying deception or fraudulent emotional expressions.

Table 1

The Four-Branch Model of Emotional Intelligence

Four Branches	Types of Reasoning
Managing emotions	• Effectively manage others' emotions to achieve a desired outcome • Effectively manage one's own emotions to achieve a desired outcome • Evaluate strategies to maintain, reduce, or intensify emotional response • Monitor emotional reactions to determine their reasonableness • Engage with emotions if they are helpful; disengage if not • Stay open to feelings, as needed, and to the information they convey
Understanding emotions	• Recognize cultural differences in the evaluation of emotions • Understand how a person might feel in the future (affective forecasting) • Recognize likely transitions among emotions (i.e., anger to satisfaction) • Understand complex and mixed emotions • Differentiate between moods and emotions • Appraise the situations that are likely to elicit emotions • Determine the antecedents, meanings, and consequences of emotions • Label emotions and recognize relations among them
Facilitating thought	• Select problems based on emotional state to facilitate cognition • Leverage mood swings to generate different cognitive perspectives • Prioritize thinking by directing attention according to present feeling • Generate emotions as a means to relate to the experiences of another person • Generate emotions as an aid to judgment and memory
Perceiving emotion	• Identify deceptive or dishonest emotional expressions • Discriminate accurate vs. inaccurate emotional expressions • Understand how emotions are displayed depending on context or culture • Express emotions accurately when desired • Perceive emotional content in the environment, visual arts, and music • Perceive emotions in other people • Identify emotions in one's own physical states, feelings, and thoughts

Note. Adapted from "The Ability Model of Emotional Intelligence: Principles and Updates," by J.D. Mayer, D.R. Caruso, and P. Salovey, 2016, *Emotion Review*, *8*(4), p. 290 https://doi.org/10.1177/1754073916639667.

Facilitating thought using emotion consists of various skills, including emotions, to assist in judgment and recall. Furthermore, a person might produce emotion to connect to another person or re-prioritize their thinking and refocus their attention based on how they feel. People skilled in this domain can even use emotional state changes to gain different cognitive perspectives and select problems about how well their emotional state enables and enhances their cognitive state.

Understanding emotions consist of being able to categorize and synthesize emotions based on their relationship. For example, fear, anger, and disgust are negative emotions, while happiness, serenity, and joy are positive. In this domain, the person is assessed to determine the degree to which they can determine precursors to emotional states' possible consequences. Adroit individuals in this domain can understand complex and mixed emotional signals, accurately anticipate transitions from one emotional state to another, and even forecast others’ feelings under specific conditions. Finally, those who are skilled in this realm can understand how culture affects the assessment of emotion.

Managing emotions is arguably the most observable skill in the practical sense since the preceding three branches are all cognitive. This element's objective is to effectively manage one’s own and others’ emotions to achieve the desired conclusion. In this dimension, a skilled person can remain open to experiencing all feelings to capture important information about a situation. However, they are also able to disengage with emotion if it is not helpful. Furthermore, those who master this component can accurately determine the reasonableness of others' reactions to stimuli and consider, evaluate, and implement tactics to maintain, reduce, or increase the emotional state.

The ability model is widely supported and promoted by the research community because it approaches the phenomenon purely as a type of intelligence, i.e., cognitive processes to solve problems in the emotional domain (Jan et al., 2017; Kanesan & Fauzan, 2019; Mayer et al., 2016). This model's strength is anchored in its principles that emotional intelligence is strictly a type of intelligence and is measured. However, critics argue that this strictness weakens the construct by not considering personality traits as part of the measurement, thereby lowering its effectiveness in predicting elements essential to managers, such as job satisfaction and job performance (O'Connor et al., 2019).

O'Connor et al. (2019) also argued that if a model measures ability only, then the answers to the test questions should be objective, either right or wrong. However, the correct answers for the Mayer, Salovey and Caruso Emotional Intelligence Test (MSCEIT) are determined by popular opinion by test subjects and experts in the field of psychology (Ackley, 2016). Although the developers of the MSCEIT have applied due diligence to create a sophisticated and scientifically sound test to measure emotional intelligence, the lack of absoluteness in identifying the correct answer makes it vulnerable to continued skepticism.

Finally, Herpertz et al. (2016) contend that the Mayer, Salovey, and Caruso model overlaps within their four branches and lacks empirical evidence to include all four branches. Mayer et al. (2016) acknowledge the less-than-perfect fit and the need for more evidence to support their model, yet they stand firm to their four-branch design based on their rich collective theoretical understanding of human psychology.

Trait Model

Petrides and Furnham (2000) introduced the trait model of emotional intelligence as an innate characteristic of personality versus an ability. Instruments that measure this construct represent a person’s typical behavior in certain situations (O'Connor et al., 2019). Unlike the ability model, which asserts that emotional intelligence can significantly improve over time with training and experience, the trait model promotes the idea that a person’s emotional intelligence remains relatively unchanged over their lifetime (Kanesan & Fauzan, 2019). Conversely, the ability model of emotional intelligence connects to skill-based philosophy, positing that emotional intelligence can be improved with education, training, and experience (Kanesan & Fauzan, 2019).

The trait model overlaps with the personality constructs, such as the Big Five, as researchers (for example, Petrides et al., 2016) assert that genetics are responsible for a significant portion of personality traits, including trait emotional intelligence. Petrides et al. (2016) developed a way to measure trait emotional intelligence that consisted of 15 elements organized under four categories (Table 2): well-being, self-control, emotionality, and sociability.

Strengths of this approach include the excellent predicting capability of job satisfaction and job performance (O'Connor et al., 2019). However, critics argue that this construct is not a form of intelligence since it does not conform to the definition of the word (Kanesan & Fauzan, 2019). Instead, they consider this model another method to analyze personality. However, Pérez-González et al. (2020) provided comprehensive evidence of the value of the trait model for understanding an individual's emotional competence. Other researchers embrace the value of both the ability and trait models resulting in a mixed model approach.

Table 2

Domains and Elements of Trait Emotional Intelligence (EI)

Global Trait EI	High scorers perceive themselves as . . .
Well-being	
• Self-esteem	. . . successful and self-confident
• Trait happiness	. . . cheerful and satisfied with their lives.
• Trait optimism	. . . confident and likely to “look on the bright side of life.”
Self-control	
• Emotional control	. . . capable of controlling their emotions.
• Stress management	. . . capable of withstanding pressure and regulating stress.
• Impulse control	. . . reflective and less likely to give into their urges.
Emotionality	
• Emotion perception	. . . clear about their own and other people’s feelings.
• Emotion expression	. . . capable of communicating their feelings to others.
• Relationships	. . . capable of having fulfilled personal relationships
• Trait empathy	. . . capable of taking someone else’s perspective.
Sociability	
• Social awareness	. . . accomplished networkers with excellent social skills.
• Emotion management (others)	. . . capable of influencing other people’s feelings.
• Assertiveness	. . . forthright, frank, and willing to stand up for their rights.
• Adaptability*	. . . flexible and willing to adapt to new conditions.
• Self-motivation*	. . . driven and unlikely to give up in the face of adversity.

Note. *These facets feed into the global trait EI score without going through any factor. Adapted from “Developments in Trait Emotional Intelligence Research,” by K.V. Petrides, M. Mikolajczak, S. Mavroveli, M. Sanchez-Ruiz, A. Furnham, and J. Pérez-González, 2016, *Emotion Review, 8*(4), p. 335 https://doi.org/10.1177/1754073916650493.

Mixed-Model

Emotional intelligence was popularized by Goleman (1995). Goleman described emotional intelligence as competencies in personal and social domains (Jan et al., 2017). While many researchers argue there must be a singular way to conceptualize emotional intelligence (ability or trait), other researchers, such as Goleman, assert that the diversity of opinion and perspectives provides a rich and robust understanding of the phenomenon (Oyewunmi, 2018). Therefore, models that do not fit neatly into ability or trait yet blend the two approaches are considered mixed models.

Goleman's (1995) emotional intelligence model consists of four competencies, each containing several factors. The two personal competencies are self-awareness and self-management. The two social competencies are social awareness and relationship management (Jan et al., 2017; Kanesan & Fauzan, 2019; Oyewunmi, 2018). O'Connor et al. (2019) showed that mixed models, such as Goleman's, are instrumental in predicting success in the workplace and offer insights into areas of opportunity for individuals to improve their job-related competencies.

Bar-On (2006) theorized that emotional intelligence consisted of combining personality traits and emotional competencies. The Bar-On model strays from the conventional naming of the phenomenon by calling it emotional-social intelligence, thereby clarifying the model's nomenclature as more complex than ability or trait models. The Bar-On model consists of five categories. The first category is *intrapersonal*, which includes factors such as self-regard, assertiveness, and independence. The second category is *interpersonal*, which includes empathy, social responsibility, and interpersonal relationships. The third category, *stress management*, considers how well a person tolerates stress and controls impulses. The fourth category, *adaptability*, examines a person's ability to employ reality-testing, solve-problems, and remain flexible. The last category, *general mood*, determines the person's optimism and happiness (Bar-On, 2006; Jan et al., 2017; Kanesan & Fauzan, 2019).

While researchers highlight the strengths of the mixed model as comprising the best of both ability and trait models, especially in the context of the workplace (for example, O'Connor, 2019), others see it as outside the scope of *intelligence* because of the significant overlap in the personality domain (Herpertz et al., 2016; Kanesan & Fauzan, 2019). Notwithstanding the critical reviews, the mixed model provides value for scholar-practitioners in the domain of organizational leadership and management (Oyewunmi, 2018).

Selected Emotional Intelligence Model

Contemporary researchers typically view emotional intelligence as an ability, trait, or mixed model (see, for example, Fotopoulou et al., 2021; Haleem & Ur Rahman, 2018; Kanesan & Fauzan, 2019). Salovey and Mayer (1990) developed the ability model that presents emotional intelligence as a cognitive capability. Kanesan and Fauzan (2019) asserted this can be improved over time with training and learning, yet Ackley (2016) asserted the ability to improve over time is limited due to the person's innate skills or lack thereof. The trait model depicts emotional intelligence as an element of a relatively constant personality over a person's lifetime. Instruments that measure trait emotional intelligence tend to calculate an individual's typical behavior versus maximal performance (ability model) (O'Connor et al., 2019). The mixed model consists of a combination of traits, social skills, and competencies. Mixed model measures tend to overlap with other personality measures and are often considered variants of the trait model (Fotopoulou et al., 2021).

I chose the ability model by Salovey and Mayer (1990) for several reasons. First, I wanted to anchor my study on the pioneers of emotional intelligence (Salovey & Mayer, 1990). The ability model is grounded in ontological clarity, i.e., approaching emotional intelligence as a type of intelligence versus a personality trait. It is important to note that critics attack the trait and mixed model as a mere enhancement of Big Five personality models and is, therefore, not a discrete phenomenon from personality (O'Connor et al., 2019, p. 4). Because the ability model, as described by Salovey and Mayer (1990) and later Salovey et al. (2016), is widely accepted by the scientific community (Kanesan & Fauzan, 2019; O'Connor et al., 2019; Rezvani et al., 2019), it has significant credence. Furthermore, a succinct measuring instrument was essential to increase the likelihood of successful participation in my study. Therefore, I selected the 16-element WEIP-S, developed by Jordan and Lawrence (2009), and based on the Salovey and Mayer (1990) model, as the best fit for my study.

Summary and Conclusions

This literature review provides evidence that the Reason (1997) theoretical model for safety culture is well-established and widely respected, especially in the aviation community. Wang and Sun (2014) enhanced Reason's model by adding teamwork culture. The review also offers proof that the Salovey and Mayer (1990) emotional intelligence model is firmly grounded in science and is widely recognized by scholars. The synthesis of studies, to include evidence that emotional intelligence improves teamwork, shows that safety culture and emotional intelligence theoretically connect, enabling the exploration of the two constructs' relationship.

Scientifically sound research supports the claim that safety culture positively influences safety performance, and the body of scholarly knowledge validates the predictive association between emotional intelligence and successful teamwork. However, scientific evidence is lacking that connects emotional intelligence to safety culture in aviation. My study may fill this knowledge gap. The results may benefit aviation safety managers so they better understand the value of both safety culture and emotional intelligence in reducing human error, serious incidents, and accidents.

In Chapter 3, I describe how I measured this relationship by employing the survey instruments for safety culture (Wang & Sun, 2014) and emotional intelligence (Jordan & Lawrence, 2009), explicitly analyzing relationships among the variables of interest.

Chapter 3: Research Method

The purpose of this quantitative descriptive correlational study was to explore the relationship between emotional intelligence, the independent variable, and safety culture, the dependent variable, among professionals in the business aviation industry. This research may fill the gap in understanding the relationship between emotional intelligence and safety culture in aviation, with the intent to provide safety leaders with the increased knowledge to improve effectiveness in human error management and aviation safety.

The research question was, To what extent is there a relationship between emotional intelligence and the safety culture in the business aviation industry? For each of the eight measures of safety culture, the null hypothesis was that there is no relationship between any of the independent variables (emotional intelligence and four demographic variables) and safety culture. The alternate hypothesis was that there is a relationship between at least one of the independent variables (emotional intelligence and demographic variables) and safety culture.

The null hypothesis claims that there is no relationship between any of the independent variables and the dependent variable. Said another way, if the change in the dependent variable associated with a one-unit change in the j^{th} independent variable is the regression coefficient, β_j, the hypothesis for each of the eight dependent variables is depicted mathematically as follows:

$$H_0: \beta_1 = \beta_2 = \ldots = \beta_5 = 0$$

H_A: at least one $\beta_j \neq 0$.

The primary independent variable was emotional intelligence (X_{EI}). I also examined demographic attributes as independent variables to include age (X_A), gender (X_G), job position (X_J), and how many years they have been with the company (X_Y). The influence of the primary independent variable may be moderated by demographic variables. The primary dependent variable, safety culture (Y_{SC}), was an aggregate measure quantified by the ISCM (Wang & Sun, 2014). The seven additional dependent variables, which are subscales, measure more specific attributes of safety culture. These included priority culture (Y_P), standardizing culture (Y_S), flexible culture (Y_F), learning culture (Y_L), teamwork culture (Y_T), reporting culture (Y_R), and just culture (Y_J). This research may fill the gap in understanding the relationship between emotional intelligence and safety culture in aviation, with the intent to provide safety leaders with the increased knowledge to improve effectiveness in human error management and aviation safety.

In the following sections, I describe the research design and the rationale for it. I then provide a comprehensive description of the methodology and data analysis plan, so the study can be replicated by other researchers. I end the chapter by identifying threats to validity.

Research Design and Rationale

I adopted a post-positivism worldview for this study because my theoretical lens is based on careful observation and measurement (Creswell & Creswell, 2018, p. 6). I chose a non-experimental survey design since an experimental approach requires manipulation of the variables, which would not be ethical since the variables include psychological attributes (e.g., emotional intelligence) of human participants (Fisher, 2017). Therefore, I used a survey design to collect data and included regression analyses of the data to provide an understanding of the relationships between the variables.

My survey design represented a cross-sectional study using questionnaires for data collection. The data were collected at a point in time via an online questionnaire. For the sample of business aviation personnel, the online questionnaire was optimal for data collection since it is efficient and reduces cost in comparison to onsite interviews or paper questionnaires that require physical postal services. Online surveys also provide participants with increased privacy, which should aid in improving the response rate (Cox, 2016).

I conducted MLR analyses to investigate the effects of emotional intelligence and demographic factors on safety culture in the business aviation industry. I operationalized emotional intelligence measurements using the WIEP-S developed by Jordan and Lawrence (2009) and based on the Salovey and Mayer (1990) theoretical model. I operationalized the measurement of safety culture and its seven sub-scales using Reason's (1997) theoretical model, enhanced by Wang and Sun (2014), hereafter referred to as the ISCM test. Wang and Sun described the integrated model as having many subcultures, including a teamwork culture. Team performance has been shown to be significantly related to emotional intelligence (Rezvani et al., 2019; Stephens & Carmeli, 2016; Zhou et al., 2020).

Methodology

Population

The population for this study consisted of business aviation personnel located in the United States, comprising more than 1.2 million people (National Aviation Business Aviation Association, n.d.), delimited to control for effects of national culture. All participants were adult professionals, ages 18 or older, who were full-time employees in organizations that operated business aircraft. All the data were self-reported by the participants who volunteered to take part in the study.

The target population was pilots, cabin crew (flight attendants), aircraft maintenance technicians, flight dispatchers/schedulers, and management personnel in the business aviation sector. I chose the business aviation domain for two reasons. First, this sector of aviation is under-studied compared to the scheduled airline industry. Second, due to my experience as a leader in this industry, I developed an extensive contact list, most of whom are business aviation professionals. The sample frame included members of the target population who were on my contact list, consisting of approximately 9,500 people.

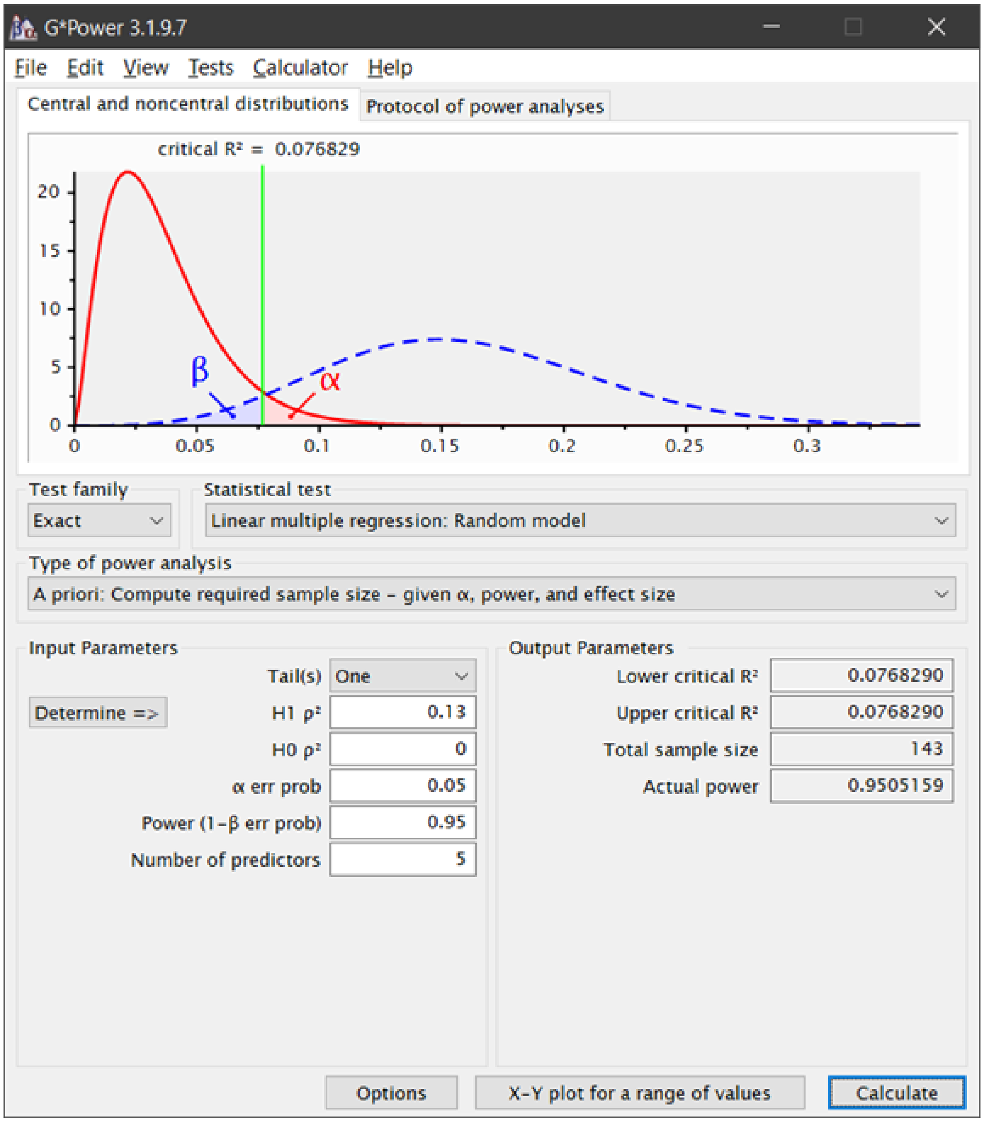
Sampling and Sampling Procedures

I used a convenience, nonprobability sampling technique to generate the sample. The participants were invited from my business aviation contact list developed from over 20 years of networking in the business aviation industry. The study invitation (Appendix A) included a brief description of the study, stated the eligibility requirements, and provided interested participants with a link to the online survey platform service (SurveyMonkey) that hosted the study. Interested participants were then asked to read the consent form and click the “Continue” button if they gave their consent to participate in the study. This directed them to the online questionnaire. After clicking on the link and providing their consent, participants completed the online questionnaire that consisted of a brief demographic survey (Appendix B) and two psychometric surveys: WEIP-S and the ISCM.

I computed an a priori sample size using G*Power software (Version 3.1.9.7; Faul et al., 2009; see Figure 5). I applied the Exact test and multiple linear regression: Random model in G*Power with these parameters: tails (one), confidence $(1 - \alpha) = .95$, power $(1 - \beta) = .95$, effect size (ρ^2) = .13 (medium; translated from $f^2 = .15$), and five independent (predictor) variables. Based on that analysis, the minimum sample size was 143. A Type I error probability of .05 is standard for scientific research (Cohen, 1988; Creswell, 2014; Hazra & Gogtay, 2016).

Figure 5

Required Sample Size



Note. Computation for required sample size given alpha, power, and effect size.

Effect size is expressed in G*Power as a hypothesis. The intent is to determine if an effect exists, meaning that there is a specified influence (predictability) on the dependent variable by a regression model. The null hypothesis is there is no effect—the coefficients for all predictors are zero, which means that none of the variance in the response is due to variance in the predictors. Therefore, in G*Power, *H*0 is $\rho^2 = 0$. The effect size, then, is expressed as the alternate hypothesis. A significant and meaningful effect would be one for which ρ^2 exceeds the specified effect size. Therefore, it is a one-tailed test (Faul et al., 2009). Similar research has used a medium effect size of .15 (Pan et al., 2018).

For power, .80 is typically used (Cohen, 1988). For a power of .80, the G*Power computation results in a sample size of 109. Regarding power and confidence, I wanted to detect true effects among my predictors so that my statistical test showed significance for an influential predictor, consistent with my purpose and research question. Therefore, I wanted to reasonably minimize the probability of a Type II error. Also, the cost of minimizing the Type II error (.05 instead of .20) and achieving a desirable statistical power in my test, given a specified alpha and effect size, was not excessive in that the increase in minimum sample size was acceptable, especially since I planned to send out a very large number of questionnaires to candidate participants, as ensuring adequate participation in the survey may be challenging. Research shows that web-based surveys have a response rate 11% lower on average than other modes (see Fan & Yan, 2010; Sammut et al., 2021), which can be increased by 15% with reminders (Sammut et al., 2021; Saleh & Bista, 2017).

Survey response rates are influenced by several factors. These include survey design, the interest level of the participant, communication method, and assurance that the information they provide remained confidential (Saleh & Bista, 2017). Therefore, due to the potential of a relatively lower response rate for the online survey, I incorporated the recommendations of Sammut et al. (2021) to maximize this rate, which included a simple design, conciseness, reminder emails, and a subject line that was interesting. I applied these methods to counter nonresponse bias.

Cheung et al. (2017) provided evidence that nonresponse bias significantly and negatively impacts the ability to generalize research findings when specific segments of the population do not participate in the study. Also, the participants, in general, may represent the more educated and healthier subset of the population with lower-risk behaviors. However, Hendra and Hill (2019) concluded that lower response rates were not significantly correlated with nonresponse bias. Regardless of the effect of nonresponse bias, I aimed to collect sufficient data to ensure rigorous and reliable analysis and conclusions. Therefore, because I needed at least 143 completed and valid surveys, with an anticipated 40% return rate or less, I needed to send out at least 358 invitations. To compensate for other factors that may reduce the response rate, I sent over 9,500 survey invitations using SurveyMonkey as the host platform. I used all valid, returned questionnaires even if the number exceeded my calculated minimum sample size, which increased power and confidence for the same effect size. I performed a post hoc power analysis to calculate the improvement in power and confidence since the sample size was larger than required.

Procedures for Recruitment, Participation, and Data Collection

I recruited participants for the study from my business aviation contact list developed from over 20 years of networking in the industry. After receiving IRB approval for this study (approval no. 08-22-22-0620991), I sent invitations via SurveyMonkey to over 9,500 business aviation contacts. Each invitation included a brief description of my study, eligibility requirements, an informed consent section, and the link directing participants to the online survey. The participants were informed that they could exit the questionnaire at any time without any negative consequences. If they clicked “Continue,” they were directed to the online questionnaire.

The entire online questionnaire took approximately 8 minutes to complete. After completing the questionnaire, participants were thanked via an exit page on the SurveyMonkey portal. The survey link remained operational for approximately 4 weeks to achieve the minimum sample size of valid and complete questionnaires.

After adequate data were collected, I downloaded the information onto my personal computer via Excel spreadsheet. Both my personal computer and SurveyMonkey account were password protected. I was the only person with access to my personal computer and the SurveyMonkey account that hosted the questionnaire and the data. I did not collect any personal identification information, so the risk of a breach of personal data was minimized. I reviewed the data for completeness and outliers, then uploaded the information into SPSS, where I conducted comprehensive analyses to include descriptive, graphical, and multiple regression.

Instrumentation and Operationalization of Constructs

To conduct this study, I used one instrument with three parts. I collected demographic data in the first part. I measured emotional intelligence with the WEIP-S in the second part and measured safety culture with the ISCM test in part three. I received permission from Jordan to use the WEIP-S and from Wang to use the ISCM in my study at no charge (Appendix C).

Previous Use of Instruments

Michinov and Michinov (2022) conducted two studies to validate the factor structuring of the WEIP-S instrument using confirmatory factor analysis (CFA), computing comparative fit index (CFI), Tucker-Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root-mean-squared residual (SRMR), where an acceptable structure is indicated when CFI and TLI are close to .95, RMSEA is close to .06, and SRMR is close to .08. Study 1 revealed CFI of .96, TLI .93, RMSEA .05, and SRMR .04. Study 2 results included CFI of .96, TLI of .95, RMSEA of .06, and SRMR of .03. These two studies supported the assertion that the WEIP-S four-factor structure was suitable for measuring team emotional intelligence. Furthermore, Michinov and Michinov conducted four subsequent studies, which confirmed the instrument's test-retest reliability, convergent validity, and predictive validity.

Wang and Sun (2014) demonstrated the reliability of the ISCM by administering the questionnaire to 123 participants in Tianjin, China. They input the data into SPSS, which computed a Cronbach's alpha of .856. Wang and Sun (2012) administered the

ISCM test to several commercial airline companies in Europe and Asia. Although there is limited information about the application of this instrument, the construct is sound since it is based on Reason's (1997) model.

Basis for the Development of the Instruments

Jordan and Lawrence (2009) developed the WEIP-S to fill the need for a relatively brief instrument to measure emotional intelligence that was grounded on a sound theoretical model. They chose the Salovey and Mayer (1990) framework because it was well established, highly focused on a type of intelligence, and did not expand into other areas of personality measurement. Wang and Sun (2012) developed the ISCM test to meet a specific task assigned to their working group supporting the European Commission Project FP6 Human Integration into the Lifecycle of Aviation Systems (HILAS).

Sufficiency of Instruments to Answer Research Questions

Both instruments were well-suited to answer the research question, which explored the degree to which there is a relationship between emotional intelligence and safety culture. The WEIP-S provided one score for emotional intelligence, which is the average response among the 16 items in the questionnaire. The ISCM test provided scores for each of the seven secondary dependent variables (subcultures) that I was interested in. Table 3 provides an overview of how the ISCM measures the seven subcultures of safety culture.

Table 3

ISCM Subculture Measurements

Subculture	Measured by participant responses to statement numbers
Priority Culture	1, 2, 3, 4, 5
Standardizing Culture	6r, 7r, 8r, 9r
Flexible Culture	10, 11, 12, 19, 20
Learning Culture	14, 15, 21, 22, 23, 24
Teamwork Culture	16, 17, 18r, 29, 30
Reporting Culture	25, 26, 27, 28r
Just Culture	13r, 31, 32

Note. “r” indicates the element must be reverse scored since a higher score in these elements represents a negative effect on safety culture.

I employed a single online questionnaire that included the WEIP-S, ISCM, and demographics. The demographic data included age, gender, job position (pilot, aircraft maintenance technician, scheduler/dispatcher, management, other), and how long they had been with the company (years). The demographic data were not directly related to the study variables. However, this was an exploratory study to determine the relationship between emotional intelligence and safety culture, and the causes, influences, and explanations of these relationships (effects) are not fully known, which is why this study also included demographic data. Moreover, explanatory factors often interact. Therefore, a complete assessment of the relationships and effects begins by considering a broad array of the influences on the effect, which might include factors with no previous theoretical basis; but, instead, based on subject matter expertise and the possibility of being a significant influence. The influence of any one factor depends on the presence and interaction with other factors. The influence of a factor may be moderated by (depends on) other factors, including demographics, which in human phenomena are influential. Stating the influence of a factor on a response is incomplete and invalid without qualifying the assertation based on the presence of other factors. The intent of the analysis was to determine which of the factors, primary and demographic, in combination, were influential (i.e., as part of a significant predictive model). Some factors proved to be insignificant.

Pilot Study

I conducted a pilot study to verify the validity, effectiveness, and efficiency of both the WEIP-S and ISCM test. To accomplish this, I recruited 31 volunteer participants who worked for a single business aviation organization that I was familiar with. The results of the study showed the organization had a good safety culture, which I had already assessed as an aviation safety auditor in a previous project with this organization, which provided subjective evidence of validity. Feedback from the participants indicated that the survey instrument was efficient since it took an average of only 8 minutes to complete, and they reported that the survey instrument was easy to understand and complete. I made no changes to the instrument following the pilot study.

Data Analysis Plan

I conducted a descriptive analysis of the independent and dependent variables to determine their means, standard deviations, and range of scores. I conducted analyses to display scatterplots and histograms to determine if the data met the assumptions for multiple regression analysis. I then conducted bivariate correlation and multiple regression analyses to determine if the variables were correlated and if emotional intelligence predicts safety culture or any of the seven subcultures. I controlled for the demographic data as covariates in each of the regression analyses.

Analysis Plan

From SPSS, I used graphical analysis and descriptive statistics to analyze the variables and check the MLR assumptions. I used MLR to determine the relationship between the independent variables (emotional intelligence and demographics) and the dependent variables (safety culture and the seven subcultures); to construct a predictive model. Predictive modeling was used to select the independent variables that constitute the model that best predicts the dependent variable. The predictive model was also used to assess the sensitivity of the dependent variable to changes in the independent variables.

Multiple Linear Regression

In the following sections, I present a general description of the MLR and regression model-building process. The description of MLR and regression modeling is synthesized and adapted from multiple sources (see Aczel & Sounderpandian, 2006; Levine et al., 2011; Warner, 2013).

MLR and regression model-building are used to construct a predictive model for the dependent variables. Predictive model-building is used to select the independent variables and two-factor interactions (2FIs) that constitute the model that best predicts the dependent variable. The predictive model is also used to assess the sensitivity of the dependent variable to changes in the independent variables.

The regression model is depicted mathematically as follows:

$$Y = \beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k + \varepsilon.$$

where the independent variables (X_1 to X_k) predict Y (including 2FIs)

Y = the dependent variable

β_0 = the Y-intercept, or the value of Y if the value of all Xs = 0

β_j = the coefficient for the independent variable X_j; the slope of the regression line; or the amount that Y will change per 1 unit change of X_j

X_j = the j^{th} independent variable (which may be a 2FI)

ε = random error in Y.

Hypotheses

Null hypothesis. The null hypothesis for the overall multiple regression model (the hypothesis regarding the influence of the Xs on Ys) is that there is no significant relationship between any of the independent variables and the dependent variables, depicted mathematically as follows:

$$H_0: \beta_1 = \beta_2 = \ldots = \beta_k = 0.$$

Alternative hypothesis. There is a linear relationship between at least one independent variable and the dependent variable, depicted mathematically as follows:

H_A: at least one $\beta_j \neq 0$.

Hypotheses are tested regarding the overall model (testing if there is a relationship between the dependent variables and a set of independent variables [a regression model]) using the *F* test (and its associated *p* value). The *F* test assesses whether the set of independent variables (regression model) predicts the dependent variable. The *t* test is employed as part of and throughout the regression modeling process to evaluate the influence of each prospective independent variable and its contribution to the predictability of the regression model. Adjusted R^2, the coefficient of determination, indicates the extent to which the independent variables contribute to the variance in the dependent variable.

Assumptions

MLR assumes the following (Aczel & Sounderpandian, 2006; Warner, 2013; Williams et al., 2013), which are evaluated as part of the analyses:

- **Numerical variables:** Both the independent and dependent variables must be numerical. Categorical independent variables must be converted to numerical using dummy variables.
- **Linearity:** A scatter plot is used to determine a straight-line relationship between the independent variables and the dependent variable.

- **Homoscedasticity:** A scatter plot is used to determine homoscedasticity (the variation of the residuals, or error terms, is constant for all values of the independent variables).
- **Absence of multicollinearity:** Variance inflation factors (VIFs) are used to assess the absence of multicollinearity (no relationship among independent variables). VIF values greater than 5 suggest the presence of multicollinearity. When multicollinearity is present, independent variables are eliminated sequentially, starting with the variable with the highest VIF.
- **Normally distributed residuals:** A normal probability plot is used to check the normality of residuals.
- **Independence (no autocorrelation):** A scatterplot is used to assess independence. Also, a Durbin-Watson value of 2.0 indicates no autocorrelation.
- **No significant outliers:** Outliers include any data that exceed three standard deviations. Data exceeding this threshold are not included in the analysis.

Model-building

Regression model-building involves selecting the independent variables and 2FIs to develop the model that best predicts the dependent variable. Model-building is performed in four stages: Stage 1 relies on theory, previous research, empirical results, and subject matter expertise to identify candidate independent variables. Stage 2 is a screening stage, in which regression techniques are employed to identify and eliminate candidate independent variables that are not likely to be significant predictors of the dependent variable. Stage 3 is a stage in which the remaining candidate independent variables and their 2FIs are analyzed using multiple regression techniques. In Stage 4, the results from the various regression techniques employed in Stage 3 are compared and considered as a collaborative body of evidence to select the final predictive model.

In Stages 2 and 3, model-building uses several regression techniques collaboratively to select the independent variables that comprise the final and best predictive model of the dependent variable. These include *best-subsets regression* and two forms of *stepwise regression*: *purposeful sequential regression* and *statistical regression*. All regression techniques are employed to generate statistical evidence to select the best predictive model while overcoming some of the deficiencies of any one technique.

Best-subsets regression. This technique uses SPSS to assess all the independent variables in the data set remaining after the initial check of assumptions. The process finds the best combination of independent variables based on several criteria, including Mallows' C_P statistic and adjusted R^2 (James et al., 2021; Pennsylvania State University, 2018).

Stepwise regression. Stepwise regression is an iterative analysis, beginning with the full set of remaining independent variables, adding or eliminating independent variables one by one, and checking regression outcomes each time to consider the influence of individual independent variables and their contribution to the strength of the overall regression model (based on significance and adjusted R^2). I employed two regression approaches. *Statistical regression* relies on automated SPSS methods (*stepwise*, *backward*, and *forward*). *Purposeful sequential regression* employs a series of manual, individual regression analyses using the SPSS *enter* method.

Two-factor Interactions

Significant 2FIs indicate that the influence of one independent variable on the dependent variable depends on the value of a second independent variable. 2FIs are calculated as the cross-product of the independent variables, then tested as part of the MLR analysis and model-building process.

The assessment of 2FIs occurs after the first two screening stages of regression model-building are accomplished. The 2FIs assessed are the pairs of independent variables remaining after variable screening. The influence or predictability of any independent variable (whether a primary variable or demographic variable) is dependent on the presence of other variables, and there is often significant interaction among them.

Threats to Validity

External Validity

Convenience sampling can pose a risk to external validity. All the participants were recruited from my business aviation contact list. Therefore, the results of my study may not be generalizable to all business aviation organizations. However, I mitigated this risk by ensuring that the personnel that I solicited represented a mix of organizations and multiple job categories.

In addition, those who chose to participate in my study about emotional intelligence and safety culture may share common traits in emotional intelligence and safety culture versus the general business aviation population. This risk of bias was low since those who chose to participate scored each element based on their perception of the team's emotional intelligence and safety culture. Therefore, people on their team who did not participate may still have influenced the results based on their perceived behaviors by those who did participate in the study.

Internal Validity

Because my study was a nonexperimental, cross-sectional survey design, I was unable to assert cause-and-effect conclusions from the data. However, logical conclusions can be made regarding the predictive attributes of emotional intelligence as it relates to safety culture. Also, there was a risk for self-presentation and response bias since the instruments employed in my study were self-report measures. My primary defense to mitigate this threat was ensuring the anonymity of the responses. Also, the risk was reduced because each participant's assessment was related to their perception of the team's behavior for both emotional intelligence and safety culture versus self.

Construct Validity

Threats to construct validity were minimal because I employed only validated, peer-reviewed and published instruments to measure emotional intelligence and safety culture. Jordan and Lawrence (2009) provided evidence of construct validity for the WEIP-S through a series of tests, including scale evaluation, discriminant validity, reliability, and test–retest stability. Wang and Sun (2014) provided evidence of construct validity for the ISCM by implementing it in several airline companies in China and Europe, where the results indicated its design effectiveness.

Ethical Procedures

I received approval to collect data from the Institutional Review Board. My approval number was 08-22-22-0620991. I ensured that all participants were adults (18 years or older) and employed by business aviation organizations in the United States. They were solicited from my self-developed aviation contact list. I ensured confidentiality throughout the research process. I did not collect any personal information that would enable the identification of a participant. Participation in the study did not elevate the participants' safety risk above normal daily life. Interested individuals were asked to click on a link embedded in the recruitment message (see Appendix A). This directed them to an informed consent page where they provided their agreement to proceed in participating in my study. The data remained confidential, and only I had access to the data. I stored all data on a personal Google account. I will delete the data after 5 years have passed since data collection.

Summary

In this chapter, I presented the research design, rationale, and chosen methodology to investigate the relationships, both correlative and predictive, between emotional intelligence and safety culture among business aviation professionals. I hypothesized that there would be a significant relationship between emotional intelligence and various measures of safety culture moderated by demographic attributes. The results of the study will be presented in Chapter 4.

Chapter 4: Results

The purpose of this quantitative, descriptive, correlational study was to explore the relationship between emotional intelligence, the primary independent variable, and safety culture, the primary dependent variable, among professionals in the business aviation industry. The research question directly addressed this purpose, and for each of the measures of safety culture, there were null and alternative hypotheses. In addition to the aggregate measure of safety culture, I also tested the degree to which emotional intelligence is related to each of the seven sub-cultures of safety culture described by Wang and Sun (2014). I also included demographic independent variables in the analysis because they were likely to be moderators of the relationship between the primary independent variable and the dependent variables. In this chapter, I present the results of the pilot study, which was conducted with a corporate aviation organization with seven jet aircraft and 31 personnel. I then describe the data collection process for the main study, followed by the analysis and results.

Pilot Study

I conducted a pilot study to validate the design of the consent form, the viability of the data collection instruments in the context of my research (viability of capturing demographic data and scores for emotional intelligence and safety culture), and the data collection process. I also verified the basic procedures in the analytical method (MLR) by conducting a preliminary analysis of the relationship between the primary independent variable (emotional intelligence) and one dependent variable (an aggregate measure of safety culture).

I solicited a business aviation organization that consisted of pilots, maintenance technicians, schedulers, and managers. I sent the consent form with the data collection instrument link to all aviation employees, and 31 people participated by completing the survey. Seven of the 32 elements for safety culture required reverse-scoring, and the pilot study also validated the efficient conduct of this process. The regression analysis provided an initial insight that, based on this small pilot sample, *X(EI)* was a significant predictor of *Y(SC)* with an adjusted R^2 of .411 and p value less than .001. I made no changes to the instrument or procedures as a result of the pilot study.

Data Collection

The data collection process lasted for 36 days (September 7 to October 13, 2022). I sent the invitation and consent form to 9,500 contacts in the business aviation industry, which was 1,500 more than I originally proposed. But only 257 surveys were collected (2.7% participation rate). Several participants asked if the email was legitimate and not spam or a phishing attack. The low participation rate is likely due to these concerns. Another possibility for the low participation rate could be due to email software automatically flagging the email as junk or spam.

Of the 257 surveys completed, I discarded 30 because they were incomplete. No surveys were discarded due to outliers because all the survey responses, other than demographics, were multiple choice (Likert Scale). However, the 227 valid and completed surveys exceeded the minimum sample size of 143 as calculated by G*Power (Faul et al., 2009).

Table 4 provides a breakdown of job functions. Most business aviation aircraft do not use a cabin crew member because it is not required by federal regulations for less than 19 passengers. Therefore, the low number of cabin crew participating in the study was expected for this population. Additionally, the population pilot-to-technician and pilot-to-scheduler ratio is 3:1 (NBAA, 2022), so a high ratio of pilots versus schedulers, technicians, and managers was expected for this sample. Table 5 shows the gender ratio for the sample. This ratio represents the gender ratio in the business aviation industry (see Lutte, 2019).

Table 4

Frequency of Sample Job Function

	Count	Percentage
Total	227	100%
Pilot	111	48.9%
Cabin Crew	6	2.6%
Technician	25	11.0%
Scheduler	20	8.8%
Management	53	23.3%
Other	12	5.3%

Note. Adapted SPSS output for descriptive statistics.

Table 5

Frequency of Participant Gender

	Count	Percentage
Total	227	100%
Male	185	81.5%
Female	36	15.86%
Other	6	2.64%

Note. Adapted SPSS output for descriptive statistics.

Table 6 depicts descriptive statistics for noncategorical variables. The age range of participants spanned 57 years (21 to 78 years of age), with the frequency distribution shown in Figure 6. The range for years of employment extended 42 years (0 to 42 years of employment), with the frequency distribution shown in Figure 7.

Table 6

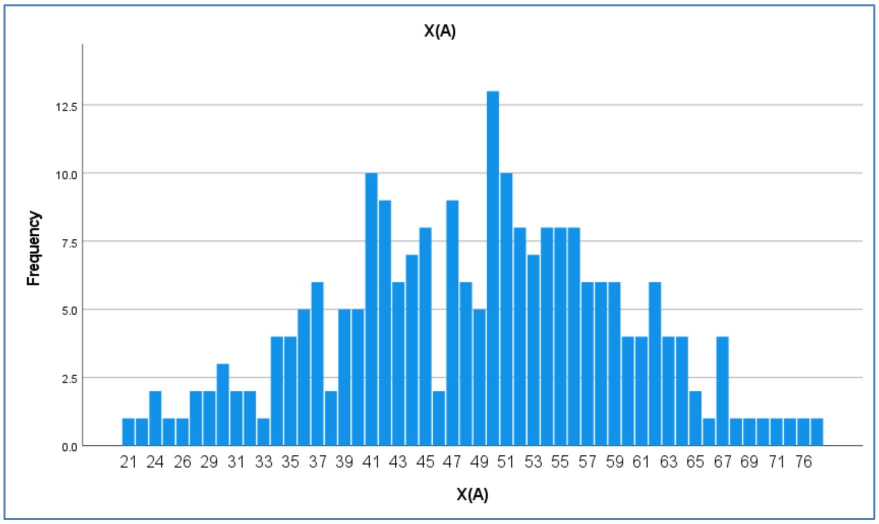
Min, Mean, Max, and Standard Deviation for Non-Categorical Variables

	N	Min	Max	Mean	Std Dev
X(A)	227	21	78	48.72	10.85
X(Y)	227	0	42	7.91	7.926
X(EI)	227	2.75	5.00	3.9169	.45961
Y(SC)	227	2.25	5.00	4.0921	.52174
Y(P)	227	2.40	5.00	4.2705	.63856
Y(S)	227	2.00	5.00	4.0738	.66917
Y(F)	227	1.80	5.00	4.2361	.55806
Y(L)	227	1.67	5.00	4.1013	.64952
Y(T)	227	2.40	5.00	4.0925	.52553
Y(R)	227	1.25	5.00	3.8161	.67471
Y(J)	227	1.00	5.00	3.9205	.78509

Note. SPSS descriptive analysis output for sample.

Figure 6

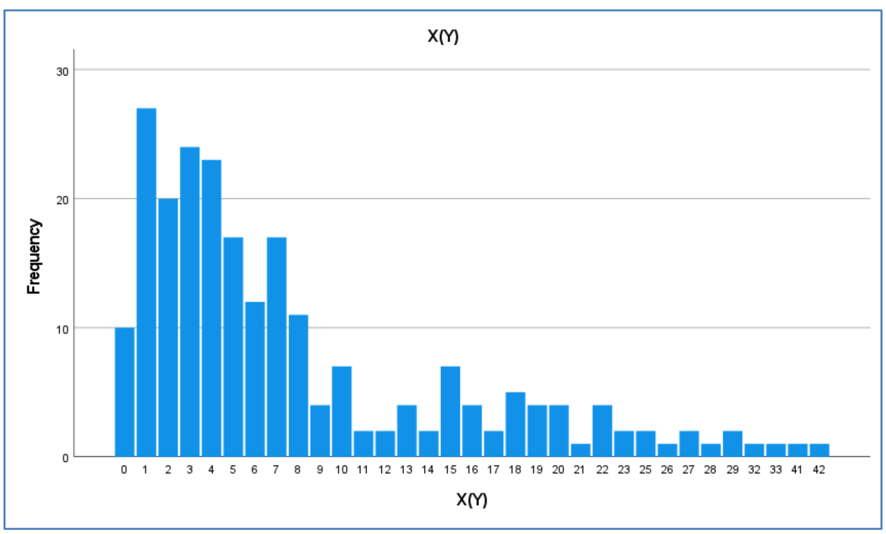
Age Frequency Distribution Chart for the Sample



Note. SPSS frequency descriptive analysis output Age, *X(A)*.

Figure 7

Years Employed Frequency Distribution Chart for the Sample



Note. SPSS output for years of employment.

Study Results

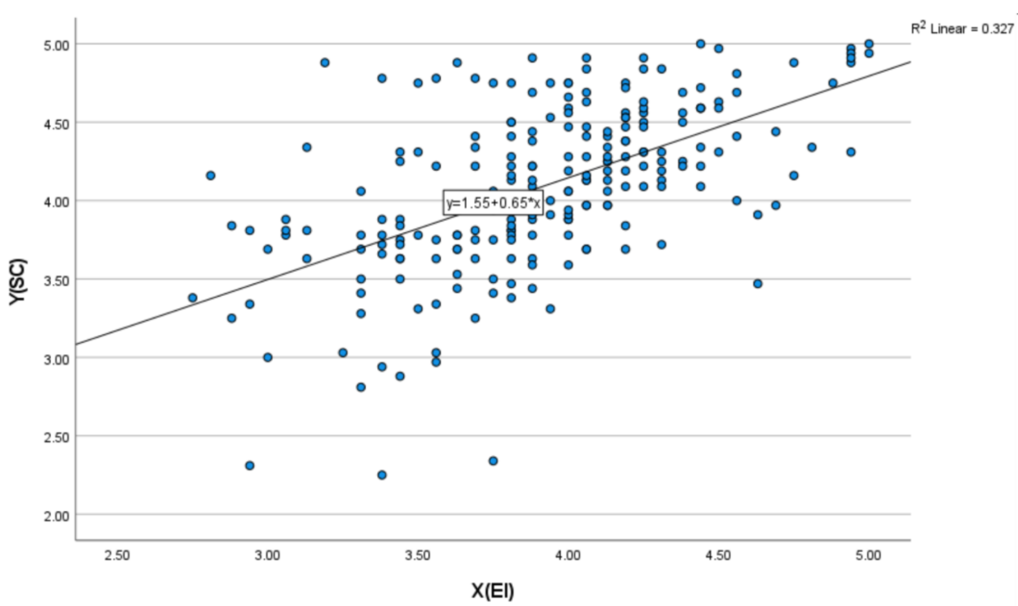
To perform a preliminary test of assumptions, I ran an initial regression analysis with the full set of independent variables using the SPSS enter method. No transformations of the data were required since all the assumptions were met. The assumptions tested and validated include the following:

- All independent variables were discrete or continuous numerical variables.
- There was a continuous, numerical dependent variable.
- No overly influential cases: No significant outliers biasing the model. The outlier criterion was set at three standard deviations, and no data exceeded this threshold.
- No autocorrelation: Residuals were independent of each other. I checked autocorrelation using the Durbin-Watson statistic; a value of 2.0 means that there is no autocorrelation detected in the sample) The Durbin-Watson statistic was near 2.0 for all dependent variables, indicating no autocorrelation.
- No multicollinearity: I checked for multicollinearity using variance inflation factors (VIFs) from SPSS (a VIF greater than 5 suggests the presence of multicollinearity). Only dummy independent variables exhibited high VIFs (greater than 5), which was to be expected. However, the VIFs for all numerical independent variables (*X(EI)*, *X(A)*, *X(Y)*) were less than 2.0.

- Linear Relationships: Scatterplots showed no obvious nonlinear relationships or patterns between the independent variables and the dependent variables. The scatterplots did not depict any significant changes in variance over the values of the independent variables.
- Homoscedasticity: The variance of residuals appeared equal across the values of the independent variables (scatterplot of standardized residuals vs. independent variable values to show whether points were equally distributed across all values of the independent variables). A typical scatterplot is shown in Figure 8 for the residuals versus *X(EI)*.

Figure 8

Scatterplot Depiction of the Relationship Between Y(SC) and X(EI)

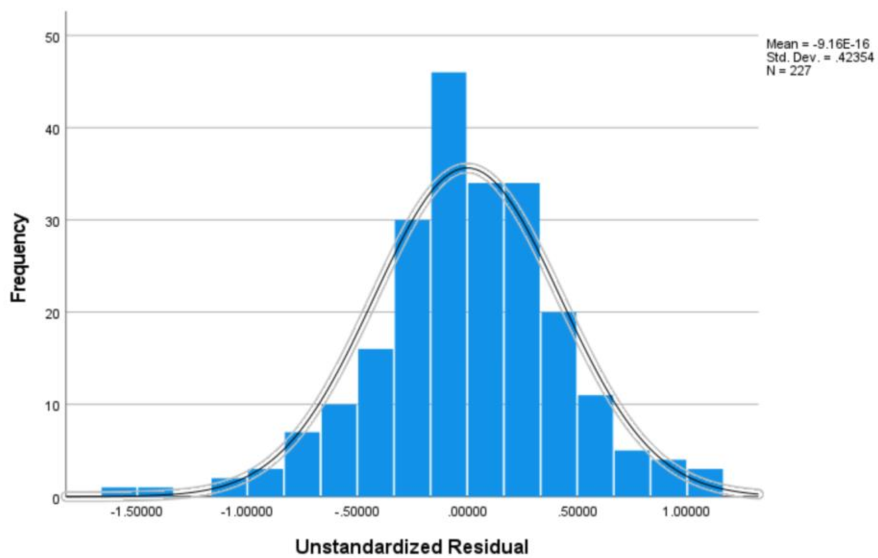


Note. SPSS scatterplot of *X(EI)* versus *Y(SC)*.

- Normality: Residuals were normally distributed (normal probability plot of residuals). No severe departures from normality were found initially. This is depicted in the histogram of unstandardized residuals (Figure 9) and the plot of unstandardized residuals (Figure 10).

Figure 9

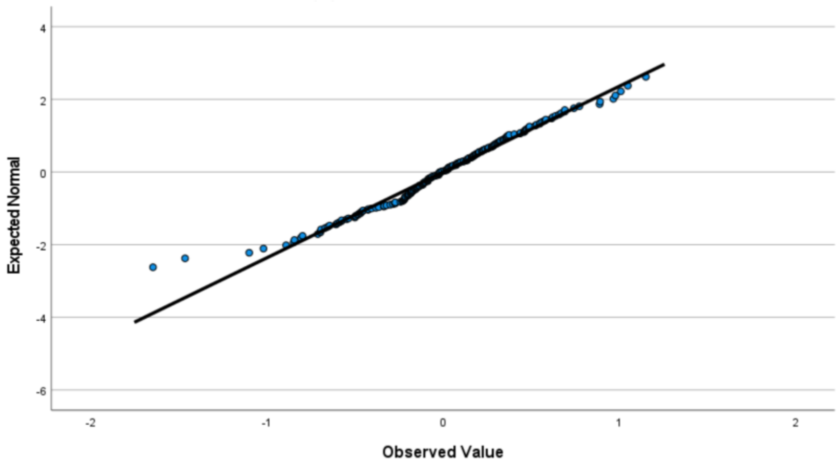
Histogram of Unstandardized Residuals



Note. SPSS output showing residuals were normally distributed.

Figure 10

Plot of Unstandardized Residuals



Note. SPSS output shows no severe departures from normality.

Model-Building Set-up

I employed MLR to determine the relationship between the independent variables and each dependent variable. Because the statistical and practical significance of each predictor is highly dependent on the presence of other explanatory variables, predictive model building using MLR was used to select the independent variables and factor interactions that constitute the model that best predicted each dependent variable. The predictive model was also used to assess the sensitivity of the dependent variable to changes in the predictors. As part of regression model building, I employed several regression model-building techniques collaboratively to select the predictors that comprised the final and best predictive model of the DV. These included best-subsets regression and two forms of stepwise regression: purposeful sequential regression and statistical regression (backward and forward).

Missing Variable Bias

All regression techniques were employed collaboratively to generate statistical evidence to select the best predictive model while overcoming some of the deficiencies of any one technique. I used several strategies to combat missing variable bias. The intent was to detect the specified effect with high probability (high statistical power), avoiding the false negative or failure to detect (Type II) error. The tradeoff was accepting a reasonable risk of a Type I error (false positive, detecting an effect that is not present) in the interest of avoiding missing variable bias but at the cost of a loss of precision (as a result of potentially adding noise to the model as a consequence of including a nonsignificant or nuisance variable). This translated into using a relatively liberal value for the selection criterion for predictors (see Heinze & Dunkler, 2017; Heinze et al., 2018).

The significance of each independent variable was calculated in SPSS using a *t* test and its *p* value. I used a variable selection criterion of $p < .20$. This indicated a willingness to accept a higher risk of the Type I error to construct the best predictive model. Finding the best predictive model meant minimizing the probability of a Type II error—$\beta = .05$ and statistical power of .95. I conducted a post hoc computation of statistical power ($1 - \beta = .997$) based on an actual sample of n = 227 records. Given the desired confidence ($1 - \alpha = .95$; for the model) and a medium effect size (H1 $\rho^2 = .13$), the probability of a Type II statistical error (false negative) was nearly zero.

The primary criterion for including a predictor in the model was its contribution to model goodness-of-fit (adjusted R^2). The final predictive model was used to determine which predictors are included in a statistically significant predictive model of the DV, along with the sensitivity analysis to explain how much the dependent variable is predicted to change with a change in the value of a predictor.

SPSS Protocol

I set up analyses in the SPSS analytical tool (model-building using the Regression/Linear module). In this module, I performed these tasks:

- Selected the dependent variable and independent variables.
- Chose the specific regression method (*enter, backward,* or *forward*).
- Selected desired statistics (estimates, covariance matrix, model fit, R^2 change, descriptives, collinearity diagnostics, Durbin-Watson casewise diagnostics).
- Selected the desired plots (for post hoc final testing of assumptions).
- Other choices, including the level of significance (α).

I also used the SPSS extension for *best-subsets* regression.

Regression Model-Building

I performed regression model-building in five stages. In *Stage 1*, I relied on theory, previous research, empirical results, and subject matter expertise to identify candidate independent variables. In *Stage 2*, I scrubbed the data set for missing or corrupt data, outliers, and the need to consolidate or eliminate independent variables due to sample size issues. I used analysis in SPSS and screened the independent variables for violations of assumptions using MLR and the SPSS *enter* method. Stages 3 through 5 were more complex and described in detail as follows.

Stage 3. A screening stage, in which regression techniques were employed to identify and eliminate candidate independent variables that the analysis demonstrated were not likely to be significant predictors of the dependent variable—that did not contribute to the goodness-of-fit of the model. Stage 3 was performed using multiple segments.

Segment A. I conducted a *best-subsets* regression analysis of the model using SPSS with all the independent variables in the data set remaining after the initial check of assumptions, including multicollinearity. The process finds the best combination of independent variables based on several criteria:

- Criterion 1: Mallows' C_P statistic, which measures differences between a fitted regression model and a true model along with random error. This step is to ensure the model is not over-specified (populated with too many non-significant independent variables contributing little to the adequacy of the model). I considered as acceptable the models for which the C_P was close to or less than $k + 1$, where k is the number of independent variables.
- Criterion 2: Adjusted R^2 (the percentage of variation in the dependent variable that is attributed to the model). This is a measure of the fit and strength of the predictability of the model. Among those models for which $C_P < k + 1$, I noted those with the highest adjusted R^2.

- Criterion 3: Parsimony (fewest terms), interpretability (SME and analyst judgment), and satisfaction of model assumptions (residual analysis). However, I was conservative about eliminating independent variables without evidence that they do not contribute to improved model fit.

I noted which models met the criteria—which combinations of independent variables were candidates for the final predictive regression model. I noted which independent variables were included in each acceptable model and which independent variables would be eliminated by choosing any of the acceptable or best models.

Segment B. I then ran a series of *statistical regression* analyses using automated SPSS methods: *stepwise*, *backward*, and *forward*. Each stepwise method, in some cases, resulted in a different model (different set of independent variables). In SPSS, I set the criteria for entry and removal conservatively at .20 and .201, respectively. I noted which independent variables were included in the final model(s) of each stepwise regression procedure and the adjusted R^2 of each of the final models. I did not rely on any single automated stepwise analysis to eliminate any independent variables but considered the cumulative evidence when deciding to eliminate independent variables.

Segment C. I performed a *purposeful sequential regression* analysis—a series of regression analyses using the SPSS *enter* method beginning with the full set of remaining independent variables, with $\alpha = .20$. After each run, I noted the change in adjusted R^2. If there was a decrease, I noted which predictor's elimination caused it and considered its p value. I noted the p value for each predictor. I decided whether to eliminate a predictor based on its p value > α. If all p values < α, I stopped. Otherwise, I eliminated the predictor with the highest p value.

I then ran the next model. I continued iteratively, using the elimination criteria (adjusted R^2 and p value) and judgment until the independent variables all were significant and adjusted R^2 was no longer increasing by eliminating independent variables. I listed model compositions (terms in the model) from segment A (*best-subsets*), segment B (*statistical regression* methods), and segment C (*purposeful sequential regression*). I noted which independent variables were consistently included or excluded. I ran different combinations and checked for an increase in adjusted R^2 after model runs. I noted which models improved adjusted R^2. I noted which independent variables were consistently significant (p values < .20).

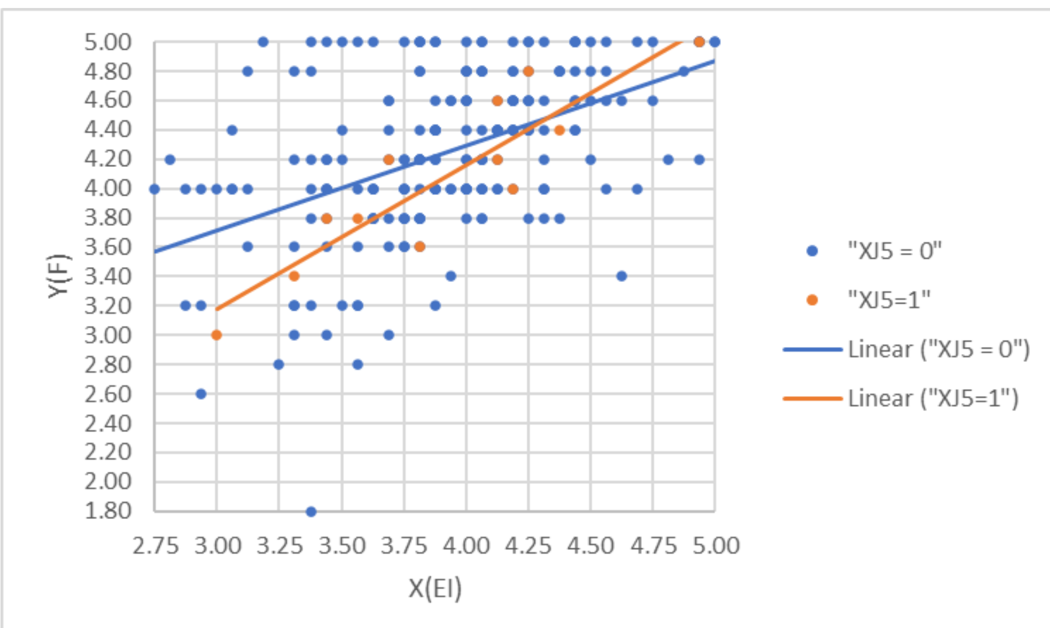
Segment D. I selected the best preliminary model (combination of independent variables) based on the evidence from segments A through C.

Stage 4. I added 2FIs for analysis and model-building and repeated the model-building segments A through C with all remaining independent variables plus the 2FIs among the remaining independent variables (using *best-subsets, statistical regression*, and *purposeful sequential regression*). I considered all 2FIs but used judgment to ensure they made sense operationally. The 2FI terms at this point were treated in the regression like any other predictor. I continued using α = .20. Once again, I compared the best models from each segment and tried various combinations checking for increases or decreases in adjusted R^2. I determined whether a predictor was significant as a contributor to the predictability of the model or if it was more likely a moderating variable as part of 2FIs.

Segment E. I used a combination of graphical analysis and statistical analysis (*p* value) to determine if any statistically significant and practically relevant 2FIs existed for the predictive model for each DV. Graphical analysis was more applicable for the 2FIs when their significance was marginal. Figure 11 shows a typical 2FI, with the independent variable, *X(EI)*, and the dependent variable, *Y(F)*, moderated by *XJ5*, a 2FI called *XEI*XJ5*.

Figure 11

Two-Factor Interaction Between Two Independent Variables



Note. The 2FI is indicated graphically by the non-parallel lines, each representing a different value of *XJ5*.

Stage 5: Select a Final Predictive Model. I compared the candidate independent variables, 2FIs, and models using the cumulative evidence from the first four stages and their segments in the model-building process and selected a final model based on these criteria. I relied on the results from the various multivariate techniques employed in Stages 3 and 4 to compare and consider as a collaborative body of evidence to select the final predictive model to include the following considerations:

- The inclusion criterion ($p < .20$) of the independent variables and 2FIs
- The best combination of independent variables and 2FIs meeting the criteria from the preceding analyses (Mallows C_P near and less than $k + 1$, and the highest adjusted R^2)
- Fewest independent variables while maintaining the highest or nearly highest adjusted R^2 (parsimony)
- Assessment of independent variables as individual contributors to the model or as moderating variables that are part of 2FIs (statistical and graphical analysis)
- Analyst judgment

The final model for each of the dependent variables is depicted in Table 7, along with F statistics, p values, and adjusted R^2s.

Table 7

Final Predictive Model for Each Dependent Variable

	Y(SC)	*Y(P)*	*Y(S)*	*Y(F)*	*Y(L)*	*Y(T)*	*Y(R)*	*Y(J)*
Adj R^2	0.328	0.278	0.123	0.265	0.276	0.420	0.181	0.125
F	56.16	18.44	8.94	21.83	18.24	55.49	25.97	11.78
p <.001	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
XEI	✓	✓	✓	✓	✓	✓	✓	✓
XA					✓			
XJ1			✓		✓		✓	
XJ2			✓			✓		
XJ3		✓		✓				
XJ5		✓	✓					
XY	✓			✓	✓			✓
XJ3_XEI		✓						✓
XJ5_XEI		✓						
XY_XJ5				✓				
XA_XJ5					✓			
XJ2_XY						✓		

Note. Independent variables eliminated during the model-building sequence are not listed.

Hypothesis Tests

For each of the DVs, I completed a hypothesis test (*F* test of the overall model and associated *p* value; compared to the specified level of significance from the SPSS ANOVA table). For all analyses, I rejected the MLR null hypothesis because the value of *p* was less than or equal to .05. I concluded that there was sufficient evidence that the alternate hypothesis was true; that at least one coefficient ≠ 0. For each of the DVs, there is sufficient evidence that the model is a significant predictor of the DV.

Regarding individual predictors, their contribution to goodness-of-fit (adjusted R^2) was the primary criterion for inclusion in the model. All of the individual independent variables and 2FIs in each of the final predictive regression models met the variable selection criterion (all $p < .20$). For each of the independent variables and 2FIs in the final models, I rejected the null hypothesis (coefficient = 0) and concluded there was sufficient evidence that the alternate hypothesis is true (coefficient ≠ 0).

For each of the independent variables and 2FIs that were eliminated in the model-building process using *purposeful sequential regression*, I failed to reject the null hypothesis and concluded that there was insufficient evidence to conclude that their coefficients ≠ 0.

Final Predictive Model

The final predictive model can be expressed in terms of a regression equation with the computed unstandardized coefficients for independent variables and 2FIs from the SPSS Coefficients table (Table 6 illustrates the predictors in the model for each of the dependent variables):

$$\hat{Y} = b_0 + b_1X_1 + \ldots + b_kX_k$$

where

k = the number of predictors in the model (independent variables or 2FIs),

b_0 = the intercept of the constant of the model,

b_i = the unstandardized coefficient for X_i,

and X_i = the i^{th} predictor.

Explaining the Final Model

For the final model of each of the eight dependent variables, I rejected the null hypotheses and provided the answer to my research question, To what extent is there a relationship between emotional intelligence and safety culture in the business aviation industry? The following sections provide the evidence to support each of the alternative hypotheses.

Alternative Hypothesis for Y(SC)

The final model (Table 8) was composed of *X(EI)* and *X(Y)*. Based on $p < .001$ and $F = 56.16$, I rejected the null hypothesis and concluded that the alternate hypothesis was true; at least one coefficient ≠ 0. The final predictive model was a statistically significant predictor for *Y(SC)* and can be expressed as a regression equation with the computed unstandardized coefficients for the independent variables from the SPSS Coefficients table expressed as follows:

$$Y(SC) = 1.511 + (.648)X(EI) + (.006)X(Y)$$

The final model had an adjusted $R^2 = .328$, indicating that 32.8% of the variation in *Y(SC)* could be attributed to the predictive model. This also indicated that approximately 67% of the variation in *Y(SC)* may be attributed to other explanatory variables or random variation (noise).

Table 8

Final Model Analysis for Y(SC)

	Adj. R^2	*F*	*p*	Coefficients
Model Summary	.328	56.16	<.001	
Constant				1.511
X(EI)				.648
X(Y)				.006

Note. Adapted from SPSS output for Model Summary, ANOVA, and Coefficients.

Alternative Hypothesis for Y(P)

The final model (Table 9) was composed of *X(EI), X(J3), X(J5), X(J3)X(EI),* and *X(J5)X(EI).* Based on $p < .001$ and $F = 18.44$, I rejected the null hypothesis and concluded that the alternate hypothesis was true; at least one coefficient ≠ 0. The final predictive model was a statistically significant predictor for *Y(SC)* and can be expressed as a regression equation with the computed unstandardized coefficients for the independent variables from the SPSS Coefficients table expressed as follows:

$$Y(P) = 1.708 + (.661)X(EI) - (1.469)X(J3) - (1.922)X(J5) +$$

$$(.328)X(J3)X(EI) + (.444)X(J5)X(EI)$$

The final model had an adjusted $R^2 = .278$, indicating that 27.8% of the variation in *Y(P)* could be attributed to the predictive model. This also indicated that approximately 72% of the variation in *Y(P)* may be attributed to other explanatory variables or random variation (noise).

The 2FI, *X(J3)X(EI),* indicates that the relationship between *X(EI)* and *Y(P)* is moderated by *X(J3)*; the relationship changes depending on the value of *X(J3)*. When

X(J3) = 1 (i.e., the respondent's job function is "Scheduler"), the value of *Y(P)* is increased by *(.328)X(EI)*. However, when *X(J3)* = 0, the relationship between *X(EI)* and *X(P)* remains unchanged with regards to *X(J3)*; the 2FI *X(J3)X(EI)* = 0.

The 2FI, *X(J5)X(EI)*, indicates that the relationship between *X(EI)* and *Y(P)* is moderated by *X(J5)*; the relationship changes depending on the value of *X(J5)*. When *X(J5)* = 1 (i.e., the respondent's job function is "Other"), the value of *Y(P)* is increased by *(.444)X(EI)*. However, when *X(J5)* = 0, the relationship between *X(EI)* and *X(P)* remains unchanged with regards to *X(J5)*; the 2FI *X(J5)X(EI)* = 0.

Table 9

Final Model Analysis for Y(P)

	Adj. R^2	*F*	*p*	Coefficients
Model Summary	.278	18.44	<.001	
Constant				1.708
X(EI)				.661
X(J3)				-1.469
X(J5)				-1.922
X(J3)X(EI)				.328
X(J5)X(EI)				.444

Note. Adapted from SPSS output for Model Summary, ANOVA, and Coefficients.

Alternative Hypothesis for Y(S)

The final model (Table 10) was composed of *X(EI), X(J1), X(J2),* and *X(J5).* Based on $p < .001$ and $F = 8.94$, I rejected the null hypothesis and concluded that the alternate hypothesis was true; at least one coefficient ≠ 0. The final predictive model was a statistically significant predictor for *Y(S)* and can be expressed as a regression equation with the computed unstandardized coefficients for the independent variables from the SPSS Coefficients table expressed as follows:

$$Y(S) = 2.090 + (.502)X(EI) + (.391)X(J1) + (.178)X(J2) - (.259)X(J5)$$

The final model had an adjusted R^2 = .123, indicating that 12.3% of the variation in *Y(S)* could be attributed to the predictive model. This also indicated that approximately 88% of the variation in *Y(S)* may be attributed to other explanatory variables or random variation (noise).

Table 10

Final Model Analysis for Y(S)

	Adj.R^2	*F*	*p*	Coefficients
Model Summary	.123	8.94	<.001	
Constant				2.090
X(EI)				.502
X(J1)				.391
X(J2)				.178
X(J5)				-.259

Note. Adapted from SPSS output for Model Summary, ANOVA, and Coefficients.

Alternative Hypothesis for Y(F)

The final model (Table 11) was composed of *X(EI), X(Y), X(J3),* and *X(Y)X(J5).* Based on $p < .001$ and $F = 21.38$, I rejected the null hypothesis and concluded that the alternate hypothesis was true; at least one coefficient ≠ 0. The final predictive model was a statistically significant predictor for *Y(F)* and can be expressed as a regression equation with the computed unstandardized coefficients for independent variables and 2FIs from the SPSS Coefficients table expressed as follows:

$Y(F) = 1.901 + (.583)X(EI) + (.009)X(Y) - (.165)X(J3) - (.025)X(Y)X(J5)$

The final model had an adjusted $R^2 = .265$, indicating that 26.5% of the variation in *Y(F)* could be attributed to the predictive model. This also indicated that approximately 74% of the variation in *Y(F)* may be attributed to other explanatory variables or random variation (noise).

The 2FI, *X(Y)X(J5)*, indicates that the relationship between *X(Y)* and *Y(F)* is moderated by *X(J5)*; the relationship changes depending on the value of *X(J5)*. When *X(J5)* = 1 (i.e., the respondent's job function is "Other"), the value of *Y(F)* is reduced by *(.025)X(Y)*. However, when *X(J5)* = 0, the relationship between *X(Y)* and *X(F)* remains unchanged with regards to *X(J5)*; the 2FI *X(Y)X(J5)* = 0.

Table 11

Final Model Analysis for Y(F)

	Adj.R^2	*F*	*p*	Coefficients
Model Summary	.265	21.38	<.001	
Constant				1.901
X(EI)				.583
X(Y)				.009
X(J3)				-.165
X(Y)X(J5)				-.025

Note. Adapted from SPSS output for Model Summary, ANOVA, and Coefficients.

Alternative Hypothesis for Y(L)

The final model (Table 12) was composed of *X(EI), X(A), X(Y), X(J1), and X(A)X(J5)*. Based on $p < .001$ and $F = 18.24$, I rejected the null hypothesis and concluded that the alternate hypothesis was true; at least one coefficient ≠ 0. The final predictive model was a statistically significant predictor for *Y(L)* and can be expressed as a regression equation with the computed unstandardized coefficients for independent variables and 2FIs from the SPSS Coefficients table expressed as follows:

$$Y(L) = 1.490 + (.721)X(EI) - (.006)X(A) + (.009)X(Y) + (.409)X(J1) + (.005)X(A)X(J5)$$

The final model had an adjusted R^2 = .276, indicating that 27.6% of the variation in *Y(L)* can be attributed to the predictive model. This also indicated that approximately 72% of the variation in *Y(L)* may be attributed to other explanatory variables or random variation (noise).

The 2FI, *X(A)X(J5)*, indicates that the relationship between *X(A)* and *Y(L)* is moderated by *X(J5)*; the relationship changes depending on the value of *X(J5)*. When *X(J5)* = 1 (i.e., the respondent's job function is "Other"), the value of *Y(L)* is increased by *(.005)X(A)*. However, when *X(J5)* = 0, the relationship between *X(A)* and *X(L)* remains unchanged with regards to *X(J5)*; the 2FI *X(Y)X(J5)* = 0.

Table 12

Final Model Analysis for Y(L)

	Adj.R^2	*F*	*p*	Coefficients
Model Summary	.276	18.24	<.001	
Constant				1.490
X(EI)				.721
X(A)				-.006
X(Y)				.009
X(J1)				.409
X(A)X(J5)				.005

Note. Adapted from SPSS output for Model Summary, ANOVA, and Coefficients.

Alternative Hypothesis for Y(T)

The final model (Table 13) was composed of *X(EI), X(J2),* and *X(J2)X(Y).* Based on p < .001 and F = 55.49, I rejected the null hypothesis and concluded that the alternate hypothesis was true; at least one coefficient ≠ 0. The final predictive model was a statistically significant predictor for *Y(T)* and can be expressed as a regression equation with the computed unstandardized coefficients for independent variables and 2FIs from the SPSS Coefficients table expressed as follows:

$$Y(T) = 1.234 + (.733)X(EI) - (.249)X(J2) + (.022)X(J2)X(Y)$$

The final model had an adjusted R^2 = .420, indicating that 42.0% of the variation in *Y(T)* could be attributed to the predictive model. This also indicated that approximately 58% of the variation in *Y(T)* may be attributed to other explanatory variables or random variation (noise).

The 2FI, *X(J2)X(Y),* indicates that the relationship between *X(Y)* and *Y(T)* is moderated by *X(J2)*; the relationship changes depending on the value of *X(J2)*. When *X(J2)* = 1 (i.e., the respondent's job function is "Technician"), the value of *Y(L)* is increased by *(.022)X(Y),* regarding the 2FI, since *X(J2)* is also an independent variable in this model. However, when *X(J2)* = 0, the relationship between *X(Y)* and *X(T)* remains unchanged with regards to *X(J2)*; the 2FI *X(J2)X(Y)* = 0.

Table 13

Final Model Analysis for Y(T)

	Adj.R^2	*F*	*p*	Coefficients
Model Summary	4.20	55.49	<.001	
Constant				1.234
X(EI)				.733
X(J2)				-.249
X(J2)X(Y)				.022

Note. Adapted from SPSS output for Model Summary, ANOVA, and Coefficients.

Alternative Hypothesis for Y(R)

The final model (Table 14) was composed of *X(EI)* and *X(J1)*. Based on $p < .001$ and $F = 25.97$, I rejected the null hypothesis and concluded that the alternate hypothesis was true; at least one coefficient ≠ 0. The final predictive model was a statistically significant predictor for *Y(R)* and can be expressed as a regression equation with the computed unstandardized coefficients for independent variables from the SPSS Coefficients table expressed as follows:

$$Y(R) = 1.323 + (.634)X(EI) + (.382)X(J1)$$

The final model had an adjusted $R^2 = .181$, indicating that 18.1% of the variation in *Y(R)* could be attributed to the predictive model. This also indicated that approximately 82% of the variation in *Y(R)* may be attributed to other explanatory variables or random variation (noise).

Table 14

Final Model Analysis for Y(R)

	Adj.R^2	*F*	*p*	Coefficients
Model Summary	.181	25.97	<.001	
Constant				1.323
X(EI)				.634
X(J1)				.382

Note. Adapted from SPSS output for Model Summary, ANOVA, and Coefficients.

Alternative Hypothesis for Y(J)

The final model (Table 15) was composed of *X(EI), X(Y),* and *X(J3)X(EI).* Based on $p < .001$ and $F = 11.78$, I rejected the null hypothesis and concluded that the alternate hypothesis was true; at least one coefficient ≠ 0. The final predictive model was a statistically significant predictor for *Y(J)* and can be expressed as a regression equation with the computed unstandardized coefficients for independent variables and 2FIs from the SPSS Coefficients table expressed as follows:

$$Y(J) = 1.710 + (.543)X(EI) + (.014)X(Y) - (.082)X(J3)X(EI)$$

The final model had an adjusted $R^2 = .125$, indicating that 12.5% of the variation in *Y(J)* could be attributed to the predictive model. This also indicated that approximately 87.5% of the variation in *Y(J)* may be attributed to other explanatory variables or random variation (noise).

The 2FI, *X(J3)X(EI)*, indicates that the relationship between *X(EI)* and *Y(J)* is moderated by *X(J3)*; the relationship changes depending on the value of *X(J3)*. When *X(J3)* = 1 (i.e., the respondent's job function is "Scheduler"), the value of *Y(J)* is reduced by *(.082)X(EI)*. However, when *X(J3)* = 0, the relationship between *X(J)*, *X(EI)*, and *X(Y)* remains unchanged with regards to *X(J3)*; the 2FI *X(J3)X(EI)* = 0.

Table 15

Final Model Analysis for Y(J)

	Adj. R^2	*F*	*p*	Coefficients
Model Summary	.125	11.78	<.001	
Constant				1.710
X(EI)				.543
X(Y)				.014
X(J3)X(EI)				-.082

Note. Adapted from SPSS output for Model Summary, ANOVA, and Coefficients.

Summary

The research question was, To what extent is there a relationship between emotional intelligence and safety culture in the business aviation industry? The analysis provided in this chapter provides a response to the research question. By examining an aggregate index of safety culture, as well as its seven subscales, there was a consistent and significant relationship between emotional intelligence and safety culture. That relationship was moderated by the presence of other predictors and 2FIs.

The analysis revealed that the relationship between *X(EI)* and *Y(SC)* was statistically significant, with a p value < .001. For each unit of change in *X(EI)*, *Y(SC)* increased by 0.648. Based on adjusted R^2, approximately 33% of the variance in *Y(SC)* was explained by changes in *X(EI)* and *X(Y)*.

For the subcultures of safety culture, the following relationships were determined:

- ~ 28% of the variance in *Y(P)* can be explained by *X(EI)*, *X(J3)*, *X(J5)*; and the

2FIs *X(J3)X(EI),* and *X(J5)X(EI).*

- ~ 12% of the variance in *Y(S)* can be explained by *X(EI), X(J1), X(J2),* and *X(J5).*
- ~ 27% of the variance in *Y(F)* can be explained by *X(EI), X(Y), X(J3),* and the 2FI *X(Y)X(J5).*
- ~28% of the variance in *Y(L)* can be explained by *X(EI), X(A), X(Y), X(J1), and* the 2FI *X(A)X(J5).*
- ~42% of the variance in *Y(T)* can be explained by *X(EI), X(J2),* and the 2FI *X(J2)X(Y)*.
- ~18% of the variance in *Y(R)* can be explained by *X(EI)* and *X(J)*.
- ~13% of the variance in *Y(J)* can be explained by *X(EI), X(Y),* and the 2FI *X(J3)X(EI).*

All of the residuals were normally distributed. There was more than adequate sample size, leading to high statistical power and confidence and a very precise test of effects. This leads to high confidence in the outcomes of the hypothesis tests and conclusions drawn from the statistical analysis and model-building. The key findings of my analysis include the following:

- Emotional Intelligence, *X(EI)*, is always a predictor of all scales related to safety culture.
- The strongest model for safety culture, *Y(SC)*, with an adjusted R^2 of .328 was *Y(SC) = 1.511 + (.648)X(EI) + (.006)X(Y)*

- The strongest model for teamwork culture, *Y(T),* with an adjusted R^2 of .420, was $Y(T) = 1.234 + (.733)X(EI) - (.249)X(J2) + (.022)X(J2)X(Y)$
- The best-fit models for priority culture *Y(P)*, flexible culture *Y(F),* and learning culture *Y(L)* revealed adjusted R^2 scores between .200 and .300 (medium influence).
- Even though they were statistically significant, the models with adjusted R^2 scores between .100 and .200 reflected less influence, including reporting culture, *Y(R)*, standardizing culture, *Y(S)*, and just culture, *Y(J)*.

In Chapter 5, I will review the purpose and nature of this study and why it was conducted. I will interpret the findings, indicate the limitations, explain the implications for professional practice, and make recommendations for future research. Furthermore, I describe the positive social change this research contributes to and offer my final conclusions.

Chapter 5: Discussion, Conclusions, and Recommendations

The purpose of this quantitative descriptive nonexperimental correlational study was to explore the relationship between emotional intelligence, the independent variable, and safety culture, the dependent variable, among professionals in the business aviation industry. The findings of the study addressed the gap in the body of knowledge needed for aviation safety managers to effectively promote a safety culture with regard to emotional intelligence to reduce human error in their organizations. In addition to the aggregate measure of safety culture, I tested the degree to which emotional intelligence was related to each of the seven subcultures of safety culture described by Wang and Sun (2014). I also considered the moderating effect of demographic variables on the relationship between emotional intelligence and safety culture. Secondary dependent variables included the seven subcultures of safety culture: priority culture, standardizing culture, flexible culture, learning culture, teamwork culture, reporting culture, and just culture. The analyses revealed a significant and positive correlation between emotional intelligence and safety culture (and all seven subcultures).

Interpretation of Findings

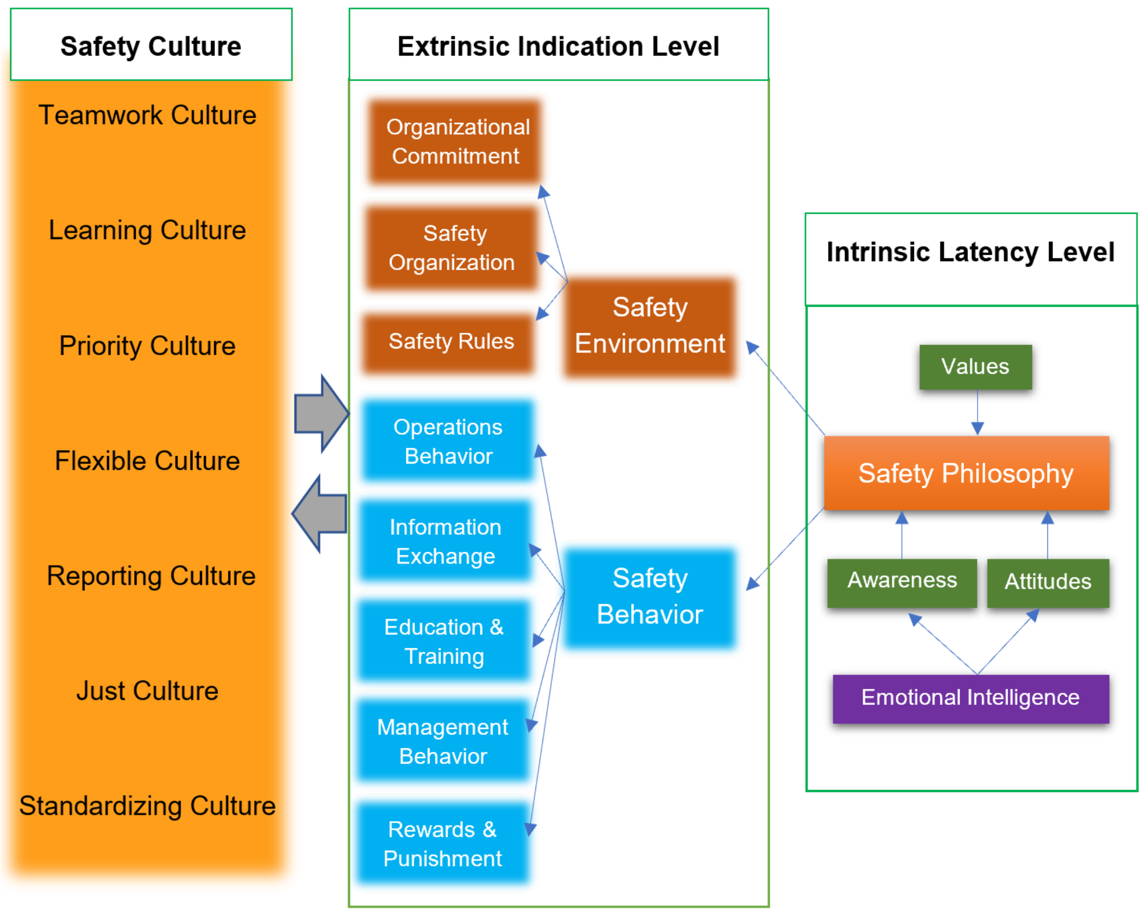
My findings confirm the results of other studies, especially those related to the health care industry, that emotional intelligence can improve team performance and safety culture. In the following sections, I describe the practical meaning (for operations and management) of each of my findings and how they support, refute, or extend the body of knowledge in the discipline of safety management with reference to theoretical frameworks, as appropriate and applicable.

Emotional Intelligence Predicts Safety Culture

My study provides evidence that emotional intelligence is a significant predictor for safety culture and all its seven sub-scales, as modeled by Wang and Sun (2014), who enhanced the original theoretical model by Reason (1997) by adding teamwork culture, standardizing culture, and priority culture. The best predictive model showed that emotional intelligence, moderated by demographic variables, was able to account for up to a third of the variation in safety culture. This finding supports previous studies, primarily in the health care industry, that conclude emotional intelligence positively influences safety culture (see, for example, Pan et al., 2018; Rezaei & Salehi, 2018). This finding could also extend the ISCM by including emotional intelligence as a precursor to attitude and awareness at the intrinsic level (Figure 12). Safety attitude is a collection of psychological factors that include mental and emotional states related to safety decision-making (Wang et al., 2009). Furthermore, a higher level of emotional intelligence enhances a person's ability to perceive and understand a situation (awareness) and improves safety decision-making in teams (Hersing, 2017).

Figure 12

Enhanced Integrated Safety Culture Model with Emotional Intelligence



Note. Emotional intelligence added to the intrinsic level due to its global effect on all sub-scales of safety culture and connectedness to awareness and attitudes (see Figure 3).

Operationally, this finding indicates that all personnel may benefit from working in teams and organizations that possess higher levels of emotional intelligence because they will have higher levels of psychological safety (Zhou et al., 2020) and therefore increased trust that they can report errors, violations, and other safety issues without retribution (Hudson 2003; Reason, 1997). From a management perspective, improvements in emotional intelligence and safety culture improve safety information sharing with the benefit of reducing human error (Reason, 1997) and harmful events (Berry et al., 2020; Fox et al., 2021), thereby improving the work environment and safety performance of the organization.

Emotional Intelligence is a Strong Predictor of Teamwork Culture

My study provides evidence that emotional intelligence is a strong predictor for the safety culture subscale, teamwork culture. This finding supports previous studies of the positive relationship between emotional intelligence and teamwork (see, for example, Jamshed & Majeed, 2019; Michinov & Michinov, 2022; Rezvani et al., 2019). The findings also support the theoretical model by Wang and Sun (2012) that identifies teamwork skills, experience sharing, and effective communication as essential to teamwork culture. Therefore, the positive and powerful relationship between emotional intelligence and teamwork culture is logical since teams with healthy emotional intelligence are better able to manage their individual and collective emotional states to efficiently communicate, share ideas, and achieve individual and team goals.

From a worker's perspective, when colleagues trust each other, freely share safety-related experiences, and communicate effectively, they are better informed and aware of the safety risks in their organization and operational environment. From a management perspective, achieving significant strategic safety objectives requires effective teamwork. Therefore, knowledge and understanding of the importance of emotional intelligence and its influence on teamwork culture is paramount.

Emotional Intelligence is a Moderate Predictor of Learning Culture

My study provides evidence that emotional intelligence is a moderate predictor for safety culture sub-scale learning culture. This finding supports previous studies regarding the positive influence of emotional intelligence on learning (for example, Stephens & Carmeli, 2016; Zhou et al., 2020). From an operational perspective, teams with healthy emotional intelligence share information and learn from one another more effectively because their psychological safety is higher (Zhou et al., 2020). From a management perspective, organizations with robust collective emotional intelligence are better able to adapt to a changing environment, which improves resiliency and sustainability.

Emotional Intelligence is a Moderate Predictor of Priority Culture

My study provides evidence that emotional intelligence is a moderate predictor for the safety culture sub-scale, priority culture. Operationally, because priority culture assumes safety is a core value to be considered paramount during the decision-making process, teams with healthy emotional intelligence focus on this virtue while effectively collaborating, communicating, and even compromising to achieve an optimized solution that reduces safety risks to the lowest acceptable level (Hersing, 2017). From a management perspective, organizations with robust collective emotional intelligence are better able to debate, collaborate, prioritize safety, and establish meaningful strategic objectives that influence and inspire productive and safe operational behavior.

Emotional Intelligence is a Moderate Predictor of Flexible Culture

My study provides evidence that emotional intelligence is a moderate predictor for the safety culture sub-scale, flexible culture. This supports previous research that indicates flexibility is an attribute of emotional intelligence (for example, Ackley, 2016; Bar-On, 2006; Satuf et al., 2020). Because a flexible culture assumes the organization can effectively adapt to ever-changing situations, teams with healthy emotional intelligence contribute to a flexible culture because they effectively manage their emotions under the stress of change, use their emotions to understand the evolving environment, and facilitate decision-making to achieve desired outcomes. From a management perspective, organizations with robust collective emotional intelligence and flexibility are better able to pivot, refocus, and re-establish new tactical objectives to achieve success. Because resiliency and adaptation are essential for sustainability and growth, emotional intelligence is a fundamental requirement at the team and organizational levels.

Emotional Intelligence is a Weak Predictor of Reporting Culture

My study provides evidence that emotional intelligence is a significant but weak predictor for the safety culture sub-scale reporting culture. Wang and Sun's theoretical model for reporting culture evaluates three areas: (a) the degree to which the organization has implemented a safety information reporting system; (b) the extent to which people use it; and (c) how effectively management provides feedback to the reporter (Wang &

Sun, 2012). Because these three dimensions have little to do with managing the emotional states of individuals or teams, weak predicting power is expected. Operationally, workers need emotional intelligence to receive critical but constructive feedback from management, especially regarding the self-reporting of errors and violations. Managers also need to exercise astute emotional intelligence when providing feedback to maintain trust with the reporter.

Emotional Intelligence is a Weak Predictor of Just Culture

My study provides evidence that emotional intelligence is a significant but weak predictor for the safety culture sub-scale, just culture. Wang and Sun's theoretical model for just culture evaluates two areas: (a) the implementation and fairness of safety supervision mechanisms; and (b) the extent of implementing reward and punishment mechanisms in the organization (Wang & Sun, 2012). Because these two dimensions have little to do with managing the emotional states of individuals or teams, weak predicting power is expected. Operationally, workers need emotional intelligence to be monitored by their supervisor and accept correction when necessary without becoming angry or upset. From a management perspective, supervisors also need to exercise effective emotional intelligence when rewarding or correcting behavior so that the worker feels respected while core values, such as excellence and professionalism, are upheld.

Emotional Intelligence is a Weak Predictor of Standardizing Culture

My study provides evidence that emotional intelligence is a significant but weak predictor for the safety culture sub-scale, standardizing culture. Wang and Sun's theoretical model for standardizing culture evaluates two areas: (a) the degree to which the organization implements safety rules, regulations, and standards; and (b) the degree to which the organization and individuals comply with the instituted rules and regulations and conform to the documented standards (Wang & Sun, 2012). Because these two dimensions have little to do with managing the emotional states of individuals or teams, weak predicting power is expected. However, workers need emotional intelligence to effectively discuss problematic policies, processes, and procedures with their colleagues and management personnel without becoming upset or angry. Likewise, managers should apply astute emotional intelligence when listening to the complaints of workers who report problems with the rules or lack of standardization.

Limitations of the Study

Scholars debate the ontological essence of both emotional intelligence and safety culture constructs. I mitigated these risks by utilizing questionnaires founded on widely respected research. Jordan and Lawrence (2009) designed the WEIP-S to reflect the theory of Salovey and Mayer (1990), as explained by Salovey (1997). Wang and Sun (2014) designed their safety culture instrument from the theory established by Reason (1997), who is globally recognized as one of the most respected psychologists and safety theorists in the aviation community (ICAO, 2018).

I used convenience sampling (non-probability) versus probability sampling of the target population, resulting in selection bias (El-Masri, 2017). Therefore, the findings and conclusions may not be generalizable since the participants may represent a sub-group who pursue and promote safety more actively than the mean population.

Self-selection bias was a potential risk for my study. I sent the questionnaires to a wide variety of business aviation personnel. Thousands of people had the option to participate. Therefore, those who chose to participate versus those who did not may represent a proactive subculture within business aviation and not necessarily the whole. As a result, my study's findings may reflect the attitudes and culture of people who are more progressive than those who chose not to participate.

Another limitation of my study was that the Wang and Sun (2014) instrument is relatively new and not yet rigorously validated by other researchers. This threat was mitigated because Wang and Sun built their instrument on Reason's construct for safety culture, a paradigm that is widely promoted around the world by ICAO, third-party aviation safety audit companies, and national aviation regulatory authorities.

Recommendations

Although my survey instrument was well-designed and enabled the participant to complete it efficiently in only 8 minutes (average), processing the data would have been more efficient without the reverse scoring. Therefore, I recommend the ISCM be modified so that all the statements are positive, so reverse scoring is not necessary.

Also, because the participation rate was so low (less than 3%), I recommend future studies be conducted on large business aviation organizations with more than 100 aircraft. These organizations typically have at least 1,000 employees, and senior leadership could help promote the study to ensure a robust participation rate. It is conceivable that with effective promotion by managers, the study could generate participation from at least 500 people per large organization. Furthermore, if the study were conducted on two large organizations, the findings could be compared between the two organizations.

Zhou et al. (2020) concluded that emotional intelligence is essential for individuals in teams to have psychological safety, which is the freedom to express their ideas and be their genuine selves without fear of negative responses from their team. Psychological safety is a must for future teams built on diversity and inclusion. Bisbey et al. (2019) concluded that psychological safety enables a positive safety culture. Therefore, I recommend that future research exploring the relationship between emotional intelligence and safety culture consider incorporating psychological safety data collection as well.

Implications

The evidence from my research and analysis could be used to support efforts to integrate emotional intelligence assessments into personnel recruitment and hiring processes. This differentiating variable could help organizations more effectively choose new members who have a higher likelihood of successfully integrating into the team environment and also increase the chances of developing high-performing teams.

Because emotional intelligence appears to positively influence teamwork culture, aviation safety leaders should consider integrating emotional intelligence training into the training programs related to critical high-reliability teams, such as multi-crew aircraft flight decks, aircraft maintenance, flight dispatch, and others considered essential to safe operations. The FAA's guidance document for crew resource management (CRM), *Advisory Circular 120-51E*, pertains to all aviation professionals, not just pilots (FAA, 2004). CRM is synonymous with teamwork among aviation technical teams. In this advisory circular, the FAA described the need for team members to be assertive and yet respectful toward other team members and highlighted the need to stay calm and effectively resolve conflict within the team. However, the guidance lacks specific information related to emotional intelligence, which would greatly enhance the overall training program for CRM by helping individuals understand the concepts and the skills needed to manage their emotional state and that of their team members, thereby preventing conflict or, more effectively managing through it. By not addressing emotional intelligence in CRM training, critical decision-making processes will continue to be at risk with regard to cognitive bias, as described by Hersing (2017). Therefore, work needs to be done to include emotional intelligence attributes in future CRM training and evaluation programs.

Overall, my research analysis may contribute to positive social change. My findings provide aviation safety leaders with meaningful information about the relationship between emotional intelligence and safety culture. The evidence provides safety managers with information to support prudent decisions related to managing human error, the primary cause of incidents and accidents in the aviation industry. As a result, my findings may contribute to healthier organizational cultures, lower error rates, lower incident rates, and less risk to business aviation stakeholders.

Conclusions

For more than two decades, scholars and practitioners have argued that emotional intelligence is just as important as cognitive skills because highly successful organizations are typically built on high-performing teams, not individuals. Negative emotional states reduce individual and team performance, especially in the decision-making process. Individuals with keen emotional intelligence are able to manage their emotional state and the emotional states of those around them to achieve desired outcomes.

Effective teamwork is essential in high-reliability industries such as health care and aviation, where human error can lead to loss of life. Although researchers in the health care industry have made significant contributions to the body of knowledge to make the connection between emotional intelligence, safety culture, and error reduction, the aviation industry is just beginning to embark upon this journey. My research provides evidence that emotional intelligence significantly predicts safety culture, especially through the teamwork subculture in business aviation. Therefore, aviation safety leaders should commit to learning more about the benefits of emotional intelligence education and training to improve team performance and safety culture in all functional areas of aviation. By doing so, they can reduce harmful errors and improve overall safety risk management.

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Appendix A: Invitation to Participants

Walden University
College of Management and Technology
100 Washington Avenue South
Minneapolis, MN 55401

Invitation to Participate in a Research

If you are a pilot, cabin crew member, aircraft maintenance technician, scheduler or dispatcher, or in management over any of these functions, in an organization that operates business aircraft, I ask that you please participate in this study. I am conducting research on "Emotional Intelligence and Safety Culture in Business Aviation," to fulfill the requirements of earning a Doctor of Philosophy degree at Walden University.

I invite you to take part in this research study because your experience as an aviation professional could potentially assist aviation safety leaders in formulating strategies to improve safety culture and reducing human error in the business aviation community.
I respectfully request 15 minutes of your time to complete the survey linked to this message. The questions seek your honest opinion regarding your work group's emotional intelligence and safety culture. There are no right or wrong answers. The information you provide will remain confidential. All data will be stored in a password protected electronic format to ensure your confidentiality. The results of this study will be used solely for scholarly purposes, and therefore shared with Walden University representatives.

Your participation in this study is voluntary. There are minimal risks associated with participating in this survey and you will not receive any monetary compensation for participation. You may choose not to participate. Additionally, if you decide to participate in this study, you have the opportunity to discontinue participation at any time. The research results will be presented as aggregate, summary data only. Should you desire to have a copy of the research study results, please email me at Sonnie.Bates@waldenu.edu

Sincerely,
Sonnie Bates, Ph.D. Candidate at Walden University

Appendix B: Online Questionnaire

This questionnaire and the associated collected data are confidential. All participants will remain anonymous. All results from the survey will represent a group from an individual's perspective. Your participation in this survey is voluntary and greatly appreciated.

Section 1 Demographics

1. What is your age?
2. What is your gender? (Male, Female, Prefer not to say, Other)
3. What is your primary job position? (Pilot, Cabin Crew, Aircraft Maintenance Technician, Scheduler/Dispatcher, Management, Other).
4. How long have you been with the company (years)?

Section 2 Emotional Intelligence

Each of the following items asks you about the typical emotions or reactions associated with your team. After deciding whether a statement is generally true, use the 5-point scale to respond to the statement. Please circle the “1” if you strongly disagree that this is like your organization, the “2” if you somewhat disagree that this is like your organization, “3” if you neither agree nor disagree that this is like your organization, the “4” if you somewhat agree that this is like your organization, and the “5” if you strongly agree that this is like your organization. There are no right or wrong answers. Please give the response that best describes your organization.

1) I can explain the emotions I feel to team members.

2) I can discuss the emotions I feel with other team members.

3) If I feel down, I can tell team members what will make me feel better.

4) I can talk to other members of the team about the emotions I experience.

5) I respect the opinion of team members, even if I think they are wrong.

6) When I am frustrated with fellow team members, I can overcome my frustration.

7) When deciding on a dispute, I try to see all sides of a disagreement before I come to a conclusion.

8) I give a fair hearing to fellow team members' ideas.

9) I can read fellow team members 'true' feelings, even if they try to hide them.

10) I am able to describe accurately the way others in the team are feeling.

11) When I talk to a team member, I can gauge their true feelings from their body language.

12) I can tell when team members don't mean what they say.

13) My enthusiasm can be contagious for members of a team.

14) I am able to cheer team members up when they are feeling down.

15) I can get fellow team members to share my keenness for a project.

16) I can provide the 'spark' to get fellow team members enthusiastic.

Section 3 Safety Culture

How well do you think each of the following statements applies to your organization according to the following five-point scale: Strongly disagree (1), Disagree (2), Unsure (3), Agree (4), Strongly agree (5)

1) Safety is given a definite priority when it conflicts with the company's other interests, e.g., economic.

2) To ensure safety goals are achieved, everyone's responsibilities are clear.

3) Our organization is properly equipped, staffed, and supported with financial resources.

4) I am satisfied with working conditions and the equipment used in my work.

5) The safety management committees and department managers perform their duties and play an active role in preventing and investigating incidents.

6) Our policies, processes and procedures related to safety are inadequate.

7) Our policies, processes, and procedures related to safety are not updated in a timely manner.

8) I do not know all of the safety rules that should be followed at work.

9) I don't always fully comply with company policies, processes, or procedures.

10) Safety inspections and risk assessments are carried out regularly in my company.

11) The hazards found in safety inspections and risk assessments are rectified promptly.

12) I am given sufficient opportunities to make suggestions and participate in the safety decision making and implementing process.

13) Violation of policies, processes, or procedures happen frequently in my company.

14) There is an active learning atmosphere within my company.

15) I am used to improving my skills through learning actively in my company.

16) Team spirit and cooperation are well promoted in my company.

17) I am happy to offer help when my colleagues need support or assistance at work.

18) When other people make mistakes at work, I don't always point them out immediately, as I think it's none of my business or I'm afraid of making that person feel embarrassed.

19) I can effectively identify safety risks during my work.

20) I can effectively apply mitigation measures after discovering safety risks.

21) Safety education and training are carried out frequently in my company.

22) As a result of safety education and training, the ability of staff to recognize and deal with risks has been improved significantly.

23) Self-learning and knowledge-sharing among staff are encouraged in my company.

24) There are various ways to facilitate knowledge-sharing in my company.

25) Safety information reporting, including mandatory and confidential safety reporting, is carried out in my company.

26) The company safety information reporting system is operated well and used widely.

27) I often contribute and obtain all kinds of safety information through the company safety information reporting system.

28) I do not always receive feedback in a timely manner after I make a safety suggestion.

29) In my organization, we learn from incidents/accidents that have happened in the industry and in our company.

30) I can often improve my experience and knowledge through communicating with my colleagues.

31) The rewards and punishment measures of the company are fair, just and open.

32) I am satisfied with my company’s rewards and punishment measures.

Appendix C: Approval to Use Instruments

Re: ISCM
1 message

Lei Wang <wanglei0564@hotmail.com> Tue, Jan 26, 2021 at 9:20 AM
To: Sonnie Bates <sonnie.bates@gmail.com>

Hi Sonnie,

Thanks for your attention on our safety culture work finished several years ago.

You are welcome to use it and I attached the related paper & questionaire here.

Best regards,

Lei

From: Sonnie Bates
Sent: Monday, January 25, 2021 6:19 AM
To: wanglei0564@hotmail.com
Subject: ISCM

Hello Lei Wang

I would like permission to use your ISCM as an instrument in my dissertation to earn a PhD. Also, if you approve, please send me a link so I can learn more about how to use the instrument.

Thank you

Sonnie

Sonnie G. Bates
https://www.linkedin.com/in/sonnie-bates/
+1 (603) 233-7196

On Thu, Dec 2, 2021 at 12:21 AM Peter Jordan <peter.jordan@griffith.edu.au> wrote:

Hi Sonnie

Thanks for your email and your interest in using the WEIP.

The WEIP is public domain - so there are no fees or permissions required to use it. But that also means no fancy documentation or support. Generally those using it draw normative data from previously published studies using the WEIP. You can find published validation papers in Google Scholar by searching WEIP. I have used it previously in training as a reflective tool or a discussion starter and it has worked pretty well. I have also used it in published research. Of course acknowledgement of the source would be appreciated.

I am attaching the initial validation paper for that measure. I have got pretty good results using it as have other researchers. The items are in the factor analysis in Table 2. The paper also has instructions on how to administer the WEIP-S. Let me know if you have any questions and good luck with your project.
Regards
Peter

Peter J. Jordan (PhD)
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