MEASURING THE IMPACT OF BURNOUT AMONG CERTIFIED REGISTERED NURSE ANESTHETISTS PRACTICING IN THE UNITED STATES

by

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ABSTRACT

BRIAN DEL GROSSO. Measuring the impact of burnout among Certified Registered Nurse Anesthetists practicing in the United States. (Under the direction of DR. A. SUZANNE BOYD)

The comprehensive analysis of the impact of job demands and job resources on burnout among Certified Registered Nurse Anesthetists (CRNAs) in the U.S. utilized a sample of 152 CRNA participants who responded to an online electronic survey administered by the AANA. The JDR theoretical framework guided hypotheses development. Structural Equation Modeling (SEM) methods validate the proposed hypotheses. The findings are instrumental in understanding the interplay between job demands and job resources in relation to burnout within the CRNA cohort.

Descriptive statistics highlighted the distribution of job-related stress and support measures, with the Oldenburg Burnout Inventory scores indicating a moderate level of burnout among participants. Correlation analysis revealed significant relationships between job factors and burnout dimensions, with collaboration, decision latitude, and organizational support negatively correlated with exhaustion and disengagement, suggesting their potential protective effects against burnout.

The SEM analysis provided a robust framework for assessing the direct and indirect correlations between job demands, job resources, and burnout. The regression paths confirmed job demands as a strong predictor of burnout, with a significant positive effect. Job resources exhibited a complex relationship with burnout, with an indirect buffering effect that did not reach statistical significance in the mediation analysis, although the overall relationship between job demands and burnout was significant.

The results underscore the significance of job demands as predictors of burnout among CRNAs and illuminate the nuanced role of job resources. This lays a fertile ground for future

research to build upon, potentially leading to targeted interventions aimed at mitigating burnout among CRNAs and policy revision and changes that ensure CRNAs have access to needed resources and supports related to job demands.

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To my parents and wife: Thank you for your love and unwavering support throughout this process. You all believed in me, even at times when I didn't believe in myself. To my wife, Lindsay: Through it all, a pandemic, kids, doctoral program, and my job, you were inspirational and motivating. To my parents: Thank you for always pushing me to do what I love and not let the hard be hard.

To my friends: Thank you for your understanding and support for what it meant to me to undertake this journey. You always made sure I was okay. You were my pillars, my brothers.

I am a better husband, father, friend, son, and scholar because of every one of you. Thank you.

DEDICATION

This work is dedicated to all those healthcare providers that struggle with burnout. Healthcare is an extreme and turbulent job, and the chaos of the pandemic only made it more extreme and turbulent. Never doubt your worth or your value. You are never alone. You are the backbone of the U.S. healthcare system.

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LIST OF ABBREVIATIONS

Abbreviation	Definition
AANA	American Association of Nurse Anesthetist
ANS	Autonomic Nervous System
APN	Advanced Practice Nurse
AW	Areas of Worklife
BBI	Bergen Burnout Inventory
BM	Burnout Measure
CBI	Copenhagen Burnout Inventory
CINAHL	Cumulative Index to Nursing and Allied Health Literature
COR	Conservation of Resources
CPC	Continued Professional Certification
CRNA	Certified Registered Nurse Anesthetist
CSACD	Collaboration and Satisfaction about Care Decisions
DCM	Demand Control Model
DP	Depersonalization
DV	Dependent Variable
EE	Emotional Exhaustion
ERI	Effort-Reward Imbalance
HMR	Hierarchical Multiple Regression
IV	Independent Variable
JCQ	Job Content Questionnaire
JD-R	Job Demands-Resources
JDRS	Job Demands-Resources Scale
JDS	Job Diagnostic Survey
MBI	Maslach Burnout Inventory
MTMM	Multi-Trait, Multi-Method
NASEM	National Academy of Sciences, Engineering, and Medicine
OCQ	Organizational Climate Questionnaire
OLBI	Oldenburg Burnout Inventory
PA	Personal Accomplishment
RQ	Research Question
SEM	Structural Equation Modeling
SMBM	Shirom-Melamed Burnout Measure
SPSS	Statistical Package for the Social Sciences
UWES	Utrecht Work Engagement Scale
WIS	Workplace Incivility Scale

CHAPTER 1: INTRODUCTION

The current landscape of healthcare continues to expose its providers to elevated levels of stress that affect healthcare providers' wellbeing, ultimately leading to the experience of burnout. Burnout is widely considered to be an occupational and personal risk for healthcare providers (Morais et al., 2006; Schaufeli et al., 2017). Existing research has demonstrated that burnout has negative effects on the healthcare system in its entirety (Schaufeli et al., 2017). Burnout not only reduces patients' quality of care and satisfaction but also has harmful effects on the provider and the organization (Maslach & Leiter, 2016). Effects on the provider include mental, physical, and psychosocial issues, while effects on the organization include turnover costs and decreased job satisfaction (Maslach & Leiter, 2016). Before the onset of the COVID-19 global pandemic, the impact of burnout in the U.S. healthcare workforce was well established. It was estimated that between 35% and 54% of nurses and physicians in the United States were suffering from burnout (National Academies of Sciences, Engineering, and Medicine [NASEM], 2019). A recent study by Shanafelt et al. (2022) found healthcare providers had a higher rate of burnout compared to non-healthcare providers (37.9% vs 27.8%). Challenges presented by the pandemic have been shown to exacerbate the prevalence of burnout among U.S. healthcare providers (Leo et al., 2021; Prasad et al., 2021).

The likely continuing increase in provider burnout is of growing concern throughout the healthcare industry (NASEM, 2019). Burnout's contribution to widespread negative consequences within the healthcare industry has placed maximizing provider wellbeing and mental health at the top of many healthcare organizations minds (NASEM, 2019). Regardless of the amount of attention this syndrome receives, many fall short in the ability to manage burnout. Experts hypothesize that this is due to each industry's unique environment and operating conditions and have cautioned readers that generalization of study results outside of the industry that was studied can result in a misrepresentation of those variables (Bakker & Demerouti, 2017). There may be common job-related characteristics contributing to burnout in that individual provider; however, burnout is context-specific to that individual's work environment and, therefore, empirical research should be more specific. The JD-R model was used to better understand the influence of specific job demand and resource factors on burnout amongst certified registered nurse anesthetists (CRNAs). This quantitative, exploratory study population is CRNAs practicing in the United States. Although there has been an increased empirical focus on CRNA burnout, the extent of the relationship between burnout and job-related characteristics remains poorly understood which, in turn, may result in an ongoing negative impact on the providers and the organizations and communities they serve. The study's overall goal to address the relationship between job-related characteristics and burnout in CRNAs and use the JD-R perspective is to increase the understanding of the impact of specific job-related characteristics contributing to burnout. Further understanding of this impact may provide a path towards appropriate interventions.

Background of Study

The anesthesia specialty is one of the more stressful work environments, with prevalence rates being as high as 59% and ranking in the top half of all medical specialties (De Hert, 2020; Sanfilippo et al., 2017). CRNAs are a critical part of the anesthesia workforce, responsible for approximately 65% of the anesthetics provided in the United States (Del Grosso & Boyd, 2019). CRNAs are advanced practice nurses (APNs) with graduate-level educations. CRNAs are highly trained and skilled clinical nurse specialists who have gained a high degree of respect within the surgical services arena. They are the sole anesthesia providers in nearly all rural hospitals and the primary providers of anesthesia for the U.S. Armed Forces (Del Grosso & Boyd, 2019). Research has demonstrated CRNAs' abilities to provide "safe, high-quality, and cost-effective anesthesia services" to numerous patient populations (Del Grosso & Boyd, 2019, p.205). During the COVID-19 pandemic, CRNAs unique airway skills and experience in the management of critical-care patients resulted in added workflow demands. Changes in the healthcare system have resulted in CRNAs managing an aging, complex patient population while faced with increasing time pressure, complex medical technology, and a lack of resources. The growing demands by healthcare facilities for cost-efficient, safe anesthesia services coupled with the challenges created by the pandemic, have led to a further mismatch between job demands and job resources, ultimately increasing the risk of burnout and its associated negative outcomes (Aron et al., 2021).

The critical role CRNAs play within the healthcare industry has resulted in increased research focusing on CRNA burnout (see Boyd & Poghosyan, 2017; Del Grosso & Boyd, 2019; Mahoney et al., 2020). Common themes that have emerged as primary factors contributing to burnout include work overload, lack of autonomy and collaboration, increased production pressures, and lack of control and social support (Boyd & Poghosyan, 2017; Mahoney et al., 2020). Negative outcomes related to increased CRNA burnout have been associated with intent to quit, increased turnover, workplace aggression, and decreased job satisfaction (Boyd & Poghosyan, 2017; Mahoney et al., 2020).

Statement of the Problem

The lack of a generally accepted definition of burnout and its multifactorial origins continues to create empirical and theoretical challenges for those interested in understanding the syndrome. Prior to this study, there was increased attention towards evaluating the relationships between job-related factors and burnout within the nursing anesthesia specialty; however, the ability to manage burnout appropriately has remained limited. For example, an American Association of Nurse Anesthetists (AANA) membership survey published in May 2019 demonstrated that 34% suffered from work-related stress (AANA, 2019a). In 2022, the AANA's membership survey found that 60% of its members felt their schedule and work demands had a negative impact on their practice (AANA, 2023).

The limited success in alleviating CRNA burnout may be related to several gaps within the literature.

First, rigorous research on the root causes of burnout specific to CRNAs practicing in the United States remains limited. Empirical research on burnout within the nursing anesthesia specialty has primarily involved mixed samples of anesthesia providers (i.e., anesthesiologists and trainees) or has been pooled with other healthcare providers (see Hyman et al., 2011; Shah et al., 2019). "Burnout is an individual experience that is specific to the work context" and influences such as the occupational environment, professional background, and individual characteristics can influence data outcomes (Del Grosso & Boyd, 2019, 207). For example, Chiron et al. (2010) demonstrated that junior French anesthesiologists scored higher on emotional exhaustion when compared to senior anesthesiologists. In contrast, Meeusen et al. (2011) demonstrated that older Dutch nurse anesthetists' greater emotional exhaustion scores compared to younger nurse anesthetists. Every specialty within the healthcare industry has its unique demands and resources and, therefore, requires its own research and attention (Bakker, & Demerouti, 2007).

Second, studies that have involved CRNAs practicing in the United States lack theoretical models as a guide towards understanding the impact of job-related factors on burnout

(Del Grosso & Boyd, 2019). The origins of burnout's conceptualization have resulted in a subjective, often vague understanding of its development. To help understand the complex etiopathogenesis of burnout, a multitude of explanatory models have been used to guide burnout research. Empirical research without theoretical guidance can become vague and overinclusive, resulting in misinterpretations of other concepts and/or management of the findings. For instance, the lack of a theoretical foundation can result in discriminant validity questions such as burnout being confused with stress and depression (Schaufeli, Maslach, & Marek, 2017). Stress, if chronic, can result in burnout, and burnout can lead to depression; however, both concepts exist independently (Schaufeli et al., 2017).

A second challenge related to the lack of theoretical framework in empirical research is the understanding of the development of burnout. Burnout is conceptualized as an individual problem that is specific to the work context, however, a lack of a theoretical model can create misconceptions (Schaufeli et al., 2017). This misconception often results in interventions targeting the individual instead of the organization (Del Grosso & Boyd, 2019). For instance, organizations often use individual strategies (i.e., meditation, yoga, retreats) rather than changes to the work context and its demands (i.e., increasing job control over schedules, electronic record applicability) (Del Grosso & Boyd, 2019; Maslach & Leiter, 2016). Individual-centered approaches have been found to be relatively ineffective, considering that a healthcare provider has little control over the work environment (Maslach & Leiter, 2016). A report by the NASEM (2019) noted that the unsuccessful implementation of interventional strategies may be related to work system factors that contribute to burnout being highly variable and context dependent. Empirical research that is grounded in foundational theory may provide a comprehensive path toward understanding the root causes of burnout among CRNAs.

Finally, researchers evaluating a concept like burnout should view a theoretical framework as the "blueprint" of their empirical study, creating alignment between conceptual understanding and methodological approach (Schaufeli et al., 2017). Having a theoretical framework allows the researcher to specify the variables, the levels of measurement, and how to appropriately analyze those variables. For instance, the JD-R model views job demands and job resources as constructs of work-related factors, meaning they are not directly measured. Therefore, selection of a statistical method for analysis will have to align with this theoretical understanding to prevent a misunderstanding with conclusions related to the analysis. Therefore, expanding on current empirical knowledge of the relationship between job-related characteristics and burnout in CRNAs by applying the JD-R perspective may help further understanding as well as managing its impact on this nursing specialty.

Purpose of the Study

The purpose of this quantitative exploratory study is to further evaluate the relationship between previously identified job demand and job resource variables and burnout among CRNAs practicing in the United States. A modified version of the Job Demands-Resources (JD-R) model (see Figure 1) to include measured variables specific to the nursing specialty was used as the theoretical framework to further understand the burnout syndrome within this nursing specialty. A strong theoretical foundation may provide an easier path for understanding the implications job-related factors have on this nursing specialty given burnout's multifactorial origins. The predictor variables, *job demands* and *job resources*, and these were measured by a myriad of questionnaires specific for the evaluation of these variables. The outcome variable, *burnout,* which and was measured using the Oldenburg Burnout Inventory (OLBI). Each job-related factor specific to the nursing specialty in relation to its impact on burnout was evaluated and compared. Understanding the role each factor plays in burnout and disengagement may help clinicians and administrators better identify and manage the variables' impact on the specialty.

Demographic characteristics included have been used in previous research evaluating CRNA burnout. This dissertation is intended to contribute to the existing literature by addressing the theoretical and empirical gaps related to the development of burnout among CRNAs practicing in the United States.

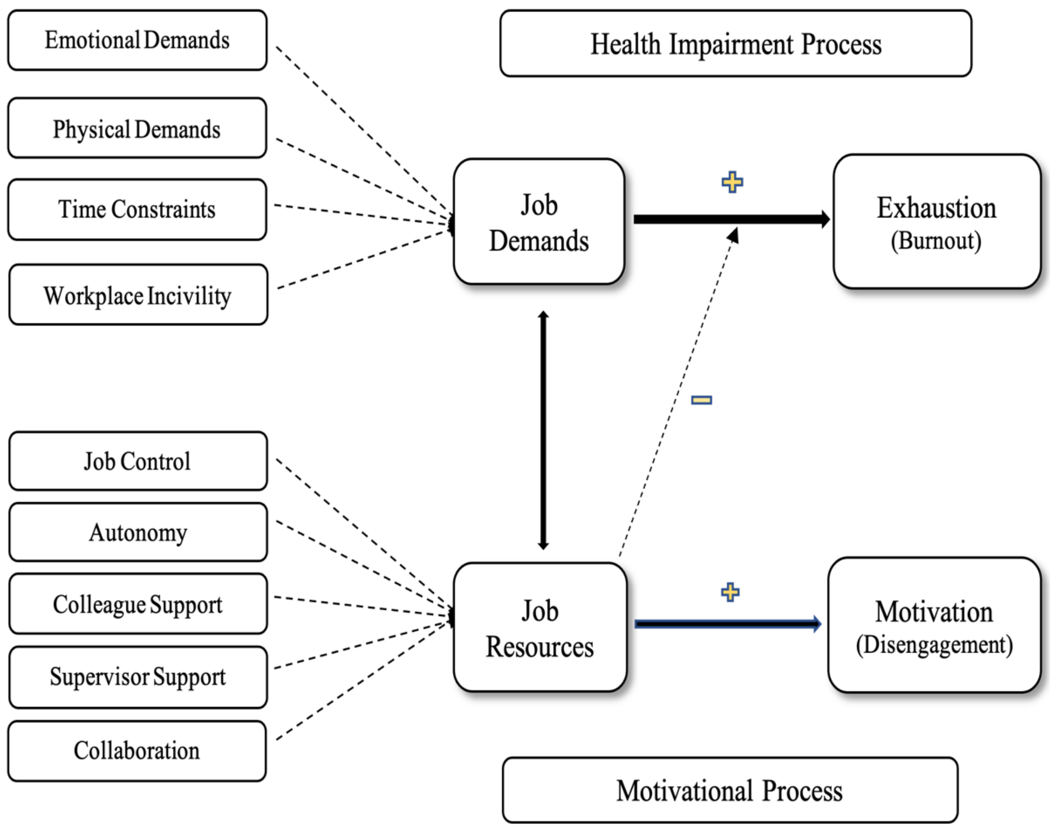

Figure 1.

The Job Demands-Resources Model of Certified Registered Nurse Anesthetists

Note. This flowchart was adapted from, "The Job Demands-Resources Model of Burnout" by E. Demerouti, A.B. Bakker, F. Nachreiner, and W.B. Schaufeli, 2001, *Journal of Applied Psychology, 86(3)*, p. 502.

Theoretical Framework

The JD-R model (see Figure 2) was used as the framework to address the study's research questions and hypotheses. The JD-R model is considered one of the leading stress models. The central assumption of this model theorizes that burnout is directly related to the balance between specific working conditions of that profession (Bauer & Hammig, 2014). These working conditions are classified into two broad categories: job demands and job resources (Bakker & Demerouti, 2007). *Job demands* are defined as physical, psychological, social, or organizational characteristics of the job that result in physical and/or psychological efforts that result in physiological and/or psychological costs (Demerouti et al., 2001). *Job resources* are the physical, psychological, social, or organizational aspects of the job that (a) aide in achieving work goals, (b) reduce the associated physiological and psychological costs secondary to high job demands, and (c) stimulate personal growth, learning, and development (Demerouti et al., 2001).

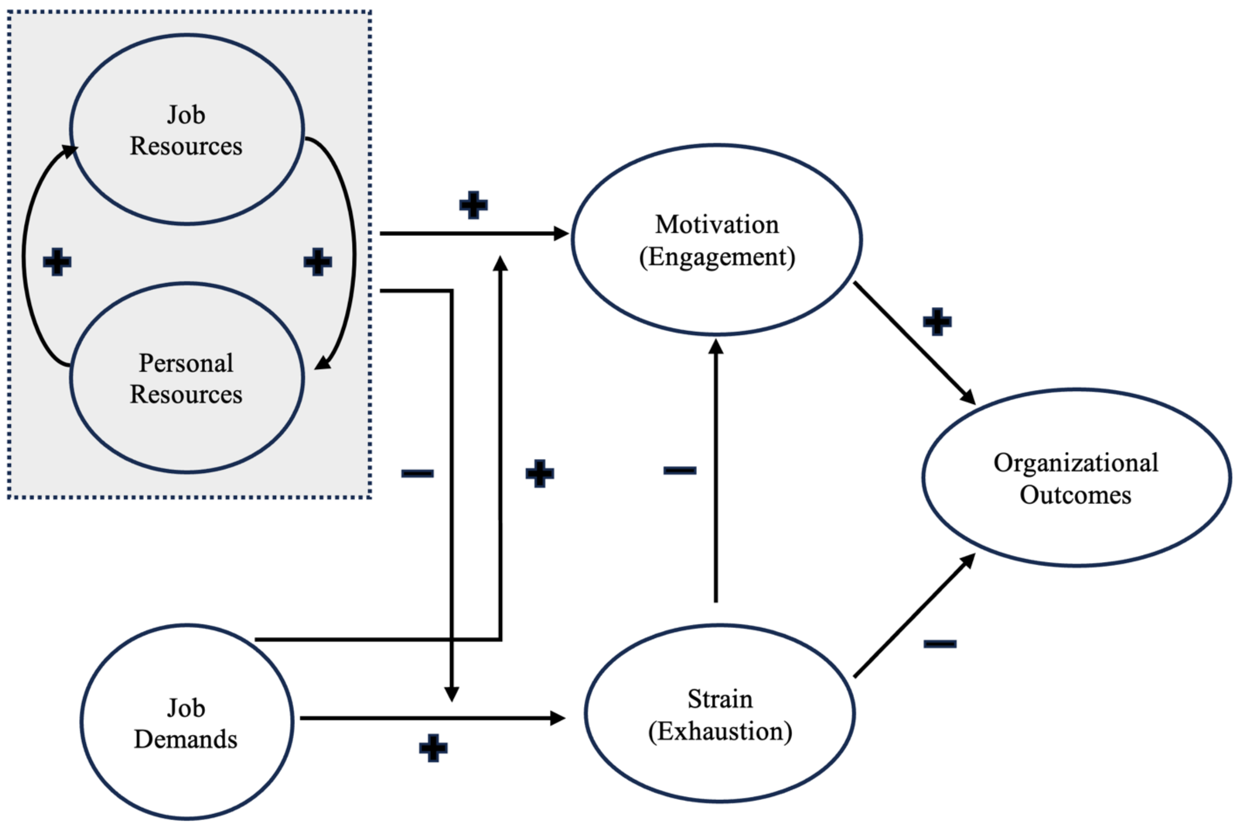

Figure 2.

The Job Demands-Resources Model of Burnout

Note. Updated JD-R flowchart overview that includes personal resources and organizational outcomes. From "Job Demands-Resources Theory: Taking Stock and Looking Forward" by A.B. Bakker and E. Demerouti, 2017, *Journal of Occupational Health Psychology, 22*(3), p. 275.

The JD-R model proposes that the interaction between high job demands and poor job resources creates the burnout syndrome—exhaustion and disengagement (Demerouti et al., 2001; Schaufeli & Taris, 2013). *Burnout* is defined as "a psychological phenomenon that emerges from a prolonged response to chronic interpersonal job-related stressors" (Del Grosso & Boyd, 2019, 207). The JD-R model theorizes that one develops burnout secondary to two processes. The first process, the health impairment process, predicts prolonged exposure to certain job demands that have resulted in intensive physical, affective, and cognitive strain resulting in *exhaustion* (Demerouti, Mostert, & Bakker, 2010; Lesener et al., 2019). In the second process, the lack of job-related resources results in the inability to meet the demands of the job, resulting in withdrawal behavior (Bakker & Demerouti, 2007). The consequence of this withdrawal behavior is *disengagement*, which refers to creating distance from one's work (Demerouti et al., 2001).

The JD-R model is designed to comprehensively explain not only how and why an imbalance between job demands and resources results in burnout but also how the development (and management) of burnout is highly dependent on specific constellations of working conditions and on "individual experiences" of these working conditions (Demerouti et al., 2001). The universality of the JD-R model and prior application to a variety of healthcare specialties makes it an appropriate framework for providing an increased understanding of job demands and job resources and burnout among CRNAs.

Research Questions and Hypotheses

The following research questions were addressed:

RQ 1. To what extent is there a relationship between previously identified job demands and job resources on burnout in a national sample of CRNAs practicing in the United States?

H_a1: Specific job demands and job resources (as measured by subscales of the survey) will have a statistically significant correlation with burnout in CRNAs practicing in the United States.

RQ 2. Is there a difference in the relationship between previously identified job demands (emotional demands, workload, time constraints, and workplace incivility) with burnout dimensions (exhaustion and disengagement)?

H_a2: Job demands, and not job resources, will be the stronger predictor of burnout in CRNAs practicing in the United States.

RQ 3. Is there a difference in the relationship between previously identified job resources (job control, autonomy, colleague support, supervisor support, collaboration) with burnout dimensions (exhaustion and disengagement)?

H_a3: Job resources, and not job demands, will be the stronger predictor of disengagement in CRNAs practicing in the United States.

RQ 4. Is there a difference in the degree of correlations among previously identified job-related variables (as measured by subscales of the survey) with burnout dimensions—exhaustion and disengagement?

H_a4: Job resources, which include job control, autonomy, colleague support, supervisor support, and collaboration, will moderate the positive relationship between job demands and burnout, such that the relationship between job demands and burnout will be less positive.

Nature of the Study

The nonexperimental quantitative exploratory design that examined the degree of relationship between *job demands, job resources*, and *burnout*, as well as its dimensions as operationalized by the Oldenburg Burnout Inventory (OLBI) scale—*exhaustion* and *disengagement* (Demerouti, Bakker, Nachreiner, & Schaufeli, 2001). The primary objective was to evaluate the relationship between job-related characteristics and burnout in CRNAs and use the JD-R perspective is to increase the understanding of the impact of specific job-related characteristics contributing to burnout and its associated dimensions—exhaustion and disengagement. The secondary objective was to evaluate how each job-related characteristic specific to the study population affects burnout, and its associated dimensions, both independently and interdependently. A quantitative approach was used for several reasons: (a) generalizations from previous burnout research relative to the nursing anesthesia specialty will be a focus; (b) a quantitative method is deductive and hypothesis-centered, thus allowing the different relationships among the variables to be tested; and (c) literature related to CRNA burnout is limited, so replication or building from this study is vital to future research focused on identifying and evaluating the implications of burnout for practitioners in this nursing specialty (Abbot & McKinney, 2013).

A cross-sectional survey design in a natural environment without any influence from researchers is considered optimal (Abbott & McKinney, 2013). An online self-report Qualtrics survey built from five primary instruments analyzed the relationship between burnout and job characteristics. A survey link to the survey was distributed to 3,000 randomly selected CRNAs via email from the American Association of Nurse Anesthetists (AANA). An additional follow-up email was sent seven days prior to the survey's 4-week timeframe.

The survey results were exported from Qualtrics to the Statistical Package for the Social Sciences (SPSS) for analysis. The following instruments measured the predictor variables: Job Demands-Resources Scale (JDRS), Job Content Questionnaire (JCQ), and Collaboration and Satisfaction about Care Decisions (*CSACD*) measure. The outcome variable, burnout, was measured by the Oldenburg Burnout Inventory (OLBI). Demographic variables include age, gender, marital status, years of experience, ethnic background, hours worked per week, type and size of the hospital, by whom the participant is employed, the practice setting, and years at the current practice were included. After all the completed data was cleaned and screened, descriptive statistics were computed using SPSS to provide an overview of the sample demographics and to assess the distribution of the main study variables. This included measures of central tendency, variability, and frequency distributions for categorical variables. Structural equation modeling (SEM) and correlation analyses performed in R were used for inferential analysis. This type of analysis was ideal for this study because the study's constructs of interest (i.e., job demands, job resources, exhaustion, disengagement) are theoretically best represented as latent variables secondary to them being constructs inferred from multiple observed indicators (Davvetas, Diamantopoulos, Zaefarian, & Sichtmann, 2020). Additionally, SEM considers measurement error, providing a more nuanced understanding of the relationships between variables (Davvetas et al., 2020).

Assumptions

Five assumptions impacted the study. First, CRNAs survey respondents were honest and free from bias while using the self-reported online survey. Second, participants were honest when reading the exclusion criteria for study participation. Third, the participants read the instructions of each survey section prior to answering the questions that followed. Fourth, CRNAs experienced and understood the experience of burnout secondary to job-related characteristics. Finally, the results from a survey that had a strong theoretical foundation would not only provide a stronger path towards a better understanding of the implications job-related factors have on this nursing specialty but also help leadership better tailor interventions towards the reduction of burnout.

Scope of Delimitations

The study sample was limited to CRNAs who were active members of the AANA, currently providing direct anesthesia care and providing anesthesia care within the United States. Survey distribution is governed by the AANA Department of Research policies which prevent any email solicitation for research participants and limit survey distribution to 3,000 participants. Researchers can further limit the sample size when filling out the "AANA Electronic Survey" application. For this study, students or trainees, CRNAs not actively providing weekly anesthesia care, and those practicing outside of the United States were excluded from the study sample.

The survey questions specifically focused on job-demands, job-resources, demographics, exhaustion, and disengagement of CRNAs actively providing anesthesia care to patients in the United States. The survey questions were based on common themes identified from previously published studies that have emerged as primary factors contributing to burnout in CRNAs. The common themes included work overload, lack of autonomy and collaboration, increased production pressures, workplace incivility, and lack of control and social support (Boyd & Poghosyan, 2017; Mahoney et al., 2020).

Limitations

The study is subject to several limitations.

First, online surveys may pose the following challenges: (a) Surveys have a poor response rate. According to the AANA's Department of Research (AANA, n.d.), CRNA response rates are less than 9 percent which may result in having a limited data set, thus affecting external validity of the findings; (b) The AANA has tight restrictions on how the survey is distributed, communicated, and the number distributed. This methodology affects how many surveys can be sent out and how survey reminders are communicated to participants; (c) This is an online survey from a third party (AANA), so the researcher could not be immediately available to answer participant questions. This may have resulted in participants not finishing the survey. Second, there is a risk of self-selection bias. Participants may feel they are or are not experiencing burnout in the workplace and decide whether or not to participate in the survey according to these perceived feelings. Third, CRNAs have faced additional work-related challenges due to the COVID-19 pandemic since starting to design this research. Researchers (see Aron et al, 2021; Prasad et al., 2021) have demonstrated that the increased constraints faced by healthcare providers have resulted in a drastic increase in occupational strain, such as burnout. Third, the nature of the study using self-reported response rates may have resulted in a selective memory bias secondary to the negative effects from the pandemic. Finally, the onset of the pandemic created a two-year gap between proposal and execution of research. Every effort was made to maintain up-to-date information, both empirically and theoretically.

Significance of the Problem

The limited exploratory research and lack of theoretical frameworks to provide a path towards the identification and evaluation of specific job-related factors contributing to CRNA burnout has resulted in limited success with respect to alleviating burnout within the nursing anesthesia specialty. Studies have demonstrated statistical significance between CRNA burnout and turnover, intent to quit, and job satisfaction (Lea et al., 2022; Mahoney et al., 2020). The significance of these negative outcomes is concerning for several reasons. First, healthcare facilities continue to depend on CRNAs as the answer to achieving a safer, cost-efficient healthcare environment. This has resulted in CRNAs making up an increasing share of the anesthesia workforce. Second, anesthesia providers in rural hospitals are primarily made up of CRNAs (AANA, 2020). These rural hospitals are considered critical access hospitals. The anesthesia services provided by CRNAs in rural America provide critical care for patients who would have to drive hours away otherwise or just not get the care needed (AANA, 2020). Third, advancements in medical technology have placed higher demands on surgical and interventional procedures, which will increase the need for anesthesia services (Mahoney et al., 2020). The inability to appropriately identify, evaluate, and manage CRNA burnout coupled with the growing administrative and clinical complexities of the U.S. healthcare system may cause further strain on the stability of this nursing specialty that is already facing a critical deficit in workforce numbers, ultimately, resulting in the inability to provide cost-saving, high-quality care to patients in need (Negrusa et al., 2021).

Chapter Summary

CRNAs are a critical part of the anesthesia workforce, responsible for approximately 65% of the anesthetics provided in the United States (Del Grosso & Boyd, 2019). The nursing specialty is known and respected for the "ability to provide safe, high-quality, and cost-effective anesthesia services" to numerous patient populations, including critical access hospitals (Del Grosso & Boyd, 2019, p. 207). While there has been an increased academic and clinical focus on the understanding of factors contributing to burnout, the ability to alleviate burnout within this nursing specialty has remained limited (see Boyd & Poghosyan, 2017; Del Grosso & Boyd, 2019; Mahoney et al., 2020). The growing demands by healthcare facilities for cost-efficient, safe anesthesia services coupled with the challenges created by the pandemic, resulted in a further mismatch between job demands and job resources. The challenges in current evaluation and management of burnout in CRNAs may be secondary to the following gaps (a) ongoing limited research evaluating burnout in the nursing specialty and (b) lack of theoretical guided empirical research. The inappropriate identification and management of burnout places a risk of further strain on the stability of this nursing specialty, which is already facing a critical deficit in workforce numbers (Negrusa et al., 2021). This has a system-level impact on the nursing anesthesia specialty, healthcare organizations, and the patients they care for.

The study used a quantitative exploratory design to evaluate the relationship between job-related characteristics and burnout in CRNAs. It used the JD-R perspective is to increase the understanding of the impact of specific job-related characteristics contributing to burnout and its associated dimensions—exhaustion and disengagement. The specific aims of the study were as follows:

Aim 1: To examine the extent of *job demands* and *job resources* specific to CRNAs practicing in the United States and their relationship towards overall *burnout* as well as its specific dimensions—*exhaustion* and *disengagement*.

Aim 2: To examine the relationship strength of the specific *job demands* and *job resources* and the *burnout* dimensions—*exhaustion* and *disengagement*.

Aim 3: To examine if *job resources* (as measured by job control, autonomy, colleague support, supervisor support, and collaboration) have a moderating effect on the relationship between *job demands* and *burnout*.

The study's overall goal of applying the JD-R model in addressing the relationship between job-related characteristics and burnout in CRNAs practicing in the United States is to increase the understanding of the impact of these specific job-related factors contributing to burnout which in turn may provide a path towards appropriate interventions. Therefore, a quantitative approach using descriptive and inferential statistics was used to examine these relationships.

CHAPTER 2: LITERATURE REVIEW

The increased exposure to occupational demands placed on CRNAs is a growing concern within this nursing specialty (Farina et al., 2020). The anesthesia specialty is considered to have one of the most stressful work environments among other healthcare specialties (Sanfilippo et al., 2017). CRNAs are a critical part of the anesthesia workforce, responsible for approximately 65% of the anesthetics provided in the United States (Del Grosso & Boyd, 2019). Changes in the healthcare system have resulted in CRNAs managing an aging, complex patient population while faced with increasing time pressure, complex medical technology, and a lack of resources. The pandemic further strained this nursing specialty secondary to exposure to unprecedented emotionally distressing situations, longer shifts with greater patient acuity and isolation from friends and family. The current empirical and theoretical gaps in the literature create further challenges in the understanding and management. Therefore, the ability to appropriately identify and manage burnout within this nursing specialty is vital to its ability to continue to provide the safe, high-quality care to those in need. The study's overall goal of applying the JD-R model in addressing the relationship between job-related characteristics and burnout in CRNAs practicing in the United States is to increase the understanding of the impact of these specific job-related factors contributing to burnout which in turn may provide a path towards appropriate interventions.

This chapter provides a review of relevant literature. This chapter will provide a general overview of previous theoretical and empirical research on burnout, a review of burnout within the anesthesia profession, and an overview of the CRNA nursing specialty. Various constructs that provide the framework for the JD-R model are discussed such as job demands, job resources, and burnout. The last section reviews the literature on burnout's impact related to the nursing anesthesia specialty. Each chapter builds from the previous section with the intent to build a greater understanding of burnout relative to the nursing anesthesia community, the current gaps in the literature, and the implications of the current study.

Certified Registered Nurse Anesthetists (CRNAs)

Nurses have been providing anesthesia care to patients since the American Civil War; however, nursing anesthesia wasn't officially recognized until 1956, when the credential became official (AANA, 2023). CRNAs are advanced practice nurses (APNs) with graduate-level education. Ranked by U.S. News & World Report as one of the best health care jobs in the United States, the career path toward becoming a CRNA requires 7–9 years of education and experience (AANA, 2023). Candidates must have a minimum GPA of 3.0 from a baccalaureate degree in nursing, a GRE score greater than 300, several years of critical care experience with advanced career achievements such as advanced certifications (i.e., Critical Care Nursing Certification), and an interview that evaluates each candidate's critical care experience and knowledge to gain entrance into 1 of 130 accredited nurse anesthesia programs (AANA, 2023). Once accepted into an accredited nursing anesthesia program, students undergo approximately three years of rigorous academic and clinical preparation, graduating with a doctoral degree. After successful completion of a program, each nursing anesthesia student must then pass the National Certification Examination (NCE) to become a CRNA.

CRNAs are a critical part of the anesthesia workforce who have gained a high degree of respect within the surgical services arena. CRNAs provide anesthesia in collaboration with various healthcare professionals such as surgeons, dentists, podiatrists, and anesthesiologists (AANA, 2023). Anesthesia administered by a CRNA is recognized as the practice of nursing and when administered by a physician anesthesiologist, it is recognized as the practice of medicine.

Regardless of the professional background, the practice of providing anesthesia is the same. In the United States, more than 61,000 CRNAs provide approximately 65% of the anesthetics in every setting where anesthesia is delivered (Del Grosso & Boyd, 2019). They are the sole anesthesia provider in more than 80% of the rural hospitals (AANA, 2023). CRNAs have full practice authority in every military branch, providing anesthesia care to U.S. military personnel on the front lines since World War I (Del Grosso & Boyd, 2019). In 2001, the Centers for Medicare & Medicaid Services gave state governors the authority to opt out of the physician supervision rule (AANA, 2023). Currently, CRNAs may practice in 22 U.S. states without physician supervision. Despite various criticism around the safety of allowing a nursing specialty to have increased autonomy, research has demonstrated CRNAs' abilities to provide safe, high-quality, and cost-effective anesthesia services to numerous patient populations (Dulisse & Cromwell, 2010). Additionally, according to Gallup's Honesty and Ethics poll, CRNAs continue to be among the nation's most trusted professions in the US (AANA, 2023).

Burnout

Defining Burnout

The psychological symptoms of burnout were described as early as the 1950s; however, the term was introduced into the psychological literature in the 1970s by Freudenberger (1974) and Maslach (1976) (Schaufeli et al., 2017). Borrowed from the illicit drug scene, Freudenberger defined burnout among clinic volunteers as gradual emotional depletion, loss of motivation, and reduced commitment (Schaufeli, Leiter, & Maslach, 2009). Independently, Maslach's doctoral work with human service workers discovered burnout developed when workers felt emotionally exhausted, resulting in negative perceptions and feelings about their patients and their own professional competence (Schaufeli et al., 2009). Over 50 years after its initial introduction which has produced thousands of publications dedicated towards the theoretical and empirical understanding of the concept, the development of burnout is still vehemently debated (Del Grosso & Boyd, 2019; Qiao, & Schaufeli, 2011). Researchers believe some of the context's fragmented state may stem from its multifactorial origins (Schaufeli et al., 2017). Contrary to other psychological concepts that are derived from scholarly theory, the initial approach was exploratory in nature and utilized various techniques derived from either a social (i.e., Maslach) or clinical (i.e., Freudenberger) psychological perspective (Schaufeli et al., 2017). Its "grass-root introduction as a social and clinical phenomenon and a lack of attention to a theoretical foundation resulted in researchers struggling to integrate and evaluate a construct without a conceptual framework" (Del Grosso & Boyd, 2019, p. 207; Schaufeli et al., 2017).

The lack of a generally accepted definition and ongoing debate regarding its development has resulted in confusion and a generalized misunderstanding of the identification and management of the concept (Del Grosso & Boyd, 2019; Maslach & Leiter, 2016; Schaufeli et al., 2017). This resulted in varied meanings of the term and an over-expansion of the concept (Schaufeli et al., 2017). Most studies continue to identify burnout as a job-related outcome and seek to understand the effect of its development and impact on the workforce. Burnout, the concept, what constitutes it, what contributes to its development, and the associated consequences, remains without common ground. However, decades of focused attention towards establishing what it means to be "burned out" has revealed common themes that define its conceptualization: (1) burnout is considered a work-related syndrome that emerges from a prolonged response to chronic interpersonal job-related stressors, (2) burnout is a psychological experience of feelings and attitudes towards one's job, and (3) it is an individual's experience that is specific to the work context (Maslach, & Leiter, 2017; Schaufeli, Maslach, & Marek, 2017).

Assessment Of Burnout

As characteristics describing burnout started to become more formalized, research became more descriptive, constructive, and empirical (Schaufeli et al., 2017). During this period, numerous books and articles outlined various models, proposed ideas, and presented evidence of burnout's conceptualization (Maslach et al., 2016). There was a greater focus on the assessment of burnout through the development of measurement tools (Maslach et al., 2016). It was during this empirical phase of burnout research that the first standardized measures were developed—the Maslach Burnout Inventory (MBI) scale and the Burnout Measure (BM) (Schaufeli, Maslach, & Marek, 2017). The MBI and BM created a more systematic approach to identifying burnout which increased scholarly focus (Schaufeli et al., 2017). However, the multifactorial origins of burnout's development have resulted in various measures proposed, each one being based on the author(s) assumptions about the development of burnout (Schaufeli et al., 2009). To date, hundreds of burnout measures have been developed and used; however, only a dozen have been demonstrated through various psychometric analysis to be valid instruments for quantifying burnout in healthcare providers (Shoman et al., 2021).

The distinction between instruments is whether they measure burnout as a single or multidimensional concept (Maslach & Leiter, 2016; Schaufeli et al., 2009). For example, Maslach describes burnout as a sequential three-dimensional syndrome that is operationalized by the MBI scale as—exhaustion, depersonalization, and personal accomplishment (Maslach & Leiter, 2016). The Oldenburg Burnout Inventory (OLBI) assesses a two-dimensional construct—exhaustion and disengagement. Measures that focus on a single dimension of burnout focus on the exhaustion dimension alone; however, they differentiate between the various types of exhaustion (Maslach & Leiter, 2016). For example, the Shirom-Melamed Burnout Measure (SMBM) and the Copenhagen Burnout Inventory (CBI) are considered single-dimension measures that focus only on the exhaustion dimension; however, the SMBM distinguishes between physical fatigue, emotional exhaustion, and cognitive weariness whereas the CBI focuses on the physical and psychological aspects of exhaustion (Kristensen, Borritz, Villadsen, & Christensen, 2005). Proponents of the single-dimensional measure burnout as a decrease in energetic resources, regardless of the occupational context (Qiao & Schaufeli, 2011).

The debate of whether burnout instruments assess single or multiple dimensions continues to the present day (Maslach & Leiter, 2016). Although there are other measures (i.e., Bergen Burnout Inventory (BBI)) that conceptualize and measure burnout with three dimensions, most have fallen out of favor over time (Maslach & Leiter, 2016). The most widely used burnout measure is the Maslach Burnout Inventory (MBI) which is based on Maslach's definition and three-dimensional assumption of burnout (Maslach & Leiter, 2016). Proponents of the three-dimensional perspective of burnout argue that it occurs in sequential stages (Maslach & Leiter, 2016). According to the authors (Maslach & Jackson, 1981) of the MBI, exhaustion develops first secondary to exposure to high demands in the work environment, followed by detachment and negative feelings towards the job (depersonalization), eventually resulting in feelings of inadequacy and failure on the personal level (reduced personal accomplishment) (Maslach & Leiter, 2016).

To date, the MBI and its operational definition of burnout are often referred to as the "gold standard" of burnout measurement; however, several arguments have been made regarding the need for all three dimensions (Qiao & Schaufeli, 2011). First, studies (Kristensen et al., 2005;

Lee & Ashforth, 1996; Qiao & Schaufeli, 2011) evaluating the correlation among the three dimensions of burnout have consistently demonstrated job demands correlate with the exhaustion dimension and job resources with the depersonalization dimension. The third dimension, personal accomplishment, has been demonstrated to have the weakest correlation with job-related variables (Lee & Ashford, 1996). From a theoretical perspective, researchers have argued that personal accomplishment develops independently of the other two dimensions secondary to it being more of a personality characteristic (Maslach et al., 2016; Schaufeli et al., 2017). Reviews conducted by Dall'Ora and colleagues (2020) and Aronsson and colleagues (2017) included over 60 studies evaluating the significance between job-related factors and burnout. The studies (Dall'Ora et al., 2020; Aronsson et al., 2017) found less than 50% measured and reported burnout with all three subscales, with the majority of the studies focusing solely on the exhaustion dimension. Shoman et al. (2021) conducted a systematic review evaluating the psychometric properties of the MBI and found low-quality of evidence to support MBI's three-dimensional structure. Second, critics have argued that the MBI addresses what burnout is instead of addressing the underlying reasons for how and why it occurs (Kristensen et al., 2015). Third, questions in each subscale are phrased in the same direction; exhaustion and depersonalization scales are worded negatively, and the personal accomplishment scale is worded positively, which may create artificial clustering of factors (Halbesleben & Demerouti, 2005; Kristensen et al., 2015). Finally, the MBI focuses only on the affective aspect of the exhaustion dimension (Halbesleben & Demerouti, 2005). Researchers (Kristensen et al., 2015; Qiao & Schaufeli, 2011) have suggested that including other aspects of the exhaustion dimension (i.e., cognitive and physical) allows for a more inclusive understanding of the degree of exhaustion experienced (Halbesleben & Demerouti, 2005).

In attempting to overcome methodological and conceptual challenges related to a three-dimensional construct, Demerouti & Nachreiner (1996) developed the OLBI which conceptualizes burnout as a two-dimensional construct that includes an exhaustion and disengagement. The *exhaustion* dimension captures a broader conceptualization of exhaustion by including the physical and cognitive aspects whereas the disengagement dimension is considered a counterpart to the MBI's depersonalization dimension and refers to the distancing of oneself from one's work and the experience of negativity towards work in general (Demerouti & Nachreiner, 1996; Halbesleben & Demerouti, 2005). The OLBI consists of questions that have both positive and negative wording (Halbesleben & Demerouti, 2005). Compared to the MBI which was not derived from existing theory, the OLBI was developed based on the JD-R model (Demerouti, Bakker, Nachreiner, & Schaufeli, 2001). Halbesleben and Demerouti (2005) conducted a series of psychometric analyses (multi-trait, multi-method (MTMM) and confirmatory factor analysis) to test the validity and reliability of OLBI compared to the MBI in 2599 employees in the United States (Halbesleben & Demerouti, 2005). The results demonstrated acceptable reliability (test-retest and internal consistency) and validity (factorial, convergent, and discriminant) (Halbesleben & Demerouti, 2005).

Researchers continue to support and widely acknowledge the multidimensionality of burnout; however, there continues to be theoretical and practical discussions made regarding burnout as a single dimension that warrant a brief overview (Brenninkmeijer & VanYperen, 2003). Proponents of a single dimensional approach argue burnout has been primarily correlated to the exhaustion dimension and the addition of other dimensions creates various empirical and theoretical challenges (Brenninkmeijer & VanYperen, 2003). For example, Kristensen and colleagues (2005) have argued the three dimensions are theoretically different—an individual state (emotional exhaustion), a coping state (depersonalization), and an outcome (reduced personal accomplishment). They argue each dimension should be studied separately (Kristensen et al., 2005). Second, when considering a strong desire to establish a clinical diagnosis for burnout, researchers (Brenninkmeijer & VanYperen, 2003; Kristensen et al., 2005) have argued that a single-dimensional construct has the advantage of simplifying results (Maslach et al., 2016; Schaufeli et al., 2017).

Critics of the single-dimensional assumption argue that empirical studies (Cox, Tisserand, & Taris, 2005; Demerouti & Nachreiner, 1996; Lee & Ashforth, 1996) "have provided greater support for a multidimensional approach, conceptualizing burnout as unidimensional fails to distinguish it from related constructs such as anxiety, work-related stress, and depression, therefore, would lose the ability to identify specific factors and outcomes related to burnout properly" (Del Grosso & Boyd, 2019, p.206; Maslach et al., 2016; Schaufeli, Leiter, & Maslach, 2009; Schaufeli et al., 2017). Although burnout researchers (Kristensen et al., 2005; Schaufeli & Taris, 2013) have acknowledged it can be measured with less than three dimensions, they argue reducing burnout to a single dimension, regardless of whether it includes different aspects of exhaustion, creates redundancy (i.e., fatigue) and psychometric challenges (i.e., construct proliferation) (Maslach et al., 2016).

Overall, the primary objective of all these burnout measures is to enable researchers to obtain empirical evidence on the nature of the development of burnout, its causes, and its consequences (Maslach & Leiter, 2016). The continued disorganized research has resulted in "measures used to assess burnout is often closely linked to the author's assumptions of the construct" (Del Grosso & Boyd, 2019, p. 206; Maslach et al., 2016; Schaufeli et al., 2017). This has resulted in researchers wanting to quantify burnout in a particular group, but "they must look beyond the instrument's face value and understand the scale's conceptual meaning" (Del Grosso & Boyd, 2019, p. 206; "Maslach et al., 2016). For example, the use of the MBI implies the researcher accepts burnout as being viewed as a psychological syndrome of emotional exhaustion, depersonalization, and reduced personal accomplishment that occurs in individuals doing work (Maslach & Leiter, 2016).

Conceptual Models

The advancements through measurement scales allowed for a greater exploration of variables and their impact on the development of burnout; however, many of the studies were without a theoretical framework (Maslach et al., 2016; Schaufeli et al., 2017). Studies that are grounded in a conceptual model are the basis for deriving and testing hypotheses, which allow for a clear interpretation of whether the findings are supportive of the researcher's ideas towards the concept (Schaufeli et al., 2017). However, as the burnout concept matured, various models were used to help explain the development of burnout (Delgrosso & Boyd, 2019; Maslach & Leiter, 2016). Initial models primarily focused on the relationship between multidimensional assumptions of burnout and whether dimensions went in sequential order (Maslach & Leiter, 2016). Contributions from the industrial-organizational psychology field provided models that were primarily based on theories about job stress and imbalances within the job that would result in strain on that individual (Maslach & Leiter, 2016). Subsequently, three developmental models have emerged from these conceptual advancements and continue to be heavily utilized within the healthcare industry—the Job Demands-Resources (JD-R) model (Demerouti, Bakker, Nachreiner, & Schaufeli, 2001), the Conservation of Resources (COR) model (Hobfoll, 1989), and the Areas of Worklife (AW) model (Maslach & Leiter, 2016).

The JD-R model views burnout as developing when individuals experience relentless job demands and have poor resources available to address those demands (Demerouti, Bakker, Nachreiner, & Schaufeli, 2001). The COR model builds on motivational theory and assumes when individuals view resources of value as being threatened, they strive to protect and or maintain these resources (Hobfoll, 1989). Burnout develops secondary to the loss or impending loss of these resources (Hobfoll, 1989). Both the COR and JD-R models are based on imbalances between job demands and job resources. The AW model frames job-related stressors as an imbalance between person and job fit (Leiter, & Maslach, 1999). Mismatches in any of the identified six areas (control, reward, community, fairness, values, and workload) may result in the experience of burnout (Leiter, & Maslach, 1999; Schaufeli et al., 2017). The AW model differs from the other models in that it conceptualizes burnout as a state versus a process (Leiter, & Maslach, 1999).

Researchers have raised concerns that despite thousands of studies being published a year, most of them have been concerned with psychometric properties of instruments and have been more descriptive versus explanatory (Bakker & de Vries, 2021). Literature during the past few decades has demonstrated significant progress towards understanding burnout as a work-related syndrome in which the individual operates (Maslach & Leiter, 2016). Common themes that seem to be underlying in most of the conceptual models include burnout results from an imbalance between high demands and low resources, burnout is a result of continued (chronic) exposure to job-related demands, and burnout results from conflict, either from interactions among members of the job or from job-related characteristics (Dall'Ora et al., 2020; Maslach & Leiter, 2016).

Causes And Outcomes of Burnout

Regardless of the model selected, most theoretical models make causal assumptions that certain factors (situational and individual) lead to an individual's experience of burnout which, in turn, causes certain outcomes (situational and individual) (Maslach & Leiter, 2016). It is important to note that most of the research evaluating a model's causal assumptions has not been tested directly but, instead, through cross-sectional designs (Maslach & Leiter, 2016). However, the theoretical and empirical advancements in burnout research over the years have built a large correlational data base that has provided support for several common characteristics between burnout and its causes and consequences (Delgrosso & Boyd, 2019; Maslach & Leiter, 2016).

First, burnout is commonly referred to a psychological syndrome describing an individual's response to emotional and interpersonal stressors at work (Schaufeli et al., 2017; Swider & Zimmerman, 2010). Causes of burnout are generally divided into situational factors (i.e., job-related characteristics) which are the primary correlates of its development and individual factors, including personality traits and demographic characteristics (i.e., age, gender) (Schaufeli et al., 2017). Situational factors include job demands and job resources (lack of) whereas individual factors include personality traits that may predispose individuals to burnout (Maslach et al., 2016; Schaufeli et al., 2017). Research demonstrated that job-related factors have a stronger correlation to burnout compared to individual-related factors, particularly to the exhaustion domain (Maslach et al., 2016; Maslach et al., 2001; Schaufeli et al., 2009; Schaufeli et al., 2017). Prolonged exposure to job demands, employees become exhausted and begin to disengage themselves from work (Bakker & de Vries, 2021). Common job-related factors include stressful events, role ambiguity, high workload, role conflict, and lack of control (Ahola et al., 2017; Hyman et al., 2017). For example, Dall'Ora et al. (2020) found evidence that workload (including job-related tasks that contribute to workload (i.e., staffing levels), low control, and psychological demands of the work environment) was associated with burnout, in particular the exhaustion dimension. Job-related resources have shown consistent evidence in their relationship (negative) to burnout, particularly the disengagement (cynicism) dimension (Bakker & de Vries, 2021; Maslach et al., 2016). Additionally, job resources have been shown to weaken (or buffer) the link between job demands and burnout (Bakker & de Vries, 2021; Maslach et al., 2016). Common job-related resources include social support, autonomy, and skill variety (Maslach et al., 2016).

Research on burnout antecedents has historically focused on organizational and occupational antecedents with minimal reference to the impact individual-level causes (Bakker & Costa, 2014; Swider & Zimmerman, 2010). The studies that have included individual factors have primarily focused on demographic variables (i.e., age, gender, socioeconomic status) and have been wavering, demonstrating weak correlations (Bakker & Costa, 2014; Maslach et al., 2016; Swider & Zimmerman, 2010). However, given research has demonstrated that personality is not only relatively stable over time but may influence the way an individual views their work environment and its associated stressors, the past two to three decades have seen increased interest (Bakker & Costa, 2014; Swider & Zimmerman, 2010). Burnout researchers have increased focus on the relationship between personality traits such as the big five personalities and burnout (Sider & Zimmer, 2010). For example, Swider and Zimmerman (2010) conducted a meta-analytic path modeling (n = 115) that explored the relationship between the Big Five personality traits and burnout. Together, the regression analyses demonstrated that all five of the personality traits demonstrated strong correlations with the MBI's three dimensions of burnout, particularly on the emotional exhaustion dimension (Swider & Zimmerman, 2010). However, only Neuroticism had a moderate relationship with all three dimensions (Swider & Zimmerman, 2010). Although understanding how individual factors such as personality and demographic characteristics impact burnout is critical, a gap remains with theoretically relevant, empirically tested research (Maslach & Leiter, 2016; Schaufeli et al., 2017).

Second, burnout is recognized as a direct occupational hazard for individuals (Morais et al., 2006; Schaufeli et al., 2017). Individuals suffering from burnout have a higher risk towards of a range of psychological and physical health problems that have included alcohol consumption, musculoskeletal pain, anxiety, depression, sleep disturbances, and memory impairment (Bakker & Costa, 2014; Salvagioni et al., 2017). Studies evaluating the physical consequences of burnout have found cardiovascular disease, depression, and pain being more frequently reported (Salvagioni et al., 2017). Studies have demonstrated a direct correlation between the levels of burnout, with higher levels leading to a faster physical health deterioration (Bakker & Costa, 2014; Salvagioni et al., 2017). A systematic review by Salvagioni et al. (2017) found employees with high burnout levels had twice the risk of developing musculoskeletal pain (generalized pain, neck-shoulder pain, back pain, and disability secondary to pain). Some experts hypothesize these negative consequences are secondary to the autonomic nervous system (ANS) and the hypothalamic-pituitary-adrenal (HPA) axis becomes exhausted from burnout (Salvagioni et al., 2017).

Finally, burnout has a negative effect on the culture and climate of individual employees and their work teams from an organizational perspective. Studies have demonstrated a direct correlation between employees suffering from burnout and at least one withdrawal behavior such as tardiness, absence, or turnover (Bakker & Costa, 2014). For example, Dall’Ora et al. (2020) conducted a review that found a moderate relationship between burnout and intention to leave, sickness absence, job performance, and general health in nurses. In a similar study, Chiron et al. (2010) also found a strong correlation between burnout, incivility, and high turnover. Salvagioni et al. (2017) found studies evaluating burnout consequences prospectively demonstrated increased withdrawal symptoms with higher levels of burnout. From a healthcare perspective, burnout negatively influences a provider's ability to deliver high-quality, safe care, which subsequently results in poor patient outcomes and patient safety (Abraham, Zheng, & Poghosyan, 2020; Nahrgang, Morgeson, & Hofmann, 2011). For instance, a meta-analysis conducted by Salyers et al. (2017) evaluated 82 studies from 1982 to 2015 that demonstrated statistical significance between burnout and quality of patient care.

Construct Proliferation Challenges

Advancements in burnout research have allowed for a greater understanding of the concept; however, there remains a conceptual overlap (*construct proliferation*) with terms (i.e., depression, anxiety, and occupational stress) that preceded it continues to cause some misunderstandings (Schaufeli et al., 2009; Schaufeli et al., 2017). Construct proliferation "occurs when "new" constructs are theoretically or empirically indistinguishable from existing constructs" (Del Grosso & Boyd, 2019, p. 207; Shaffer et al., 2016). Integrating burnout into larger conceptual models (i.e., stress models) has created some clarity; unfortunately, debates on the construct's appropriate dimensions continue to undermine its empirical distinctiveness (i.e., *discriminant validity*) (Schaufeli et al., 2017). Studies that have used psychometric tests (i.e., multi-trait-multi-method or confirmatory factor analysis) to empirically demonstrate burnout's distinctiveness have resulted in highly subjective and variable interpretations (Shaffer et al., 2016).

The two most common concepts of burnout that are misunderstood are stress and depression (Farina et al., 2020). Although prolonged stress can result in burnout and prolonged burnout can result in depression, each concept is individually separate (Schaufeli et al., 2017). This means that with appropriate coping mechanisms, some providers can thrive in stressful environments, and other providers suffering from depression do not necessarily experience burnout at work (Bianchi, Schonfeld, & Laurent, 2015; Delgrosso & Boyd, 2019). Stress is defined as physical and or psychological reactions to demands on the body. In contrast, depression is a negative affective state that interferes with daily life, not just the job (Farina et al., 2020). The debate on whether burnout falls on the spectrum of similar concepts like depression or stress remains. Criticisms of burnout's singularity still elicit hundreds of articles and article responses that argue for a more inconclusive construct. A meta-analysis evaluating over 90 peer-reviewed publications found there was no clear distinction between depression and burnout (Farina et al., 2020). The lack of clarity between burnout and other contexts like depression and stress, overlapping of factors and symptoms is possible and researchers must be diligent in understanding each concepts unique differences (Bianchi et al., 2015; Aron et al., 2021). Another study (Farina et al., 2020) emphasizes the value of using an appropriate theoretical model in guiding the measurement of burnout in a group like nursing anesthesia providers.

Interventions

The resulting cost of burnout at the individual and organizational level has placed ongoing focus on various interventional strategies and their ability to manage the syndrome. Interventional approaches are generally classified based on the assumed level of burnout primary, secondary, or tertiary and according to whom they target individual, organizational, or both (Ahola et al., 2017; Chiron et al., 2010; Maslach & Leiter, 2016). Primary interventions serve as a preventative strategy by targeting known risk factors among employees (Ahola et al., 2017). Secondary interventions aim to decrease symptoms of burnout by targeting those individuals or groups that have quantitatively demonstrated high risk of burnout (Ahola et al., 2017). Tertiary interventions aim to prevent adverse consequences of burnout by targeting those individuals or groups that have demonstrated to have high levels of burnout (Ahola et al., 2017). Interventional strategies that are individual-focused attempt to increase one's psychological and coping resources. Examples include enhancing coping skills, social support, or relaxation techniques (i.e., yoga, meditation). Organizationally focused strategies attempt to decrease various stressors within that individual's work environment (Ahola et al., 2017; Chiron et al., 2010; Maslach & Leiter, 2016). Examples include job redesign interventions, improvements in leadership style(s), and increasing coping skills. An individual approach is reactionary, treating those with a degree of burnout and designed to alter health behaviors secondary to occupational stress, whereas an organizational approach is proactive through the promotion of long-term employee wellness by making changes at the organizational level (Cohen, Pignata, Bezak, Tie, & Childs, 2023).

Research on burnout has primarily focused on the conceptual development of burnout (i.e., characteristics, theoretical models, and statistical methods in assessment) which has resulted in limited attention towards alleviating and or management of burnout (Ahola et al., 2017; Cohen et al., 2023). Despite the consensus among scholars that burnout is a syndrome that emerges from a prolonged response to chronic interpersonal stressors on the job, most reviews (Ahola et al., 2017; Cohen et al., 2023) have found studies conducting interventional strategies are individual-focused. Taken together, several reviews (Ahola et al. 2017; Cohen et al., 2023) found that 44 out of 51 studies were individual strategies. There are pragmatic reasons (i.e., costs and easement) why this approach may seem reasonable. However, research has demonstrated that situational and organizational factors have a greater impact on burnout versus individual factors (Ahola et al., 2017; Maslach & Leiter, 2016). For example, a review conducted by Cohen and colleagues (2023) found 3 of the 33 studies that implemented organizationally focused interventions (job crafting strategies, decreased workloads, and increased peer support program) demonstrated a significant reduction in burnout scores that were sustainable through their follow up assessments; whereas 5 of the 30 studies that conducted individually focused interventions (relaxation techniques, promotion of positive mindset) had statistically significant reduction in burnout scores. Although organizational interventions have greater success in reducing burnout, the studies remain small, and the effects are limited (Bakker & de Vries, 2021). Limitations in the success of burnout interventions have commonly been related to several reasons such as interventions not accounting for the structural causes of burnout in the work environment but majority of interventions focus at the individual level, all employees are treated as one unit, heterogeneous designs, lack of longitudinal assessments, and ongoing challenges with interpretation of burnout's conceptualization (Ahola et al., 2017; Bakker & de Vries, 2021; Cohen et al., 2023; Maslach & Leiter, 2016). The complexity of the interaction between the multitude of factors contributing to the development of burnout highlights the importance of taking a multifactorial (individual and organizational) approach guided by a theoretical model when considering burnout interventions (Bakker & de Vries, 2021). For example, following the JD-R model, job demands are considered primary factors of burnout and have a negative impact on employee health and organizational outcomes whereas job resources are primary factors of engagement and improve employee motivation and performance (Bakker, Demerouti, & Isabel

Sanz-Vergel, 2014). Therefore, interventions that combine specific measures aimed at the organizational and individual levels will be highly effective (Bakker et al., 2014).

Burnout in the Anesthesia Profession

Advancements that have helped improve patient safety combined with healthcare reforms have resulted in high demanding, stressful work environments that can expose the anesthesia provider to numerous stressors (Hyman et al., 2017; Sanfilippo, Noto, & Foresta, 2017). Although anesthesia providers' response to the pandemic demonstrated the specialty's depth in critical care and airway knowledge, the arrival of the pandemic also placed higher occupational strain on this specialty (Aron et al., 2021). Providers were often faced with prolonged hours with limited supplies and equipment to protect themselves as well as care for their patients (Aron et al., 2021). The concerns about burnout's impact on anesthesia providers and its associated negative effects on patients and healthcare organizations have led to an increased empirical focus on this psychological syndrome (Hyman et al., 2017). A meta-analysis conducted by Rodrigues et al. (2018) demonstrated that anesthesia has one of the highest prevalence rates (42.7%) of burnout across specialties.

The ability to accurately quantify the prevalence of burnout within the anesthesia specialty remains a challenge. For instance, Aron and colleagues (2021) estimated that the prevalence rates of burnout within the anesthesiology specialty ranged from 14% to 65%. Much of this challenge is related to the previously discussed challenges in the ongoing disagreement around the construct's conceptualization (Aron et al., 2021; Rodrigues et al., 2018). Regardless of where the true prevalence rate lands, studies continue to demonstrate burnout remains a significant concern and some would argue it has reached a critical point (Aron et al., 2021; Hyman et al., 2017). Although studies evaluating burnout among anesthesia providers have yielded wide variation in burnout prevalence rates, determinants, and consequences, there have been some obvious factors that have a higher correlation towards burnout in the profession (Aron et al., 2021; Del Grosso & Boyd, 2019). Studies (Afonso, Cadwell, Staffa, Zurakowski, & Vinson, 2021; Aron et al., 2021; Del Grosso & Boyd, 2019; Nyssen & Hansez, 2008) have found common contributors to burnout among anesthesia providers to include loss of autonomy, decreased control, high workload, clinical task complexity, fear of harming the patient, and lack of support. Effects of burnout on anesthesia providers have been shown not only to include negative adverse consequences towards the individual provider but also financial and patient care consequences on an organization (Del Grosso & Boyd, 2019). A review by Aron and colleagues (2021) found burnout in anesthesia providers resulted in medical errors, decreased patient satisfaction, and worsened patient care attitudes and practices. Kluger et al. (2008) and De Oliveira Jr. et al. (2013) found burnout to be negatively correlated with job satisfaction and positively correlated with lower quality of care. On the individual level, consequences of burnout in anesthesia providers have included increased turnover rate, increased alcohol and cigarette consumption, and difficulties with acute and chronic pain (De Oliveira Jr. et al., 2013; Mahoney et al., 2020; Meeusen, Van Dam, Brown-Mahoney, Van Zundert, & Knape, 2010). Sociodemographic characteristics contributing to burnout have included hospital type, gender, age, facility type, practice setting, and employment status (Afonso et al., 2021; Aron et al., 2021; Del Grosso & Boyd, 2019). It is important to note that the degree of correlation between sociodemographic characteristics and burnout in anesthesia providers is highly variable and study dependent (Del Grosso & Boyd, 2019). For instance, Nyssen & Hansez (2008) and Afonso et al. (2021) found younger anesthesiologists had a higher correlation to burnout, whereas Meeusen et al. (2010) found no correlation between CRNA burnout and age.

The identification of several common themes among various anesthesia providers may make it reasonable to pool the results together and develop an interventional strategy from such findings; however, burnout is an individual experience that is specific to the work context (Del Grosso & Boyd, 2019). Influences such as occupational environment (i.e., work setting, managerial support), professional background (i.e., nurses, ACPs, physicians), demographic variables (i.e., sex, race, experience), and personality traits can vastly influence data outcomes (Hyman et al., 2017; Schaufeli et al., 2017). Hyman and colleagues (2017) found male anesthesiologists had a higher total burnout score compared to female anesthesiologists whereas De Oliveira Jr. and colleagues (2013) found female anesthesiology residents had higher burnout scores compared to male anesthesiology residents. Lederer, Kinzl, Trefalt, Taweger, and Benzer (2006) found job-related factors leading to burnout among Austrian anesthesiologists included limited complexity of work, lack of time control, and lack of ability to participate compared to the study by Morais, Maia, Azevedo, Amaral, and Tavares (2006) found “job-related factors such as strained work relationships, unskilled leaders, work overload, and surgeon attitudes resulted in burnout among Portuguese anesthesiologists” (Del Grosso & Boyd, 2019, p. 208). Therefore, valid concerns can be raised about the possibility that situational variables can act as moderators and create inaccurate assumptions and interventions of burnout without greater context-specific research.

Review of CRNA Burnout[1]

The widespread negative consequences of burnout among anesthesia providers are an increasing concern. According to the JD-R, each occupation has a unique set of job-related

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[1] With permission (see Appendix A), a portion of the material reported in this chapter is from the author’s previous work “Burnout in nurse anesthetist: An integrated review.” Published in the *American Association of Nurse Anesthetist Journal*, Copyright 2019.

contributors that impact burnout (Maslach & Leiter, 2016). Therefore, it is important to evaluate specific job-related factors and burnout among CRNAs practicing in the United States. To better understand the primary objective of this study, the following section will review and discuss the literature on burnout's impact related to the nursing anesthesia specialty. Specifically, with permission granted by the AANA, the integrated literature review on CRNA burnout is from the author's, "Burnout in nurse anesthetist: An integrated review" (Del Grosso & Boyd, 2019).

Burnout research in the U.S. healthcare industry has seen dramatic growth in the past two decades to the point that professional healthcare organizations started to recognize its importance in clinician wellbeing (Farina, Horvath, Lekhnych, Chavevz, & Griffis, 2020). Studies (see Britt, Koranne, & Rockwood, 2017; Dyrbye et al., 2017) that evaluated burnout among different providers found anesthesia providers to be at a particularly higher risk of burnout compared to other specialties. Scholarly focus increased towards evaluating the relationship between job-related characteristics and burnout among different types of anesthesia providers and anesthesia trainees. However, there were concerns about the paucity of research that focused on CRNA burnout. Del Grosso and Boyd (2019) conducted an integrative literature review to identify common conceptual and methodological processes and evaluation of research focused on the nursing anesthesia specialty. The primary objective of the review was to examine and discuss burnout in CRNAs practicing in the United States (Del Grosso & Boyd, 2019).

We used Torraco's (2017) suggestions for an integrated review by using the PICOS (Table 1) approach to guide our literature search strategies. Studies were eligible for inclusion if they were conducted in the United States, evaluated actively practicing CRNAs, and evaluated burnout by subscales or overall burnout instrument(s). Additionally, the criteria included English articles published in peer-reviewed journals from January 1974 to February 2018. Exclusion criteria were publications that were reviews, editorials, opinions, trainees, outside of a clinical setting, not practicing in the United States, and studies that used instruments nonspecific to identified burnout dimensions. A comprehensive search was conducted using the following databases: Pubmed, Cumulative Index to Nursing and Allied Health Literature (CINAHL), PsychINFO, PsychARTICLES, and Google Scholar. The search focused on keywords and medical subject headings (MeSH) that included *"perioperative wellness," "perioperative burnout," "perioperative stress," "anesthesia wellness," "anesthesia burnout," "anesthesia professional burnout," "anesthesia stress," "anae* AND burnout," "anae* AND stress," "anes* AND burnout," "anes* AND stress."* Additional searches included secondary literature reviews and primary journals: *AANA Journal, Anesthesia Analgesia, Current Opinion in Anesthesiology, and Anesthesia*. Following the same literature search process mentioned above and to align with the current study's objectives, the date range was updated to include articles through June 2023.

Table 1.

PICOS: Population, Intervention, Comparison, Outcomes, and Study Designs

PICOS	Characteristics of studies included for the comprehensive search
Participants	CRNAs actively practicing within the United States in any setting
Intervention	Assessment of Burnout
Comparison	None
Outcomes	Risk of burnout evaluated either by subscales or overall burnout
Study Design	Empirical studies that utilized a burnout measurement scale

Note. Adapted from "Writing Integrative Literature Reviews: Guidelines and Examples," by R.J. Torraco, 2005, *Human Resource Development Review*, 4(3), 356–367.

We followed Liberati et al. (2009), who recommended a four-phase flow diagram (Figure 3) as a checklist to help evaluate the search results. The initial search revealed a total of 67 potential articles based on keywords, MeSH terms, and additional sources. The abstracts were reviewed for eligibility and 21 articles were removed. An additional 28 articles were removed because they were either outside of the United States, involved anesthesia trainees, or included only anesthesiologists. The remaining 18 articles were reviewed in their entirety to ensure they met our strict criteria, in which 12 additional articles were removed for various reasons such as review articles, inability to isolate CRNA-specific results, and evaluating burnout by using stress measurement tools. The results of the literature search yielded six studies (Elmblad et al., 2014; Hyman et al., 2014; Lea et al., 2022; Mahoney et al., 2020; Shah et al., 2019; & Vells et al., 2021) which directly measured burnout of CRNAs practicing within the United States. The six studies were selected for in-depth review and evaluation.

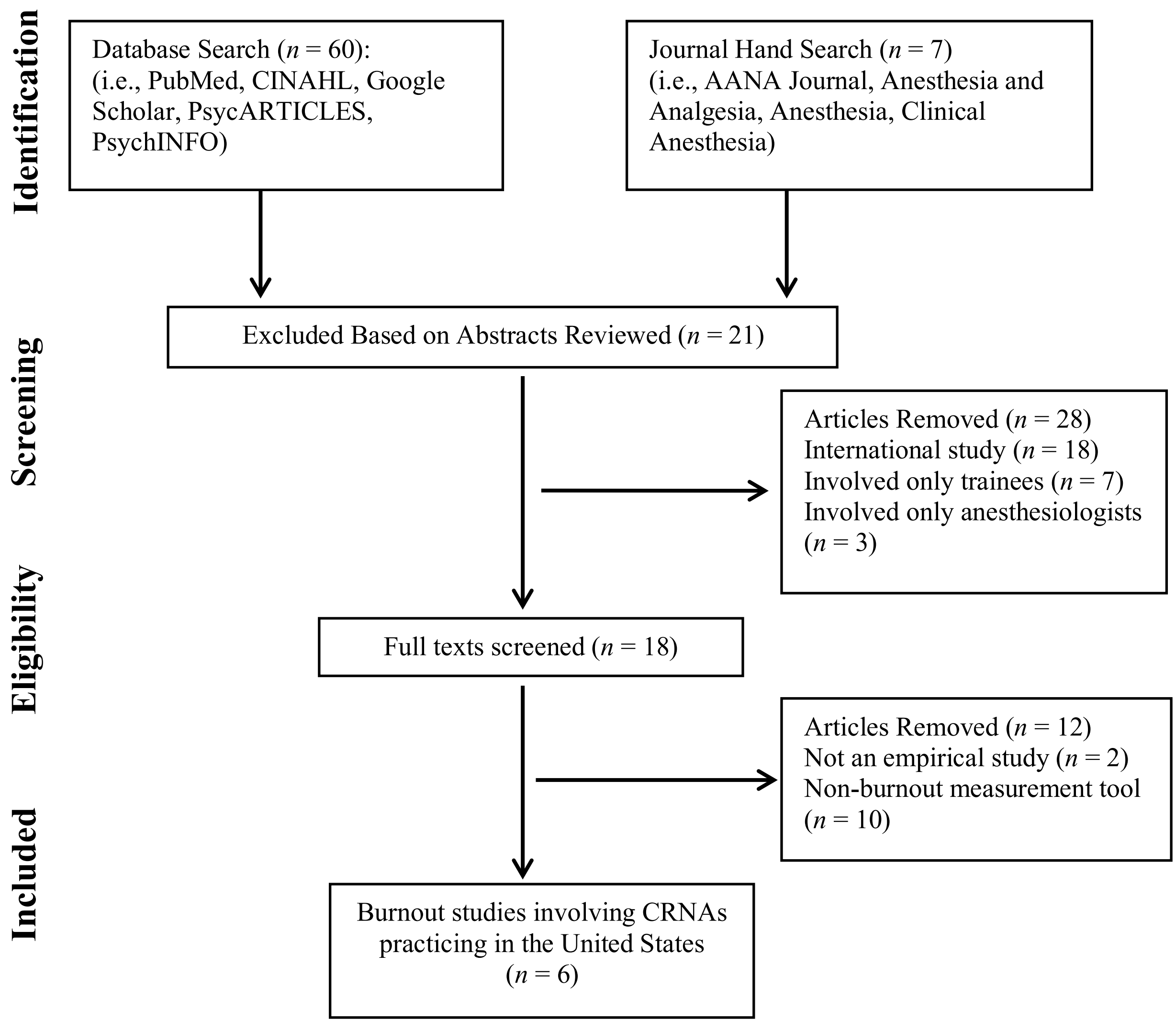

Figure 3.

Literature Search Flow Diagram

Note. CINAHL = Cumulative Index to Nursing & Allied Health Literature. AANA Journal = American Association of Nurse Anesthetists Journal. CRNAs = Certified Registered Nurse Anesthetists. Adapted from "The Prisma Statement of Reporting systematic Reviews and Mata-Analyses of Studies That Evaluate Health Care Interventions: Explanation and Elaboration" by Liberati et al., 2009, *Journal of Clinical Epidemiology, 62(10),* p. 4.

Description Of Studies

. Four studies (Hyman et al., 2011; Lea et al., 2022; Mahoney et al., 2020; Shah et al., 2019; & Vells et al., 2021) were quantitative studies of cross-sectional design with data collection from surveys. One study (Elmblad et al., 2014) was a mixed-methods study that used surveys with three open-ended questions to address CRNA coping strategies towards incivility within the workplace. A variety of sampling strategies were used. In three of the studies (Elmblad et al., 2014; Lea et al., 2022; & Mahoney et al., 2020), a randomized sample of CRNAs was chosen from CRNA professional membership email listservs. Of these, two studies (Elmblad et al., 2014; Lea et al., 2022) recruited at the state level, while one study (Mahoney et al., 2020) recruited from the national AANA membership roster. The remaining three studies (Hyman et al., 2011; Shah et al., 2019; & Vells et al., 2021) were convenience samples from various practice settings within academic-based hospital systems. Response rates of six individual studies ranged as low as 3.2% (Lea et al., 202) to as high as 90% (Vells et al., 2021), with sample sizes ranging from 40 (Vells et al., 2021) to 385 (Elmblad et al., 2014). All studies used survey questions that were validated burnout instruments; however, one study (Hyman et al., 2011) modified the MBI-HSS response range and wording because the authors felt it would be more applicable to the work environment being tested.

Table 2.

Summary from Literature Review of Empirical Studies Evaluating CRNA Burnout

Author and Year	*N*	Sample	Measurement Instruments	Significant Findings
Elmblad et al., 2014	385	CRNAs in Michigan	NIS CBI 3 open ended incivility questions	Experienced moderate to moderately high incivility levels. Workplace incivility and burnout were statistically significant. Gender, worked hours per week, years of experience, and burnout were not statistically significant.
Hyman et al., 2011	145	Staff in academic center in Tennessee	MBI-HSS Social Support and Personal Coping Survey	Compared to physicians, CRNAs (*n* = 20) had lower burnout and work satisfaction scores. Lack of control and insufficient emotional support contributed to CRNA burnout. Personal support contributed to decreased burnout in CRNAs.
Lea et al., 2022	155	CRNAs in Texas and Massachusetts	JDS CRNA OCQ OLBI	39% of the CRNAs were burned out and 40% were disengaged High burnout contributed to decreased job satisfaction. Feedback was statistically significant in moderating burnout. Organizational climate was statistically significant to burnout.
Mahoney et al., 2020	266	CRNA members of the AANA	PI OLBI JDS WWBS	Personality characteristics (agreeableness, openness, and stability), feedback, skill variety and autonomy decreased burnout significantly whereas worked hours increased burnout. Task significance had minimal impact on burnout.
Shah et al., 2019	89	Staff at academic center in Kansas	MBI-HSS	12.5% of CRNAs (*n* = 32) experienced high levels of EE. Compared to residents and anesthesiologists, CRNAs had lowest EE scores.
Vells et al., 2021	40	CRNAs at academic center in Pennsylvania	MBI	72% of CRNAs experienced moderate levels of EE and 25% experienced high levels of EE. 36% of CRNAs experienced moderate to high levels of DP. 14% of CRNAs experienced low levels of PA. CRNAs engaged in BACSP intervention had statistically significant decrease (24%) in EE scores while PA and DP scores were found to be statistically insignificant.

Note. CRNAs = Certified Registered Nurse Anesthetists; NIS = Nursing Incivility Scale; CBI = Copenhagen Burnout Inventory; MBI-HSS = Maslach Burnout Inventory—Human Services Survey; JDS = Job Diagnostic Survey; OCQ = Organizational Climate Questionnaire; OLBI = Oldenburg Burnout Inventory; PI = Personality Inventory; WWBS = Work & Wellbeing Survey; EE = Emotional Exhaustion dimension of the MBI; DP = Depersonalization dimension of the MBI; PA = Personal Accomplishment dimension of the MBI.

Themes From Reviewed Studies

Four studies (Elmblad et al., 2014; Hyman et al., 2011; Lea et al., 2022; & Mahoney et al., 2020) evaluated similar demographic characteristics. The four studies had similar descriptive summaries—age (M = 44–51 years old), years of experience (M = 15.6–18.5 years), Female (M = 49%–69%), and full-time employment (M = 45%–86%). Greater than 50% practiced in a type of hospital setting (i.e., community or academic). These four studies were in alignment with the 2023 AANA membership survey.

Lea et al. (2022) and Mahoney et al. (2020) conducted data analyses with structural equation modeling (SEM) while the rest of the studies utilized a form of linear regression analysis. In addition to demographic characteristics, several studies measured job characteristics against burnout. These included autonomy, workload, job-control, task identity, personality traits, organizational support, social support, and incivility. Two studies, Elmblad et al., 2014 and Vells et al., 2021, evaluated the impact of coping mechanisms on burnout. Burnout measures included the Maslach Burnout Inventory (MBI), Oldenburg Burnout Inventory (OLBI), and Copenhagen Burnout Inventory (CBI). The prevalence rates of CRNA burnout ranged from 12.5% to 72%. One study (Hyman et al., 2011) did not mention a specific CRNA burnout score. Regardless of the measure used, to date, there is no agreed-upon cut-off point that categorizes an individual as burnt out (Demerouti, Mostert, & Bakker, 2010). Each of the studies reviewed defined their cutoff point for burnout. Based on the six studies reviewed, several common themes emerged as factors that may cause burnout in CRNAs practicing in the United States. These job-related factors included workplace behaviors, job-related support, workload, job control, and autonomy.

Discussion

The initial review conducted by Boyd and Del Grosso (2019) resulted in only two studies (Elmblad et al., 2014 and Hyman et al., 2014). Updating the literature search to include February 2018 to June 2023, an additional four studies (Lea et al., 2022, Mahoney et al., 2020; Shah et al., 2019; & Vells et al., 2021) were identified as matching the primary search criteria. The literature review synthesized the findings from previous empirical studies related to working conditions that contributed to burnout among CRNAs practicing in the United States. The common job-related factors contributing to burnout in this nursing specialty consisted of workplace behaviors, job-related support, workload, job control, and autonomy. Consistent with reviews (Aaron, et al., 2021; Afonso et al., 2021; Sanfilippo et al., 2017) evaluating other healthcare professions such as nursing and physicians, our review found that organizational factors were the primary contributors towards burnout within this nursing specialty. Also consistent with other literature reviews (Aaron et al., 2021; Afonso et al., 2021; Sanfilippo et al., 2017), demographic characteristics correlation to burnout varied among studies.

The results of the literature review demonstrated an increased focus towards evaluating burnout's impact on CRNAs; however, several gaps in the literature remain. First, the expansion of the literature review by five years yielded only an additional four studies, indicating a paucity of burnout research that focuses on CRNA burnout within the United States. Determinants and outcomes of burnout differ within various working environments, depending on the unique demands and resources that exist in that specific work context (Rothmann, Mostert, & Strydom, 2006). CRNAs function in a variety of practice models and occupational settings that may each have their unique demands and outcomes specific to that work context. The lack of empirical research decreases the ability to find common frequencies and sources of burnout specific to this nursing specialty. Without an understanding of specific causes of burnout, it hinders the understanding of the ramifications and potential solutions. Continuing to expand on current empirical research through additional integrated research of the relationship between work-related factors and burnout in CRNAs practicing in the United States remains.

Secondly, the review found all six studies utilized burnout measurement tools that have been extensively evaluated however, none of the six studies utilized a theoretical framework to guide their research. The lack of theoretical models is concerning because their primary purpose is to provide specific causal assumptions of individual and situational factors causing people to experience burnout, and once burnout occurs, resulting in certain outcomes (Maslach et al., 2017). There is a lack of a common operational definition of burnout, which complicates efforts to establish criterion validity. To advance the understanding of any organizational construct, we must also be able to measure and analyze it appropriately. Burnout remains without defined operational boundaries which has resulted in each scale being based on how the author conceptualizes burnout. Focusing on core research principles such as building upon existing models and measurement tools with strong psychometric properties may provide an easier path towards understanding burnout within the CRNA profession.

Theoretical Foundation for the Development of Burnout in CRNAs

The JD-R model (see Figure 4) served as the framework to address the study's research questions and hypotheses. The following section will review JD-R's development to provide further appreciation of the rationale for using the model's key principles to evaluate burnout in CRNAs practicing in the United States.

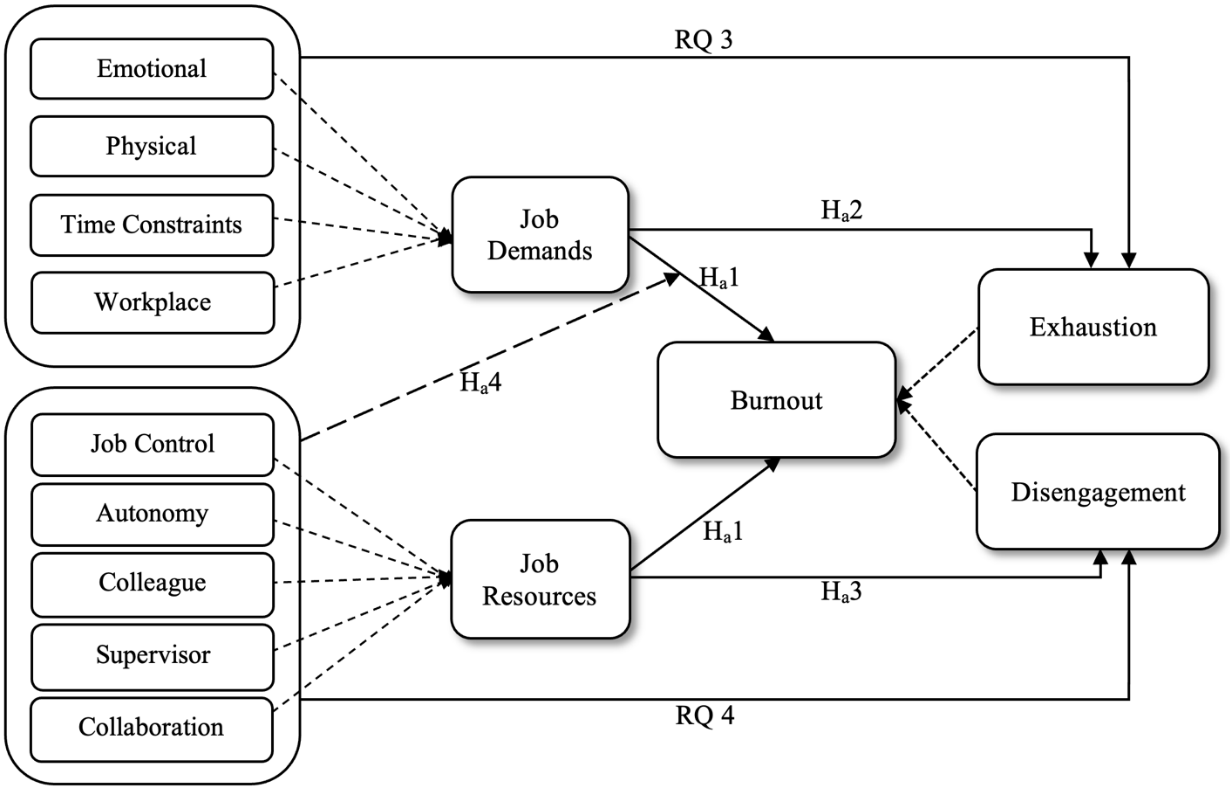

Figure 4.

The Job Demands-Research Model: CRNA Job Characteristics and Burnout Relationship

Note. See text for full statements of research questions and hypotheses. The following are greatly abbreviated. Not all research questions are included in this figure.

H_a1. Specific job demands/resources will correlate with burnout. H_a2. Job demands (not job resources) will be the stronger predictor of burnout. H_a3: Job resources (not job demands) will be the stronger predictor of disengagement. RQ 3. How strongly do specific job demands correlate with exhaustion? RQ 4. How strongly do specific job resources correlate with disengagement? H_a4. Job resources will moderate the positive relationship between job demands and burnout, such that the relationship between job demands and burnout will be less positive.

Historical Development

In the late 1990s and early 2000s there was a general acceptance of the burnout syndrome being viewed as the result of job-related factors (Bakker & Demerouti, 2007). The dramatic increase in empirical research demonstrated the profound impact job-related factors had on an employee's development of burnout (Bakker & Demerouti, 2007). Measures like the MBI identified a wide range of job-related characteristics as possible causes of burnout (Bakker & Demerouti, 2017). However, burnout measures focus on what burnout is and whether it is present, but not on how or why it occurs (Bakker & Demerouti, 2017). This theoretical gap resulted in several researchers proposing models that offered different perspectives towards an understanding of how and why burnout developed (Bakker & Demerouti, 2007). Popular models like the demand-control model (DCM), conservation of resources theory (COR), and the effort-reward imbalance (ERI) model dominated empirical research and demonstrated the impact between job-related characteristics and burnout. For example, Karasek's (1979) DCM theorized strain was the result of employees experiencing high demands and low personal control over how to meet those demands (Karasek, 1979). This means that if an employee were exposed to high demands at work but had control over the ability to meet those demands, the individual would not experience stress (Karasek, 1979; Bakker & Demerouti, 2007). Like the DCM, the ERI model developed by Siegrist and colleagues (1986) emphasized a balance between input and output of job-related characteristics, in particular, efforts and rewards. The primary assumption was that when employees experience high effort output but have low reward, a deficit occurs which is a risk factor for poor health outcomes (Siegrist, J., Siegrist, K., & Weber, 1986). Another popular model was Hobfoll's (1989) COR theory which states individuals strive to obtain and maintain resources of value and when job demands threaten these resources, stress ensues. According to the COR, individuals seek out ways to obtain and maintain the resources of value and can experience stress at the potential or actual loss of these valued resources (Hobfoll, 1989; Schaufeli & Taris, 2013).

Every work environment has its unique environment and associated job-related demands and resources that impact an individual's risk of stress. Earlier models lacked several common, and key principles for addressing the development of burnout (Bakker & Demerouti, 2007). According to Bakker and Demerouti (2007), earlier models (a) presented a one-sided view of job demands (stress) or job resources (motivation), (b) included variables that were broad and thought to be the same across all types of work environments, (c) were restricted to a given or defined number of predictor variables that were not flexible towards other job roles, and (d) were too simplistic and did not build on theoretical perspectives of other models. For example, both the DCM and ERI models were simple and straightforward, focusing on specific job demands and job resources, the DCM on job control, the ERI on salary, esteem, and status control. Critics like Bakker and Demerouti argued the simplicity of these models neglected the reality of the work environment by focusing only on experiences of a few variables and not allowing for individualized experiences (Bakker & Demerouti, 2007). The COR expanded on the types of job resources; however, the theory is based on a one-sided view (job resources) and neglects the impact of job demands (Bakker & Demerouti, 2007). These overlapping problems created the need for a theoretical model that allowed flexibility by considering multiple viewpoints and allowing for the inclusion of all job-related characteristics (Bakker & Demerouti, 2014).

Demerouti's work revealed job demands and resources formed two different categories, each with its own relationship to what she believed were the core dimensions of burnout-engagement and disengagement (Bakker & Demerouti, 2007). The authors of the JD-R model assume the development of burnout follows two processes (Demerouti et al., 2001). The first process states high demands within the work environment results in constant strain on the individual, eventually causing exhaustion (Demerouti et al., 2001). In the second process, limited resources within the work environment led to a further inability of employees meeting the job demands, eventually resulting in disengagement (Demerouti et al., 2001). Evaluating 374 employees from 21 different occupations across Germany, Demerouti et al. (2001) tested the assumption that job demands were the most predictive of exhaustion, whereas job resources were the most predictive of disengagement and that the contribution of each in explaining burnout may vary across the occupations. The authors used the OLBI measure and observer ratings to evaluate job characteristics and conducted a series of structural equation analyses (LISREL), which successfully demonstrated burnout is a dichotomous trait and its symptoms are determined by job characteristics specific to that work environment (Demerouti et al., 2001). After its introduction into burnout literature, the JD-R model was revised by Schaufeli and Bakker (2004) to include engagement and has undergone several further modifications since its introduction (Bakker & Demerouti, 2007; Bakker & Demerouti, 2017). The authors (Demerouti et al., 2001) argue the JD-R model provides the greater flexibility needed to better understand the development of burnout and its associated consequences by allowing for the inclusion of job-related characteristics (job demands and job resources) that are unique to different work environments (Bakker & Demerouti, 2017).

Overview Of the Job Demands-Resources Model

Since the JD-R's initial introduction into research, the model's flexibility, and ability to be tailored to any type of work environment has been recognized as one of the leading job stress models (Schaufeli & Taris, 2013). Over the years, multiple theoretical propositions regarding the model have been developed and tested; although all these propositions are relevant to further understanding the development of burnout in the nursing anesthesia specialty, this section will primarily focus on those propositions that impact the study's primary objectives.

The central assumption of the JD-R model is regardless of the occupation, each job has its own specific risk factors associated with job stress which can be classified as either job demands or job resources (Bakker & Demerouti, 2007; Crawford, LePine, & Rich, 2010). This assumption allows for a highly flexible model that can be applied to all work environments and be tailored to specific occupations under evaluation. Job demands are defined as physical, psychological, social, or organizational characteristics of the job that result in physical or psychological efforts that result in physiological or psychological costs (Demerouti et al., 2001). Building on the model of compensatory control, the JD-R model theorizes when job demands are high, additional efforts are required to complete the required job task, which requires physical and psychological energy expenditures (Demerouti et al., 2001; Schaufeli & Taris, 2013). Employees will attempt to recover through various methods such as coping mechanisms, job resources, or recovery time; however, when recovery becomes inadequate to meet the demands, the state of sustained stress eventually results in a state of emotional and physical exhaustion, the energetic component of burnout (Demerouti et al., 2001; Schaufeli & Taris, 2013). According to the model, exhaustion is defined as a consequence of extended exposure to specific job demands like intense physical, affective, and cognitive strain (Demerouti et al., 2001; Lesener, Gusy, & Wolter, 2019) The definition of job demands was further expanded by Crawford and colleagues (2010) to include hindering and challenging job demands. Challenging job demands are perceived as opportunities to learn and grow and are positively associated with engagement, whereas hindering job demands are perceived as constraints or barrier and negatively associated with engagement (Craword et al., 2010; Lesener et al., 2019).

Job resources are the physical, psychological, social, or organizational aspects of the job that are functional in achieving work goals and reducing job demands and the associated physiological and psychological costs or stimulating personal growth, learning, and development (Demerouti et al., 2001). The views of job resources are in alignment with Hobfoll's (1989) conservation of resources (COR) theory, which states that individuals are motivated to protect, maintain, and accumulate resources (Bakker & Demerouti, 2007). Therefore, resources not only serve as protection against the impact of job demands but also function in their own nature (Bakker & Demerouti, 2007). Job resources can be found at every level of the organization and can be task level (performance feedback), interpersonal level (colleague support), and organizational level (supervisor mentorship/coaching) (Schaufeli & Bakker, 2004; Bakker & Demerouti, 2017). The presence of job resources results in engagement, whereas the absence or depletion results in disengagement (Bakker & Demerouti, 2007).

Current literature supports that job-related characteristics are primary predictors of burnout; however, research has also demonstrated the role personal resources may play in the JD-R model and burnout (Bakker & Demerouti, 2017; Schaufeli & Taris, 2013). Personal resources refer to the psychological beliefs of self that people hold regarding how much control and impact they may have over their environment (Demerouti et al., 2001). According to the JD-R model (fifth assumption), personal resources act similarly to job-related resources. They can: (a) direct positive effect on work engagement, (b) buffer the impact job demands have on burnout or enhance positive effects resources have on engagement, and (c) enhance the desirable impact of job demands on the motivational process (Demerouti et al., 2001; Schaufeli & Taris, 2013). The impact of personal resources was not part of the current dissertation; however, understanding the role that personal resources may play in the development of burnout is important for future research.

The second assumption of the JD-R states job demands and job resources initiate two different psychological processes: a health impairment process, and a motivational process (Bakker & Demerouti, 2007; Demerouti et al., 2001). The first process follows Hockey's (1993) model of compensatory control and is considered the energetic process that links job demands with negative health outcomes (Schaufeli & Bakker, 2004). The health impairment process occurs when chronic exposure to job demands results in the depletion of employees' mental and physical resources (i.e., coping responses) that lead to the depletion of energy (i.e., exhaustion) and eventual health-related problems (Bakker & Demerouti, 2007). The health impairment process aligns with research that burnout may lead to certain health problems such as depression, cardiovascular disease, and musculoskeletal pain (Schaufeli & Taris, 2013). For example, a review conducted by Hall, Johnson, Watt, Tsipa, & O'Connor, (2016) analyzed 27 studies of burnout's impact on provider wellbeing. The authors found 59.3% of the articles reviewed had demonstrated provider burnout resulted in a correlation with poor wellbeing (i.e., depression, anxiety, and mental health) (Hall et al., 2016).

According to the motivational process job resources may have either an intrinsic role that fosters employees' growth and development or an extrinsic role that allows for an individual achieve their work tasks (Bakker & Demerouti, 2007; Demerouti et al., 2001). The intrinsic role follows the Self-Determination Theory (Deci & Ryan, 1985) that assumes individuals have a basic need for autonomy, competence, and feedback to increase intrinsic motivation (Schaufeli & Bakker, 2004). The extrinsic role follows the Effort-Recovery Model (Meijman & Mulder, 1998) that assumes work environments that offer adequate resources will foster an employee's dedication to the work task (Schaufeli & Bakker, 2004). For example, supervisor support through feedback may promote learning which increases job skills, whereas decision latitude may promote autonomy (Schaufeli & Taris, 2013). When job demands and job resources are high, the JD-R model postulates (fourth assumption) that these jobs can be active jobs that challenge the employee secondary to the motivational process of job resources (Bakker & Demerouti, 2007;

Demerouti et al., 2001). Bakker, Demerouti, De Boer, and Schaufeli (2003) hypothesized this dual pathway in their study that evaluated nutrition production employees (*n* = 214). The study demonstrated job demands were unique predictors of burnout and indirectly of absence duration whereas job resources were unique predictors of organizational commitment and indirectly of absence frequency (Bakker et al., 2003).

Schaufeli and Bakker (2004) extended the second assumption by including engagement which links job resources and organizational outcomes. The JD-R model assumes the intrinsic and extrinsic motivational roles can promote a positive relationship between employee and work (Bakker & Costa, 2014; Schaufeli & Taris, 2013). Schaufeli and Bakker (2004) defined this as work engagement which is a positive, fulfilling, work-related state of mind that is characterized by vigor, dedication, and absorption. They included work engagement into the model and hypothesized that it mediates the relationship between job resources and organizational outcomes (i.e., turnover and job satisfaction) (Schaufeli & Taris, 2013). Schaufeli and Bakker (2004) used SEM to test this model on four independent samples (*n* = 1698), which demonstrated (a) engagement is predicted by available job resources, (b) burnout and engagement are negatively related, and (c) engagement mediated the relationship between job resources and turnover intentions. Nahrgang and colleagues (2011) conducted a meta-analysis that was based on 203 studies that demonstrated support for the JD-R model's dual pathways through which job demands and job resources related to safety outcomes. They found job resources included knowledge of safety, autonomy, and a supportive environment motivated employees and increased engagement (Nahrgang et al., 2011). The expansion of the JD-R model to include engagement is important because it not only demonstrates that engagement and burnout are conceptually different but that interventional approaches should aim at their strategies accordingly (Schaufeli and Bakker, 2004).

Job demands and job resources are considered to initiate two separate processes; however, they can have different levels of interactions (Demerouti et al., 2001). The third assumption follows the definition of job resources' ability to decrease the impact of job demands and states job resources may buffer the impact of job demands on the exhaustion component of burnout (Demerouti et al., 2001; Schaufeli & Taris, 2013). The third assumption expands on Karasek's (1979) DCM hypothesis that job control and or support may offset the impact of job demands by theorizing that several different job resources may buffer both quantitative (work pressure) and qualitative (emotional) job demands (Bakker, Demerouti, & Euwema, 2005). This assumption postulates that when employees have many job resources available to them, their ability to manage high demands is improved. The amount of interaction between job demands and job resources is dependent on the specific job characteristics of that work environment (Bakker et al., 2005). Taken together, studies by Bakker et al. (2005) and Xanthopoulou et al. (2007) validated this assumption by demonstrating more than half of all possible interactions between job demands (i.e., workload, emotional demands, physical demands) and job resources (i.e., autonomy, social support, feedback) were significant (Schaufeli & Taris, 2013).

The JD-R model is a flexible model that provides a theoretical understanding of the development of burnout, its antecedents, and consequences. Cross-sectional (Bakker, Demerouti, de Boer, & Schaufeli, 2003; Bakker, Demerouti, & Schaufeli, 2003) and longitudinal studies (Lesener et al., 2019) have supported its primary assumptions and provided evidence of the relationship between antecedents and burnout within the work environment. Further, its flexibility allows for it to be integrated into any work environment, regardless of its complexity, making it a desirable model for this dissertation.

Chapter Summary

Burnout, what constitutes it, what contributes to its development, and what its consequences are, continue to be discussed without consistent terminology. These challenges in identifying and measuring burnout have resulted in a great assortment of prevalence rates, antecedents, and outcomes among the different anesthesia specialties (i.e., anesthesiologists, CRNAs, and Anesthesia Assistants). Researchers believe some of the context's fragmented state may stem from its multifactorial origins (Schaufeli et al., 2017). Hundreds of burnout measures have been developed and used; however, only a dozen have demonstrated through various psychometric analyses that they are valid instruments for quantifying burnout in healthcare providers (Shoman et al., 2021). The distinction between instruments is whether they measure burnout as a single or multidimensional concept (Maslach & Leiter, 2016; Schaufeli et al., 2009). The measures used to assess burnout are often closely linked to the author's assumptions of the construct (Maslach et al., 2016; Schaufeli et al., 2017). Many of the original studies lacked theoretical framework and measures like the MBI identified a wide range of job-related characteristics as possible causes of burnout (Bakker & Demerouti, 2017). However, burnout measures focus on what burnout is and whether it is present, but not on how or why it occurs (Bakker & Demerouti, 2017). This theoretical gap resulted in several researchers proposing models that offered different perspectives toward an understanding of how and why burnout developed (Bakker & Demerouti, 2007). Theoretical attention towards establishing what it means to be "burned out" revealed several common themes that define its conceptualization: (a) burnout is considered a work-related syndrome that emerges from a prolonged response to chronic interpersonal job-related stressors, (b) burnout is a psychological experience of feelings and attitudes towards one's job, and (c) it is an individual's experience that is specific to the work context (Maslach, & Leiter, 2017; Schaufeli, Maslach, & Marek, 2017). Today, burnout is commonly referred to as psychological syndrome describing an individual's response to emotional and interpersonal stressors at work (Schaufeli et al., 2017; Swider & Zimmerman, 2010). Causes of burnout are generally divided into situational factors (i.e., job-related characteristics) which are the primary correlates of its development and individual factors, including personality traits and demographic characteristics (i.e., age, gender) (Schaufeli et al., 2017). Despite the advancements in burnout literature, substantial disagreements among research experts in the field regarding the conceptualization and measurement of burnout remains (Leo et al., 2021). Choosing the appropriate survey tool and interpreting the results needs to go beyond face value and be grounded in a theoretical model (Aron et al., 2021; Del Grosso & Boyd, 2019).

Burnout is recognized as a direct occupational hazard for individuals and has widespread negative effects on the healthcare industry in its entirety (Morais et al., 2006; Schaufeli et al., 2017). Individuals suffering from burnout have a higher risk of a range of psychological and physical health problems that have included alcohol consumption, musculoskeletal pain, anxiety, depression, sleep disturbances, and memory impairment (Bakker & Costa, 2014; Salvagioni, et al., 2017). From an organizational perspective, burnout has a negative effect on the culture and climate of individual employees and their work teams. Anesthesia providers are at a higher risk of suffering from burnout when compared to other healthcare specialties. Prior to the COVID-19 pandemic, CRNAs were already facing significant challenges secondary to daily exposure to high job-related demands. These challenges included critical shortages of providers, demands for increased production pressures on an aging population, increased complexity in the medical management of patients, and greater public expectations that healthcare delivery is seamless, safe, and free of adverse events. Throughout the pandemic, anesthesia departments scrambled to acquire personal protective equipment to protect their providers and decrease the risk of exposure. Supply chains were severely disrupted, which impacted the ability to care for the surge in patients, and many CRNAs had different roles and responsibilities. The pandemic has since drastically decreased; however, components of these experiences, as well as ongoing patient demands, and supply chain challenges, place a further increased risk of burnout in the nursing specialty.

The literature review evaluating the relationship between work related factors and burnout in CRNAs practicing in the United States demonstrated common job-related factors contributing to burnout in this nursing specialty consisted of workplace behaviors, job-related support, workload, job control, and autonomy. Consistent with studies (Aaron et al., 2021; Afonso et al., 2021; Sanfilippo et al., 2017) evaluating healthcare professions such as nursing and physicians in that our review demonstrated organizational factors being the primary contributors towards burnout. The review demonstrated several gaps in the literature remain. First, only six empirical studies were found that evaluated the relationship between job characteristics and burnout among CRNAs practicing in the United States, indicating a paucity of burnout research. The inability to appropriately identify, evaluate, and manage CRNA burnout coupled with the growing administrative and clinical complexities of the U.S. healthcare system may cause further strain on the stability of this nursing specialty that is already facing a critical deficit in workforce numbers, ultimately, resulting in the inability to provide cost-saving, high-quality care to patients in need (Negrusa et al., 2021). Second, all six studies utilized burnout measurement tools that have been extensively evaluated however, none of the studies utilized a theoretical framework to guide their research. Studies that are grounded in a conceptual model are the basis for deriving and testing hypotheses, which allow for a clear interpretation of whether the findings are supportive of the researcher's ideas regarding the concept (Schaufeli et al., 2017).

When measuring job-related burnout in any healthcare specialty, a researcher must consider the complex functions and intertwined networking structure of the modern-day healthcare environment. The healthcare industry has changed dramatically over the past decade and events like the pandemic further accelerated factors already negatively impacting its providers. The JD-R allows for greater flexibility in operationalizing burnout and its associated factors which allows for a more realistic understanding of its development in that specific job role (Bakker & Demerouti, 2007; Bakker & Demerouti, 2017). The JD-R model gives the researcher the ability to include job-related factors that are unique to CRNA work environment and therefore, create an overarching model that can measure and evaluate burnout factors and outcomes. The JD-R model views burnout as developing when individuals experience relentless job demands and have poor resources available to address those demands (Demerouti et al., 2001). The JD-R's central theory is that regardless of the occupation, factors leading to burnout can be categorized as either job demands or job resources. Work environments with high job demands and low job resources, exhaustion and disengagement develop which in turn leads to burnout. Although there have been several modifications to the JD-R, the primary assumptions within the model remain its foundation: (a) job demands predict burnout (exhaustion) and job resources predict work engagement (disengagement), (b) efforts required to meet excessive job demands results in exhaustion and health impairment process whereas lack of job resources prevents the ability to meet work-related goals which results in disengagement and lack of motivation process, and (c) job resources can moderate the impact job demands have on burnout (Demerouti et al., 2001; Lesener et al., 2019).

Burnout is an individual experience that is specific to the work context and influences such as the occupational environment, professional background, and individual characteristics which can influence data outcomes (Del Grosso & Boyd, 2019). Every specialty within the healthcare industry has its unique demands and resources and, therefore, requires its own research and attention (Bakker & Demerouti, 2007). There has been an increased empirical focus on CRNA burnout; however, the extent of the relationship between burnout and job-related characteristics remains poorly understood which, in turn, may result in an ongoing negative impact on the providers and the organizations and communities they serve. Therefore, the study's overall goal of addressing the relationship between job-related characteristics and burnout in CRNAs and using the JD-R perspective is to increase the understanding of the impact of specific job-related characteristics contributing to burnout. Further understanding of this impact may provide a path towards appropriate interventions.

CHAPTER 3: METHODOLOGY

Introduction

CRNAs are a critical part of the anesthesia workforce, responsible for approximately 65% of the anesthetics provided in the United States (Del Grosso & Boyd, 2019). The growing demands by healthcare facilities for cost-efficient, safe anesthesia services coupled with the challenges created by the pandemic, have led to a mismatch between job demands and job resources, ultimately increasing the risk of burnout and its associated negative outcomes within this nursing specialty (Aron et al., 2021). There has been an increased empirical focus towards evaluating and understanding burnout within the nursing specialty which have resulted in the identification of several common work characteristics (i.e., work overload, autonomy, collaboration, job control, and support) related to increased risk of CRNA burnout. Negative outcomes related to increased CRNA burnout have been associated with intent to quit, increased turnover, workplace aggression, and decreased job satisfaction (Boyd & Poghosyan, 2017; Mahoney et al., 2020). The limited exploratory research and lack of theoretical frameworks to provide a path towards the identification and evaluation of context-specific job-related factors contributing to CRNA burnout has resulted in limited success with respect to alleviating burnout within the nursing anesthesia specialty. The inability to appropriately identify, evaluate, and manage CRNA burnout coupled with the growing administrative and clinical complexities of the U.S. healthcare system may cause further strain on the stability of this nursing specialty that is already facing a critical deficit in workforce numbers, ultimately, resulting in the inability to provide cost-saving, high-quality care to patients in need (Negrusa et al., 2021).

The primary purpose of the study was to further evaluate the relationship between previously identified job demand and job resource variables and burnout among CRNAs practicing in the United States. A modified version of the JD-R model (see Figure 1) to include measured variables specific to the nursing specialty was used as the theoretical framework to further understand the burnout syndrome within this nursing specialty. The study's overall goal of applying the JD-R model in addressing the relationship between job-related characteristics and burnout in CRNAs practicing in the United States is to increase the understanding of the impact of these specific job-related factors contributing to burnout which in turn may provide a path towards appropriate interventions. Chapter 3 will discuss the methodology process conducted to address the research questions and hypotheses related to these relationships. The section is organized into several parts that include the research questions and hypotheses, study design, sampling procedures, instrumentation, validity concerns, ethical procedures, data collection procedures, data analysis, and summary.

Research Questions and Hypotheses

I used the JD-R model (see Figure 2) as the framework to address the study's research questions and hypotheses. The central assumption of this model theorizes that burnout is directly related to the balance between specific working conditions of that profession (Bauer & Hammig, 2014). These working conditions are classified into two broad categories: job demands and job resources (Bakker & Demerouti, 2007). The JD-R model proposes that the interaction between high job demands and poor job resources creates the burnout syndrome which is operationalized by the dimensions—exhaustion and disengagement (Demerouti et al., 2001; Schaufeli & Taris, 2013). The study addressed the following questions and hypotheses (Figure 4):

RQ 1. To what extent is there a relationship between previously identified job demands and job resources on burnout in a national sample of CRNAs practicing in the United States?

H_a1: Specific job demands and job resources (as measured by subscales of the survey) will have a statistically significant correlation with burnout in CRNAs practicing in the United States.

RQ 2. Is there a difference in the relationship between previously identified job demands (emotional demands, workload, time constraints, and workplace incivility) with burnout dimensions (exhaustion and disengagement)?

H_a2: Job demands, and not job resources, will be the stronger predictor of burnout in CRNAs practicing in the United States.

RQ 3. Is there a difference in the relationship between previously identified job resources (job control, autonomy, colleague support, supervisor support, collaboration) with burnout dimensions (exhaustion and disengagement)?

H_a3: Job resources, and not job demands, will be the stronger predictor of disengagement in CRNAs practicing in the United States.

RQ 4. Is there a difference in the degree of correlations among previously identified job-related variables (as measured by subscales of the survey) with burnout dimensions—exhaustion and disengagement?

H_a4: Job resources, which include job control, autonomy, colleague support, supervisor support, and collaboration, will moderate the positive relationship between job demands and burnout, such that the relationship between job demands and burnout will be less positive.

Research Design and Rationale

The study was an exploratory, cross-sectional analysis that was designed to evaluate the relationship between previously identified job demand and job resource variables (independent variables) and burnout (dependent variable) among CRNAs practicing in the United States. Utilizing the JD-R model as the theoretical framework, this study sought to elucidate how specific job-related characteristics contribute to burnout, characterized by the dimensions of exhaustion and disengagement. The study took place in a natural environment without any influence from me; therefore, a cross-sectional design is considered optimal (Abbott & McKinney, 2013). Although cross-sectional studies are unable to make causal inferences, they allow researchers to survey a sample when the setting is uncontrolled (Abbott & McKinney, 2013). Cross-sectional studies are also considered optimal when evaluating the relationships between multiple variables (Abbott & McKinney, 2013).

The analysis was grounded in a quantitative approach, where data was collected through an 82-item survey that was distributed electronically. Aligning with the JD-R model, the survey was designed to capture a comprehensive range of job-related characteristics (predictor variables), including workload, time constraints, emotional and physical demands, workplace incivility, and available job resources such as autonomy, control, and social support that previous studies have demonstrated to be common predictors of burnout (outcome variable) among CRNAs practicing in the United States. The survey assessed burnout as operationalized by the two dimensions—exhaustion and disengagement. The survey also included demographic variables and two open ended questions addressing additional information around job demands and job resources.

Together with the use of hypotheses to test assumptions within the JD-R model, a quantitative approach was the most appropriate method (McCusker & Gunaydin, 2015). Benefits of a quantitative approach include: (a) generalizations from previous burnout research relative to the nursing anesthesia specialty will be a focus; (b) a quantitative method is deductive and hypothesis-centered, thus allowing the different relationships among the variables to be tested; and (c) literature related to CRNA burnout is limited; therefore, replication and/or building from this study is vital to future research focused on identifying and evaluating the implications of burnout for practitioners in this nursing specialty (Abbot & McKinney, 2013).

After IRB approval was obtained and AANA application completed, a link to the survey was distributed to 3,000 randomly selected CRNAs via email from the AANA. An additional follow-up email was sent seven days prior to the survey's four-week timeframe. The data collected from the survey was exported from Qualtrics to the Statistical Package for the Social Sciences (SPSS) and prepared for descriptive and inferential analysis using SEM and path analysis in R.

Methodology

Population

The target population of interest was CRNAs who were active members of the American Association of Nurse Anesthetists (AANA) and practicing in a clinical setting within the United States. CRNAs are advanced practice nurses (APNs) with graduate-level education. The career path towards becoming a CRNA requires seven to nine years of education and experience (AANA, 2023). Candidates must have a minimum GPA of 3.0 from a baccalaureate degree in nursing, a GRE score greater than 300, several years of critical care experience with advanced career achievements such as advanced certifications (i.e., Critical Care Nursing Certification), and an interview that evaluates each candidate's critical care experience and knowledge to gain entrance into one of 130 accredited nurse anesthesia programs (AANA, 2023). Once accepted into an accredited nursing anesthesia program, students undergo approximately three years of rigorous academic and clinical preparation, graduating with a doctoral degree. After completing a program, each nursing anesthesia student must then pass the National Certification Examination to become a CRNA. Maintenance of clinical practice as a CRNA requires an active nursing license, 100 hours of continuing education, and core competency modules every four years as well as a Continued Professional Certification Assessment (CPCA) exam every eight years (AANA, 2023).

Sample Size

The calculation of sample size is considered best practice by many researchers as well as a requirement in most major peer-reviewed journals (Jobst, Bader, & Moshagen, 2023). Statistical power is defined as the estimation of the planned study's sample size that will produce the data output's ability to detect the actual effect was present (Jobst et al., 2023). SEM's flexibility allows for the evaluation of complex associations, use of different types of variables, and comparisons across different types of models, however, it also requires higher sample sizes (Jobst et al., 2023; Kyriazos, 2018). Inadequate sample sizes in SEM methodology have a negative impact towards fit indices (i.e., chi-squared and goodness-of-fit indices), model estimators, model complexity, multivariate normality assumptions, and variable independence (Jobst et al., 2023; Kyriazos, 2018). To date, there continues to be a lack of consensus and often conflicting guidance for researchers regarding sample size requirements and analysis (Jobst et al., 2023; Wolf, Harrington, Clark, & Miller, 2013).

SEM sample size planning has often relied on "rule of thumb" where researchers would consider a standard sample size of > 200 as adequate power for statistical analysis (Kyriazos, 2018). However, this standardized number has been often debated with ranges of sample sizes from as low as 40 to as high as 1000, depending on the complexity of the model (Jobst et al., 2023; Kyriazos, 2018). The rule of thumb process as morphed into "blue chips" methodology that includes a ratio of the number of people (N) to the number of estimated parameters (q) (Kyriazos, 2018). Researchers have recommended SEM analysis with normal distribution, the ratio has ranged from 10:1 to 20:1 (Jobst et al., 2023; Kyriazos, 2018).

The past decade has increased the use of statistical methods that determine appropriate sample sizes based on model, model comparison, sample, and targeted level of significance (Jobst et al., 2023; Kyriazos, 2018). However, these methods (i.e., The Critical N (CN) Statistics, The Monte Carlo Method, and The Satora Sarris Method) are complex and are limited by model constraints (Jobst et al., 2023). Following the recommendations from Kyriazos (2018), I followed the blue-chips method that proposes the ratio of number of people (*N*) to the number of estimated parameters (q) be considered. A widely accepted ratio of *N*:q is 20 people per estimated parameter for baseline SEM analysis (Kyriazos, 2018). This studied included a sample size that indicated an appropriate size for observing true relationships in the data set presented in this study.

Sample And Sampling Procedures

The target population is CRNAs who are actively practicing anesthesia within the United States. The AANA (2023) reported that at the end of December 31, 2022, there were over 61,000 CRNAs and nursing anesthesia residents. CRNAs were recruited from the AANA (2023) national membership database, which represents approximately 86% of the 61,000 CRNAs. The average response rate to surveys by CRNAs is 9% (AANA, n.d.). To maximize this response rate, I chose the maximum number of participants allowed by the AANA Department of Research (3,000 participants). Study inclusion criteria included (a) being an active member of the AANA, (b) currently providing direct anesthesia care, and (c) providing anesthesia care within the United States. Exclusion criteria included (a) being a current student/trainee, (b) does not provide weekly anesthesia care, and (c) practices outside of the United States.

The survey was submitted through the AANA membership listserv after the UNC Charlotte Institutional Review Board (IRB) and AANA survey application approval. Under the AANA Department of Research guidelines, members demographics, work characteristics, and associated email addresses are kept confidential. The AANA membership email listserv contains active, inactive, and retired CRNAs and the request was for a subgroup of members who were actively practicing anesthesia—a randomized stratified sampling method. The ability to target a specific group of CRNAs within the membership may allow for a more precise conclusion.

Procedure For Recruitment

The AANA has a strict policy for the administration and solicitation of CRNAs to participate in surveys. The recruitment process was a multi-step process that expanded over three months (January 2023 to March 2023). First, I contacted the AANA Department of Research to request access to the AANA membership listserv. The large number of requests for access to the AANA membership email listserv requires the researcher to send a brief research proposal which consisted of my dissertation topic approval write-up. Once approved, I followed the steps for submission of a survey through the AANA membership listserv, which requires an application submission and approval from the AANA Department of Research in addition to the UNC Charlotte IRB Approval. The application (see Appendix B) must include: (a) an endorsement letter from the dissertation chair, (b) IRB approval, (c) the dissertation proposal document, (d) the survey instrument, and (e) payment for a pre-determined number of surveys issued (AANA, n.d.). Second, I contacted The Office of Research Protections and Integrity at UNCC to fill out an IRB application. The study received IRB approval (see Appendix C) for Exempt Category 2 on January 19, 2023 (IRB-23-0078). Third, the AANA application required endorsement from a doctoral student's dissertation chair which was completed by Dr. A. Suzanne Boyd, Ph.D., MSW, ACSW, FNAP, on January 24, 2023 (see Appendix D). Finally, the application "AANA Electronic Survey" was completed and submitted on March 27, 2023, with approval on March 29, 2023 (see Appendix E).

Procedures For Participation

The AANA does not give out members' email addresses. Survey distribution is managed by the AANA Department of Research. The maximum number of survey participants is 3,000 (AANA, n.d.). After survey application approval, the AANA sent an email to 3,000 participants with a link to the survey on Qualtrics. The email contained a recruitment letter (see Appendix F) that briefly summarized the study's primary objectives and the importance of the study. The email highlighted that the study was voluntary, participation could be exited at any given point, and no identifying information would be collected. Additionally, the email informed participants that participation in the study did not pose risk to their safety or wellbeing. When participants clicked on the link, a statement about implied consent was listed and by clicking on the "next" button, it was implied that consent was given to participate in the survey. The survey was launched on April 17, 2023, with an email reminder sent on April 24, 2023, and ran for a 4-week timeframe. According to a large review and meta-analysis by Jia, Furuya-Kanamori, Qin, Jia, & Xu (2021), there was a dose-response relationship in survey responses when monetary incentives were used. Therefore, at the end of the survey, there was an option for the participant to enter a drawing for a chance to win a Starbucks gift card. The instructions stated that clicking on the link would detach them from the survey to maintain their privacy. Participants who clicked on the link provided only their email addresses. Four $25 Starbucks gift cards were distributed to four participants whose email addresses were drawn using a random draw system.

Data Collection

The study setting was an electronic environment via an online survey through Qualtrics at UNC Charlotte. Qualtrics was chosen because it provides data to the researcher stripped of all identifiers and is free for all UNC Charlotte students, and it is capable of surveying and analyzing large samples and numbers of variables. Additionally, Qualtrics gives the researcher an all-in-one approach to conducting quantitative research. It allows for the preparation and administration of quantitative data into a format that can be easily analyzed either by the Qualtrics program or exported to a statistical software package. Prior to the go-live date of the survey, copy of the survey and link were verified for quality assurance by my dissertation chair. Additionally, Bonnie Lowth, the program manager for the AANA Research and Quality Division, tested the link. The survey was completed and ended on May 15, 2023. Survey results were downloaded to an Excel document and saved on a password-protected cloud service, Dropbox. In the consent, the participant agreed to allow me to use the data for a secondary analysis post-final defense. However, the data will be destroyed five years after the final defense date (April 9, 2024).

Instrumentation

The following section will highlight the operational definition of the study variables, how each variable was measured, and how scores were calculated and reported. The variables and associated measures used were guided by the JD-R model and previously published empirical studies (Elmblad et al., 2014; Hyman et al., 2014; Lea et al., 2022; Mahoney et al., 2020; Shah et al., 2019; & Vells et al., 2021) that identified and evaluated the job characteristics leading to the experience of burnout in CRNAs practicing in the United States. The *predictor variables* include *job demands* (i.e., emotional and physical demands, time constraints, and workplace incivility) and *job resources* (i.e., job control, autonomy, colleague support, supervisor support, and collaboration) and the outcome variable is burnout (i.e., emotional exhaustion and disengagement). Additionally, the study explored the mediating relationship of specific job-related resources on job demands and burnout.

Using an 82-question survey that combined the Oldenburg Burnout Inventory (OLBI), Job Demands-Resources Scale (JDRS), Workplace Incivility Scale (WIS), Collaboration and Satisfaction about Care Decisions (*CSACD*) measure, Job Content Questionnaire (JCQ), and demographics, participants provided self-reports of their job demands, the job resources available, and their level of burnout over the past 30 days of work. Each instrument used Likert scales and has been extensively studied, demonstrating high validity and reliability. subscales were kept in their original format to prevent any scale validity challenges. Heggestad and colleagues (2019) reviewed over 2,000 scales within four major journals that demonstrated that subscales from primary measures had limited, if any, effect on the validity of scale scores when subscales were kept in their original format. Authors granted written permission to use the respective scales (see Appendices G, H, I, K). The following instruments require sharing the data with the scale owner post defense completion. I contacted the UNC Charlotte Data Security Officer, Dr. Michael Moore, who sent the application to be filled out when the data needs to be shared (completed post defense, no later than May 12, 2024).

Additionally, an open-ended qualitative question was added to the end of the job demands and job resources sections of the survey that were not included in the analysis. The purpose of these two questions was to gain additional insights into job-related characteristics that contribute to CRNA burnout that have not been addressed in previous research. Respondents were asked to "Thinking back to the past 30-days of work, were there any other job-related demands that had a direct impact on your daily work-environment?" for job demands and "Thinking back to the past 30-days of work, were there any other job-related resources that had a direct impact on your daily work-environment?" Following data collection, thematic analysis was employed using line-by-line codes to group qualitative data into themes. The information gained from these questions is for future research purposes.

Job Demands-Resources Scale (JDRS)

The JDRS was developed by Jackson and Rothmann (2005) to measure job demands and resources. The original scale consisted of 48 items that were based on the JD-R model, a literature review, and interviews with educators in South Africa. An exploratory factor analysis determined seven factors could be extracted (Jackson & Rothmann, 2005). Principle component analysis (PCA) demonstrated 43 of the 48 items on the JDRS loaded on the following seven factors—organizational support, growth opportunities, overload, job insecurity, relationship with colleagues, control, and rewards (Jackson & Rothmann, 2005 A larger follow-up study confirming the psychometric properties of the JDRS was conducted by Rothmann, Mostert, and Strydom (2006) and included 2,717 employees in different organizations in South Africa. The primary study objective was to explore the JDR's construct validity, reliability, and equivalence (same construct measured across different cultural groups) (Rothmann et al., 2006). The results of a simple PCA extracted five factors that included growth opportunities, organizational support, advancement, overload, and job insecurity (Rothmann et al., 2006). A subsequent second order PCA of the five factors resulted in a two-factor structure that represented job demands (i.e., overload) and job resources (i.e., growth opportunities, organizational support, advancement, and job security), which aligns with the JD-R framework principal assumptions that different work characteristics can be grouped into two categories—job demands and job resources (Rothmann et al., 2006). The study used the following JDR measure subscales (with corresponding Cronbach's alpha values)—overload ($\alpha = .76$) and organizational support ($\alpha = .92$) (Rothmann et al., 2006).

The eight-item overload subscale of the JDRS was used to measure the job demands—workload, time pressure, and emotional demands. Overload refers to the amount of work, mental load, and emotional load (Rothmann et al., 2006). Sample questions included: "Do you have too much work to do?" and "Do you work under time pressure" (Rothmann et al., 2006). The 18-item Organizational Support Subscale was used to measure the job resource-interpersonal relationships (i.e., colleague and supervisory support). Rothmann and colleagues (2006) defined organizational support as relationships with the leadership, dissemination of information, communication within the organization, and social support from colleagues. Sample questions included: "Can you count on your colleagues when you come across difficulties in your work?" and "Do you get along well with your supervisor?" (Rothmann et al., 2006). JDRS questions are scored on a 4-point Likert scale ranging from 1 (never) to 4 (always). JDRS scoring is derived from the summed scores of the individual questions (Rothmann et al., 2006). Higher values indicate a greater level of either demands or resources (Rothmann et al., 2006). The JDRS is free to use and requires written permission from the author and sharing of the results post-research (see Appendix G).

Workplace Incivility Scale (WIS)

The Workplace Incivility Scale (WIS) that was developed by Cortina, Magley, Williams, & Langhout (2001) measure workplace incivility. Confirmatory factor analysis (CFA) demonstrated the scale items appropriately represented the construct in evaluating 1,180 public health employees (Cortina et al., 2001). Cortina, Kabat-Farr, Leskinen, Huerta, & Magley (2013) added additional questions to capture a greater context of the environment as well as to include experiences of specific behaviors. The factor loading calculations for the test items ranged from .58 to .84 (Cortina et al., 2001; Cortina et al., 2013). Additionally, the WIS scale items demonstrated high reliability with an alpha coefficient of .89 (Cortina et al., 2001; Cortina et al., 2013). Workplace incivility has been defined as a low-intensity, deviant behavior with ambiguous intent to harm the individual that violates the mutual respect within the work environment (Cortina et al., 2001; Elmblad et al., 2014). Several studies (Boyd & Poghosyan, 2017; Elmblad et al., 2014; Sakellaropoulos, Pires, Estes, & Jasinski, 2011) have demonstrated a correlation between CRNAs exposed to workplace aggression and burnout. Elmblad et al. (2014) used linear regression to assess the association between incivility and burnout when controlling for demographic variables. The authors demonstrated that even when controlling for demographic characteristics, incivility was strongly correlated ($p < .001$) to CRNA burnout (Elmblad et al., 2014). Sakellaropoulos and colleagues (2011) demonstrated a significant positive correlation ($p < .001$) between CRNA stress and work-related aggression that included verbal, active, and direct abuse.

The WIS 10-item Likert-type scale measures the frequency of an individual's experience of incivility within the workplace (Cortina et al., 2001; Cortina et al., 2013). According to its authors (Cortina et al., 2001; Cortina et al., 2013), the scale items measure one's personal experience of rudeness, insensitivity, or demeaning behaviors from management and work colleagues over a specified period. Aligning with the rest of the study questions, I chose over a period of previous 30 days. Questions on the WIS are scored on a 5-point Likert scale ranging from 1 (never) to 5 (many times). Sample questions included: “Made insulting or disrespectful remarks about you” and “Ignored you or failed to speak to you” (Cortina et al., 2001; Cortina et al., 2013). WIS scoring is derived from the summed scores of the individual questions with higher values indicating a greater level of uncivil behavior (Cortina et al., 2001; Cortina et al., 2013). The WIS is free to use, and permission was obtained from the author (see Appendix H).

Job Content Questionnaire (JCQ)

The origins of the JCQ can be traced back to the early 1980s when the core questions were developed from the U.S. Quality of Employment Survey database (Karasek et al., 1998). However, the 49-item questionnaire was formalized by Karasek et al. (1998) to measure social and psychological job-related characteristics. The JCQ includes seven subscales that measure—job skill discretion, job decision-making authority, job decision latitude (skill discretion + decision authority), job demands, coworker support, supervisor support, and job insecurity (Karasek et al., 1998). The demand-control model (Karasek et al., 1979) serves as the theoretical foundation for the JCQ. The DCM theorizes job strain is caused by high job demands (overload and time pressure) and low job control (Karasek, 1979; Karasek et al., 1998). Therefore, the JCQ is designed to measure job-related characteristics that contribute to high-demand/low-control which includes psychological demands, decision latitude, social support, physical demands, and job insecurity (Karasek et al., 1998). Karasek and colleagues (1998) evaluated the JCQ reliability and validity across six studies in 4 countries (n = 16,601) that demonstrated an overall Cronbach’s alpha for men and women of .74 and .73, respectively. To date, the JCQ is one of the more popular psychosocial working-characteristics scales. It has been used internationally and translated in over 20 different languages (Karasek et al., 1998). The JCQ has been used and validated in various occupational contexts such as healthcare (see Alexopoulos et al., 2015;

Bagheri Hosseinabadi et al., 2019), public service professions (see Choi et al., 2014), and office workers (see Maizura et al., 2009).

The JCQ is rated on a 5-point Likert-type scale where answers range from 1 (strongly disagree) to 5 (strongly agree). Prior to using and analyzing the JCQ, the author purchased (license #67427508504) the right to use the instrument and its scoring procedural user guide from the JCQ Center Global ApS (see Appendix I). The JCQ to evaluate the job resources—job control and autonomy. Job control was measured by the 6-item job decision latitude (skill discretion + decision authority) subscale that consists of a Cronbach's alpha of .76 (Karasek et al., 1998). According to Karasek et al. (1998), an employee's control over their job is measured by two separate but highly correlated subdimensions: skill discretion and decision authority. Skill discretion is the skills and creativity required for employee flexibility in deciding what skills are needed to complete the job (Karasek et al., 1998). Decision authority is the ability for providers to make decisions about their work (Karasek et al., 1998). Autonomy was measured by three items from the decision authority subscale that demonstrated a Cronbach's alpha of .68 (Karasek et al., 1998). Sample questions included: "My job allows me to make a lot of decisions on my own" and "I have an opportunity to develop my own special abilities" (Karasek et al., 1998). Responses from each sub-scale were averaged to determine the sum of each scale.

Collaboration and Satisfaction About Care Decisions (*CSACD*) Measure

The *CSACD* was originally designed to measure collaboration and satisfaction with nurse-physician care decisions in the intensive care unit (ICU). The *CSACD* was designed in response to the psychometric challenges of the Decision About Transfer (DAT) scale (Baggs, 1994). A convenience sample (n = 58) of pediatric ICU nurses and physicians were asked to consider the physician-nurse collaboration towards the care decision regarding their most recent

ICU transfer to a less acute setting (Baggs, 1994). Content validity of the nine items (seven collaboration and two satisfaction) was supported by an expert panel of nurses and physicians (Baggs, 1994). The reliability of their responses demonstrated a Cronbach's alpha of .95 (Baggs, 1994). Confirmatory factor analysis supported the construct validity of a two-factor structure—collaboration and satisfaction (Baggs, 1994). *CSACD* has since been adapted for care areas outside of the ICU (see Aaberg et al., 2019; Baggs, 1994; Bettinelli et al., 2015).

The CRNA's daily work environment necessitates a multidisciplinary collaborative approach with other healthcare providers such as physicians, nurses, perfusionists, and surgical technologists. Additionally, CRNAs can function in a variety of care delivery settings that include collaboration with another physician, sole provider, and anesthesia care team model (CRNA-Anesthesiologist) (AANA, 2023). No single model is better than the other; however, according to the AANA (2023) membership statistics survey, the predominant model among providers practicing in the United States is the anesthesia care team model. The anesthesia work environment is considered one of the more stressful environments in healthcare (Del Grosso & Boyd, 2019). The anesthesia care team model adds an interpersonal component that requires a cooperative approach toward providing care to patients. According to Alves (2005), CRNAs rated job-related interpersonal conflicts within the care team model as a primary driver for job-related strain. Jones and Fitzpatrick (2009) conducted a mix-methods study that compared CRNA-Anesthesiologist attitudes towards collaboration towards their care team model. The authors (Jones & Fitzpatrick, 2009) found those who spent more than 50% of their time working in a care team model were less satisfied with the collaboration within the care team model. The themes that emerged from the survey found communication, interpersonal skills, and autonomy as being primary drivers towards satisfaction of collaboration (Jones & Fitzpatrick, 2009).

Collaboration will be measured by the Collaboration and Satisfaction about Care Decisions (*CSACD*) measure. The *CSACD* consists of 9-items measured on a 7-point Likert-type scale. Six questions measure the core dimensions of collaboration, and one measures global satisfaction with collaboration. The author (Baggs, 1994) defines collaboration as a physicians and nurses working together, sharing responsibility for problem-solving and decision-making to manage the care of patients. The 7-item collaboration measures range from 1 (strongly disagree) to 7 (strongly agree). Sample questions included: “Team members planned together to make decisions about care for this patient” and “Decision-making responsibilities for this patient were shared among team members” (Baggs, 1994). These seven items are summed to yield a score ranging from 7 (no collaboration) to a maximum of 49 (complete collaboration). Two questions measure satisfaction with the decision-making process and the decision itself (Dougherty et al., 2005). Satisfaction is defined as the degree to which providers are pleased with the decision-making process (Baggs, 1994). The two-item satisfaction measures range from 1 (not satisfied) to 7 (very satisfied). Sample questions included: “How satisfied are you with way the decision was made for this patient, that is, with the decision-making process, not necessarily with the decision itself” and “How satisfied were you with the decision made for this patient” (Baggs, 1994). The two items are summed, which equates to a range from 2 (not satisfied) to a maximum of 14 (very satisfied). The 9- items are totaled to create an overall score per subject. The primary study objective was to understand the degree of relationship between job-related demands and resources and burnout within the nursing anesthesia specialty. Therefore, a summed score of the nine items was used to indicate the degree of collaboration among CRNA respondents. The instrument is free to use with the stipulation that the author, Dr. Judith Baggs, is citation in published work (see Appendix J).

Oldenburg Burnout Inventory (OLBI)

I used the OLBI measures burnout and was originally constructed and tested among several different occupations in Germany (Demerouti, 1999; Demerouti et al., 2001). The OLBI was developed as an alternative measure to address several psychometric and theoretical shortcomings of the MBI measure (Demerouti et al., 2001). First, the items in the MBI are all worded in the same direction which can result in the artificial clustering of factors (Halbesleben & Demerouti, 2005; Kristensen et al., 2015). Second, the MBI focuses only on the affective aspect of the exhaustion dimension which can limit the understanding of the degree of exhaustion experienced (Halbesleben & Demerouti, 2005). Third, the MBI was not derived from theory but from exploratory research (Maslach, Schaufeli, & Leiter, 2001). Finally, the MBI supports a three-factor structure—exhaustion, depersonalization, and personal accomplishment. However, the third dimension, personal accomplishment, has been demonstrated to have the weakest correlation with job-related variables (Kristensen et al., 2015; Lee & Ashford, 1996).

The OLBI was constructed based on the JD-R framework and its assumption of the development of burnout (Demerouti et al., 2001). According to the JD-R model, burnout first develops as a result of demanding aspects of work which leads to constant demands and eventual exhaustion (Demerouti et al., 2001). Initially, the employee deploys resources to meet these increased demands; however, as these become depleted, withdrawal behaviors ensue, ultimately leading to disengagement (Demerouti et al., 2001). The OLBI assesses burnout on two dimensions—exhaustion and disengagement. Exhaustion is defined as a consequence of prolonged exposure to intensive physical, affective, and cognitive strain (Demerouti et al., 2001). According to Demerouti et al. (2001), this exhaustion dimension covers not only affective but also physical and cognitive aspects. Disengagement refers to the distancing of oneself from work and experiencing negative attitudes towards the work objective, content, or in general (Demerouti et al., 2001). The disengagement dimension of the OLBI is in a similar vein as the depersonalization/cynicism dimension of the MBI which refers to it as distancing oneself emotionally from service recipients; however, its items are more focused on the relationship between employees and their jobs, particular their identification with the work (Demerouti et al., 2001; Kristensen et al., 2015).

There have been and continues to be discussions related to the relationship between dimensions of burnout of which varying theoretical models have been adjusted/proposed (see Bakker, Demerouti, & Isabel Sanz-Vergel, 2014; Block et al., 2020; Schaufeli, Maslach, & Marek, 2017). As it pertains to the OLBI, one common discussion involves the temporal relationship between dimensions (Block et al., 2020), such as whether individuals experience exhaustion prior to, simultaneously with, or after the experience of disengagement. The research remains limited secondary to a lack of longitudinal research; however, there is a general acceptance that the exhaustion dimension is experienced first (Block et al., 2020; Maslach & Leiter, 2016; Schaufeli, Maslach, & Marek, 2017). Another discussion is around the discriminant validity between the OLBI's engagement and disengagement dimensions. According to Demerouti and colleagues (2003), engagement and disengagement are separate and bipolar dimensions. Demerouti et al. (2010) conducted a study examining the dimensionality between engagement and disengagement in a sample (n = 528) of South African employees. Using the MBI, OLBI, and the Utrecht Work Engagement Scale (UWES), they hypothesized bipolar relationships between engagement and vigor as well as disengagement and cynicism (Demerouti et al., 2010). The authors, using confirmatory factor analyses, were able to demonstrate that disengagement and cynicism were on opposite ends of the continuum, but were unsuccessful in proving their second hypothesis that engagement and vigor constructs are on opposite ends of the continuum (Demerouti et al., 2010). They concluded that OLBI's dimensions should not be used independently but as a whole and that the OLBI remains a well-validated assessment tool for burnout (Demerouti et al., 2010).

The OLBI has been validated and used in numerous studies. The exhaustion and disengagement subscales have a Cronbach's alpha of .82 and .83, respectively (Demerouti et al., 2003). Originally constructed in German, Halbesleben and Demerouti (2005) conducted a multi-trait, multi-method study and confirmatory factor analysis on 2,599 employees across two samples from the United States. Halbesleben and Demerouti (2005) were able to demonstrate acceptable test-retest reliability (moderate correlation $r = .51$, $p < .001$, for exhaustion; $r = .34$, $p < .01$, for disengagement) and internal consistency (ranging from .74–.87). The factor validity of the scale was also tested and demonstrated the scale was able to support its two-factor measurement model (Halbesleben & Demerouti, 2005). Halbesleben and Demerouti (2005) evaluated internal consistency between the OLBI and MBI and were able to demonstrate that Cronbach's alpha scores were consistently greater than .70. Therefore, the OLBI can be viewed as an acceptable alternative measure to the MBI. The OLBI has been successfully used in healthcare (see Mahoney et al., 2020; Tipa et al., 2019) and academic settings (see Block et al., 2020; Reis et al., 2015).

The OLBI is a 16-item scale that includes both negatively and positively framed questions that assess the two core dimensions of burnout-exhaustion and disengagement (Demerouti et al., 2010). The OLBI is based on the JDR model that assumes job-related characteristics can be grouped into demands and resources which are primarily positive and negative, respectively (Demerouti et al., 2001). Exhaustion includes eight questions such as:

"After my work, I regularly feel worn out and weary" and "After my work, I regularly feel totally fit for my leisure activities" (Demerouti et al., 2010). Disengagement includes eight questions such as: "I frequently talk about in a negative way" and "I get more and more engaged in my work" (Demerouti et al., 2010). Each item is rated on a 4-point Likert-type scale where answers range between 1 (strongly agree) to 4 (strongly disagree). There are four negatively worded (marked by [R]) statements on each dimension which was used for reverse coding. The OLBI is free to use with permission from the primary author, Dr. Evangelia Demerouti (see Appendix K).

A major problem in the assessment of burnout is the lack of general acceptance of clinically validated criteria for what is or is not burnout in an individual (Block, Bair, & Carillo, 2020; Schaufeli et al., 2001). The OLBI does not specify or recommend a value indicating burnout (Block et al., 2020; Schaufeli et al., 2001). However, its scores are simply measures of the strength of the overall and individual burnout construct with higher values indicating greater level of burnout, exhaustion, and disengagement, respectively. A similar process from studies was followed (Block et al., 2020; Lea et al., 2022; Mahoney et al., 2020) that evaluated burnout in anesthesia providers. These studies used threshold values for the classification of burnout into "high", "moderate", and "low" levels that were calculated by splitting the scores into thirds (Peterson et al., 2008; Schaufeli et al., 2001; Tipa, Tudose, & Pucarea, 2019). Mean summed scores were calculated for overall burnout and for each dimension.

Demographics

A short 10-item survey that collected demographic variables that included age, gender, marital status, years of experience, ethnic background, and hours worked per week. Additional demographic information such as the type and size of the hospital, employer type, practice setting, and years at the current practice was collected to provide an overall picture of the sample characteristics and facilitate future subgroup analysis for potential relationships within the nursing anesthesia specialty.

Data Analysis Plan

Preliminary Data Analysis

At the end of the four-week survey period, data was extracted from Qualtrics to a Microsoft Excel file, which was saved on an encrypted, password-protected Dropbox folder. The measures that were used to collect data for the predictor variables included subscales from the JDRS for workload, time pressure, emotional demands, and interpersonal support; the JCQ for control and autonomy; the *CSACD* measure for collaboration; the OLBI measures the outcome variable, burnout. Demographic questions regarding age, gender, marital status, years of experience, ethnic background, hours worked per week, type and size of the hospital, by whom the participant is employed, the practice setting, and years at the current practice were included. The first part of the data analysis plan included a preliminary assessment of the data. Prior to any generation of statistical analysis, data was cleaned and screened for complete responses. Survey responses of any questions that had not been answered was removed. Data was then transformed according to the scale and measured variable. This included correct scoring of reverse scored items (i.e., OLBI measure), recoding of values associated with categorical variables (i.e., gender, hospital type, marital status), and creating formulas for independent variables (i.e., JCQ measures—job control and autonomy).

Then, data were exported from the Excel document to IBM Statistical Package for the Social Sciences (SPSS) Version 28. Multivariate outliers were identified to evaluate their influence on the data set (i.e., error vs. influential outliers) (Aguinis et al., 2013). Multivariate outliers are observations in a data set that are significantly different from the overall pattern of the collective variables being studied (Aguinis et al., 2013). Error outliers are data points that are outside the normal deviation because of inaccuracies whereas influential outliers are accurate data points that lie outside the standard deviation but still contain valuable information (Aguinis et al., 2013). Outliers result in changes to parameter estimates and can lead to false acceptance or rection of the intended hypotheses (Aguinis et al., 2013). Mahalanbois D^2 values, Cook's Distance, and boxplot visuals were used to evaluate the outliers. The Mahalanbois D^2 is the distance of each measured variable from the center of distribution, taking into account the correlation between variables and within each variable (Aguinis et al., 2013). The larger the Mahalanobis D^2 value is, the larger the outlier and risk to multivariate normality (Aguinis et al., 2013). Cook's Distance is a combined measure of leverage and residual values, therefore providing a comprehensive view of an outlier's impact on the model's prediction power (Choongrak & Storer, 1996). Cases with a Cook's Distance of 4/N (N representing the number of cases) were flagged for detailed investigation and cross reference with cases identified as outliers from the Mahalanobis D^2 analysis. Boxplots help identify symmetry as well as outliers of the data set. Outliers are greater than 2 standard deviations from the mean of the measured variable output. Variables identified as outliers were further evaluated by case number to further evaluate the impact and decide to keep or remove the outlier(s). The combined use of Mahalanobis D^2 and Cook's distance provides a strong methodological approach to detecting and excluding outliers, ensuring that the final model reflects the underlying data without influence from extreme data points.

Descriptive Statistics

Data outputs were carefully examined to look at the sample characteristics and variable relationships. Descriptive statistical analysis included measures of central tendency, variability, and frequency distributions for all data. Correlations were used to determine the strength and direction between variables. The sample is based on the obtained demographic characteristics. The primary purpose of the demographic data is to help build a profile of the sample for subsequent analysis. Categorical variables (i.e., gender, ethnicity, marital status) were assessed using frequency tables. Interval and ratio variables (i.e., hours worked and years of experience) were assessed using central tendency measures. Measures of central tendency (mean, mode, standard deviation, range) were used for all variables used in this study.

Inferential Statistics

The primary objective for the use of inferential statistics in this study was to further investigate the relationships between previously identified job demands and job resources, and burnout among Certified Registered Nurse Anesthetists (CRNAs) in the United States. Utilizing the Job Demands-Resources (JD-R) model as the theoretical framework, this study sought to elucidate how these specific aspects of the work environment contribute to burnout, characterized by the dimensions of exhaustion and disengagement. SEM and correlation analyses were performed using IBM SPSS in R. The Integration Plug-in for R came from the extension hub which is a set of extension commands that are implemented in R. The primary reason for using the R plug-in is that it facilitates data sharing and replication through its open access portal (visit r-project.org). This would give greater access to conduct secondary analysis post-doctoral period where access to SPSS software through UNC Charlotte may be limited.

SEM is a multivariate technique that combines multiple regression and factor analysis to estimate a set of hypothesized relationships between latent and observed variables simultaneously (Hair et al., 2021). Compared to first generation multivariate statistical techniques (i.e., multiple regression, logistical regression, and hierarchical regression), SEM has several advantages that make it the appropriate statistical methodology to test the study's hypotheses with the assumptions of the JD-R model (Berndt, & Williams, 2013; Davvetas et al., 2020). First, SEM does not have a default model like traditional methods. This requires researchers to provide a formal specification of a model to be estimated and tested to support hypothesis with theory and prior research (Hair, et al., 2021). Second, SEM is a multivariate technique that allows for one to simultaneously model and estimate (i.e., parameter estimates) complex relationships among multiple variables, both observed (measured) and unobserved (latent constructs) (Davvetas et al., 2020; Hair et al., 2021). SEM uses a single framework that integrates path analysis, factor analysis, and regression that allows for a more comprehensive understanding of these relationships and underlying constructs (Davvetas et al., 2020). Third, SEM considers real world application with each observed variable having a certain degree of measurement error (Hair et al., 2021). Fourth, compared to a traditional linear significance test that determine variable relationships and amount of variance, SEM uses multiple tests (i.e., Comparative Fit Index (CFI), Root Mean Squared Error of Approximation (RMSEA)) when evaluating how well the proposed model fits the data and determine if modifications are necessary (Hair et al., 2021). Fifth, SEM explores causality between exogenous and endogenous variables by direct and indirect relationships (Davvetas et al., 2020). However, causality is only valid under the guide of a theoretical support (Davvetas et al., 2020). Finally, SEM resolves challenges related to multicollinearity because multiple measured variables are required to describe latent constructs (Hair et al., 2021).

Prior research (Boyd & Poghosyan, 2017; Del Grosso & Boyd, 2019; Mahoney et al., 2020) have demonstrated work overload, workplace incivility, job control, autonomy, collaboration, and interpersonal support as common job-related characteristics contributing to burnout. However, the studies lacked theoretical guidance towards understanding the extent of the impact of these job-related factors have on burnout (Del Grosso & Boyd, 2019). Empirical research without theoretical guidance can become vague and overinclusive, resulting in misinterpretations of other concepts and/or management of the findings. Of similar studies that evaluated burnout among CRNAs in the United States, only two of them (Lea et al., 2022; Mahoney et al., 2020) conducted data analyses with SEM while the rest utilized a form of linear regression analysis. Multiple regression assumes perfect measurement of variables in an imperfect reality. The lack of strong predictive variables can contribute to poor association between variables or reliability of the measurement tool. A researcher's choice of appropriate statistical methodology is a vital step in the analysis with wrong selection creating misinterpretations of the findings and conclusions about its future implications. Theory driven empirical research helps align a researcher's questions and hypotheses about a complex construct with appropriate design approach and analysis plan (Hair et al., 2021).

The proposed hypothesized model aims to further understand the complex independent and interdependent relationships that job characteristics have on *burnout* in a complex environment. The primary goals of SEM analysis for this study were to understand and test the complex interrelationships among observed variables and the constructs, *job demands* and *job resources* (Hair et al., 2021; Morrison, Morrison, & McCutcheon, 2017). The ability to use a comprehensive statistical approach to test hypothesis regarding the relationships between observed and latent variables is considered causal modeling (Davvetas et al., 2020). SEM allows the researcher to test for indirect effects that an independent variable had on a dependent variable but may indirectly impact another dependent variable (Hair et al., 2021). SEM analysis allows for further ability to evaluation, refinement, and understanding of relationships between previously identified job-related factors and burnout but also account for unanticipated variable relationships that may be limited in standard statistical methods.

There are two components of a SEM—measurement component and a structural component (Hair et al., 2021). The measurement component includes measured variables (observed or indicators) in rectangles that are linked to latent variables (unmeasured variable) that are in ovals. Paths (arrows) that run from latent variables to observed variables are factor loadings that express the strength of the relationship between the latent and indicator variable(s) (Hair, et al., 2021). According to Hair et al. (2021), it is a general rule of thumb that latent variables are measured by three indicators (observed variables). The structural component of the model includes arrows that link the latent variables (Hair, et al., 2021). Covariances between latent variables are represented by two-headed arrows (Hair et al., 2021).

After initial and descriptive data analysis was conducted, I conducted model assumptions for SEM. In addition to identifying and evaluating outliers and missing data, SEM assumptions include multivariate normality. SEM uses maximum-likelihood (ML) estimation and therefore models should be evaluated in similar fashion as regression (Morrison et al., 2017). The evaluation of the assumptions included examining the symmetry and frequency of the distribution through Q-Q plots and skewness and kurtosis calculations (Ross & Willson, 2017). Skewness measures the degree of symmetry of the variable’s distribution where kurtosis measures for influential outliers through heavy-tailed or light-tailed relative to normal distribution (Morrison et al., 2017). Data that does not follow a continuous and multivariate normal distribution impacts standard error (underestimates) and goodness-of-fit (overestimation of fit indices) (Berndt, & Williams, 2013).

To answer the research questions and a set of hypothesized relationships within the constructs of the proposed research model (Figure 4) two models were constructed that consisted of three latent variables (i.e., *job demands, job resources, and burnout*) and eight observed variables which included six exogenous (independent) variables (i.e., *decision latitude, decision authority, collaboration, organizational support, workload,* and *workplace incivility*) and two endogenous (dependent) variables (i.e., e*xhaustion* and *disengagement*). This research applied a covariance-based SEM approach with R.

Regular Model: The structural model (Figure 5) tested the direct relationships between *job demands, job resources*, and *burnout* without mediation. The model parameters were estimated using the Maximum Likelihood (ML) method and all analysis are conducted on variance-covariance matrices (Hair et al., 2018). A measured variable (i.e., manifest variable, indicator) are those variables directly measured versus latent variable (i.e., factor or construct) is a construct not directly or exactly measured (Hair et al., 2018). Variables in the model can be either endogenous, influenced by other variables in the model, or exogenous, variables that are not influenced by other variables in the model (Hair et al., 2018). The endogenous variable acts as the dependent variable in one equation but can then become independent in another equation whereas exogenous variables always act as independent variables (Hair et al., 2018).

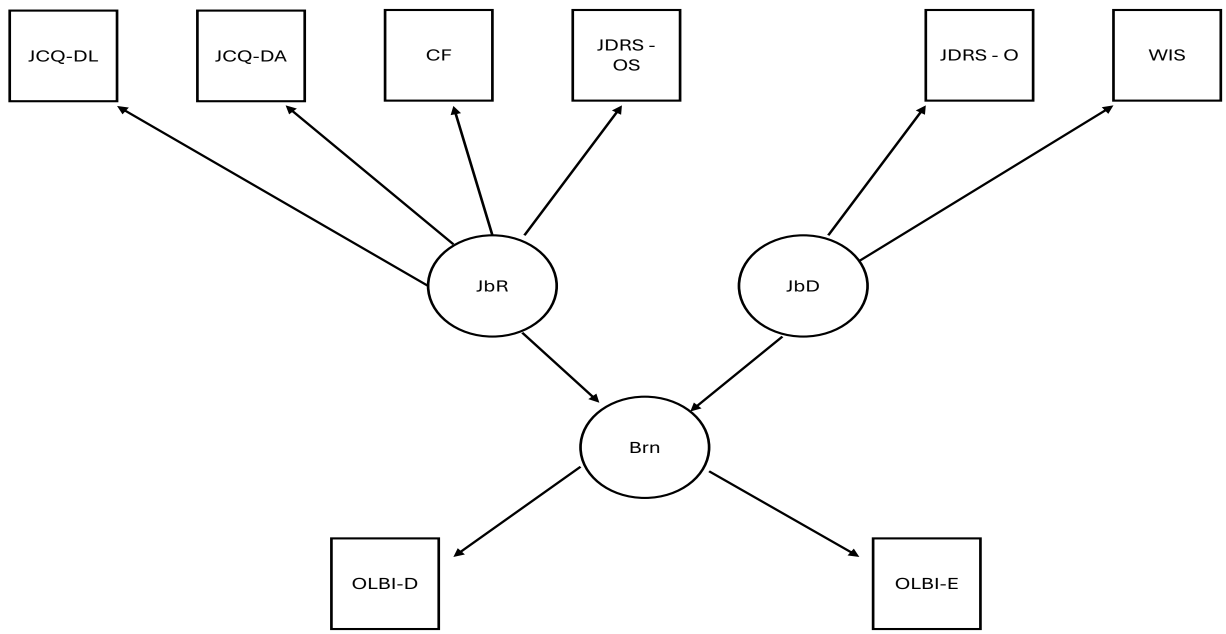

Figure 5.

Conceptual Path Diagram of Direct Relationships between Job Demands, Job Resources and Burnout

Note. SEM model outlining relationships between Job Resources (JbR), Job Demands (JbD), and Burnout (Brn). Rectangles = observed variables that include Decision Latitude (JCQ-DL), Decision Authority (*JCQ-DA*), Collaboration (CF), Organizational Support (*JDRS-OS*), Work Overload (*JDRS-O*), and Workplace Incivility (WIS) which are indicators for latent variables JbR and JbD. Circles—latent variables. Single-headed arrows = directional relationships. Observed variables for Burnout are Exhaustion (*OLBI-E*) and Disengagement (*OLBI-D*) which are indicated by Brn.

Prior to evaluating goodness of fit, assessing each indicator for reliability and validity a necessary step (Morrison et al., 2017). This step is primarily accomplished using confirmatory factor analysis (CFA), however, when measurement instruments are grounded in theory and kept in their original format, original scale reliability is acceptable (Morrison et al., 2017). Structural equation model goodness of fit is determined by the number of similarities between relationships in a given model (i.e., parameter estimates) and covariance matrix (Hu, & Bentler, 1999; Peugh, & Feldon, 2020). Model goodness-of-fit was assessed with several fit indices, including the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of

Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). Fit indices compare the hypothesized model to a baseline model (Hair et al., 2018). Although it is common to use Chi-square for model fit assessment, it is highly sensitive to sample sizes less than 200 (Hair et al., 2018; Kumar & Kumar, 2015). CFI considers the differences between measured data and the theoretical model (Hair et al., 2018). A good fit is considered with CFI value of greater than or equal to 0.95 (Hair et al., 2018). The RMSEA measures approximation error between observed covariance and the hypothesized model covariance (Hair et al., 2018). RMSEA is a valuable measure because it is independent of the sample size. Suggested adequate fit is an RMSEA value of less than or equal to 0.06 (Hair et al., 2018). SRMR solves for questionnaires that have a wide range of Likert-type scales (Hair et al., 2018). SRMR is a measure of the average of the absolute correlation residual which is the different between observed and predicted correlation matrix. SRMR values less than or equal to 0.08 are considered acceptable (Hair et al., 2018). The TLI assesses how well the estimated model fits to the alternative (null) baseline model. The TLI criterion for adequate fit is greater than or equal to 0.95 (Kumar & Kumar, 2015). Several reviews evaluating various cutoffs for multiple fit indices suggested to minimize statistical errors (Type I and Type II), researchers should use a combination of fit indices (Kumar & Kumar, 2015). In addition, covariances between job demands and job resources were estimated to understand their interrelationships.

Moderation Model: A moderator is a variable that affects the direction (strength) of the relationship between the independent variable and dependent variable (Baron & Kenny, 1986). Moderation analysis in SEM uses latent variables versus observed variables which has greater reliability because variances in measurement error in one observed variable will not impact the other observed variables, thus having little to no impact on the latent variable (Hopwood, 2007).

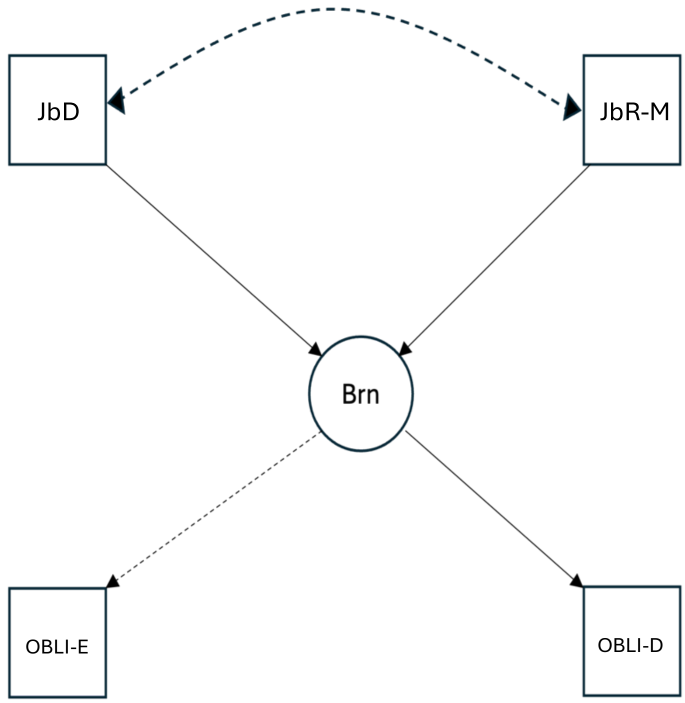

Figure 6.

Conceptual Path Diagram of Moderating Relationship of Job Resources on Job Demands and Burnout

Note. SEM model evaluating the moderating role of Job Resources (JbR-M) in the relationship between Job Demands (JbD), and Burnout (Brn). Rectangles = observed variables that include Job Demands (JbD) as discussed in the direct relationship SEM model: Decision Latitude (JCQ-DL), Decision Authority (JCQ-DA), Collaboration (CF), Organizational Support (JDRS-OS), Work Overload (JDRS-O), and Workplace Incivility (WIS), which are indicators for latent variables JbR and JbD, and the moderation effect (JbD*JbR). Circles = latent variables. Single-headed arrows = directional relationships. Observed variables for Burnout are Exhaustion (OLBI-E) and Disengagement (OLBI-D) which are indicated by Brn.

The second model (Figure 6) explored the interaction effect between the predictor and moderator variables. This interaction effect represents how the relationship between the predictor and outcome variables changes as the moderator variable varies. The same fit indices were used to assess model fit.

The results provided estimates of the model parameters, including factor loadings for the latent variables, regression weights, and variances. Significance testing was performed for all parameter estimates to assess the strength of the relationships between constructs. All tests were two-tailed, with a significance level set at .05. The results from these analyses provided insights into the complex interplay between job demands, resources, and burnout among CRNAs. The first model (regular model) tested the overall hypothesized relationships within the JD-R framework, where burnout was regressed on both job demands and job resources.

The second model (moderation model) examined how *job resources* (moderating variable) affects the direction (strength) of the relationship on *job demands* and *burnout*. *Job demands* is defined as a latent variable indicated by *JDRS Overload* (*work demand, emotional demands*, and *time constraints*) and *WIS* (*workplace incivility*). *Job resources* were indicated by *decision Latitude* (job control) and *authority* (autonomy) from the *JCQ*, *collaboration* from the *CSACD* measure, and *organizational support* (*colleague* and *supervisory*) from the *JDRS*. *Burnout* was measured overall and using the *exhaustion* and *disengagement* subscales from the *OLBI*. Path analysis within SEM was conducted to estimate and interpret the interaction effects between the predictor and outcome variables as the moderator variable varies. Direct paths from job resources to job demands (a), and from job demands to burnout (c), were included. The moderation model investigated the relationship between *job demands* and *burnout* with *job resources* as a mediating factor. Specifically, the interaction term (ab) between *job resources* and *job demands* was examined to assess how changes in *job resources* affect the strength or direction of the relationship between *job demands* and *burnout*.

Threats to Validity

This study is a quantitative cross-sectional exploratory study that utilized a predictive survey to gain input from 152 CRNAs practicing in the United States regarding their work characteristics and feelings of burnout. Although quantitative surveys allow for the researcher to capture large amounts of data from a population, the research design and procedures may threaten its internal and external validity. Validity is how well the data measures what it is supposed to measure (Furr, 2011). Discussing threats to validity provides information about potential flaws in the research which allows the reader to understand the context of the results. Additionally, discussing threats (and limitations) helps provide directions for future research. Several types of validity that may have impact on this study should be discussed.

Internal Validity

Internal validity refers to the confidence the researcher has that the changes observed in the dependent variable can be explained by the independent variable or some other factor (Hinkin, Tracey, & Enz, 1997). The nonexperimental study design and took place in a natural environment without any influence from the author; therefore, one can assume there would be a limited impact on the internal validity of this study (Hinkin et al., 1997). However, several considerations relative to the study internal validity should be addressed. The historical effect refers to events that happen in the participants environment that may impact the conditions of the study, thus affecting the outcome (Hinkin et al., 1997). This study questions hypothesized that specific job-related variables would impact the degree of burnout within CRNAs. The specific variables were based on previous studies (Elmblad et al., 2014; Hyman et al., 2014; Lea et al., 2022; Mahoney et al., 2020; Shah et al., 2019; & Vells et al., 2021). Several of these studies were prior to the pandemic which research (see Aron et al., 2021; Prasad et al., 2021) has demonstrated had a direct impact on the CRNA work environment. Two qualitative questions for *job demands* and *job resources* were added in hopes of identifying any job-related characteristics that may have been outside of survey content questions.

Scale Validity

Scale validity (i.e., content, criterion, and construct) is the degree to which an instrument measures the dimension or construct it was developed to measure (Boateng et al., 2018).

Concerns of validity relative to this study come from the survey instrument. Before a tool can be considered valid, it must demonstrate reliability (Boateng et al., 2018; Furr, 2011). Reliability refers to the degree to which the scores reflect the variable being measured in a sample (Furr, 2011). The most common way to calculate the reliability of a scale's internal consistency is Cronbach's alpha which is the accuracy to which the items measure the same construct (Hinkin et al., 1997). Each of the scales used demonstrated adequate and somewhat high Cronbach alpha scores. The survey instruments used in the survey included the OLBI, JDRS, WIS, CSACD, and JCQ. The OLBI measured burnout and has a total scale Cronbach's alpha of .70 (Demerouti et al., 2003). The exhaustion and disengagement subscales have a Cronbach's alpha of .82 and .83, respectively (Demerouti et al., 2003). The JDRS subscales also had high internal consistency (with corresponding Cronbach's alpha values)—overload ($\alpha = .76$) and organizational support ($\alpha = .92$) (Rothmann et al., 2006). The WIS has a Cronbach's alpha of .89 (Cortina et al., 2001; Cortina et al., 2013). The *CSACD* measure has a Cronbach's alpha of .95 (Baggs, 1994). The JCQ evaluates the job resources—job control and autonomy. Job control was measured by job decision latitude (skill discretion + decision authority) subscale that consists of a Cronbach's alpha of .76 (Karasek et al., 1998). Autonomy was measured by the decision authority subscale which demonstrated a Cronbach's alpha of .68 (Karasek et al., 1998). Combining the five mentioned instruments into one survey may also cause challenges to the individual scale's psychometric testing (i.e., reliability and validity) and conceptual fit (i.e., scale matches the variable that one wishes to measure) (Robinson, 2018). Attempts to mitigate these concerns, recommendations from Heggestad and colleagues (2019) and Robinson (2018) to maintain scales in their original format were followed. Additionally, all scales used underwent numerous psychometric evaluation studies and have been successfully used in similar studies.

Sample Size

Achieving an appropriate sample size for results to be statistically significant and generalizability of the results to the population. The use of sample size calculation has a direct impact on research results (Malone, Nicholl, & Coyne, 2016). Inadequate sample sizes in SEM methodology have a negative impact towards fit indices (i.e., chi-squared and goodness-of-fit indices), model estimators, model complexity, multivariate normality assumptions, and variable independence (Jobst et al., 2023; Kyriazos, 2018). These risks can be decreased by following the guidelines of (a) measures with good, standardized coefficients (> .70), (b) use of RMSEA, and (c) use of equality constraints on unstandardized coefficients of observed variables (indicators) (Kyriazos, 2018). However, regardless of the statistical adjustments made to the analysis part of the study, one cannot generalize the results to individuals that do not share common personal and job-related characteristics. The National response rate to surveys by CRNAs is less than 10% of the overall AANA membership (AANA, 2023).

Other considerations that can impact sample size are relative to using self-report survey methods. These include nonresponse bias and the Hawthorne effect. Strategies taken to alleviate these challenges included personalized email regarding the study that explained participants were anonymous and could exit the survey at any point in time and the option to enter into a drawing for a chance to win a Starbucks gift card.

Ethical Procedures

The study followed all ethical requirements and guidelines outlined by the AANA Department of Research and the UNC Charlotte Office of Research Protections and Integrity, as well as the UNC Charlotte IRB. The IRB was approved for Except Category 2 on January 19, 2023 (IRB-23-0078) (see Appendix C). The only identifiable risks involved were related to the discomfort of the questions. The AANA has a strict policy for the administration and solicitation of CRNAs to participate in surveys. The AANA does not give out members' email addresses and survey distribution is managed by the AANA Department of Research. After survey application approval, the AANA sent an email to 3,000 participants with a link to the survey on Qualtrics. The email contained a recruitment letter that briefly summarized the study's primary objectives and importance of the study. Additionally, the email highlighted the study was voluntary, participation could be exited at any given point, and no identifying information would be collected. When participants clicked on the link, a statement about implied consent was listed and by clicking on the "next" button, it was implied that consent was given to participate in the survey. At the end of the survey, there was an option for the participant to enter a drawing for a chance to win a Starbucks gift card. The instructions informed the participant that by clicking on the link, it would detach them from the survey to maintain their privacy. Participants who clicked on the link provided only their email address only. At the end of the four-week survey period, data was extracted from Qualtrics to a Microsoft Excel file which was saved on an encrypted, password-protected Dropbox folder. The data was exported from Qualtrics to Statistical Package for the Social Sciences (SPS`S) for analysis. The data collected did not include any identifying information other than gender, age, hours worked, type of practice, and marital status.

Summary

The quantitative exploratory study evaluated the relationship between previously identified job demand and job resource variables (independent variables) and burnout (dependent variable) among 152 CRNAs practicing in the United States. The primary objective was to evaluate the relationship between job-related characteristics and burnout in CRNAs and use the JD-R perspective to increase the understanding of the impact of specific job-related characteristics contributing to burnout and its associated dimensions—exhaustion and disengagement. The secondary objective was to evaluate how each job-related characteristic specific to the study population affects burnout, and its associated dimensions, both independently and interdependently. The predictor variables include job demands (i.e., emotional and physical demands, time constraints, and workplace incivility) and job resources (i.e., job control, autonomy, colleague support, supervisor support, and collaboration). The outcome variable includes burnout (i.e., emotional exhaustion and disengagement). Additionally, this study explored the mediating relationship of specific job-related resources on job demands and burnout.

An 82-item cross-sectional, predictive survey design was captured through the Qualtrics program. The study followed all ethical requirements and guidelines outlined by the AANA Department of Research and the UNC Charlotte Office of Research Protections and Integrity, as well as the UNC Charlotte IRB (see Appendix C). Althubaiti (2022) and Dillman, Smyth, & Christian's (2015) recommendations of 10 observations per variable for sample size calculations in studies using multiple regression models were applied to determine sample size. The Dillman method, which recommends oversampling by 75% was also used (Dillman et al., 2015). The survey was sent to 3,000 participants through the AANA membership listserv after application and AANA approval (in addition to UNC Charlotte IRB approval) and available for a 4-week period with a follow-up email in Week 2. First, the data were exported from Qualtrics into an encrypted Microsoft Excel document where data was cleaned, and incomplete responses were removed. Then, data were exported from the Excel document to Statistical Package for the Social Sciences (SPSS) Version 28 for analysis. According to the UNC Charlotte IRB approval letter (see Appendix C), data must follow OneIT guidelines for data handling. The data was stored in a

UNC Charlotte cloud-based system that is password protected. Descriptive and inferential statistical analyses were conducted, and procedures decrease risks to threats to the validity of the study applied. Chapter 4 provides the results from operationalizing the comprehensive analysis plan outlined in Chapter 3.

CHAPTER 4: RESULTS

Research evaluating CRNA burnout has demonstrated statistical significance between CRNA burnout and turnover, intent to quit, and job satisfaction (Lea et al., 2022; Mahoney et al., 2020). Despite an increase in empirical research evaluating the relationships between job-related factors and burnout within the nursing anesthesia specialty, the ability to manage burnout appropriately has remained limited. The inability to appropriately identify, evaluate, and manage CRNA burnout coupled with the growing administrative and clinical complexities of the U.S. healthcare system may cause further strain on the stability of this nursing specialty that is already facing a critical deficit in workforce numbers, ultimately, resulting in the inability to provide cost-saving, high-quality care to patients in need (Negrusa et al., 2021).

The study addresses the following gaps in research (a) ongoing limited empirical research evaluating burnout in the nursing specialty, (b) lack of empirical research grounded in theoretical framework, and (c) mismatch between statistical methodology with the conceptualization of burnout. Therefore, the study's overall goal of applying the JD-R model in addressing the relationship between job-related characteristics and burnout in CRNAs practicing in the United States is to increase the understanding of the impact of these specific job-related factors contributing to burnout which in turn may provide a path towards appropriate interventions.

The study was grounded by three aims.

Aim 1: Examine the extent of job demands and job resources specific to CRNAs practicing in the United States and their relationship towards overall burnout as well as its specific dimensions—exhaustion and disengagement.

Aim 2: Examine the relationship strength of the specific job demands and job resources and the burnout dimensions—exhaustion and disengagement.

Aim 3: To examine if job resources (as measured by job control, autonomy, colleague support, supervisor support, and collaboration) have a moderating effect on the relationship between job demands and burnout.

The dissertation addressed the following research questions and hypotheses:

RQ 1. To what extent is there a relationship between previously identified job demands and job resources on burnout in a national sample of CRNAs practicing in the United States?

H_a1: Specific job demands and job resources (as measured by subscales of the survey) will have a statistically significant correlation with burnout in CRNAs practicing in the United States.

RQ 2. Is there a difference in the relationship between previously identified job demands (emotional demands, workload, time constraints, and workplace incivility) with burnout dimensions (exhaustion and disengagement)?

H_a2: Job demands, and not job resources, will be the stronger predictor of burnout in CRNAs practicing in the United States.

RQ 3. Is there a difference in the relationship between previously identified job resources (job control, autonomy, colleague support, supervisor support, collaboration) with burnout dimensions (exhaustion and disengagement)?

H_a3: Job resources, and not job demands, will be the stronger predictor of disengagement in CRNAs practicing in the United States.

RQ 4. How do previously identified job resources (as measured by subscales of the survey) moderate the relationship with burnout dimensions—exhaustion and disengagement?

H_a4: Job resources, which include job control, autonomy, colleague support, supervisor support, and collaboration, will moderate the positive relationship between job demands and burnout, such that the relationship between job demands and burnout will be less positive.

The exploratory, cross-sectional analysis evaluated the relationship between previously identified job demand and job resource variables and among CRNAs practicing in the United States. Utilizing the JD-R model as the theoretical framework, this study examined how specific job-related characteristics contribute to burnout, characterized by the dimensions of exhaustion and disengagement. The quantitative analysis examined data collection through an 82-item electronically administered survey. The study population consisted of 152 CRNAs currently practicing across different settings in the United States. Participant recruitment and data collection lasted over a four-week period, after which the data was carefully extracted and prepared for CB-SEM analysis in R. The method allowed for the testing of several hypotheses regarding the predictors of burnout and the potential moderating effects of job resources on the job demands-burnout relationship.

Chapter 4 presents the collected data and the analysis results. The chapter is organized in a stepwise fashion according to how the data was evaluated and analyzed. The primary sections included (a) preliminary data management, (b) preliminary data analysis, (c) descriptive statistics, (c) SEM model fit, (d) correlation analysis, and (e) hypothesis testing. A summary of the analysis concludes the chapter.

Preliminary Data Collection Management

Step 1 includes an initial analysis process for extracting the data collected from Qualtrics to a Microsoft Excel file, which was saved on an encrypted Dropbox folder. The final data set contained answers from an 82-question survey that combined the Oldenburg Burnout Inventory (OLBI), Job Demands-Resources Scale (JDRS), Workplace Incivility Scale (WIS), Collaboration and Satisfaction about Care Decisions (CSACD) measure, and the Job Content Questionnaire (JCQ). Each instrument used Likert scales and has been extensively studied, demonstrating high validity and reliability (Cronbach's $\alpha > .68$). Any of the subscales used were kept in their original format to prevent any scale validity challenges (Heggestad et al., 2019). The evaluation and calculations of the measures were based on the original article's author recommendations (please refer to Chapter 3—Instruments for detailed explanation).

Job demands.

Job demands were captured by the JDRS overload subscale and the WIS. Survey questions 9 to 19 included JDRS's 8-item Overload Subscale that measures the job demands—workload, time pressure, and emotional demands. JDRS scoring were calculated via the summed scores of the individual questions (Rothmann et al., 2006). Higher values indicate a greater level of either demands or resources (Rothmann et al., 2006). The 10-item WIS Subscale, Questions 20 to 29 measured the frequency of an individual's experience of incivility within the workplace (Cortina et al., 2001; Cortina et al., 2013). WIS scores were calculated via the summed scores of the individual questions with higher values indicating a greater level of an individual experiencing uncivil behavior at work (Cortina et al., 2001; Cortina et al., 2013).

Job resources.

Job resources were measured by the JCQ Job Decision Latitude and Decision Authority Subscales, the JDRS Organizational Support Subscale, and the CSACD scale. Questions 31 to 39 comprise the JCQ to evaluate the job resources—job control and autonomy. The JCQ provided a scoring procedural user guide from the JCQ Center Global ApS (see Appendix I). Job control which was measured by the 6-item Job Decision Latitude Subscale (Karasek et al., 1998). The JCQ required the formula

$$[\,Q34 + Q36 + Q37 + Q38 + Q39 + (5 - Q35)\,] * 2$$
$$+ [\,Q31 + Q33 + (5 - Q32)\,] * 4$$

to be built and used to represent a respondent's level of job control. Higher scores represented a feeling of greater control over one's work environment. Autonomy was measured by the 3-item job decision authority subscale (Karasek et al., 1998). The JCQ required the formula

$$[\,Q31 + Q33 + (5 - Q32)] * 4$$

to be built and used to represent a respondent's level of autonomy. The greater the score, the greater level of experienced autonomy. Questions 40 to 48 represented the 9-item CSACD scale to measure collaboration within a hospital work environment (Baggs, 1994). The nine items are totaled to create an overall score per subject. Higher scores equate to higher levels of collaboration. Questions 49 to 65 represented the JDRS 18-item Organizational Support Subscale to measure the job resource—interpersonal relationships (i.e., colleague and supervisory support) (Rothmann et al., 2006). JDRS scores are calculated via the summed scores of the individual questions (Rothmann et al., 2006).

Burnout.

The Oldenburg Burnout Inventory (OLBI) to measure burnout. Questions 67 to 82 represented the 16-item scale that included both negatively and positively framed questions that assess the two core dimensions of burnout-exhaustion and disengagement (Demerouti et al., 2010). Questions 68 (R), 70 (R), 71, 74 (R), 76, 78 (R), 80, and 82 measured the exhaustion dimension and questions 67, 69 (R), 72 (R), 73, 75 (R), 77 (R), 79, and 81 measured the disengagement dimension. There are four negatively worded (marked by [R]) statements on each dimension to reverse code. Scores for each dimension were calculated and then for the overall burnout score. SPSS allows reverse coding all the indicated responses to negatively keyed items on a scale following several transformation steps. There are no standard cutoff scores to indicate burnout, therefore, scores followed prior OLBI studies (see Peterson et al., 2008; Schaufeli et al., 2001; Tipa, Tudose, & Pucarea, 2019). Threshold values for the level of burnout experience included (a) overall burnout scores-low (< 44), medium (44–59), or high (> 59), (b) exhaustion scores—low (< 21), medium (21–29), or high (> 29), and (c) disengagement scores—low (< 24), medium (24–31), or high (> 31). Summed scores were calculated for overall burnout and then for each dimension (Tiipa et al., 2019).

Preliminary Data Analysis

Step 2 includes data exported from the Excel document to IBM Statistical Package for the Social Sciences (SPSS) Version 28. Next data cleaning and evaluation of the SEM model assumptions:(a) no missing data, (b) appropriate sample size, (c) removal of outliers, (d) multivariate normality, (e) homogeneity of variance and (f) scale measurement reliability (Curran, 2003; Hair et al., 2023).

Missing data

Step 3 includes examination of data for completeness, specifically any surveys with incomplete responses for which a score could not be calculated were removed. A listwise deletion versus using other SEM methods was chosen because there was no way to prove that the missing data was irrelevant to study, therefore, missing responses can lead to skewness in the output (Kumar & Kumar, 2017). The survey population included 3,000 AANA members who were actively practicing anesthesia in the United States. Initial review included a total of 209 (6.9%) CRNA respondents, however, 52 entries (24%) were removed due to lack survey completion. After initial screening of the data set, 157 survey responses (5.2%) were used for further evaluation.

Outliers

Next, data was checked for multivariate outliers (Aguinis, Gottfredson, & Joo, 2013). Outliers are defined as data points that lie at a distance from other data points in a sample (Aguinis et al., 2013). Outliers are defined as data points that lie at a distance from other data points in a sample (Aguinis et al., 2013). Outliers greater than 2 standard deviations from the mean of the measured variable output were further evaluated by case number to further evaluate the impact and decide to keep or remove the outlier(s). Mahalanbois D^2, Cooks Distance, and boxplot visuals were used to evaluate the data for outliers. Cases with a Cook's Distance of 4/N (N representing the number of cases) were flagged for detailed investigation and cross reference with cases identified as outliers from the Mahalanobis D^2 analysis (Figure 7). Box plot visualization (Figure 8) provided insights into what questions were potentially causing extreme outliers, allowing for a more granular inspection of the data.

It was found that five cases exceeded both the Mahalanobis Distance and Cook's Distance outlier cutoff and were subsequently excluded from the analysis. With an Mahalanbois D^2 mean of 7.95 and a standard deviation of 5.3, the lower and upper bounds were calculated as -2.65 and 18.55, respectively, leading to the identification of 10 cases as outliers. For Cook's Distance, using a cutoff value of 0.0255, 13 outliers were identified. Upon cross-referencing the two lists, 5 cases were present on both, providing sufficient evidence to justify their exclusion from further analysis. This cross-referencing ensures that only the most influential outliers, as identified by multiple criteria, are removed.

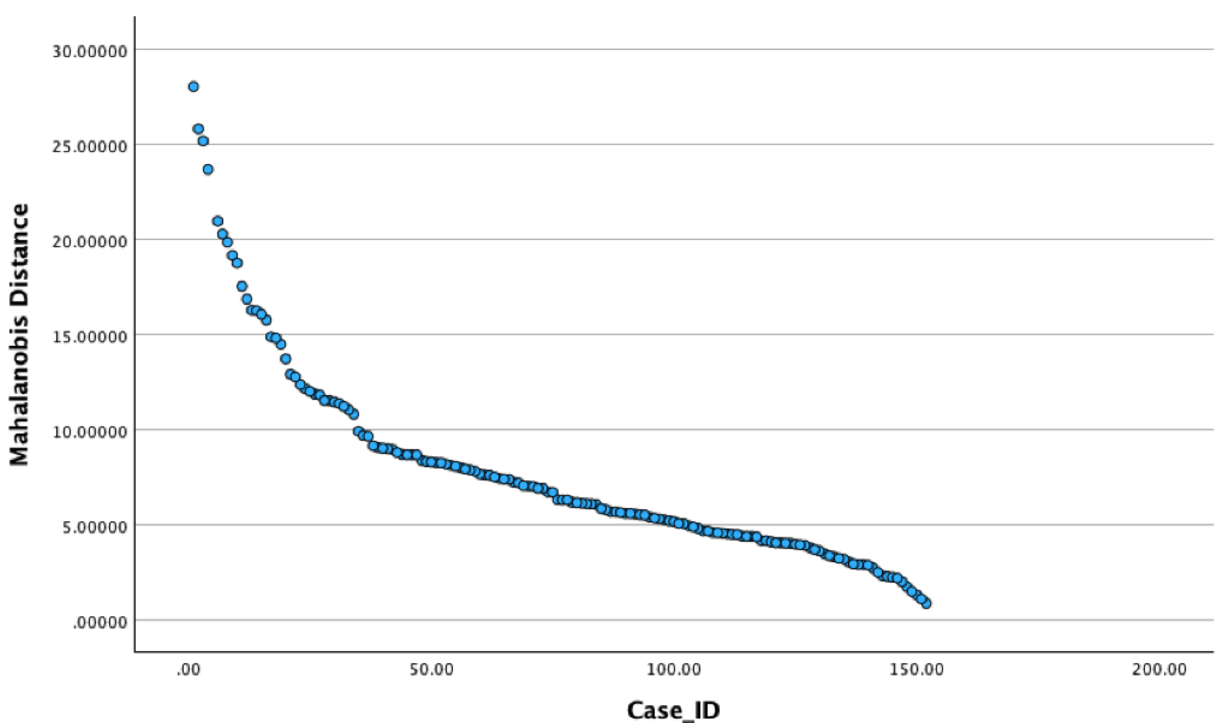

Figure 7.

Scatterplot Representing Mahalanobis Distance Versus Cooks Value for Each Case

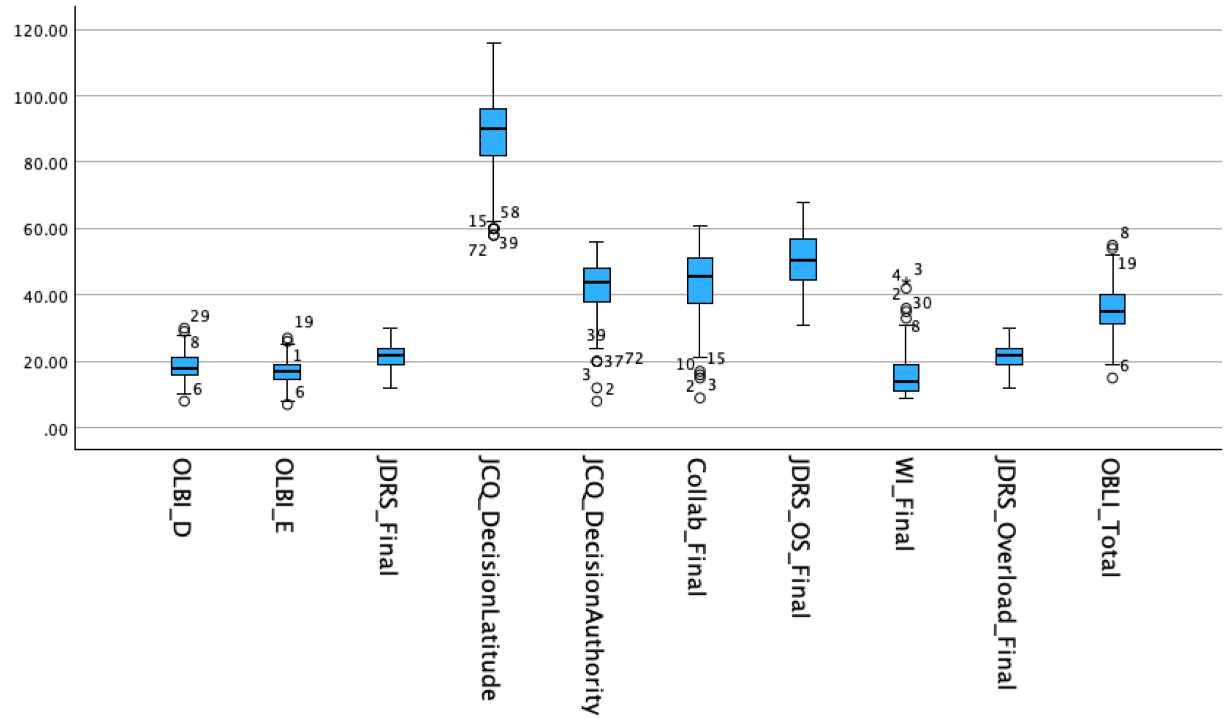

Figure 8.

Boxplots of Job Demands, Job Resources, and Burnout of CRNAs

Multivariate Normality

Step 5 includes evaluation of multivariate normality. The assumption in using SEM is that observations are from a simple random sample that follows a continuous and multivariate normal distribution (Kumar & Kumar, 2017). The evaluation of the multivariate normality included examining the symmetry and frequency of the distribution through Q-Q plots and skewness and kurtosis calculations for variables in the study (Ross & Willson, 2017). I examined normality by evaluating skewness and kurtosis (Table 3). When skewness and kurtosis values fall within +2 and −2, the data is considered normally distributed (Curran, 2003). Skewness and kurtosis values fell within the recommended range, however, workplace incivility (WIS) demonstrated on the upper end of right-skewed (1.62) and heavier tailed (leptokurtic) distributions. Distribution findings were visually examined multivariate normality through frequency distributions in Q-Q plots. Q-Q plots were chosen because, compared to histograms, they are more diagnostic secondary to their ability to evaluate distribution location, scale, and skewness in an easy visualization diagram (Aguinis et al., 2013). Figure 9 represents Q-Q plots for the burnout dimensions—exhaustion and disengagement. Figure 10 represents Q-Q plots for job demands (Figure 10a) and job resources (Figure 10b). Visual inspection of the Q-Q plots of observed against expected probability showed that the normality assumption was met in all variables except job demands (Figure 10a) which demonstrated a slightly (light tailed) left-skewed data. A deviation from the diagonal line in a concave appearance indicates the mean is less than the median secondary to several data points being considerably lower.

The data aligns well with the expected values, indicated by the closeness of the data points to the 45-degree line in these plots. Data for *disengagement* (*OLBI-D*), *exhaustion* (*OLBI-E*), *job demands*, and *job resources* for CRNAs are largely consistent with normal distribution, with only minor deviations at the tails. These minor deviations might suggest slight skewness, but overall, they support the initial assumption of normality for the underlying data real-world data in concepts like burnout do not have normal distribution (Curran, 2003). Furthermore, in SEM, transformation or deletion of outliers in slightly skewed data is less likely to improve the model (i.e., model fit indices) as a whole and, in some cases, result in degradation of model fit indices (Curran, 2003; Kumar & Kumar, 2017). Therefore, the data was left without adjustment.

Table 3.

Skewness and Kurtosis of CRNA Independent and Dependent Variables

Variable	Skewness	Kurtosis
Job Demands		
JDRS-Overload	−0.067	−0.496
WIS—Workplace Incivility	1.66	3.1
Job Resources		
JCQ—Job Control	−0.432	−0.115
JCQ—Autonomy	−0.780	0.619
JDRS—Interpersonal Support	−0.026	−0.713
CSACD—Collaboration	−0.735	0.540
Burnout		
OLBI—Total	−0.079	0.138
Exhaustion	−0.048	−0.003
Disengagement	0.095	0.119

Note. JDRS = Job Demands Resource Scale; WIS = Workplace Incivility Scale; JCQ = Job Content Questionnaire; *CSACD* = Collaboration and Satisfaction about Care Decisions; OLBI = Oldenburg Burnout Inventory

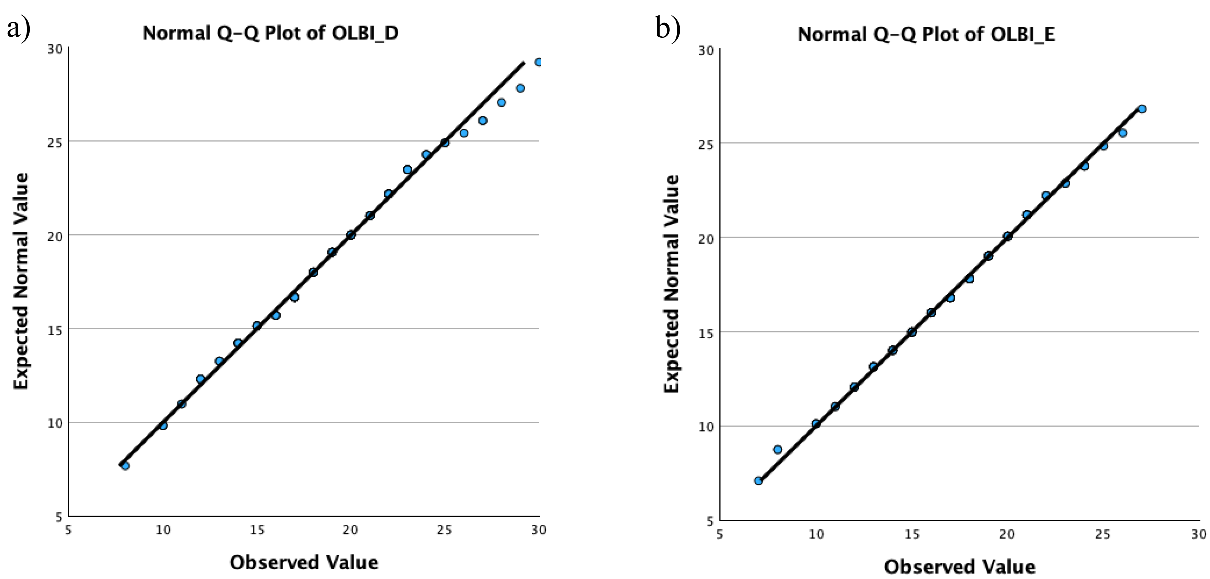

Figure 9.

Q-Q Plot of Burnout Dimensions—Exhaustion and Disengagement

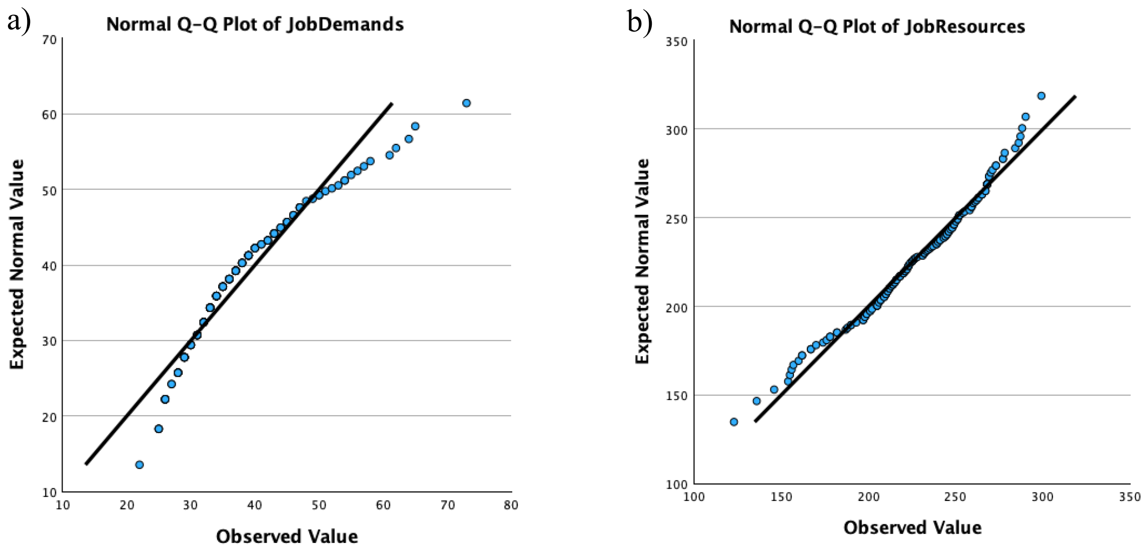

Figure 10.

Q-Q Plot of CRNA Job Demands and Job Resources

Multicollinearity.

While Q-Q plots primarily assess normality, we can use these charts to infer some aspects of variance homogeneity by observing the spread of points along the reference line. The spread along this line is uniform, suggesting homogeneity of variance.

Sample Size

After preliminary analysis and evaluation of SEM assumptions, the study's overall response 5.2% response of the 3,000 participants was below the National average response rate (9%) to surveys by CRNAs (AANA, n.d.). However, it fell within the range of similar studies which were as low as 3.2% (Lea et al., 202) to as high as 90% (Vells et al., 2021).

The sample size selection followed the general recommendation of using a blue-chips method that proposes the ratio of number of people (*N*) to the number of estimated parameters(q) be considered (Kumar & Kumar, 2017). A widely accepted ratio of *N*:q is 10–20 people per parameter estimate for SEM analysis (Kyriazos, 2018). Despite the 24% removal of survey respondents, the sample size (estimated *N* = 80 to 160) remained adequate to investigate the hypotheses of the current study. It should also be noted the six studies (Elmblad et al., 2014; Hyman et al., 2014; Lea et al., 2022; Mahoney et al., 2020; Shah et al., 2019; & Vells et al., 2021) that measured burnout of CRNAs practicing within the United States had a significant different in sample sizes, ranging from 40 (Vells et al., 2021) to 385 (Elmblad et al., 2014).

Instrument Reliability.

Measurement errors caused by measurement tools and procedures for data collection effects the model fit (Kumar & Kumar, 2017). As the variance increases in a data set, the standard error decreases which violates the normality of the data (Kumar & Kumar, 2017). Reliability refers to the degree to which the scores reflect the variable being measured in a sample (Furr, 2011). The most common way to calculate the reliability of a scale's internal consistency is Cronbach's alpha which is the accuracy to which the items measure the same construct (Hinkin et al., 1997; Kimberlin, & Winterstein, 2008). Cronbach's alpha coefficient ranges from 0.00 to 1.00, with > .70 being acceptable reliability (Kimberlin, & Winterstein, 2008).

The 82-question self-reporting survey aimed to captures a five measurement instruments for the evaluation of the independent (*job demands* and *job resources*) and dependent variable (*burnout*): OLBI, JDRS, WIS, CSACD, and JCQ. Each of the scales used has been extensively studied, demonstrating adequate Cronbach alpha scores that ranged from .68 to .95 (see Table 4). The JDRS measures—*overload* ($\alpha = .76$) and *organizational support* ($\alpha = .92$) (Rothmann et al., 2006). The WIS has a Cronbach's alpha of .89 (Cortina et al., 2001; Cortina et al., 2013). The

CSACD measure has a Cronbach's alpha of .95 (Baggs, 1994). The JCQ was used to evaluate the *job resources—job control* and *autonomy*. *Job control* was measured by *job decision latitude* (*skill discretion* + *decision authority*) subscale that consists of a Cronbach's alpha of .76 (Karasek et al., 1998). *Autonomy* was measured by the decision authority subscale which demonstrated a Cronbach's alpha of .68 (Karasek et al., 1998). The OLBI measured burnout and has a total scale Cronbach's alpha of .70 (Demerouti et al., 2003). The *exhaustion* and disengagement subscales have a Cronbach's alpha of .82 and .83, respectively (Demerouti et al., 2003).

Combining the five mentioned instruments into one survey may also cause challenges to the individual scale's psychometric testing (i.e., reliability and validity) and conceptual fit (i.e., scale matches the variable that one wishes to measure) (Robinson, 2018). According Heggestad and colleagues (2019) review of over 2,000 scales, subscales from primary measures had limited, if any, effect on the validity of scale scores when subscales were kept in their original format. Therefore, attempts to mitigate concerns by following the recommendations from Heggestad and colleagues (2019) and precautions were taken to maintain all subscales in their original format to prevent any changes to the scale's internal consistency value. For additional information regarding each measure's psychometric properties, the reader is encouraged to go to the subsection, "Instrumentation" in Chapter 3 of this dissertation.

Descriptive Statistics

Sample Characteristics

Baseline descriptive analyses were conducted on demographic information: age, gender, marital status, years of experience, ethnic background, and hours worked per week. Additional demographic information such as the type and size of the hospital, employer type, practice setting, and years at the current practice was collected to provide an overall picture of the sample characteristics, allow for comparison to similar studies, and facilitate future subgroup analysis for potential relationships within the nursing anesthesia specialty. Table 4 presents the frequencies and percentages for the demographic characteristics. The age distribution of participants was relatively even, with the majority falling within the 30–59 age range. The gender split was 69.4% female and 30.6% male. In terms of race and ethnicity, most participants identified as Caucasian/White (86.6%). The majority of respondents were married (78.3%). The years of experience as a CRNA varied among the respondents, with 26 years or more being the largest group (22.3%). Regarding tenure at their current job, nearly half reported they had been there for 0–5 years (47.1%). The respondents primarily worked in some form of hospital setting, with a majority working in medium-sized hospitals (40.8%). Concerning employment structure, slightly more than one-third of the respondents reported being hospital employees (36.3%). Practice models primarily included supervision (40.8%) or medical direction (32.5%). Nearly all respondents reported being staff providers (95.5%). Finally, work hours per week also varied, with a significant proportion working between 31–50 hours (74.5%). The present study had similar demographic results as previous studies (Elmblad et al., 2014; Hyman et al., 2011; Lea et al., 2022; & Mahoney et al., 2020) except for "years of experience." Previous studies average years of experience (M = 15.6–18.5 years) compared to current study demonstrated greater than 26 years of experience, followed by 11–15 years of experience.

Table 4.

Demographic Variables of Respondents (N = 157)

Demographic Variable	Frequency	Percent
Age Range		
20–29	1	0.6%
30–39	42	26.8%
40–49	34	21.7%
50–59	46	29.3%
60–69	34	21.7%
Gender		
Female	109	69.4%
Male	48	30.6%
Race/Ethnicity		
African American/Black	3	1.9%
Asian (East, South, Asian American)	3	1.9%
Caucasian/White	136	86.6%
European American	5	3.2%
Latino or Hispanic American	2	1.3%
Other	2	1.3%
Prefer not to answer	6	3.8%
Marital Status		
Divorced	17	10.8%
Life partner	3	1.9%
Married	123	78.3%
Single	13	8.3%
Widowed	1	0.6%
Years of Experience as a CRNA		
0–5	23	14.6%
6–10	30	19.1%
11–15	29	18.5%
16–20	22	14%
21–25	18	11.5%
26 or greater	35	22.3%
Years at Current Job		
0–5	74	47.1%
6–10	23	14.6%
11–15	20	12.7%
16–20	18	11.5%
21–25	11	7%
26 or greater	11	7%

Table 4 (continued).

Demographic Variables of Respondents (N = 157)

Demographic Variable	Frequency	Percent
Work Setting		
Endoscopy Center	4	2.5%
Large hospital (≥ 500 beds)	35	22.3%
Medium hospital (100–499 beds)	64	40.8%
Small hospital (< 100 beds)	28	17.8%
Surgery Center	17	10.8%
Office based (i.e., dental clinic)	9	5.7%
Employment Structure		
Employee of a CRNA owned group	6	3.8%
Employee of a hospital	57	36.3%
Employee of a physician owned group	52	33.1%
Independent Contractor	37	23.6%
Military/Government/VA	5	3.2%
Practice Model		
Independent	39	24.8%
Medical Direction	51	32.5%
Supervision	64	40.8%
Other	3	1.9%
Primary Job Role/Responsibility		
Instructor/Professor	2	1.3%
Management	3	1.9%
Staff provider	150	95.5%
Other	2	1.3%
Hours Worked		
1–20 hours per week	14	8.9%
21–30 hours per week	16	10.2%
31–40 hours per week	73	46.5%
41–50 hours per week	44	28.0%
51 or greater hours per week	10	6.4%

Qualitative Themes

Of 152 respondents, 75 responded to the qualitative section. Evaluation of the data found multiple missing entries and those were removed, the remaining sample included 55 for job demands and 33 for job resources. However, further review of the responses in greater detail, demonstrated similar response types in both qualitative sections. For example, work demand and short staff themes were found under job demands and job resource qualitative sections. The overall themes were summarized in Table 5.

Table 5.

Qualitative Responses for Job-Related Characteristics Impacting CRNA Daily Work Environment

Theme	Example	N
Workload	"Call is onerous. Not guaranteed day off after call." "Chaotic scheduling of cases." "Out late frequently."	23
Equipment	"Increased workload with failing equipment." "Lack of up-to-date equipment."	21
Short Staffed	"Being stuck in a room with no relief."	17
Collaboration	"Attending forgetting to relieve me." "Poor communication and collaboration with attendings."	8
Technology	"Hospital charting/IT systems and their failures/limitations." "Transition to new charting system."	6
Culture	"Lack of respect for others time."	5
Scope of Practice	"Facility is heavily slanted towards physicians."	3
Patient Acuity	"Increased ASA status of patients." "Patients being pushed to surgery centers that should not be."	3
Communication	"Poor communication with the MDAs."	1
Compensation	"Appropriately compensated for the job demands we take on."	1

Respondents most frequently indicated that (1) workload was the highest job-related demand impacting their day. Specifically, comments tended to focus on speed of OR pace and "increased workload because of lack of staff." Other common remarks centered around shift type with longer shifts having greater demands. Second common complaint was equipment related challenges (e) were indicated by respondents as creating additional job-related challenges. Next, was short staffed (3) with participants referencing the impact creating unanticipated overtime and a level of uncertainty of ability to leave work. Collaboration (4) was the next most listed qualitative response. Respondents indicated lack of collaboration with anesthesiologist created the greatest amount of daily strain. Common complaints were “lack of up-to-date equipment” or “lack of availability.” Respondents described technology (5) either was beneficial, “decreasing charting time” or challenging, “too many steps.” Culture of the work environment (6) was listed as a common indicator of frustration in the respondent comments, “Lack of respect for others time.” Scope of practice, patient acuity, compensation, supervisory support, and communication were all 3 or lower responses. Although the responses were limited, they did provide additional insight future research into how respondents viewed job related characteristics.

Descriptive Analysis of Variables and Constructs

Table 6 presents (*M*) and standard deviations (*SD*) for *job demands* and *job resources* subscales, burnout and its dimensions—exhaustion and disengagement are presented in Table 6. For *job demand* scores, the JDRS overload subscale captured *workload, time pressure,* and *emotional demands*, while the WIS captured *workplace incivility*. The overload subscale response options spanned from 8 to 32; observations ranged from 12 to 30, with an average observation of 21.1 (*SD* = 3.73). For workplace incivility, WIS response options spanned from 10 to 50; observations ranged from 9 to 44, with an average observation of 16.3 (*SD* = 6.9). The results indicated higher levels of job overload (i.e., workload, time pressure, and emotional demands) and lower levels of workplace incivility.

Job resource scores were measured by the JCQ (job control and autonomy), JDRS (*interpersonal support*), and *CSACD* (*collaboration*). *Job control* was captured by *job decision latitude* subscale with response options spanned from 50 to 125; observations ranged from 58 to 116, with an average observation of 89.1 (*SD* = 13.1). *Autonomy* was captured by *job authority* subscale with response options spanned from 8 to 56; observations ranged from 8 to 56, with an average observation of 42.6 (*SD* = 10.1). The JDRS subscale *organizational support* captured *colleague* and *supervisor support*. JDRS-organizational support subscale response options spanned from 18 to 72; observations ranged from 31 to 68, with average observation of 51 (*SD* = 8.7). For *collaboration*, *CSACD* response options spanned from 9 to 63; observations ranged from 9 to 61, with an average observation of 44.4 (*SD* = 10.8). The means indicated the sample had higher levels of *job control* and *autonomy* with medium interdepartmental *collaboration* and lower levels of organizational support.

Burnout and its dimensions, *exhaustion* and *disengagement*, were captured by the OLBI. The OLBI-total response options spanned from 16 to 64; observations ranged from 15 to 55, with average observation of 35.4. *Burnout-exhaustion* dimension response options ranged from 8 to 32; observations ranged from 8 to 30, with an average of 18.5. *Burnout-disengagement* dimension response options ranged from 8 to 32; observations from 7 to 27, average of 17. The means of the burnout total and its associated measures indicated the sample had a low level of burnout.

Table 6.

Descriptive Analysis for Variables (N=152)

Variable	Cronbach's α reliability	*Mean*	*SD*	*Min*	*Max*
Job Demands					
JDRS-Overload	.76	21.1	3.73	12	30
WIS—Workplace Incivility	.89	16.3	6.9	9	44
Job Resources					
JCQ—Job Control	.76	89.1	13.1	58	116
JCQ—Autonomy	.68	42.6	10.1	8	56
JDRS—Interpersonal Support		50.9	8.7	31	68
CSACD—Collaboration	.95	44.4	10.8	9	61
Burnout					
OLBI—Total	.70	35.4	7.3	15	55
Exhaustion	.82	18.5	4.1	8	30
Disengagement	.83	17	3.7	7	27

Note. JDRS = Job Demands Resource Scale; WIS = Workplace Incivility Scale; JCQ = Job Content Questionnaire; CSACD = Collaboration and Satisfaction about Care Decisions; OLBI = Oldenburg Burnout Inventory

Structural Equation Modeling (SEM) Model Fit

The first half of this chapter presented and discussed the data screening process and SEM assumptions. The second half of this chapter presents and discusses the analysis of the variable relationships *job demands, job resources*, and *burnout* among CRNAs. The analysis employed Covariance Based (CB) SEM using R for two separate models to test my hypotheses regarding the relationships between job demands, resources, and burnout. CB-SEM was used because it evaluated the variable relationships through the guidance of the JD-R model (Hair et al., 2018). The results provided estimates of the model parameters, including factor loadings for the latent variables, regression weights, and variances. Significance testing was performed for all parameter estimates to assess the strength of the relationships between constructs. All tests were two-tailed, with a significance level set at .05. Additionally, correlation analyses were conducted to examine the interrelationships among these variables. I did not conduct a confirmatory factor analysis (CFA) to assess the validity of the instruments before model fit testing because the measurement scales were kept in their original format and measurement purpose (Hair et al., 2021; Robinson, 2018). Each instrument used Likert scales and has been extensively studied, demonstrating high validity and reliability (Cronbach's $\alpha > .68$). Any of the subscales used were kept in their original format to prevent any scale validity challenges (Heggestad et al., 2019). The evaluation and calculations of the measures were based on the original article's author recommendations. The results from these analyses provided insights into the complex interplay between job demands, resources, and burnout among CRNAs.

Measurement Model Fit

The regular SEM model (Figure 11), was developed based on established theoretical frameworks discussed in the literature review. This model tests the direct relationships among *job demands*, *job resources*, and *burnout*. The measure of goodness-of-fit for the proposed model were conducted. The Comparative Fit Index (CFI) achieved a value of 0.846, and the Tucker-Lewis Index (TLI) reached 0.746, both nearing the conventional cutoffs ($\geq .95$) and suggesting that the model is a reasonable representation of the data. However, RMSEA was 0.204 (CI = 0.171–0.239) and SRMR 0.120 indicated marginal level of model fit. RMSEA and SRMR cutoff scores for good model fit are ≤ 0.06 and ≥ 0.08, respectively. The results of RMSEA and SRMR suggests the model has potential for further refinement (Marsh, Hau, & Wen, 2004; Peugh, & Feldon, 2020).

While the model did not achieve a perfect fit, the fit indices approached commonly accepted thresholds, suggesting that the model is reflective of the hypothesized constructs. The indices for assessing model fit—CFI, RMSEA, and SRMR—were marginally outside the ideal

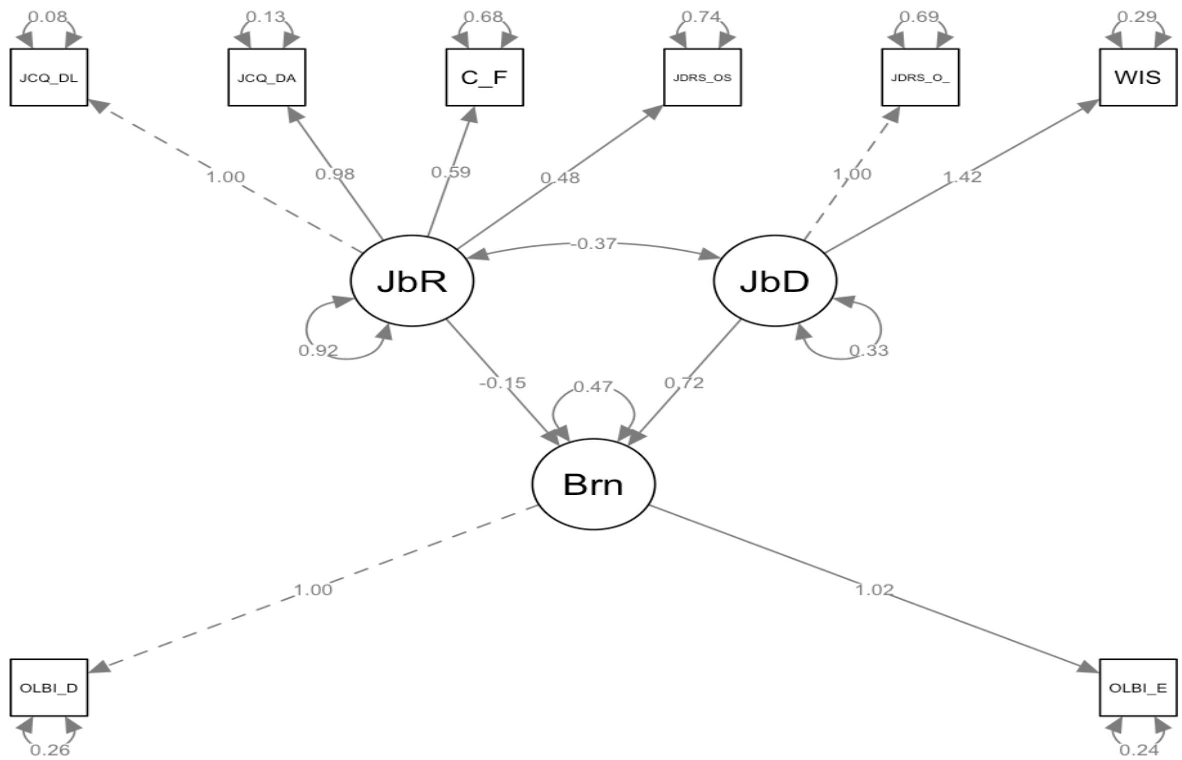

Figure 11.

Path Model of Direct Relationships between Job Demands, Job Resources and Burnout

Note. SEM model outlining relationships between Job Resources (JbR), Job Demands (JbD), and Burnout (Brn). Rectangles = observed variables that include Decision Latitude (*JCQ-DL*), Decision Authority (*JCQ-DA*), Collaboration (CF), Organizational Support (*JDRS-OS*), Work Overload (*JDRS-O*), and Workplace Incivility (WIS) which are indicators for latent variables JbR and JbD. Circles—latent variables with double-headed arrows indicating covariance and single-headed arrows indicating directional relationships (regression coefficients). Observed variables for Burnout are Exhaustion (*OLBI-E*) and Disengagement (*OLBI-D*) which are indicated by Brn. Standardized path coefficients are displayed on the connecting lines, depicting the strength and direction of the relationships.

range but within a range that is considered indicative of a substantive fit in extant literature. Research by Marsh et al. (2004), cautions against the overgeneralization of fit indices as golden rules, advocating for a more nuanced interpretation that considers the complexity of the model and the theoretical relevance of the constructs. In alignment with this view, the current study recognizes the fit indices as guidelines rather than strict benchmarks, emphasizing the importance of theoretical coherence over empirical perfection. The SEM model, therefore, despite not hitting the ridged ideals, remains a valuable contribution to understanding of the dynamics between *job demands, resources*, and *burnout*, as it isolates the key aspects of the constructs derived from the relevant theories (Marsh et al., 2004). It presents a meaningful interpretation of complex constructs that may not be entirely captured by rigid criteria.

The results presented in Table 7 provide a detailed examination of the relationships within the SEM framework. Each path in the model is represented with its estimated standardized coefficient, standard error, critical ratio, and corresponding *p* value, offering a clear quantification of the direct and indirect relationships posited in the study's hypotheses.

Table 7.

Standardized Coefficients, Standard Errors, Critical Ratios, and P-Values

Path	*Estimate*	*Std. Error*	*z* value	*p* value
Latent Variables				
Decision Latitude → Job Resources	1.000	0.034	29.412	< 0.001
Decision Authority → Job Resources	0.976	0.051	19.137	< 0.001
Collaboration → Job Resources	0.598	0.074	7.959	< 0.001
Organizational Support → Job Resources	0.484	0.076	6.386	< 0.001
Overload → Job Demands	1.000	—	—	—
Workplace Incivility → Job Demands	1.425	0.258	5.523	< 0.001
Disengagement → Burnout	1.000	—	—	—
Exhaustion → Burnout	1.015	0.122	8.311	< 0.001
Regressions				
Job Demands → Burnout	0.721	0.243	2.969	0.003
Job Resources → Burnout	−0.146	0.124	−1.177	0.234
Covariances				
Job Resources ←→ Job Demand	−0.368	0.083	−4.434	< 0.001

Note: All tests were two-tailed. *P* values are based on z-distribution. Paths without standard errors or *z* values indicate fixed parameters in the model. Measures Included: JDRS = Job Demands Resource Scale; WIS = Workplace Incivility Scale; JCQ = Job Content Questionnaire; *CSACD* = Collaboration and Satisfaction about Care Decisions; OLBI = Oldenburg Burnout Inventory

Latent variables such as *job resources* and *job demands* are well-defined through their indicators, which significantly contribute to their constructs with all paths showing p values less than .001. *Burnout*, as an endogenous latent variable, is effectively captured by its indicators, *disengagement* (*OLBI-D*) and *exhaustion* (*OLBI-E*), suggesting a strong representation of this construct. The fixed parameters for the paths from 'Overload to Job Demands' and 'Disengagement to Burnout' serve a specific function in the structural model: They establish the measurement scale for latent constructs. By fixing these parameters to an arbitrary value (typically 1.0), the model assigns a scale to the latent variable, allowing the other path estimates to be interpreted in relation to this scale.

The regression paths (Figure 11) from Job Demands to Burnout (0.721, $p = .003$) and the covariance between Job Resources and Job Demands (−0.368, $p < .001$) are particularly noteworthy. The direct path between job demands and burnout are statistically significant with the covariance indicating job demands and job resources have an inverse relationship. The variances (Figure 11) for each of the constructs and indicators further validate the model's adequacy, with job resources explaining 92.2% and job demands 32.7% of the variance, respectively. This would indicate job resources have a stronger explanatory power for the variance in burnout compared to job demands. Notably, the model explains a significant 47% of the variance in the Burnout construct, emphasizing the substantive explanatory power of the SEM model employed in our study.

Moderation Measurement Model Fit

The mediation SEM model (Figure 12) was evaluated to determine the moderation effects of *job resources* on the relationship between *job demands* and *burnout*. The results yielded intriguing insights. The model's fit indices such as the CFI and TLI were strong with values of 1.00 and 0.982 respectively, they suggest the model has captured a significant portion of the relationships being studied. The RMSEA was 0.001 (CI = 0.000 – 0.130) and SRMR 0.003 indicated good level of model fit. RMSEA and SRMR cutoff scores for good model fit are ≤ 0.06 and ≤ 0.08, respectively. The results of RMSEA and SRMR suggests the model indicates very strong fit. Both the indices are well below their respective cutoff values and have a strong theoretical foundation that justifies the variables involved (Hu, & Bentler, 1999; Peugh, & Feldon, 2020).

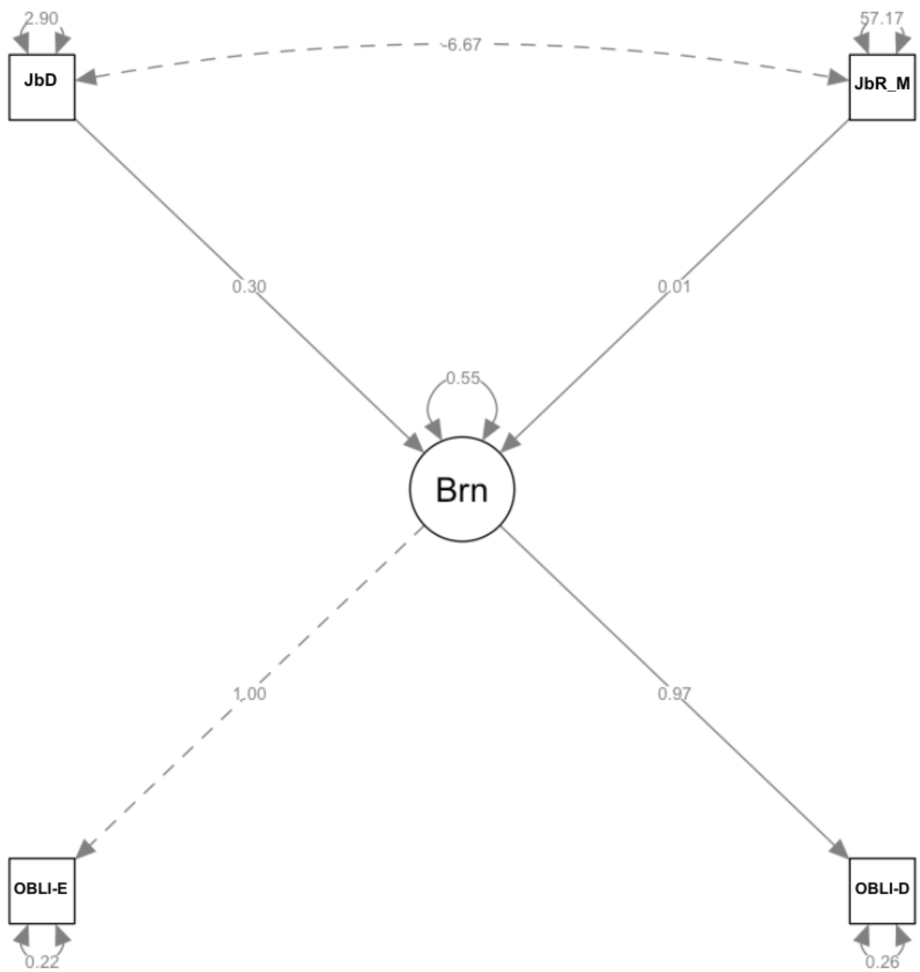

Figure 12.

Path Model of the Moderating Relationships of Job Resources between Job Demands and Burnout

Note. SEM model evaluating the moderating role of Job Resources (JbR_M) in the relationship between Job Demands (JbD), and Burnout (Brn), Standardized Regression Weights. Moderation effect (JbR_M) = Job Demands (JbD)* Job Resources (JbR). Job resources are modeled as a mediator between job demands and burnout, with direct paths from job demands to burnout and from job resources to both job demands and burnout. Rectangles = observed variables that include Job Demands (JbD) and the moderation effect variable (JbR_M). Circles—latent variables. Single-headed arrows = directional relationships. Double-headed arrows = variance. Observed variables for Burnout are Exhaustion (OLBI-E) and Disengagement (OLBI-D) which are indicated by Brn.

The moderation analysis presented in Table 8 explored the indirect effect of *job resources* on the relationship between *job demands* and *burnout*. SEM analysis revealed significant paths from the latent variables to their respective indicators. Specifically, *disengagement* (OBLI-D) was set as a fixed parameter to *burnout*, effectively scaling these latent constructs. The fixed parameters are intended to standardize the results, rather than providing unrelated values (Hu, & Bentler, 1999). This resulted in two indicators of job resources (collaboration, decision authority, decision latitude) and two indicators of *job demands* (*workplace incivility* and *job overload*).

Table 8.

Moderation Analysis of the Effect of Job Resources on the Relationship Between Job Demands and Burnout

Path	Estimate	Std. Error	*z* value	*p* value
Latent Variables				
Disengagement → Burnout	1.000	—	—	—
Engagement → Burnout	0.967	0.113	8.533	< .001
Regressions				
Job Demands → Burnout (b1)	0.303	0.048	6.303	< .001
Job Resources*Job Demand (Moderation Effect) → Burnout (b2)	0.008	0.010	0.741	0.495
Variances				
Exhaustion	0.216	0.083	2.602	0.009
Disengagement	0.264	0.080	3.294	0.001
Burnout	0.547	0.101	5.404	0.000

Note: The regression (b2) represents the mediated effect of Job Demands on Burnout through Job Resources. This effect represents the product of Job Resources and Job Demands as presented in the direct model. Paths without standard errors are fixed parameters. Measures Included: OLBI_E = Oldenburg Burnout Inventory Exhaustion Sub-scale and OLBI_D = Oldenburg Burnout Inventory Disengagement Subscale

The examination of the moderation effect of *job resources* on the *job demands-burnout* relationship showed significant findings. The direct path from *job demands* to *burnout* was statistically significant ($z = 0.303$; $p < 0.001$) representing a strong positive association, where increased *job demands* are predictive of higher levels of *burnout*. Conversely, the interaction term representing the moderation effect of *job resources* on the relationship between *job demands* and *burnout* did not reach statistical significance ($z = 0.008$; $p = 0.495$). This suggests that within the current sample and the specified model, the protective effect of *job resources* – counteracting the stress induced by *job demands* – is not empirically evident (Table 8).

Correlation Testing

Correlation analysis (Table 9) was conducted to determine the strength and direction of relationships between various job-related factors, such as workload, time pressure, and emotional demands, and the dimensions of burnout, namely exhaustion (*OLBI-D*) and disengagement (*OLBI-E*). The correlations (r) were computed using a pairwise exclusion of missing data, and all reported confidence intervals were set at the 95% level, indicating that the correlations are statistically significant.

Table 9.

Correlations Analysis of Job-Related Characteristics and Burnout

		Statistic		
Variable	Variable 2	Correlation	Lower C.I.	Upper C.I.
CSACD	*OLBI-D*	-0.471	-0.585	-0.338
	OLBI-E	-0.449	-0.567	-0.313
JCQ-DA	*OLBI-D*	-0.306	-0.443	-0.156
	OLBI-E	-0.393	-0.519	-0.251
JCQ-DL	*OLBI-D*	-0.397	-0.523	-0.255
	OLBI-E	-0.410	-0.533	-0.269
JDRS-OS	*OLBI-D*	-0.527	-0.633	-0.403
	OLBI-E	-0.414	-0.537	-0.274
JDRS-O	*OLBI-D*	0.398	0.256	0.524
	OLBI-E	0.430	0.291	0.551
WIS	*OLBI-D*	0.405	0.264	0.529
	OLBI-E	0.348	0.201	0.479

Note. Missing value handling: PAIRWISE, EXCLUDE. C.I. Level: 95.0. Collaboration and Satisfaction about Care Decisions (*CSACD*) Decision Authority (*JCQ-DA*), Decision Latitude (*JCQ-DL*), Organizational Support (*JDRS-OS*), Work Overload (*JDRS-O*), and Workplace Incivility (*WIS*). Burnout dimension-Exhaustion (*OLBI-E*) and Burnout dimension-Disengagement (*OLBI-D*)

The correlation analysis revealed several notable relationships between job factors and burnout dimensions. Collaboration (*CSACD*) was inversely related to both exhaustion ($r = -0.471$) and disengagement ($r = -0.449$), with confidence intervals indicating a moderate to strong negative correlation. This suggests that increased collaboration in the workplace is associated with lower levels of both exhaustion and disengagement. Similarly, both decision latitude (*JCQ-DL*) and decision authority (*JCQ-DA*) showed negative correlations with exhaustion ($r = -0.397$ and $r = -0.306$, respectively) and disengagement ($r = -0.410$ and $r = 0.393$, respectively), indicating that CRNAs who experience greater autonomy and control in their roles tend to report lower burnout levels.

Organizational support (*JDRS-OS*) also exhibited a strong negative relationship with exhaustion ($r = -0.527$) and disengagement ($r = -0.414$), indicating that supportive organizational structures (i.e., colleague and supervisory) can play a protective role against burnout. Conversely, workload (*JDRS-Overload*) showed a positive correlation with both exhaustion ($r = 0.398$) and disengagement ($r = 0.430$), suggesting that as job demands increase, so do feelings of burnout. Workplace incivility (*WIS*) was positively correlated with exhaustion ($r = 0.348$) and disengagement ($r = 0.405$), which implies that negative social interactions at work are associated with higher burnout levels.

In summary, the results indicate that job resources such as collaboration, decision latitude, decision authority, and organizational support are inversely related to burnout, suggesting their potential buffering effects against stressors inherent in the CRNA role. Conversely, job demands, and workplace incivility appear to be risk factors for increased burnout, highlighting the importance of managing workload and promoting a civil work environment to mitigate the adverse effects of burnout among CRNAs.

Evaluation of Hypotheses

The primary objective was to evaluate the relationship between job-related characteristics and burnout in CRNAs and use the JD-R perspective to increase the understanding of the impact of specific job-related characteristics contributing to burnout and its associated dimensions—exhaustion and disengagement. The secondary objective was to evaluate how each job-related characteristic specific to the study population affects burnout, and its associated dimensions, both independently and interdependently. After evaluation of model fit and path analysis was complete, SEM was utilized to test the proposed hypotheses (Figure 3) about the relationships between job demands, job resources, and burnout among CRNAs practicing in the United States.

Hypothesis H_a1. Hypothesis H_a1 proposed specific job demands and job resources (as measured by subscales of the survey) will have a statistically significant correlation with burnout in CRNAs practicing in the United States. The latent variable of job demands and job resources were well defined through their indicators, which significantly contributed to their constructs with all paths showing *p* values less than .001 (Table 8). However, the results suggested that H_a1 was only partially supported because job demands ($b = 0.721$, $p = .003$), not job resources ($b = -0.146$, $p = .234$), was statistically significant. This result suggests that job demands alone, may be associated with higher levels of burnout (Demerouti et al., 2001).

Hypothesis H_a2. Hypothesis H_a2 stated job demands, and not job resources, will be the stronger predictor of exhaustion in CRNAs practicing in the United States. Table 10 presents Pearson correlations between job demands, job resources, and burnout dimensions—exhaustion and disengagement. The results suggest hypothesis H_a2 was not supported secondary to job resources having a stronger correlation with the exhaustion dimension compared to job demands, $r = -.507$, $p < .001$; $r = .437$, $p < .001$, respectively. Further investigation into the measured variables of job demands, work overload (*JDRS-O*) and workplace incivility (*WIS*) demonstrated work overload correlated stronger to the exhaustion dimension compared to the disengagement dimension but was opposite for workplace incivility.

Table 10.

Pearson Correlation for Predictor Variables and Burnout Dimensions

Variable	*Job Resources*	*Job Demands*
Disengagement (*OLBI-D*)	−.510**	.463**
Exhaustion (*OLBI-E*)	−.507**	.437**

Note. **Correlation is significant at the 0.01 level (2-tailed)

Hypothesis H_a3. Hypothesis H_a3 stated job resources, and not job demands, will be the stronger predictor of disengagement in CRNAs practicing in the United States. The findings (Table 10) indicated job resources, and not job demands, were a stronger predictor of disengagement, $r = -.510$, $p < .001$; $r = .463$, $p < .001$, respectively. Further analysis (Table 9) demonstrated job resource variables, collaboration (*CSACD*), decision latitude (*JCQ-DL*), decision authority (*JCQ-DA*), and organizational support (*JDRS-OS*), displayed strong correlations towards the burnout dimensions, exhaustion and disengagement, but only organizational support variable demonstrated a stronger correlation to the disengagement dimension compared to the exhaustion dimension.

Hypothesis H_a4. Hypothesis H_a4 stated job resources, (as measured by subscales of the survey), will moderate the positive relationship between job demands and burnout, such that the relationship between job demands and burnout will be less positive. The moderation model (Figure 12) path analysis addressed the moderating effect of job resources on the relationship between job demands and burnout. The moderation analysis presented in Table 8 demonstrated the moderation effect was not significant (moderation effect = 0.008, p = .495), confirming the mediating role of job resources may not directly impact the relationship between job demands and burnout.

Summary of Major Findings

The comprehensive analysis of the impact of job demands and resources on burnout among the 152 participants CRNAs in the United States incorporated SEM to validate the proposed hypotheses. The study's findings are instrumental in understanding the interplay between job demands and resources in relation to burnout within the CRNA cohort.

Descriptive statistics highlighted the distribution of job-related stress and support measures, with the OLBI scores indicating a lower level of burnout among participants. Correlation analysis revealed significant relationships between job factors and burnout dimensions, with collaboration, decision latitude, and organizational support negatively correlated with exhaustion and disengagement, suggesting their potential protective effects against burnout.

The SEM analysis provided a robust framework for assessing the direct and indirect relationships between job demands, resources, and burnout. The regression paths confirmed job demands as a strong predictor of burnout, with a significant positive effect. Job resources exhibited a complex relationship with burnout, with an indirect buffering effect that did not reach statistical significance in the moderation analysis, although the overall relationship between job demands and burnout was significant.

The study successfully tested several hypotheses, confirming job demands strong association with burnout. However, job resources did not demonstrate a significant relationship with burnout despite its observed variables having a stronger correlation with the burnout dimensions, exhaustion and disengagement, compared to job demands. The results indicate job resources have more complex role towards the development of burnout in the nursing specialty. In conclusion, the results underscore the significance of job demands as predictors of burnout and illuminate the nuanced role of job resources. These insights are critical for developing targeted interventions to manage job demands and enhance job resources to mitigate burnout among CRNAs.

CHAPTER 5: DISCUSSION

The burnout topic has been extensively discussed and or debated for over 50 years, at which thousands of publications have been dedicated towards the theoretical and empirical understanding of the concept (Del Grosso & Boyd, 2019; Qiao, & Schaufeli, 2011). Despite this half a century long "progress," burnout, its conceptualization, associated consequences, and clinical management, remain without common ground. Researchers believe some of the context's fragmented state may stem from its multifactorial origins (Schaufeli et al., 2017). However, the exhaustive evaluation of understanding the syndrome is not without some progress. The decades of scholarly attention focused towards understanding the burnout context has resulted in some common ground regarding the conceptual pillars of the syndrome:

1. burnout is considered a work-related syndrome that emerges from a prolonged response to chronic interpersonal job-related stressors,
2. burnout is a psychological experience of feelings and attitudes towards one's job, and
3. it is an individual's experience that is specific to the work context (Maslach, & Leiter, 2017; Schaufeli, Maslach, & Marek, 2017).

Simply stated, burnout is an individual experience that is specific to the work context and influences such as the occupational environment, professional background, and individual characteristics can influence data outcomes (Del Grosso & Boyd, 2019). Like the management of complex diseases in healthcare, every specialty within the healthcare industry has its unique demands and resources and, therefore, requires its own individualized attention (Bakker, & Demerouti, 2007). This dissertation is the product of that belief towards finding forward progress in the identification and management of the burnout syndrome.

Chapter Five includes a summary of the study's background, main findings and associated limitations of the findings, implications, future recommendations, and finalized summary of the study.

Summarizing the Need for Exploring CRNA Burnout

CRNAs are a critical part of the anesthesia workforce, responsible for approximately 65% of the anesthetics provided in the United States (Del Grosso & Boyd, 2019). The nursing specialty is known and respected for the ability to provide safe, high-quality, and cost-effective anesthesia services to numerous patient populations, including critical access hospitals (Dulisse & Cromwell, 2010). The increased exposure to occupational demands, especially related to the COVID-19 pandemic, placed on CRNAs practicing in the US continues to be a growing concern within this nursing specialty (Farina et al., 2020). The growing demands by healthcare facilities for cost-efficient, safe anesthesia services coupled with the challenges created by the pandemic, resulted in a further mismatch between job demands and job resources.

Recent years have seen an increase in studies evaluating job related characteristics and burnout within the nursing specialty (Del Grosso & Boyd, 2019). A 2019 review identified six studies (Elmblad et al., 2014; Hyman et al., 2014; Lea et al., 2022; Mahoney et al., 2020; Shah et al., 2019; & Vells et al., 2021) that directly measured CRNA burnout within the United States, specifically found several common work-related characteristics associated with the burnout syndrome. These factors consisted of workplace behaviors, job-related support, workload, job control, and autonomy. Despite the increased attention, current reviews (AANA, 2019a; AANA, 2023; Boyd & Poghosyan, 2017) have pointed towards limited success in evaluation and management related to the burnout syndrome. The limited success raises concern secondary to the inappropriate evaluation and management of burnout places further strain on the stability of this nursing specialty, which is already facing a critical deficit in workforce numbers (Negrusa et al., 2021). This has system-level negative implications on the nursing anesthesia specialty, healthcare organizations, and the patients they care for. Research (Lea et al., 2022; Mahoney et al., 2020) has demonstrated a negative correlation between burnout and turnover, intent to quit, and job satisfaction among CRNAs practicing in the United States. The limited success in the evaluation and management of burnout in CRNAs may be secondary to the following gaps:

1. limited empirical research evaluating burnout in the nursing specialty,
2. lack of theoretical guided empirical research

Synopsis of the Study

The primary purpose of the exploratory, cross-sectional study was to further evaluate the relationship between previously identified *job demand* and *job resource* variables and *burnout* among CRNAs practicing in the United States. A version of the JD-R model (see Figure 1)

modified to include measured variables specific to the nursing specialty was used as the theoretical framework to further understand the burnout syndrome within this nursing specialty. The study's overall goal of applying the JD-R model in addressing the relationship between previously identified job-related characteristics and burnout in the nursing specialty was to increase the understanding of the impact of these specific job-related factors contributing to burnout which, in turn, may provide a path towards appropriate interventions. Furthermore, exploration of previously identified factors and their relationship with burnout will give insight into the current state of our knowledge of burnout's impact in the nursing specialty.

The quantitatively designed survey was electronically distributed by the AANA Department of Research to 3,000 randomly selected CRNAs that were actively practicing anesthesia in the United States. Aligning with the JD-R model (Figure 2)

To address the research questions and hypotheses, the survey was designed to capture a comprehensive range of job-related characteristics, including workload, time constraints, emotional and physical demands, workplace incivility, and available job resources such as autonomy, control, and social support that previous studies (Elmblad et al., 2014; Hyman et al., 2014; Lea et al., 2022; Mahoney et al., 2020; Shah et al., 2019; & Vells et al., 2021) have demonstrated to be common predictors of burnout in the nursing specialty.

Data collection lasted four weeks. Then, the data collected from the survey was exported from Qualtrics into Microsoft Excel for pre-analysis procedures and then downloaded to SPSS Version 28 for descriptive and inferential analysis. The predictor variables include *job demands* and *job resources*, and these were measured by a myriad of questionnaires specific for the evaluation of these variables (see Figure 1). The outcome variable was *burnout,* which was measured using the OLBI. The study sample was described based on the obtained demographic characteristics. The primary purpose of the demographic data was to help build a profile of the sample for subsequent analysis. SEM analysis was conducted to answer the research questions and hypotheses (Figure 3) by constructing two models (regular and mediation) that consisted of three latent variables (i.e., *job demands*, *job resources*, and *burnout*) and eight observed variables which included six exogenous (independent) variables (i.e., *decision latitude*, *decision authority*, *collaboration*, *organizational support*, *workload*, and *workplace incivility*) and two endogenous (dependent) variables (i.e., *exhaustion*, and *disengagement*). The results provided estimates of the model parameters, including factor loadings for the latent variables, regression weights, and variances. Significance testing was performed for all parameter estimates to assess the strength of the relationships between constructs. All tests were two-tailed with a significance level set at .05. Overall, the results from these analyses provided insights into the complex interplay between job demands, resources, and burnout among CRNAs. A more in-depth discussion of the implications the study's results had towards the nursing specialty will be discussed in the following sections.

Interpretation and Discussion of the Findings

The hypothesized path models were the product of a theoretical framework (JDR) constructed from prior theoretical and empirical research findings of work-related factors' impact towards the development of burnout. As previously mentioned in earlier chapters, there has been increased attention towards evaluating the relationships between job-related factors and burnout within the nursing anesthesia specialty but has resulted in limited success in its management (Boyd & Poghosyan, 2017; Del Grosso & Boyd, 2019). Thus, the present study was developed to address the theoretical and empirical gaps in burnout among CRNAs in the United States utilizing the JD-R model as a guide towards further understanding of previously identified factors and their relationship to burnout.

Job Demands and Job Resources as Predictors of Burnout

The JD-R model's central assumption is that burnout is directly related to the balance between specific working conditions of that profession (Bauer & Hammig, 2014). These working conditions are classified into two broad categories: job demands and job resources (Bakker & Demerouti, 2007). The JD-R model proposes that the interaction between high job demands and poor job resources creates the burnout syndrome—exhaustion and disengagement (Demerouti et al., 2001; Schaufeli & Taris, 2013). The JD-R model also postulates job demands and job resources initiate two different processes, health impairment process and motivational process, where job demands are primarily associated with exhaustion and job resources associated with disengagement (Demerouti et al., 2001; Schaufeli & Taris, 2013).

Research question RQ1 asked what the extent of the relationship between previously identified *job demands*, *job resources* and *burnout* in CRNAs practicing in the United States. The findings relevant to the evaluation of hypothesis H_a1 indicate the relationship was only partial and job demands (b = 0.721, p = .003), not job resources (b = −0.146, p = .234), were statistically significant. This output provides evidence for the theoretically posited relationships between these constructs and their influence on burnout. The variances (Figure 11) for each of the constructs and indicators further validate the model's adequacy, with *job resources* explaining 92.2% and *job demands* 32.7% of the variance, respectively. This would indicate *job resources have a stronger explanatory power for the variance in burnout compared to job demands*. The explained variance in *burnout*, particularly when considering the substantial percentage, emphasizes the theoretical and practical relevance of the model despite the absence of a significant direct relationship from *job resources* to *burnout*. Notably, the model explains a significant 47% of the variance in the *burnout* construct, emphasizing the substantive explanatory power of the SEM model employed in our study.

Research questions RQ2 and RQ3 asked what the extent of the relationships were between the specific job-related factors and the burnout dimensions. Aligning with the second assumption of the JD-R, it was posited that *job demands* (H_a2) would be a stronger predictor of exhaustion whereas *job resources* (H_a3) would be a stronger predictor of *disengagement*. In the context of SEM, analysis of the relations of these job-related characteristics went beyond simple predictive relationships often seen in formal regression methods, thus allowing for an assessment of complex, multifaceted constructs and their potential causal pathways. The model's capabilities allow for the evaluation of these complex, intertwining relationships that are consistent with the theoretical assumptions of the JD-R model.

The complexities of job-related characteristics and burnout were highlighted through evaluation beyond examining the general relationship of the latent variables with burnout. Path regressions indicated *job demands* (*b* = 0.721, *p* = .003) *were statistically significant with burnout whereas job resources demonstrated inverse relationship but did not reach significance*. However, examination of both hypotheses (H_a2 and H_a3) indicated *job resources, not job demands, having a stronger correlation with both burnout dimensions—exhaustion and disengagement*. Further evaluation of the correlations between job related characteristics and burnout dimensions indicated the complex interactions these factors play in the nursing specialty's work environment. Empirical (Mahoney et al., 2020) and theoretical (Bakker et al., 2003) research have demonstrated job demands and job resources initiate two different psychological processes, with job demands associated with exhaustion (health impairment) and job resources with disengagement (motivation). However, study results (Table 9), indicated a more complex intertwining relationship among the study variables. For instance, of the four observed resource variables, only organizational support had a stronger correlation with the disengagement dimension compared to the exhaustion dimension. The other three variables all exhibited stronger correlations with the exhaustion dimension.

The complex intertwining of the study's variables may be related to additional underlying mechanisms postulated by advancements in the JD-R model. First, the fifth assumption of the JD-R theorizes personal resources may play a similar role as job resources (Bakker & Demerouti, 2017). Research (Bakker & Demerouti, 2017; Schaufeli & Taris, 2013; Xanthopoulou, Bakker, Demerouti, & Schaufeli, 2007a) have demonstrated personal resources can be important factor towards an employee's adaptation to their work environment. Although limited, a study by Mahoney and colleagues (2020) demonstrated burnout negatively correlated with personality factors (agreeableness, stability, and openness) in a sample of CRNAs. Second, the JD-R model defines job demands as work characteristics that require effort at a physical, emotional, and psychological cost, however, studies in the past decade have demonstrated employees can view job demands as either a hinderance or a challenge based on the context of that work setting (Bakker & Demerouti, 2017). Third, the second assumption of the JD-R states job demands are primarily associated with exhaustion and job resources are primarily associated with disengagement (engagement) (Bakker & Demerouti, 2017). However, research has provided evidence that job demands and job resources also have a reciprocal effect through loss and gain spirals (Bakker & Demerouti, 2017). This raises the question on whether job demands can have a positive influence and job resources have a negative influence on an individual's experience of work (see Bakker & Demerouti, 2017; Schaufeli, Bakker, & Van Rhenen, 2009) .

Job Resources as the Moderating Variable between Job Demands and Burnout

The JD-R model's third assumption theorizes that several different job resources may buffer both quantitative (work pressure) and qualitative (emotional) job demands (Bakker, Demerouti, & Euwema, 2005). This assumption postulates that when employees have many job resources available to them, their ability to manage high demands is improved.

Research question RQ4 asked if *job resources* buffered the relationship between *job demands* and *burnout*. Specifically, it was predicted (H_a4) *job resources*, which include job control, autonomy, support, and collaboration, will moderate the relationship between *job demands* and *burnout*, such that the relationship between job demands and burnout will be less positive. The findings on H_a4 indicated the moderation effect, the moderating effect of job resources on the relationship between job demands and burnout, was positive but not statistically significant (z = 0.008, p =0.495).

The results further demonstrate the complex role between *job resources, job demands,* and *burnout*. For example, the direct effect of *job resources* on *burnout* was negative but not significant (z = −146, p =.234), suggesting that while job resources may provide some buffer against burnout, this effect was not strong enough to reach statistical significance in the current model, with an alpha value of 0.05. Furthermore, the covariance between *job resources* and *job demands* was significant and negative (z = −0.368, p < .001), indicating an inverse relationship between these constructs. This suggests that higher *job resources* might relate to lower *job demands*, supporting the buffering hypothesis of the JD-R model. However, it is important to note that the JD-R model's third assumption postulates when employees have many job resources available to them, their ability to manage high demands is improved (Bakker et al., 2005). This interaction with job demands is *dependent on the specific job characteristics of that work environment* (Bakker et al., 2005). Bakker, Demerouti, and Euwema (2005) tested this assumption by evaluating the interactions between specific combination of job-related demands and job-related resources and burnout among 1,018 educational employees. Bakker and colleagues (2005) were able to demonstrate the interaction was highly dependent upon the combination of the resources and demands.

Limitations of the Findings

The present study results not only affirm the relationships stipulated in the theoretical framework but also offer robust insights into the interplay between job demands, job resources, and burnout in CRNAs practicing in the United States. This lays a fertile ground for future research to build upon, potentially leading to targeted interventions aimed at mitigating burnout among CRNAs. However, there are important limitations that must also be considered when drawing conclusions and conducting future research.

1. **Limited survey response rate**. The survey response rate (5.2%) was less than the National average (9%). The lack of response raises concerns about the generalizability of the present study to the larger CRNA population and the ability to achieve appropriate sample size for statistical significance. For example, inadequate sample sizes in SEM methodology have a negative impact towards fit indices (i.e., chi-squared and goodness-of-fit indices), model estimators, model complexity, multivariate normality assumptions, and variable independence (Jobst et al., 2023; Kyriazos, 2018).
2. **Years of experience variance**. Overall, the current study had similar demographic characteristics to previous studies, with the exception of the current study having a higher mean in years of experience, greater than 26 years compared to 15.6–18.5 years. There are limited studies evaluating the relationship between demographics and burnout, however, the few studies (Nyssen et al, 2003; Boyd & Poghosyan, 2017) have posited an inverse relationship between years of experience and burnout which makes this a plausible reason for impacting the current study.
3. **Pooling of job-related factors**. It is worth noting that conclusions regarding the relationship between job resources and job demands and burnout may be limited by how a few of the specific work characteristics (i.e., *workload, colleague support, supervisory support,* and *job control*). Specifically, several of the measures (JDRS and JCQ) captured several job characteristics within its subscale. For example, the JDRS *organizational support* measure measured both supervisory and colleague support. Social support or interpersonal support has been demonstrated to be an effective job-related resource towards management of burnout (Ng, & Sorensen,

2008). Social support or interpersonal support includes colleague and supervisory support. A review by Ng and colleagues (2008) demonstrated these characteristics can be perceived differently. Therefore, when two different job-related characteristics are pooled under one scale, the ability to differentiate the two is convoluted.

4. **Environmental influences**. The study was conducted in the respondents own natural environment without any influences from the researcher, however, we cannot rule out the impact of events that occur in the participants environment may impact the conditions of the study (i.e., historical effect). The study hypotheses were based on common themes from previous studies evaluating the relationship of job-related characteristics and burnout in CRNAs. However, since the start of this study, CRNAs have faced, and continue to face, additional work-related challenges due to the COVID-19 pandemic. Researchers (see Aron et al, 2021; Prasad et al., 2021) have demonstrated that the increased constraints faced by healthcare providers have resulted in a drastic increase in occupational strain, such as burnout. The specific variables were based on previous studies (Elmblad et al., 2014; Hyman et al., 2014; Lea et al., 2022; Mahoney et al., 2020; Shah et al., 2019; & Vells et al., 2021), prior to the impact of the pandemic.
5. **Sample size**. Inadequate sample sizes in SEM methodology have a negative impact towards fit indices (i.e., chi-squared and goodness-of-fit indices), model estimators, model complexity, multivariate normality assumptions, and variable independence (Jobst et al., 2023; Kyriazos, 2018). To date, there continues to be a lack of consensus and often conflicting guidance for researchers regarding sample size requirements and analysis (Jobst et al., 2023; Wolf, Harrington, Clark, & Miller, 2013).

6. **Model fit indices**. Fit indices compare the hypothesized model to a baseline model (Hair et al., 2018). Fit indices are primarily used to minimize statistical errors (Type I and Type II). The recommendation is for researchers to use a combination of fit indices (Kumar & Kumar, 2015). However, there remains a lack of consensus on appropriate cutoff scores and management for goodness of fit measures with some researchers advocating for a more nuanced interpretation that takes into account the complexity of the model and the theoretical relevance of the constructs. (Kumar & Kumar, 2015; Marsh et al., 2004).

Recommendations

Despite the limitations mentioned above, the survey provided additional evidence that not only do job demands have a direct impact on burnout, but that the complex relationship between job resources, job demands, and burnout may not be fully understood. This study lays a fertile ground for future research to build upon, potentially leading towards an increased understanding and management of this syndrome. Several recommendations towards navigating the ability to advance the knowledge and management of burnout are found below.

1. **Improving response rates**. Additional research similar to the current study are a crucial first step. As indicated in the limitations, the current study faced below National average response rates. Several recommended steps may help alleviate this challenge. First, the sampling strategy consisted of a stratified random sampling method through the AANA listserv. Although this is a convenient method, historical response rates are well below a national representation. Additional sampling strategies such as nonprobability snowball sampling and convenience sampling strategies should be considered. Second, the current study used an 82-item survey that

took over 10 minutes complete. Although the psychometric properties of the individualized measures were well validated, it came at the cost of a 24% response dropout rate. Future studies need to find the balance between measures that have strong psychometric properties with appropriate survey length. Additional strategies should include monetary compensation, oversampling, and survey participant follow-up that is outside the strict guidelines set by the AANA Department of Research.

2. **Theoretical framework implications**. To date, many of the studies evaluating burnout in the nursing specialty are not grounded in a theoretical framework. Meaning, they do not use a theoretical model of burnout that hypotheses are developed and tested which, in turn, creates challenges in variables selected, interpretation of the empirical results, and raising questions regarding if the study's results are by chance or consistent with other similar studies. The ongoing disagreement related to the conceptualization and measurement of burnout continue to challenge the ability to identify and manage the syndrome. Theoretical models allow for researchers to reduce the complexity of a concept like burnout to allow for empirical and theoretical testing of hypotheses relative to that industry. Rigorous research that incorporates strong theoretical and statistical methods towards understanding the prevalence and risk factors to CRNA burnout is urgently needed.
3. **Multilevel burnout understanding**. The JD-R model outlines the multilevel influence of job demands and job resources within a work environment (Bakker, 2018). Although burnout research is at the individual level, the primary factors are predicated on organizational factors. This creates a scenario in which employees have rate limited influence over the management of high demands. However, research has

indicated there is a degree of cross-level interaction effect that warrants further investigation (Bakker, 2018). Beyond the expanding of increased burnout sampling, future research should also focus towards understanding the multilevel impact of the work environment and CRNA wellbeing.

4. **Interventional strategies**. The negative effects of burnout have led to scholars and healthcare stakeholders calling for interventional strategies in alleviating provider burnout. These strategies have included organization-directed or individual-directed or a combination of both. Unfortunately, various intervention strategies (organization-directed, person-directed, person/organization combination) have demonstrated mixed results (Awa et al., 2009; Hall, et al., 2016). For example, Awa and colleagues' (2010) review of 25 interventional studies found 80 percent were effective in alleviating burnout, however, the review by Westermann and colleagues (2012) found minimal effectiveness from the 16 interventional studies evaluated. In an ideal situation, most researchers and administrators would indicate to first understand the extent (prevalence) and impact of burnout prior to trying to manage it. However, the evidence continues to demonstrate the need for strategies focused at alleviating the strain placed on current healthcare providers. Strategies should work in a parallel process often seen in lean six sigma process improvement methods—Define, Measure, Analyze, Improve. Define through theoretical understanding of the conceptualization of burnout. Measure by ongoing research that evaluates beyond the CRNA level. Analyze the impact of the job characteristics. Improve by implementation of interventional strategies recommended by NASEM (2019) that take a systems level approach and are both individual (i.e., access to employee

wellness programs, support groups) and organizational (i.e., technology solutions, reduction of administrative burden, increase job control).

5. **National policy recommendations**. Burnout is widely recognized as a direct occupational hazard for healthcare providers (Morais et al., 2006; Schaufeli et al., 2017). Existing research has demonstrated that burnout has negative effects on the healthcare system in its entirety (Schaufeli et al., 2017). It was estimated that between 35% and 54% of nurses and physicians in the United States were suffering from burnout (National Academies of Sciences, Engineering, and Medicine [NASEM], 2019). This provides further evidence of burnout's far-reaching impact and the needed attention from a national policy level. The National Academy of Medicine (NAM) and Surgeon General have published reports (NASEM, 2019; Murthy, 2022) recognizing the negative impact burnout has on the provider and the urgency to find solutions in its management. Recommendations towards appropriate management of burnout should take a systems level approach that encompasses healthcare organizations, policy makers, insurers, and other key stakeholders. The policy changes such as strategies to increase recruitment and retention of staff, address policies that create challenges for employees seeking mental health and substance use care, recruit and expand diverse healthcare workforce, and policies that reward innovation and research.

Implications

The study successfully validated previous research that job demands had a strong association with burnout. However, job related resources did not demonstrate a significant correlation with burnout despite having a stronger correlation with its dimensions compared to job demands. The results provided new knowledge of the complex role that job resources have towards the development of burnout in the nursing specialty.

Implications for Nursing Anesthesia Specialty

CRNAs are a critical part of the anesthesia workforce, responsible for approximately 65% of the anesthetics provided in the United States (Del Grosso & Boyd, 2019). They are often the sole anesthesia providers in rural hospitals and U.S. military. Changes in the healthcare system have resulted in CRNAs managing an aging, complex patient population while faced with increasing time pressure, complex medical technology, and a lack of resources. The growing demands by healthcare facilities for cost-efficient, safe anesthesia services coupled with the challenges created by the pandemic, have led to a further mismatch between job demands and job resources (Aron et al., 2021). However, limited exploratory research towards identification and evaluation of context specific factors and burnout remain. The need for additional research was further highlighted from the current study that demonstrated the significance of job demands as predictors of burnout and highlighted the nuanced role of job resources. The inability to appropriately identify, evaluate, and manage CRNA burnout coupled with the growing administrative and clinical complexities of the U.S. healthcare system may cause further strain on the stability of this nursing specialty that is already facing a critical deficit in workforce numbers, ultimately, resulting in the inability to provide cost-saving, high-quality care to patients in need (Negrusa et al., 2021).

Implications for Healthcare Administration

Negative Outcomes such as intent to quit, increased turnover, workplace aggression, and decreased job satisfaction have been found in CRNAs with moderate to high levels of burnout (Boyd & Poghosyan, 2017; Mahoney et al., 2020). Additional negative outcomes related to burnout includes decreased quality of care and outcomes, as well as decreased patient satisfaction. The widespread negative impact related to burnout warrants further attention from healthcare administration. The complex hierarchal nature of healthcare organizations places providers in an environment with limited control over stressors, thereby limiting the effect of provider-directed strategies (Maslach et al., 2001). Although organizational strategies have demonstrated moderate effects in decreasing burnout, the complexity, and costs to implement them has limited their appeal compared to provider-directed strategies (Awa, et al., 2010). A possible solution to this problem may be found in clinical leadership (e.g. medical leaders, medical supervisors, clinical managers), who are clinicians by trade, but predominantly function in management roles (Fulop et al., 2013). Clinical leaders are considered key factors in modifying work environments that can have positive impact on provider wellness (Bakker, 2018).

Policy Implications

Changes in the healthcare system have resulted in growing demands by healthcare facilities for cost-efficient, safe anesthesia services. The current landscape of healthcare continues to expose its providers to elevated levels of stress that affect healthcare providers' wellbeing, ultimately leading to the experience of burnout. CRNAs' abilities to provide safe, high-quality, and cost-effective anesthesia services have resulted in the nursing specialty being the primary anesthesia provider throughout the United States, including most rural locations. The critical role CRNAs play within the healthcare industry warrants policy level change to help mitigate effects that have system level negative implications. Beyond just organizational and academic interventions, concrete steps towards a better system include reforming policy. For instance, current political structures that create scope of practice and autonomy challenges for

CRNAs need to be addressed. Studies have demonstrated CRNAs that practice in work environments that endorse high levels of autonomy have increased job satisfaction and lower burnout rates (Mahoney et al., 2020).

The impact of burnout continues to gain National attention. In 2019, the National Academy of Medicine published a report, "Taking Action Against Clinician Burnout: A Systems Approach to Professional Well-Being" action was needed towards the management of ongoing burnout epidemic (NASEM, 2019). The report highlighted the ongoing prevalence of burnout in healthcare providers and the limited success in interventional approaches. It provided a systems level approach and recommendations that included changing the culture of healthcare, increasing support for providers, investing in research, and enabling technology solutions (NASEM, 2019). A few years following the NAM report, the Surgeon General (Dr. Vivek Murthy) issued a similar call to action in his Surgeon General's Advisory Report (May 2022), declaring the burnout crisis a national priority (Murthy, 2022). This advisory report called for a systems level change that included specific directives for healthcare organizations, insurers, government, training intuitions and other key stakeholders (Murthy, 2022). Initiatives under this report included increased attention towards healthcare provider well-being, removal of administrative burdens, increase access to mental health, increase public health funding, and bring about a culture that supports healthcare provider well-being (Murthy, 2022).

Conclusion

Current healthcare challenges and the integral role CRNAs play in providing cost-effective, high-quality care has increased attention towards evaluating the relationships between job-related factors and burnout within the nursing anesthesia specialty. Despite recent increase in evaluation of burnouts impact on the nursing specialty, there was limited success in its management (Boyd & Poghosyan, 2017; Del Grosso & Boyd, 2019). Thus, the present study was developed to address the theoretical and empirical gaps in burnout among CRNAs in the United States utilizing the JD-R model as a guide towards further understanding of previously identified factors and their relationship to burnout.

The present study was a quantitative exploratory designed to investigate the relationship between job demands, job resources, and burnout among CRNAs actively practicing in the United States. Utilizing the JD-R model as the theoretical framework, this study sought to elucidate how various aspects of the work environment contribute to burnout, characterized by the dimensions of exhaustion and disengagement. The design allowed for the testing of several hypotheses regarding the predictors of burnout and the potential moderating effects of job resources on the job demands-burnout relationship. This methodological approach aimed to provide a path toward identifying appropriate interventions to reduce burnout among CRNAs. The study results not only affirm the relationships stipulated in the theoretical framework but also offer robust insights into the interplay between job demands, job resources, and burnout. This lays a fertile ground for future research to build upon, potentially leading to targeted interventions aimed at mitigating burnout among CRNAs. Overall, the results from these analyses provided insights into the complex interplay between job demands, resources, and burnout among CRNAs.

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APPENDIX A. AANA PERMISSION TO USE PREVIOUS AUTHORED WORK

Karen Sutkus <ksutkus@aana.com> — Jun 1, 2023, 3:05 PM
to Brian, Suzanne

[**Caution**: Email from External Sender. Do not click or open links or attachments unless you know this sender.]

- Authors can cite AANA Journal articles in their own articles without permission. *Cite* means make reference to the article by paraphrasing not using the exact words and then including a superscript citation after the paraphrased content and including AANA Journal and where the original article in AANA Journal may be found in the article's reference list.

You have permission to use parts of your article.

Karen L. Sutkus | PR & Communications Coordinator

AMERICAN ASSOCIATION OF NURSE ANESTHESIOLOGY
CRNA focused. CRNA inspired.
ksutkus@aana.com | 847.655.1140 | aana.com

AANA Annual Congress
August 18-22, 2023
One Team – One Dream
Join us in Seattle, WA, or online for nurse anesthesiology's largest educational event!

APPENDIX B. AANA SURVEY APPLICATION DOCUMENT

American Association of Nurse Anesthesiology
AANA Electronic Survey Policy and Order Form

Version 6-1-22

AANA Electronic Survey Fee Schedule (Continued)

B) Required Fees for Instrument Deployment Only:

(This option is for approved researchers whose instruments are already prepared in a survey tool system, such as SurveyMonkey, Qualtrics, etc.)

1) **$300 setup fee** for sending two emails (one survey invitation, one reminder) to the targeted recipients. The reminders will be sent to **all** recipients. (More than one reminder is not permitted.)

   - **Your email message, cover letter and instrument must be approved first by your IRB and then by the AANA research division.**
   - The cover/reminder letters or survey notes **cannot** indicate or imply that AANA supports or endorses the survey.
   - You must only provide **one survey link** to send to the recipients. Your cover letter (submitted in a Word document) must include this link.
   - AANA reserves the right to **affirm** that the approved instrument, and the survey is closed according to the approved schedule (4 weeks from launch date).

2) **Fee for number of addresses:**

# Addresses	Fee
0 – 1,500	$ 750
1,501 – 2,000	$1,000
2,001 – 2,500	$1,250
2,501 – 3,000	$1,500

***A maximum of 3,000* email *addresses* can be surveyed.** If you wish to request more than 3,000 email addresses justification for the larger sample must accompany this request. Allowing a larger sample size of email addresses is a rare occurrence and driven by the uniqueness of the survey contents and population being studied.

3) **Reminders**: One reminder will be sent one week before the survey closes. Additional reminders are not allowed for instrument deployment only surveys.

C) External Entity Fees: If you are NOT an AANA member, the fees will be different. Please add $500 to the total.

American Association of Nurse Anesthesiology
AANA Electronic Survey Policy and Order Form

Version 6-1-22

SURVEY ORDER FORM, Page 2/6 Name: Brian Del Grosso

SELECTION CRITERIA OF THE SURVEY SAMPLE

SAMPLE SIZE REQUESTED: 3000 (max allowed) [2]**(Number** (Not Range) **Required).**

SELECTING THE MEMBER TYPES OF YOUR SAMPLE: (Select all that apply)

X____ Certified (Passed exam within past 2 years – practicing)
_____ Recertified (Passed exam over 2 years ago – practicing)
_____ Student (Currently enrolled in a nurse anesthesia program)

SELECTING THE PRACTICE SETTINGS AND LOCATIONS OF YOUR SAMPLE: (Select all that apply) [3]

a. X____ All states or _____ Specific state(s) : ____________________

b. Selecting the above states(s) based on (*choose one, not both*):
X_____ State of Residence (Live) or _____ State of Membership (Work[4])

NOTE: Choosing any of the following items may dramatically decrease the email addresses that we can provide. Because these items are not required to be answered on the membership profile, we can only provide those names who have provided this information. We recommend that you refrain from narrowing down your list whenever possible.

c. X_____ Primary Employment Arrangement/Source of Income (the employment arrangement that provides the greatest portion of income): (Select all that apply)

X____ Employee of hospital
X____ Employee of office/clinic
X____ Employee of freestanding surgical center
X____ Employee of surgicenter in other institution
X____ Employee of college/university
X____ Employee of joint CRNA/physician group
X____ Employee of CRNA-only group
X____ Employee of physician-only group
X____ Army
X____ Navy
X____ Air Force
X____ Veterans Administration
X____ U.S. Public Health Service
X____ Owner/partner of CRNA-only group

APPENDIX C. IRB APPROVAL LETTER

CHARLOTTE
DIVISION OF RESEARCH

To:	Brian Del Grosso University of North Carolina at Charlotte
From:	Office of Research Protections and Integrity
Approval Date:	19-Jan-2023
RE:	Notice of Determination of Exemption
Exemption Category:	2
Study #:	IRB-23-0078
Study Title:	Measure the Impact of Burnout among Certified Registered Nurse Anesthetists Practicing in the United States

This submission has been reviewed by the Office of Research Protections and Integrity (ORPI) and was determined to meet the Exempt category cited above under 45 CFR 46.104(d). This determination has no expiration or end date and is not subject to an annual continuing review. However, you are required to obtain approval for all changes to any aspect of this study before they can be implemented and to comply with the Investigator Responsibilities detailed below.

Important Information:

1. Face masks are optional on UNC Charlotte's campus. This includes classrooms and other academic spaces. Researchers conducting HSR activities in other locations must continue to adhere to local and state requirements in the setting where the research is conducted.
2. Face masks are still required in healthcare settings. Researchers conducting HSR activities in these settings must continue to adhere to face coving requirements.
3. Organizations, institutions, agencies, businesses, etc. may have further site-specific requirements such as continuing to have a mask requirement, limiting access, and/or physical distancing. Researchers must adhere to all requirements mandated by the study site.

Your approved consent forms (if applicable) and other documents are available online at Submission Page.

Investigator's Responsibilities:

1. Amendments **must** be submitted for review and the amendment approved before implementing the amendment. This includes changes to study procedures, study materials, personnel, etc.
2. Data security procedures must follow procedures as described in the protocol and in accordance with OneIT Guidelines for Data Handling.
3. Promptly notify the IRB office (uncc-irb@uncc.edu) of any adverse events or unanticipated risks to

APPENDIX D. DISSERTATION CHAIR ENDORSEMENT LETTER FOR AANA SURVEY

The University of North Carolina at Charlotte
School of Social Work
9201 University City Boulevard
Charlotte, NC 28223-0001
School of Social Work
Phone (704) 687-7938
Fax (704) 687-1658

Date: January 24, 2023

American Association of Nurse Anesthesiology
O'Hare International Center
10275 W. Higgins Road, Suite 500
Rosemont, IL 60018

RE: Endorsement letter for the study conducted by Brian Del Grosso

I, Alice Suzanne Boyd, PhD, MSW, ACSW, FNAP, endorse Brian Del Grosso's, MS, CRNA (ID No. 83884) submission of the survey entitled "Measure the Impact of Burnout among Certified Registered Nurse Anesthetists Practicing in the United States" to the American Association of Nurse Anesthesiology Research Department for approval.

Brian Del Grosso successfully defended his dissertation proposal on June 6, 2022. I serve as his dissertation chair. Following the successful defense, an Institutional Review Board proposal was submitted to the UNC Charlotte Institutional Review Board on June 20, 2022, and was approved on January 19, 2023 (IRB-23-0078).

Should you have any questions or need additional information, please feel free to contact me at sboyd@uncc.edu/980.254.5061.

Thank you for your consideration of his survey proposal.

Sincerely,

A. Suzanne Boyd

A. Suzanne Boyd, PhD, MSW, ACSW, FNAP (Dissertation Chair/Advisor)
Program Faculty, Health Services Research Doctoral Program
Program Faculty, Doctorate in Public Health Program
The University of North Carolina at Charlotte
School of Social Work
9201 University City Blvd
Charlotte, NC 28223
Phone: 980.254.5061
Email: sboyd@uncc.edu

APPENDIX E. RECRUITMENT EMAIL AND SURVEY LINK

Subject: You are invited to a research survey, "Measuring the Impact of Burnout among Certified Registered Nurse Anesthetists Practicing in the United States"

Dear CRNA colleague:

My name is Brian Del Grosso, and I am a CRNA and PhD candidate at the University of North Carolina Charlotte in the Health Services Research Doctoral Program. I am inviting you to participate in a research study entitled "Measuring the Impact of Burnout among Certified Registered Nurse Anesthetists Practicing in the United States."

Ongoing changes to the United States Healthcare System coupled with the negative impact of the pandemic place our profession and its providers at risk of burnout. Although recent years have seen an increase in awareness and scholarly inquiry, a theoretical and empirical gap remains in understanding the extent of the relationships between specific organizational characteristics and job-related burnout. The primary objective of this study is to evaluate burnout among certified registered nurse anesthetists (CRNAs) practicing in the USA through the exploration of specific job-related antecedents of exhaustion and disengagement.

This survey has been approved by the Institutional Review Board of University of North Carolina Charlotte (IRB #23-0078). The survey includes a series of demographic and work-environment questions specific to CRNAs. The questions are not sensitive or overly personal. We do not believe you will experience any risk from participating in this study. You may choose not to take part in the study. You may start participating and change your mind and stop participation at any time. It will take you approximately 15 minutes to complete. Privacy and confidentiality will be maintained to the greatest extent possible. Responses will be consolidated and aggregated for each question, evaluated, and reported as overall findings. Responses will be stored separately on password protected file system with access limited to only myself and dissertation committee members. We may share the non-identifiable survey data with other researchers for future research studies among CRNAs without further consent.

You will not benefit personally by participating in this study. However, understanding the relationships between specific organizational characteristics and their relative importance towards CRNA burnout may provide valuable insight towards the specific management of burnout. Therefore, what is learned about these factors that impact CRNA burnout may be beneficial to the CRNA community.

At the end of the survey, you will have an option to participate in a drawing for 1 of 4 $50 Starbucks gift cards. If you choose to participate in this drawing, you will click on a separate link to enter your personal email address. The primary purpose of the link is to separate survey responses with personal identifiers. Email addresses entered for the drawing will be kept in a secured electronic folder and deleted post drawing.

If you have questions concerning the study, please contact either Brian Del Grosso (bdelgros@uncc.edu) or Dr. A. Suzanne Boyd (sboyd@uncc.edu). If you have further questions or concerns about your rights as a participant in this study, contact the Office of Research Protections and Integrity at (704) 687-1871 or uncc-irb@uncc.edu. If you have an active CRNA license and providing anesthesia in the U.S., have read and understand the information provided and freely consent to participate in the study, your informed consent will be presumed by completing this survey.

Doctoral Candidate: Brian Del Grosso MS CRNA, University of North Carolina Charlotte

APPENDIX F. PERMISSION TO USE JOB DEMANDS-RESOURCES SCALE (JDRS)

Permission to Use the JDRS

Report

Brian Del Grosso May 8, 2022

Dr. Jackson (apologies if this is a repeat message - computer cut off and unsure if original message sent),

I hope this email finds you well.

I am a Ph.D candidate working on formalizing my research proposal in order to defend in May/June of 2022. My study is on exploring the impacts specific job-demands and job-resources have on burnout and disengagement within the certified registered nurse profession (CRNA) within the United States. Research around this topic has remained limited and or without a theoretical framework. Therefore, the primary objective of this dissertation is to bridge the gap presented in the literature by using the JD-R perspective to explore the job-related antecedents of burnout specific to CRNAs practicing in the US.

One of the research instruments that I am planning on using is the JDRS. I find the instrument appropriately (naturally) aligns with the JDR model as well as with my research objectives.

As one of the primary authors, I was hoping you would be willing to give permission to use this instrument for my doctoral dissertation. I am willing to share my proposal and or data post study. I appreciate your time in reading this email.

Respectfully,

Brian

Leon T. B. Jackson to you May 10, 2022

Dear Brian, please feel free to use the scale but just share your dataset with me. My email address is leon.jackson@nwu.ac.za

APPENDIX G. PERMISSION TO USE THE WORKPLACE INCIVILITY SCALE (WIS)

Lilia Cortina <lilia@umich.edu> Mon, Jul 4, 2022, 10:38 PM

to me, Suzanne

[**Caution**: Email from External Sender. Do not click or open links or attachments unless you know this sender.]

Thank you for your interest in the Workplace Incivility Scale (WIS). You have my permission to use this scale for research purposes. The full text of the scale (both stem and items) is available in articles published in *Journal of Occupational Health Psychology* and *Journal of Management*. To download copies of those articles, please visit my lab website: https://sites.lsa.umich.edu/liliacortina-lab/.

Best of luck with your project,
Lilia Cortina

--

Lilia M Cortina, PhD
University Diversity and Social Transformation Professor
Department of Psychology
Department of Women's and Gender Studies
Department of Management & Organizations (by courtesy)

Co-Director of ICOS (https://icos.umich.edu/)

Mailing Address: Department of Psychology, 530 Church St, Ann Arbor, MI 48109-1043

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Lilia M Cortina, PhD
University Diversity and Social Transformation Professor
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University of Michigan

Web: https://sites.lsa.umich.edu/liliacortina-lab/

Mailing Address: Department of Psychology, 530 Church St, Ann Arbor, MI 48109-1043

APPENDIX H. PERMISSION TO USE THE JOB CONTENT QUESTIONNAIRE (JCQ)

JCQ CENTER GLOBAL
Karasek Job Content Questionnaire

Invoice and information and policies for using a JCQ Center instrument
An order has been created for you on JCQ Center Global ApS.

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Reg.#: 3409 Account #: 3409154077
IBAN number DK0330003409154077

SWIFT: DABADKKK

Thank you for your interest and your detailed answers to our questions about your use of the JCQ Center instrument = Usage Request Information A-G.

We find your project interesting and hope your research process is successful and we would like to thank you for joining our active community of over 1,000 registered JCQ 1.0 Users. The network has spanned the globe for two decades and supported countless research and practical contributions to the field, allowing you many references to work of other researchers and practitioners in our field.

License number 67427508504 date may 30. 2022

APPENDIX I. PERMISSION TO USE THE COLLABORATION AND SATISFACTION ABOUT CARE DECISIONS (*CSACD*)

Judith Baggs <baggsj@ohsu.edu> Mon, May 30, 2022, 6:48 PM
to me

[**Caution**: Email from External Sender. Do not click or open links or attachments unless you know this sender.]

Dear Mr. Del Brosso,

You are welcome to use the instrument.
I have attached three versions of it, a list of related references, and the original psychometric article.
I have five requests:

1. If you want to make any changes in the instrument, please send me a copy of your proposed revisions before using it
2. If you publish, cite my work appropriately
3. If you publish, do not publish the instrument so that I can maintain copyright and continue to share
4. If you publish, please send me the citation so that I may add it to my reference list
5. Let me know what you find out.

Best wishes,
Judith Baggs

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APPENDIX J. PERMISSION TO USE THE OLDENBURG BURNOUT INVENTORY (OLBI) MEASURE

Demerouti, Evangelia <E.Demerouti@tue.nl> Fri, Apr 1, 2022, 1:41AM
to me, Suzanne

[**Caution**: Email from External Sender. Do not click or open links or attachments unless you know this sender.]

Dear colleague,

I would like to thank you for your interest in the burnout instrument. The OLBI is free of charge for academic purposes and you have my permission to use it.
In the attachment, you can find the OLBI in several languages including English.

If you decide to apply it eventually, please let us know whether the instrument has the same structure in your sample as in the German and the Dutch ones.

For information regarding the validity of the instrument see this publication:
https://www.isonderhouden.nl/doc/pdf/arnoldbakker/articles/articles_arnold_bakker_219.pdf
For information regarding the cutoff scores of the OLBI see this publication:
https://www.tandfonline.com/doi/full/10.1080/00140139.2018.1464667

I look forward to hearing your results. Good luck with your study!

Best regards,

Prof. Dr. Evangelia Demerouti
Chief Diversity Officer TU/e

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