The Influence of Institutional-level Factors on Burnout Among Graduate Nursing Students

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Abstract

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Introduction:

Burnout, stemming from chronic exposure to job-related stress, has long been recognized as a significant concern among healthcare professionals, particularly nurses. With the onset of the COVID-19 pandemic, the spotlight on healthcare workers' experiences has intensified, prompting extensive research into the phenomenon of burnout. While much attention has been directed towards practicing nurses, there has been a notable gap in understanding the impact of burnout on nursing students. A systematic literature review has synthesized existing research, revealing four main themes: the scope of the issue, risk factors, protective factors, and interventions. However, the majority of studies have focused on individual-level factors, highlighting a need for further investigation into how institutional-level factors contribute to burnout among nursing students.

Methods:

This study conducted a secondary analysis of cross-sectional survey data from a larger study on burnout among underrepresented minority (URM) graduate health professional students. Factor analysis was employed to streamline the campus climate variables. Descriptive statistics were computed for both the campus climate variables and the Maslach Burnout Inventory (MBI-SS) sub-scores, the dependent variables. Statistical tests, including chi-square and t-tests, were utilized to assess significant differences in score distributions between non-URM and URM, as well as non-first-generation college student (FGCS) and FGCS subgroups. Logistic regression was employed to examine the association between institutional-level variables and scores on the MBI subscales, with regression models expanded to incorporate potential interaction terms.

Results:

This study found that 33.3% of respondents had high-level emotional exhaustion, 15.7% of respondents had high-level depersonalization, and 54.9% of respondents had high-level reduced personal achievement. In relation to institutional-level factors, this study found that higher levels of stress related to the academic environment are correlated with increased feelings of depersonalization among nursing students and that FGCS status exacerbates this relationship. Additionally, it was found that when students perceive the program environment more negatively, their sense of professional achievement tends to decrease and that URM status exacerbates this relationship.

Discussion/Conclusion:

Nursing programs should prioritize the development and implementation of preventive strategies to alleviate stressors within the academic environment and enhance the environment of the nursing program. This entails fostering positive relationships among students and between students and faculty or preceptors. While the broad recommendation to improve the program environment may seem daunting, focusing on helping students cope with their feelings about the program could offer more practical benefits. Additionally, initiatives promoting diversity, inclusivity, and tailored support services for vulnerable student groups, such as URM and FGCS, should be established. Addressing these factors contributing to burnout among nursing students is pivotal for cultivating a resilient and healthier nursing workforce, thereby enhancing patient care quality and healthcare system efficiency.

Contents

I. Introduction

Burnout is a work-related stress syndrome resulting from chronic exposure to job stress.[1] Burnout among nurses and nursing students has been the subject of extensive research and scholarly investigation, leading to a robust body of literature that illuminates the multifaceted nature of this pervasive issue.[2] Nursing has long been recognized as a physically, emotionally, and psychologically demanding profession.[3,4] Likewise, nursing students, while in the process of acquiring the skills and knowledge necessary for their future roles as healthcare professionals, are not immune to burnout. The confluence of academic demands, clinical responsibilities, and the relentless pace of healthcare environments can leave nursing students vulnerable to the insidious effects of burnout. These effects can include constant fatigue, anxiety and depression, headaches, illness, and decreased quality of life for the individual.[5–7]

The emergence of the COVID-19 pandemic, a global crisis of unprecedented scale, has cast a glaring spotlight on the experiences of healthcare professionals, including nurses. The pandemic has ushered in a new era of challenges for nurses, exacerbating preexisting stressors and introducing novel sources of stress and trauma. The challenges presented by the pandemic, such as the overwhelming patient caseload, limited resources, ethical dilemmas, and heightened risk of infection, have intensified the experiences of burnout among nursing professionals, contributing to an ongoing shortage in the profession.[8] Beyond burnout, issues such as limited enrollment in nursing programs, high demand for healthcare services, an aging workforce, and regulatory challenges further compound the shortage.[9–12]

In the post-pandemic era, it is crucial for educators, researchers, and policymakers to recognize and address the distinct challenges and stressors confronting nursing students, especially amidst the persistent national shortage of nurses. While the pandemic heightened this

shortage, factors such as limited educators, high turnover rates, and uneven workforce distribution are expected to prolong it.[9] To alleviate these shortages, it is essential to bolster the production of new nurses. Addressing burnout among nursing students is pivotal, as it can lead to dropout rates and early career attrition, exacerbating the shortage. Furthermore, mitigating burnout is imperative for maintaining high-quality care and minimizing medical errors in the profession.[13,14]

For the purposes of this study, the subject is graduate nursing students, defined as individuals who have completed a bachelor's degree in nursing (BSN) and are pursuing advanced education and training in nursing at the graduate level, including master's or doctoral programs.

The consequences of burnout are not confined to the individuals experiencing it; they ripple throughout the healthcare system and, ultimately, to the patients these nursing students care for. Ultimately, addressing burnout among nursing students is not just an act of compassion for the student but a vital strategy to ensure the future of our healthcare system.

A. Research Question

How do institutional-level factors, such as college wellness culture, class size and student-to-faculty ratio, diversity and inclusivity initiatives, and support services, affect burnout among graduate nursing students?

B. Conceptual Model

The conceptual model guiding this study was derived from the Maslach Burnout Inventory (MBI). The MBI is the most widely used operational definition and measure in burnout research. Interviews, surveys, and field observations of employees in a wide variety of

"people-oriented" professions, including healthcare, were used to develop this definition and measure of burnout.

Other than the MBI, several measures of burnout are utilized in research and clinical settings. Common measures include the Copenhagen Burnout Inventory, assessing burnout across three dimensions: personal, work-related, and client-related burnout; the Oldenburg Burnout Inventory, measuring burnout through two dimensions: exhaustion and disengagement; the Burnout Clinical Subtype Questionnaire, identifying burnout subtypes such as frenetic, underchallenged, worn-out, and resilient; and the Shirom-Melamed Burnout Measure, which assesses burnout across four dimensions: physical fatigue, emotional exhaustion, cognitive weariness, and tension.[15–18]

The MBI is widely recognized as the leading measure of burnout due to its extensive research base, which has validated it across various populations and contexts, its standardized administration, which ensures consistency and comparability across different studies and settings, and its comprehensive assessment across emotional, cognitive, and behavioral dimensions. The MBI can be broken down into the three dimensions of emotional exhaustion, depersonalization, and a sense of low personal achievement. Emotional exhaustion is a state of feeling emotionally worn-out from accumulated work stress. Depersonalization is characterized by an impaired perception of oneself, of others and/or one's environment, manifesting as an affective-symptomatic lack of empathy. Finally, reduced personal achievement refers to a decline in feelings of competence and successful achievement in work.[1] For the purposes of this study, it was these three dimensions, emotional exhaustion, depersonalization, and low personal achievement, that were used to measure burnout among the nursing student respondents.

C. Literature Review

While there has been considerable attention paid to the effects of the COVID-19 pandemic on the burnout of practicing nurses, the same level of scrutiny has not been extended graduate nursing students or even to nursing students more generally. Although the available dataset limits this study to the graduate nursing student population, the issue of burnout is pervasive throughout the entire nursing student population. To address this critical gap in knowledge, I conducted a systematic literature review to explore the landscape of burnout among nursing students in the context of the COVID-19 pandemic and its aftermath.

It is important to note that this literature review focused on nursing students in general rather than graduate nursing students, which are the subject of this study. There was not enough published literature on burnout among graduate nursing students to perform a comprehensive review and thus the search was broadened to include nursing students more generally. This presents a limitation, however I have no reason to believe the experiences of graduate and undergraduate nursing differ significantly. While there may be some differences between graduate and undergraduate nursing programs, there are also many commonalities in terms of a core curriculum, clinical experiences, professional standards, faculty expertise, interdisciplinary collaboration, and clinical practice expectations that contribute to similarities in the educational experiences of nursing students at different levels. For instance, nursing education is guided by professional standards and accreditation requirements set forth by organizations such as the American Association of Colleges of Nursing (AACN) and the Commission on Collegiate Nursing Education (CCNE). These standards help ensure consistency and quality in nursing education across different programs and levels. Similarly, nursing students at both the undergraduate and graduate levels are typically held to the same standards of practice

and professionalism when it comes to clinical care. Regardless of educational level, nursing students are expected to adhere to ethical principles, maintain patient confidentiality, communicate effectively, and provide safe and competent care under the supervision of clinical instructors.

The key search words and terms included nursing students, nursing education, nursing programs, BSN programs, burnout, emotional exhaustion, moral distress, and moral injury. These terms were combined using Boolean operators (OR, AND) to ensure a comprehensive search was conducted. Studies were identified in the PubMed and CINAHL electronic bibliographic databases. These two databases were selected for their prominence in nursing research, offering access to a vast repository of articles totaling 35 million, thereby ensuring a comprehensive review of available literature in the field.[19] Using concept-related terms, I performed searches of the title, keyword, and abstract to identify all relevant articles.

Articles published online between January, 2018 and October, 2023 were included and reviewed based on the following inclusion criteria: (a) conducted in the United States; (b) primarily addressed nursing student burnout, (c) published in English, and, (d) underwent peer review. The dates of publication were chosen to capture the latest trends on nursing student burnout given the context of the COVID-19 pandemic.

Articles were excluded after title and abstract screenings because duplicates were removed, as well as articles that were not relevant to the research question or topic area and/or articles that fell outside of the scope of this review. A total of 550 articles were identified, with 533 remaining after duplicates were removed. After title screening, 471 articles were excluded. The remaining 62 articles were screened by abstract, and 37 articles were excluded. The full-text review was conducted on 25 articles of which 19 were excluded for not meeting the inclusion

criteria. Articles were excluded because they had not been set in the U.S. (n = 8), they did not use a quantitative method (n = 2), they did not measure burnout (n = 6), they did not include undergraduate nursing students (n = 2), and the study has not yet been completed (n = 1). Additional articles were added from citation searching (n = 2) of articles that full-text review was conducted on. The remaining 8 articles were included in the study.

This review synthesized existing literature to shed light on the scope of the problem, risk and protective factors, and interventions to prevent and reduce burnout among nursing students in the era of COVID-19, ultimately contributing to a more comprehensive understanding of burnout in the nursing profession.

1. Scope of the Problem

In relation to scope of the problem, Melnyk et al. found that 63% of nursing students at the Big 10 Universities, which included the University of Illinois, Indiana University, the University of Iowa, Michigan State University, Ohio State University, Pennsylvania State University, Purdue University, the University of Maryland, and the University of Wisconsin, screened positive for burnout using the emotional exhaustion dimension of the MBI.[20] With a majority of nursing students screening positive for emotional exhaustion, this was the highest prevalence of burnout found among nursing students in this literature review. McKee-Lopez et al. found a lower prevalence of emotional exhaustion among upper-division BSN students at the University of Texas at El Paso with 22% of nursing students scoring moderate to high-level emotional exhaustion. Similarly, 24% of students scored moderate to high-level depersonalization. In comparison to the two other dimensions of the MBI, there was a higher prevalence of reduced personal achievement with 37% of students scoring moderate to high-level reduced personal achievement.[21]

Gibson et al. found that a majority of students at the University of Texas at Tyler reported moral distress ranging from mild to uncomfortable with a median score of 2.73 on the moral distress thermometer (MDT). The MDT measures moral distress, which is a slightly different but related concept to burnout. MDT scores are on a scale of 0 ("none") to 10 ("worst possible").[22] A score of 2.73 on the MDT would indicate some level of discomfort, frustration, or anguish related to moral conflicts or ethical dilemmas in one's professional role. While this MDT score is not severe, it still signifies a notable degree of distress that may warrant attention and support to address the underlying issues. Paidipati et al. found a similar MDT mean score of 2.14 among a national sample of nursing students.[23]

2. Risk Factors

The literature review revealed a multitude of contributing factors that significantly affect burnout for nursing students. Melnyk et al. found that significant predictors of burnout include having less than 7 hours of sleep per night, as well as having had sleep and/or exercise that had been negatively impacted by the COVID-19 pandemic.[20] Additionally, Jones et al. found that students at a private university in California who spent more time per week on homework and studying for exams tended to have more depersonalization. However, both students who spent 16-20 hours and those who spent less than five hours studying for exams per week reported more emotional exhaustion and reduced personal achievement, suggesting external factors may be influential. For instance, students between the ages of 24 and 33 were the most emotionally exhausted, on average, suggesting that age may be a more significant risk factor for burnout.[24]

McKee-Lopez et al. found that the number of adverse childhood events (ACEs) reported by participants had a significant positive association on burnout levels, specifically emotional exhaustion, as well as severity of depressive symptoms. ACEs encompass chronic,

unpredictable, and stress-inducing events experienced by certain individuals during childhood. These stressors include poverty, abuse or neglect, parental substance abuse or mental illness, and exposure to violence. Gender greatly impacted this association, where, as compared to males, females with higher ACE scores were more likely to report higher emotional exhaustion.[21] This suggests that the impact of ACEs on burnout may vary based on gender, with females potentially being more vulnerable to the effects of childhood adversity on emotional well-being in adulthood. Melnyk et al. also found that depression, anxiety, stress, and burnout were significantly correlated with each other.[20] This correlation implies that these mental health issues tend to co-occur, underscoring the interconnectedness of mental health concerns and highlighting the importance of addressing them comprehensively in healthcare interventions and support systems. Adding to this, Paidipati et al. found that the relationship between moral distress and suicide risk was fully mediated by depression suggesting that nursing students experiencing moral distress are more likely to develop depression, which in turn elevates their risk of suicidal thoughts or behaviors.[23]

3. Protective Factors

Moral courage and moral resilience can neutralize the effects of moral distress.[25] Moral courage is the ability to stand up for and practice that which one considers ethical, moral behavior whereas moral resilience is the capacity of a person to sustain, restore or deepen their integrity in response to moral complexity, confusion, distress, or setbacks.[25,26] Even though Gibson et al. found high rates of moral distress, they also found the mean moral courage score to be 88.15 which indicates high professional moral courage. The mean moral courage score, although being applied to nursing students, was elicited on the Moral Courage Scale for Physicians (MCSP). This indicates that despite facing challenging , such as ethical dilemmas or

conflicting values, that may evoke moral distress and, subsequently, burnout, the respondents showed courage and willingness to act in accordance with their moral principles. Students' moral resilience was lower than their moral courage with a mean score of 78.44 as measured on the Connor-Davidson Resilience Scale (CD-RISC), suggesting that students may have faced challenges or adversities that tested their ability to bounce back from moral dilemmas or stressful situations related to ethical decision-making. Moral resilience was significantly positively correlated with moral courage, age, and students having a previous degree. Although, the range of responses for both moral courage and moral resilience was wide indicating high variability within the sample population. This underscores the importance of considering and analyzing this diversity to gain a comprehensive understanding of the phenomenon being studied.[22]

College wellness culture (the collective attitudes, behaviors, and practices related to health and well-being within a college community) emerged as a protective factor. Melnyk et al. found that a higher perceived college wellness culture was associated with less depression, less anxiety, lower stress, and less burnout, although with small effect sizes. Similarly, higher student self-ratings of "I matter to my college" were associated with less burnout.[20]

Although Jones et al. found that hours spent studying was a risk factor for burnout, the study also found that students who studied between 6-10 hours per week and more than 20 hours per week reported higher levels of personal achievement, compared to students who studied between 1-5 hours per week. Students who devoted more time to homework and studying tended to experience higher levels of depersonalization. However, spending too few hours (1-5 per week) on studying may limit personal achievement.[24] There appears to be an optimal study time range for nursing students in this context. Nursing students may benefit from balancing their

study time to achieve a sense of personal achievement while considering potential trade-offs such as stress, fatigue, and burnout associated with excessive study time.

Certain recreational activities were found to help students cope with the stresses of their academic programs and work. Meditation, regular walking, and camping were found to be negatively correlated with exhaustion levels.[24]

4. Interventions

In relation to interventions to prevent and reduce burnout, Peterson et al. and Lanz conducted pilot studies to examine the effects of their respective interventions. Peterson et al. 's intervention consisted of an 8-hour online stress awareness course and an in-person 1-hour support group for nursing students at Colorado University. Peterson et al. found that post-intervention students' level of burnout decreased.[27] Lanz's intervention consisted of 5 weekly in-person group meetings teaching resilience to first-year nursing students at a Midwest university. Lanz, who had utilized a randomized control trial design, found that neither group reported significant changes in resilience or the burnout dimension of depersonalization. The burnout dimensions of emotional exhaustion and reduced personal achievement significantly decreased in the intervention group, but not the control group.[28] The findings from these two studies imply that interventions can be effective at preventing and reducing burnout among nursing students. Although, it would seem as though interventions are still in the early stages of being implemented as Cochran et al. found that no nursing schools regularly screened their students for burnout and only 9% of undergraduate nursing programs have a formal curriculum that included training in resilience.[29]

Overall, the studies show a need for evidence-based interventions such as training or curriculums in nursing programs that increase awareness of stress and build resilience in order to

mitigate the impact of stress, prevent burnout, and support nursing students.[22–24,27,28] Faculty also need to be educated on burnout among students.[21] Nursing programs should nurture a strong wellness culture to improve the mental and physical health of faculty, staff, and students.[20]

Most of the factors under study were individual-level (e.g. age, sleep, ACEs, physical and recreational activity, time spent on homework and studying for exams, moral courage and moral resilience). There is a gap in the knowledge base on institutional-level factors (e.g., college wellness culture, class size and student-to-faculty ratio, diversity and inclusivity initiatives, support services) affecting nursing student burnout, which is what my research will explore.

II. Methods

A. Study Design

This study is a secondary data analysis of data collected as part of a study on burnout among underrepresented minority (URM) graduate health professional students. The original URM study conducted a cross-sectional survey from February-June 2020.

This study was deemed not human subjects research by the University of Washington Institutional Review Board (STUDY00019300).

B. Recruitment and Data Collection

To recruit participants, the original study team recruited from all accredited nursing, dentistry, occupational therapy, pharmacy, and physical therapy programs in the U.S. that were classified as Minority Serving Institutions (MSIs) and a randomly selected sample of a matching number of Predominantly White Institutions (PWIs) from the same U.S. census division. The

authors then sent a series of study invitations and reminders to program directors or deans requesting that they forward the invitation and survey link to their students.

To be eligible to participate in the URM study, students had to be enrolled in a master's or doctoral level health professions program. All participants provided informed consent electronically. Participants were incentivized by the chance to win a $100 electronic gift card in a drawing for which an email address was collected. No other identifiable information was collected. Study materials did not mention study aims or focus on the perspectives of URM on burnout to reduce response bias and obtain a representative sample. The questionnaire was administered via REDCap (UL1 TR002319). A total of 979 individuals completed the URM survey, of which 611 completed all MBI and campus climate questions. For the purposes of this study, a subset of the data made up of the153 graduate nursing students will be used for analysis. The data was de-identified by the original URM study team prior to me being given access.

C. Measures

1. Dependent variable: Burnout score

The Maslach Burnout Inventory-Student Survey (MBI-SS), an adaptation of the MBI designed to assess burnout in university students, is a validated tool developed to measure burnout in among students.[30] The three dimensions of the MBI mentioned previously make up the three subscales of the score: emotional exhaustion (EE), being overwhelmed by emotions like sadness, frustration, or irritability because of work pressures; depersonalization (DP), feeling disconnected or indifferent towards one's job or the people one interacts with because of feeling overwhelmed or emotionally drained; and low personal achievement (PA), feeling like one's not meeting goals or succeeding in one's job, leading to a sense of disappointment and self-doubt.

Responses to items corresponding with these subscales were provided on a 7-point Likert scale with higher values referencing more frequent occurrences (0 = Never to 6 = Every day).

Example items for the MBI subscales:

- Emotional exhaustion subscale: "I feel tired when I get up in the morning and I have to face another day at the university."
- Depersonalization subscale: "I have become less enthusiastic about my studies."
- Low personal Achievement: "I believe that I make an effective contribution to the classes that I attend."

Using the standardized scoring method outlined in Maslach et al., responses to survey items were grouped by dimension with 5 items making up the EE variable, 5 items making up the DP variable, and 6 items making up the PA variable. Subsequently, each participant's score for the three subscales was calculated.[31] Subsequently, the mean for each subscale was calculated using the number of items in that subscale (EE = 5, DP = 5, PA = 6). In alignment with the original study team, each subscale was transformed into binary variables (high (1) or low (0)) depending on critical boundaries (EE=4.075, DP=4.425, and PA=4.6987) as determined by the following formulas[30]: EE is "high" if EE mean > overall EE mean + (EE standard deviation [SD]*0.50); DP is "high" if DP mean > overall DP mean + (DP SD*1.25); and, PA is "high" if PA mean > overall PA mean + (PA SD*0.10). High EE or DP scores or low PA scores indicated burnout.

2. Independent variables: Campus climate

The authors of the original URM study collected data on student stress, using an adapted version of the campus climate and stress survey developed by Johnson et al.[30] The campus climate and stress survey offers valuable insights into the various factors influencing the experiences and perspectives of a diverse range of individuals on campus.[32] In addition to

student stress, a subset of items in the adapted campus climate and stress survey examine institutional-level factors.

An analysis at the institutional level involves examining how human behavior interacts with the social environment of an organization over an extended period.[33] Broadening this definition, an institutional-level analysis seeks to understand how this environment influences or shapes different activities, whether by enabling them, shaping them in certain ways, or imposing limitations on them. According to this definition, the following items were determined to be institutional level factors: institution status (minority serving or predominantly white) item, perceptions of the campus environment section, feelings of the program environment section, perceptions of the campus environment section, feelings about the campus environment section, academic demands of coursework item (from the Academic Stress section), as well as negative classroom environment, poor relations with instructors, making connections with instructors, difficulty getting the help/advice you need in your program, and lacking connection to your program items (from the Academic Environment stress section). The study team adjusted the campus climate Likert scales' points system to be comparable with the MBI-SS (1 = no stress to 5 = severe stress/1 = no stress to 6 = severe stress). More frequent and/or severe occurrences of stress scored higher.

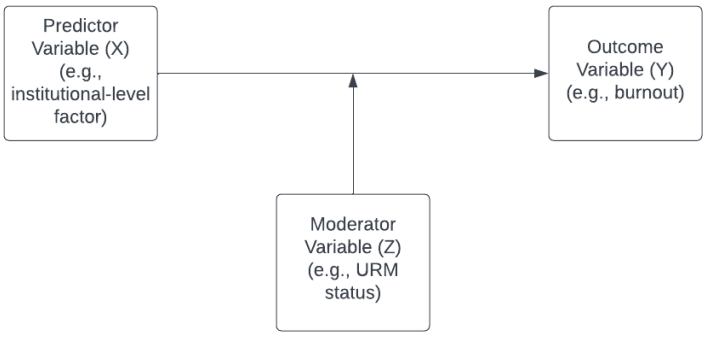
The Kaiser-Meyer-Olkin (KMO) measure is a statistical measure to determine how suited data is for factor analysis. Generally, KMO values between 0.8 and 1 indicate the sampling is adequate. The KMO measure for this dataset resulted in a value of 0.88 and so it was deemed appropriate to perform a factor analysis.

D. Statistical Analysis

There are too many independent variables to perform a regression analysis, and doing so would result in overfitting of the data. Overfitting in hypothesis testing leads to a model capturing noise along with the signal, resulting in invalid inferences about the population. It reduces the power of tests, making it harder to detect true effects, and can lead to misleading conclusions by mistaking noise for meaningful relationships. To circumvent this, I initially performed a factor analysis which allows for the simplification of the set of variables using statistical procedures that explore the underlying dimensions that explain the relationships between the multiple variables.[34] These multiple variables were combined into their underlying dimension, representing new, fewer variables for the purpose of analysis.

For each of the campus climate variables, basic summary statistics such as mean, median, standard deviation, minimum, and maximum were calculated. Similarly, frequencies and percentages for each category (low or high) of the MBI sub-score were calculated. Descriptive statistics were calculated separately for the URM and first-generation college student (FGCS) subgroups. Statistical tests (X^2 and t-tests) were performed to determine if differences between subgroups were significant. Logistic regression was used to evaluate the association of institutional-level variables with scores on the MBI subscales. Odds ratios (OR) and their respective confidence intervals were calculated to interpret the magnitude and direction of the associations between institutional factors and burnout. Additionally, the logistic regression models were extended to include possible interaction terms, including URM and FGCS status, to assess whether the relationship between institutional factors and burnout was contingent on the joint presence of specific factors (Figure 1). Likelihood ratio tests were used to compare models. A significance level of $\alpha=0.05$ was used to determine the statistical significance of the results. All analyses were performed in RStudio.

Figure 1. Flowchart of Interaction Terms/Moderator Variables



III. Results

A. Demographics

Of the 153 respondents, 11.8% identified as Hispanic or Latino, 7.8% as Asian, 6.6% as Black or African American, 2.0% as Native Hawaiian or Other Pacific Islander, 5.2% as two or more races, and 72.6% as White. In total, 24.2% of survey respondents were URM. Of survey respondents, 39.2% were FGCS, 95.4% identified as female, and 3.3% attended a minority serving institution (MSI) (Table 1).

Table 1. Demographics and Background Characteristics of MBI-SS and Campus Climate Survey

	N	%
Ethnicity		
Not Hispanic/Latino	135	88.24%
Hispanic/Latino	18	11.76%
Race		
Asian	12	7.84%
Black/African American	10	6.55%
Native Hawiian or Other Pacific Islander	3	2.00%
Native American or Alaska Native	0	0.00%
Other	9	5.88%
White	111	72.55%
Two or more races	8	5.23%
URM Status		
Non-URM	113	75.84%
URM	36	24.16%
Gender		
Male	5	3.27%
Female	146	95.42%
Other	2	1.31%
First-Generation College Student		
No	93	60.78%
Yes	60	39.22%
Age		
18-24	28	18.30%
25-34	61	39.87%
35-44	37	24.18%
45-54	20	13.07%
55+	7	4.58%
Survey Response Pre- or During Pandemic		
Pre-COVID	74	48.37%
During COVID	79	51.63%
Institutional Designation		
Historically Black Colloege or University	0	0.00%
Minority Serving Institution	2	1.31%
Hispanic Serving Institution	3	1.96%
Predominantly White Institution	52	33.99%
Other/Don't Know	96	62.75%
Year in Program		
1	53	34.64%
2	40	26.14%
3	41	26.80%
4	14	9.15%
5	5	3.27%
Graduation Year		
2020	51	33.33%
2021	53	34.64%
2022	34	22.22%
2023	14	9.15%
2024	1	0.65%

B. Factor Analysis

The null hypothesis for this factor analysis:

Null Hypothesis (H0): There is no underlying factor structure among the campus climate variables in the exploratory factor analysis model.

This null hypothesis implies that the observed relationships between the campus climate variables can be attributed to random variation rather than shared underlying factors. The presence of shared underlying factors, as opposed to random variation, is desirable for this statistical analysis as it allows me to systematically group items. Grouping items reduces the number of independent variables and avoids overfitting of the data. Traditionally, H0 is rejected when the p-value is below 0.05. However, in factor analysis, this outcome suggests an insufficient number of factors. Conversely, conventionally, H0 is not rejected if the p-value surpasses 0.05. Yet, in this scenario, it indicates sufficient factors to encompass the dataset's full dimensionality.[35]

Starting with a model that outputs only 1 factor, factor analyses were consecutively performed, changing the parameters of the analyses to include an additional factor, until a p-value>0.05 was achieved. Including 10 factors in the model was necessary to yield a p-value>0.05 (p-value=0.287). Meaning, when including 10 factors in the model, I reject H_0, that there is no underlying factor structure among the campus climate variables in the exploratory factor analysis model. The sums of squared loadings (SS loadings), or Eigenvalues, are values that represent how much each factor contributes to explaining the variation in the data. Four of the 10 factors output by the factor analysis were not interpreted because the Eigenvalues, were not greater than 1, per Kaiser's rule. This rule states that the number of factors is equal to the

number of factors with Eigenvalues greater than 1.0.[36] The six remaining factors had Eigenvalues between 1.517 and 4.472 explaining 71.2% of the variance. Factor loadings denote the correlation between survey items and factors, with higher loadings indicating a stronger relationship. Higher loadings suggests that the item contributes more to explaining the variance in the data captured by that factor. For a newly developed factor analysis, such as this, factor loadings greater than 0.5 were considered significant (Table 2).[37] Using this cut-off, individual items were grouped within the six factors that had been identified. For a full set of factor loading output, see Appendix A.

Table 2. Selected Factor Loadings

Item	Factor					
	1 - Perceptions of the campus environment	2 - Academic environment stress	3 - Feelings of the program environment	4 - Feelings about the campus environment	5 - Perceptions of the program environment Part 1	6 - Perceptions of the program environment Part 2
(1) "I would describe the overall campus environment as friendly"	0.856					
(2) "I would describe the overall campus environment as respectful"	0.921					
(3) "I would describe the overall campus environment as sensitive to who I am"	0.862					
(4) "I would describe the overall campus environment as supportive"	0.901					
(5) "I would describe the overall campus environment as integrated"	0.726					
(6) "Negative classroom environment"		0.738				
(7) "Poor relations with instructors"		0.876				
(8) "Making connections with instructors"		0.792				
(9) "Difficulty getting the help/advice you need your program"		0.784				
(10) "Lacking connection to your program"		0.7				
(11) "I generally feel comfortable in my degree program"			0.568			
(12) "I generally feel connected to others in my degree program"			0.772			
(13) "I generally feel encouraged by others in my degree program"			0.862			
(14) "I generally feel welcomed by others in my degree program"			0.786			
(15) "I generally feel comfortable on campus"				0.731		
(16) "I generally feel connected to others on campus"				0.764		
(17) "I generally feel encouraged by others on campus"				0.81		
(18) "I generally feel welcomed by others on campus"				0.74		
(19) "I would describe the environment of my degree program as friendly"					0.552	
(20) "I would describe the environment of my degree program as respectful"					0.775	
(21) "I would describe the environment of my degree program as sensitive to who I am"						0.526
(22) "I would describe the environment of my degree program as supportive"						0.691
(23) "I would describe the environment of my degree program as integrated"						0.527

The first factor consisted of five items, accounting for 17.9% of the variance, and was labeled “Perceptions of the campus environment” (PCE). This factor contained items that measure personal perceptions of the environment of the overall campus where a health professional program is located. Included in the term “campus” are experiences, feelings, and perceptions regarding the overall physical campus environment, including with students, faculty, and staff from outside of a health professional program. The second factor consisted of five items, accounting for 15.6% of the variance. This factor was labeled “Academic environment stress” (AES) because these items reflected stress caused by the classroom environment and instructor relationships. The third factor consisted of four items, accounting for 13.5% of the variance. This factor was labeled “Feelings of the program environment” (FPE) because these items reflected personal feelings of the environment of a specific health professional program, including student peers, faculty, and staff. The fourth factor consisted of four items, accounting for 11.8% of the variance, and was labeled “Feelings about the campus environment” (FCE). This factor contained items related to personal feelings of the environment of the overall campus at which a health professional program is located. The fifth factor consisted of two items, accounting for 6.2% of the variance, and was labeled “Perceptions of the program environment Part 1” (PPE1). Generally, the “Personal perceptions of the environment” contained items related to personal perceptions of the environment of a specific health professional program, including peers, faculty, staff. This factor measured the friendliness and respectfulness of a program environment. The sixth factor consisted of three items, accounting for 6.1% of the variance, and was labeled as “Perceptions of the program environment Part 2” (PPE2). This factor measured the sensitivity, supportiveness, and integration of a program environment.

Throughout the aforementioned definitions, "Feelings of…" denotes subjective emotional states like happiness, sadness, anger, or anxiety experienced by individuals. Conversely, "Perceptions of…" refers to individuals' interpretations, understandings, or beliefs about a specific situation, influenced by factors such as personal experiences, biases, cultural background, and contextual elements.

To evaluate goodness-of-fit, a residual matrix was used to assess how well the proposed factor analysis model fits the observed data, whereby numbers in the matrix close to 0 indicated that the factor analysis model was a good representation of the underlying concept (Appendix B).

1. Test for Multicollinearity

Upon determining these factors, the next step was to determine if there is any multicollinearity present. Multicollinearity is when two or more independent variables in a model are highly correlated with each other, making it difficult for the model to distinguish the individual effects of each variable on the outcome. Both correlation matrices and variance inflation factors (VIFs) were utilized to determine if multicollinearity was present. When using a correlation matrix to test for multicollinearity, high correlation coefficients, such as values close to 1 or -1, may indicate multicollinearity. The highest correlation coefficient for the model was 0.73, which represented the correlation between the PPE1 and PPE2 factors (Table 3). Considering these two factors made up the same section of the campus climate survey, a relatively high correlation between these two factors is unsurprising, however their correlation is different enough from 1 to not raise any concerns that the factors are measuring the same phenomenon. When using a VIF to test for multicollinearity, VIF values greater than 1 indicate the presence of multicollinearity, with higher values indicating more severe multicollinearity. A VIF greater than 5 is often considered an indicator of severe multicollinearity. The VIF values

for the EE subscale were: PCE = 1.75, AES = 1.40, FPE = 1.90, FCE = 1.99, PPE1 = 2.19, and PPE2 = 2.70. The VIF values for the DP subscale were: PCE = 1.88, AES = 1.39, FPE = 2.64, FCE = 2.56, PPE1 = 2.54, and PPE2 = 3.01. The VIF values for the PA subscale were: PCE = 1.68, AES = 1.44, FPE = 2.03, FCE = 1.93, PPE1 = 2.40, and PPE2 = 2.84. When taken altogether, there was no evidence of severe multicollinearity.

Table 3. Correlation Matrix of Campus Climate Factors

	PCE	AES	FPE	FCE	PPE1	PPE2
PCE	1.0000	-0.2469	0.4201	0.6108	0.3536	0.5036
AES	-0.2469	1.0000	-0.5123	-0.2570	-0.5775	-0.5353
FPE	0.4201	-0.5123	1.0000	0.5476	0.6552	0.6558
FCE	0.6108	-0.2570	0.5476	1.0000	0.3605	0.5229
PPE1	0.3536	-0.5775	0.6552	0.3605	1.0000	0.7314
PPE2	0.5036	-0.5353	0.6558	0.5229	0.7314	1.0000
Perceptions of the campus environment (PCE), academic environment stress (AES), feelings of the program environment (FPE), feelings about the campus environment (FCE), perceptions of the program environment (PPE)						

C. Campus Climate Factors

Having now aggregated campus climate survey items into the 6 factors that will be used for further analyses, descriptive statistics can be ascertained. Again, 5 and 6-point Likert scales were used to collect data on the campus climate variables (1 = strongly disagree, 5 = strongly agree/1 = strongly disagree, 6 = strongly agree), except for the academic environment stress section. For this section, which collected data on stress caused by the classroom environment and instructor relationships, lower scores on the Likert scale were considered favorable (1 = no stress, 5 = severe stress). Excluding the AES variable, the variable derived from items in the academic environment sections, average scores for the various campus climate factors range from 3.35 for PCE to 4.53 for PPE1 (friendliness and respectfulness) and medians range from 3.60 to 5.00 for those same factors. The average AES score was 0.97 and the median score was

0.80. Two factors, PCE and AES, had scores that ranged from 0.00 – 4.00. For FPE, PPE1, and PPE2 the minimum scores were 0.75, 1.00, and 0.67, respectively, and all had a maximum score of 5.00. The FCE factor had scores that ranged the entirety of the scale, from 0.00 – 5.00 (Table 4).

Table 4. Overall Campus Climate Summary Statistics

Factor	Mean	Median	SD	Min	Max
PCE	3.35	3.60	0.88	0.00	4.00
AES	0.97	0.80	1.02	0.00	4.00
FPE	4.32	4.75	0.86	0.75	5.00
FCE	4.17	4.50	1.03	0.00	5.00
PPE1	4.53	5.00	0.73	1.00	5.00
PPE2	4.22	4.33	0.96	0.67	5.00
Perceptions of the campus environment (PCE), academic environment stress (AES), feelings of the program environment (FPE), feelings about the campus environment (FCE), perceptions of the program environment (PPE)					

Descriptive statistics were calculated separately for the URM and FGCS subgroups. All the mean scores for the URM subgroups were lower than that of the non-URM subgroup, suggesting that individuals belonging to URM tended to have less stress caused by the campus climate compared to individuals in the non-URM subgroup. When comparing the mean scores between the FGCS and non-FGCS subgroups, results were mixed. The mean scores for the PCE, FPE, FCE, and PPE1 variables were higher for the FGCS subgroup compared to the non-FGCS subgroup. However, the mean scores for AES and PPE2 variables were lower for the FGCS subgroup compared to the non-FGCS subgroup (Table 5). T-testing was performed to determine if differences between non-URM and URM as well as non-FGCS and FGCS subgroups were statistically significant, and no significant differences were found.

For all factors, except for AES which is measured differently, the distribution of scores is skewed towards higher scores, for both those with low and high MBI sub-scores. This suggests

that, regardless of burnout score, participants tend to report higher scores on these factors. There is greater range of scores for those with high MBI sub-scores compared to those with low MBI sub-scores. This suggests that individuals experiencing higher levels of burnout may exhibit a wider variation in their scores on these factors compared to those with lower levels of burnout. Similarly, those with high MBI sub-scores have a lower mean score than those with low MBI sub-scores. This indicates that, on average, individuals experiencing higher levels of burnout tend to report lower scores on these factors compared to those experiencing lower levels of burnout.

For a visual representation of the distribution of Campus Climate factors by MBI-SS outcome, see Appendix C.

Table 5. Subgroup Campus Climate Summary Statistics

Factor	Mean			
	Non-URM	URM	Non-FGCS	FGCS
PCE	3.42	3.23	3.28	3.44
AES	0.93	0.99	1.00	0.93
FPE	4.37	4.28	4.30	4.34
FCE	4.25	4.14	4.15	4.20
PPE1	4.56	4.53	4.51	4.55
PPE2	4.27	4.19	4.23	4.19

Perceptions of the campus environment (PCE), academic environment stress (AES), feelings of the program environment (FPE), feelings about the campus environment (FCE), perceptions of the program environment (PPE), underrepresented minority (URM), first-generation college student (FGCS)

D. Burnout Sub-scores

Overall, 33.3% of respondents had a high score for the EE subscale of the MBI-SS, followed by 15.7% for DP subscale, and 54.9% for the PA subscale, for which a low score is considered a positive screen for burnout on that subscale (Table 6). More respondents from the URM subgroup had a high MBI score, for all the MBI-SS sub-scores, compared to the non-URM

subgroup. This suggests that individuals belonging to URM are more likely to experience higher levels of burnout across the various dimensions measured by the MBI-SS, compared to the non-URM subgroup. When comparing the MBI scores between the FGCS and non-FGCS subgroups, the distribution was similar for the EE and DP sub-scores. More respondents from the FGCS subgroup had a high MBI score for the PA sub-scores, compared to the non-FGCS subgroup (Table 7). This suggests that individuals that are FGCS are more likely to experience higher levels of burnout across the PA dimension of the MBI-SS, compared to non-FGCS individuals. Chi-squared testing for independence was performed to determine if differences between non-URM and URM as well as non-FGCS and FGCS subgroups were statistically significant, and no significant differences were found.

Table 6. Overall Maslach Burnout Inventory-Student Survey Subscale Distribution

		Low Score N (%)	High Score N (%)
MBI-SS Subscale	EE	102 (66.67%)	51 (33.33%)
	DP	129 (84.31%)	24 (15.69%)
	PA*	84 (54.90%)	69 (45.10%)
*For PA, a low score is considered a positive screen for burnout on that subscale			
Emotional exhaustion (EE), depersonalization (DP), professional achievement (PA)			

Table 7. Subgroup Maslach Burnout Inventory-Student Survey Subscale Distribution

	MBI-SS Subscale	Subgroup			
		Non-URM	URM	Non-FGCS	FGCS
Low Score N (%)	EE	78 (69.03%)	23 (63.89%)	62 (66.67%)	40 (66.67%)
	DP	97 (85.84%)	28 (77.78%)	78 (83.87%)	51 (85.00%)
	PA*	47 (41.59%)	19 (52.78%)	44 (47.31%)	25 (41.67%)
High Score N (%)	EE	35 (30.97%)	13 (36.11%)	31 (33.33%)	20 (33.33%)
	DP	16 (14.16%)	8 (22.22%)	15 (16.13%)	9 (15.00%)
	PA*	66 (58.41%)	17 (47.22%)	49 (52.69%)	35 (58.33%)
*For PA, a low score is considered a positive screen for burnout on that subscale					
Emotional exhaustion (EE), depersonalization (DP), professional achievement (PA), underrepresented minority (URM), first-generation college student (FGCS)					

E. Model Description

To perform logistic regression, I constructed models using a phased approach, starting with the campus climate factors followed by potential interaction terms. A total of four models were constructed for each of the MBI-SS subscales.

1. All Variables Model

The first model, named the 'All Variables Model', involved fitting a full model which includes all CC factor terms.

2. Pre-selection Model

The second model, named the 'Pre-selection Model' involved fitting terms determined through a pre-selection process. This process involved testing all variables, one at a time, in univariate models and afterwards including in the multivariate model all variables that had shown a significant p-value ($p \leq 0.05$). For the EE subscale, these terms included AES, FPE, FCE, PPE1, and PPE2. For the DP subscale, these terms included AES, FPE, PPE1, and PPE2. The model for the PA subscale included AES, FPE, and PPE1 terms.

3. Backwards Selection Model

The third model, named the 'Backwards Selection Model', involved fitting a full model and slowly removing terms one at a time, starting with the term with the highest p-value. Using this approach for the EE subscale resulted in only one term, PPE1, being included. For the DP subscale, AES and FPE terms were included. For the PA subscale, only one term, FPE, was included.

4. Interaction Model

A fourth model was constructed, named ‘Interaction Model’, that included additional interaction terms deemed significant by a pre-selection process. To test for the presence of interaction terms, models that include one of the two potential interaction terms, URM and FGCS, as well as a third model that includes both interaction terms in the same model were constructed. The coefficients, and subsequently the ORs, change when adding an interaction term. A large change shows value in adding an interaction term to the model.

The null hypothesis for interaction modeling:

Null Hypothesis (H0): There is no interaction effect between the URM and FGCS variables in the logistic regression model, meaning that the relationship between these variables and the log odds of the MBI sub-scores is additive rather than multiplicative.

As there was evidence of statistically significant changes in the ORs when adding an interaction term, I rejected H_0, that there is no interaction effect between the URM and FGCS variables in the logistic regression model. For the EE subscale, there was significant interaction between the FGCS term and the PPE1 and PPE2 terms. The variables associated with these interaction terms for the remainder of analyses are PPE1:FGCS and PPE2:FGCS. There was interaction between the combined FGCS and URM term and the AES term. The variable associated with this interaction term for the remainder of analyses is AES:FGCS:URM. For the DP subscale, there was significant interaction between the FGCS term and the AES and FCE terms. The variables associated with these interaction terms for the remainder of analyses are AES:FGCS and FCE:FGCS. For the PA subscale, there was significant interaction between the URM term and the FPE and PPE2 terms, as well as the FGCS term and FPE term (Table 8). The variables

associated with these interaction terms for the remainder of analyses are FPE:URM, PPE2:URM, and FPE:FGCS. The relationships that showed significance when testing for the presence of interaction terms were added to the full model for their respective MBI-SS subscales.

Table 8.1. Interaction Term Modelling Odds Ratios for the Emotional Exhaustion Subscale

Emotional Exhaustion Subscale						
	Interaction Term Model					
	URM		FGCS		Combined**	
Factor	Null	URM	Null	FGCS	Null	URM & FGCS
PCE	0.72	1.22	1.14	0.21	0.87	1.12E-14
AES	2.01	0.72	1.54	0.44	5.52*	7.40
FPE	0.54	1.29	0.86	1.29	0.10	2.35E-15
FCE	0.61	1.38	0.74	1.42	0.61	8.07E+19
PPE1	1.50	0.49	0.95	0.09*	5.62	4.16E-12
PPE2	1.65	0.66	0.69	6.96*	3.83	2.51E+07
Emotional exhaustion (EE), depersonalization (DP), professional achievement (PA), perceptions of the campus environment (PCE), academic environment stress (AES), feelings of the program environment (FPE), feelings about the campus environment (FCE), perceptions of the program environment (PPE), underrepresented minority (URM), first-generation college student (FGCS), underrepresented minority (URM), first-generation college student (FGCS)						
*Significant at p<0.05						
**The combined model exhibits perfect prediction of the outcome for certain observations, often occurring due to data separation. Although increasing the sample size can mitigate separation issues by introducing more variability, this was beyond the scope of this study. None of the odds ratios in this model reached significance, hence they are omitted from the results section but are presented in these tables for completeness. See Appendix D for Interaction Model Odds Ratios Output.						

Table 8.2. Interaction Term Modelling Odds Ratios for the Depersonalization Subscale

Depersonalization Subscale						
	Interaction Term Model					
	URM		FGCS		Combined**	
Factor	Null	URM	Null	FGCS	Null	URM & FGCS
PCE	0.67	1.34	0.91	2.31	0.35	4.30E-12
AES	1.28	1.14	2.21*	0.77	0.03	9.76E+08
FPE	0.85	0.62	0.71	0.18	120.00	6.87E-11
FCE	0.74	1.61	0.81	14.10*	0.01	2.09E+04
PPE1	2.77	0.48	0.42	6.16	7.51E+04	1.26E+13
PPE2	0.40	1.30	0.84	0.48	0.02	1.55E+09

Table 8.3. Interaction Term Modelling Odds Ratios for the Personal Achievement Subscale

Personal Achievement Subscale						
	Interaction Term Model					
	URM		FGCS		Combined**	
Factor	Null	URM	Null	FGCS	Null	URM & FGCS
PCE	0.34	1.51	0.95	2.79	0.35	4.30E-12
AES	0.96	1.14	1.71	0.59	0.03	9.76E+08
FPE	0.23*	1.61	0.95	0.12*	120.00	6.87E-11
FCE	3.08	0.67	1.12	1.11	5.97E-03	2.09E+04
PPE1	0.24	1.60	0.47	6.97	7.51E+04	1.26E+13
PPE2	5.46*	0.50*	1.15	0.96	0.02	1.55E+09

F. Model Selection and Goodness of Fit

Likelihood ratio testing was performed to assess the goodness of fit of the 'All Variables', 'Pre-selection', and 'Backwards Selection' models. Residual deviance, one of the outputs of likelihood ratio testing, is a measure of how well a logistic regression model fits the observed data by quantifying the discrepancy between the observed response values and the response values predicted by a logistic regression model. A smaller residual deviance indicates a better fit of a model to the data, meaning that a model's predictions closely match the observed outcomes. On the other hand, a larger residual deviance suggests that a model does not explain the data well and may be missing important relationships or patterns.

The residual deviance of the null model was 194.77 for the EE subscale, 132.94 for the DP subscale, and 210.63 for the PA subscale. For all three subscales the 'All Variables Model' had the least residual deviance. The residual deviance was 176.97 for the 'All Variables Model' of the EE subscale compared to 180.03 for the 'Backwards Selection Model', the worst performing model. Similarly, the residual deviance was 108.03 for the 'All Variables Model' of the DP subscale compared to 110.4 for the 'Backwards Selection Model'. The residual deviance

was 200.08 for the ‘All Variables Model’ of the PA subscale compared to 203.63 for the ‘Backwards Selection Model’.

The ‘All Variables Model’ exhibited the least residual deviance across all three subscales, making it the chosen model for reporting odds ratios (ORs), conducting post-estimation exploration, and integrating significant interaction terms to form the aforementioned ‘Interaction Model’. After constructing the ‘Interaction Model’, it demonstrated lower residual deviance compared to the next best performing model, the ‘All Variables Model’. This suggests that the ‘Interaction Model’ offers a better fit, although only slightly, as indicated in Table 9. However, even the best performing model, the ‘Interaction Model’, has high amounts of residual deviance for all of the MBI subscales. Large amounts of residual deviance suggests that the models do not fit the data well. Specifically, it indicates that the models are unable to explain a significant portion of the variance in the response variable.

Table 9. Residual Deviance

		Residual Deviance	
		Null	Under the Model
MBI-SS Subscale	Model		
EE	All Variables Model	194.77	176.97
	Pre-selection Model		176.98
	Backwards Selection Model		180.03
	Interaction Model	187.29	167.65
DP	All Variables Model	132.94	108.03
	Pre-selection Model		109.41
	Backwards Selection Model		110.4
	Interaction Model	132.94	101.76
PA	All Variables Model	210.63	200.08
	Pre-selection Model		201.92
	Backwards Selection Model		203.63
	Interaction Model	204.61	182.59
Emotional exhaustion (EE), depersonalization (DP), professional achievement (PA)			

G. Regression Output

The odds ratios (ORs) for each of the campus climate factors in the 'All Variables Model' are reported below. ORs quantify the association between burnout, the event, and the campus climate factor, the exposure, comparing the likelihood of burnout occurring among those with higher campus climate scores to that among those with lower campus climate scores. An OR greater than one indicates a higher likelihood of the event with exposure, while an OR less than one suggests reduced odds of the event occurring with exposure.[38]

1. PCE Term

The 'All Variables Model' was the only model to include the PCE term. The ORs for this term were 0.98 for the EE subscale, 1.07 for the DP subscale, and 1.04 for the PA subscale, although none of the ORs for this term were statistically significant and will thus not be interpreted.

2. AES Term

The AES term was included in both the 'All Variables Model' and the 'Pre-selection Model', as well as the DP subscale of the 'Backwards Selection Model'. In both the 'All Variables Model' and the 'Pre-selection Model', the OR for this term was 1.27 for the EE subscale. For the DP subscale, ORs ranged from 1.76 - 1.93, and for the PA subscale, the OR = 1.31 for the 'All Variables Model' and 1.30 for the 'Pre-selection Model'. While these ORs were not statistically significant, the OR for the AES variable of the DP subscale in the 'All Variables Model', which was 1.76, was statistically significant (p-value = 0.035). This can be interpreted as the odds of having a high DP score are predicted to grow about 1.76 times larger for each additional point on the AES score.

3. FPE Term

The FPE term was included in the 'All Variables Model', the 'Pre-selection Model', as well as the DP and PA subscales of the 'Backwards Selection Model'. The OR for this term was 0.78 for the EE subscale, in both models. ORs ranged from 0.54-0.70 for the DP subscale and from 0.53-0.64 for the PA subscale. While these ORs were not statistically significant, the OR for the FPE variable of the PA subscale in the 'All Variables Model', which was 0.53, was statistically significant (p-value = 0.049). This can be interpreted as each additional point on the FPE score is associated with a 47% decrease in the odds of a respondent having a high PA score. The OR for the 'Backwards Selection Model' of the DP subscale (0.58) was statistically significant, however as it was not the selected 'All Variables Model', this OR will not be interpreted.

4. FCE Term

The 'All Variables Model' includes the FCE term, as well as the EE subscale for the 'Pre-selection Model'. The ORs for this term in the 'All Variables Model' were 0.89 for the EE subscale, 1.46 for the DP subscale, and 1.24 for the PA subscale. Like the 'All Variables Model', the OR for the 'Pre-selection Model' of the EE subscale was also 0.89, although none of the ORs for this term were statistically significant (Table 10).

5. PPE1 Term

The PPE1 term was included in both the 'All Variables Model' and the 'Pre-selection Model', as well as the EE subscale of the 'Backwards Selection Model'. The OR for this term was 0.51 for the EE subscale, in both the 'All Variables Model' and 'Pre-selection Model', and 0.38 for the 'Backwards Selection Model'. The OR for the 'Backwards Selection Model' of the EE subscale (0.38) was statistically significant, however as it was not the selected 'All Variables

Model', this OR will not be interpreted. For the DP subscale, the OR = 0.97 for the 'All Variables Model' and 0.87 for the 'Pre-selection Model'. For the PA subscale, the OR = 0.97 for the 'All Variables Model' and 1.07 for the 'Pre-selection Model'. Apart from the OR for the 'Backwards Selection Model' of the EE subscale, none of the ORs for this term were statistically significant.

6. PPE2 Term

The 'All Variables Model' includes the PPE2 term, as well as the EE and DP subscales for the 'Pre-selection Model'. The ORs for this term in the 'All Variables Model' were 1.14 for the EE subscale, 0.70 for the DP subscale, and 1.13 for the PA subscale. The OR for the 'Pre-selection Model' was 1.13 for the EE subscale and 0.79 for the DP subscale, although none of the ORs for this term were statistically significant.

Table 10.1. Logistic Regression Odds Ratios for the Emotional Exhaustion Subscale

Factor	EE OR (95% CI)		
	All Variables Model	Pre-selection Model	Backwards Selection Model
PCE	0.98 (0.58-1.78)		
AES	1.27 (0.83-1.95)	1.27 (0.83-1.95)	
FPE	0.78 (0.42-1.45)	0.78 (0.42-1.45)	
FCE	0.89 (0.55-1.48)	0.89 (0.58-1.39)	
PPE1	0.51 (0.22-1.13)	0.51 (0.22-1.13)	0.38 (0.21-0.64)*
PPE2	1.14 (0.62-2.18)	1.13 (0.63-2.13)	
Emotional exhaustion (EE), depersonalization (DP), professional achievement (PA), perceptions of the campus environment (PCE), academic environment stress (AES), feelings of the program environment (FPE), feelings about the campus environment (FCE), perceptions of the program environment (PPE)			
*Significant at p<0.05.			

Table 10.2. Logistic Regression Odds Ratios for Depersonalization Subscale

Factor	DP OR (95% CI)		
	All Variables Model	Pre-selection Model	Backwards Selection Model
PCE	1.07 (0.51-2.79)		
AES	1.76 (1.04-3.01)*	1.78 (1.06-3.00)	1.93 (1.19-3.16)*
FPE	0.54 (0.23-1.22)	0.70 (0.35-1.38)	0.58 (0.32-0.997)*
FCE	1.46 (0.69-3.48)		
PPE1	0.97 (0.36-2.56)	0.87 (0.35-2.12)	
PPE2	0.70 (0.31-1.62)	0.79 (0.40-1.67)	

Table 10.3. Logistic Regression Odds Ratios for Personal Achievement Subscale

Factor	PA OR (95% CI)		
	All Variables Model	Pre-selection Model	Backwards Selection Model
PCE	1.04 (0.62-1.75)		
AES	1.31 (0.87-2.02)	1.30 (0.87-1.99)	
FPE	0.53 (0.27-0.976)*	0.64 (0.36-1.10)	0.59 (0.36-0.87)*
FCE	1.24 (0.78-2.08)		
PPE1	0.97 (0.43-2.17)	1.07 (0.54-2.12)	
PPE2	1.13 (0.61-2.12)		

For a visual representation of the distribution ORs for the 'All Variables Model' with 95% confidence intervals, see Figure 3.

Figure 3.1. Scatterplot of Odds Ratios for the Emotional Exhaustion subscale of the ‘All Variables Model’

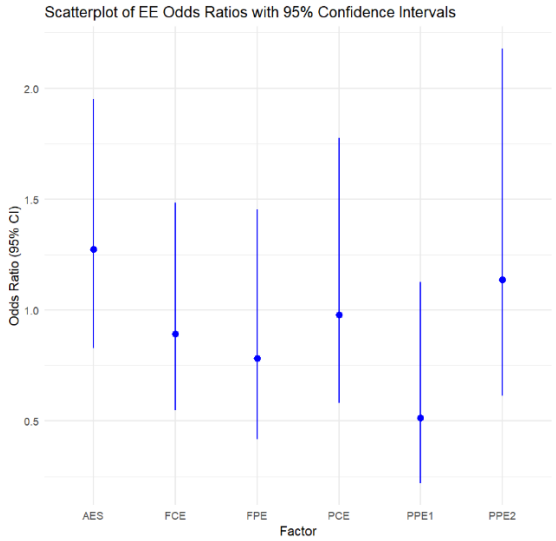


Figure 3.2. Scatterplot of Odds Ratios for the Depersonalization subscale of the ‘All Variables Model’

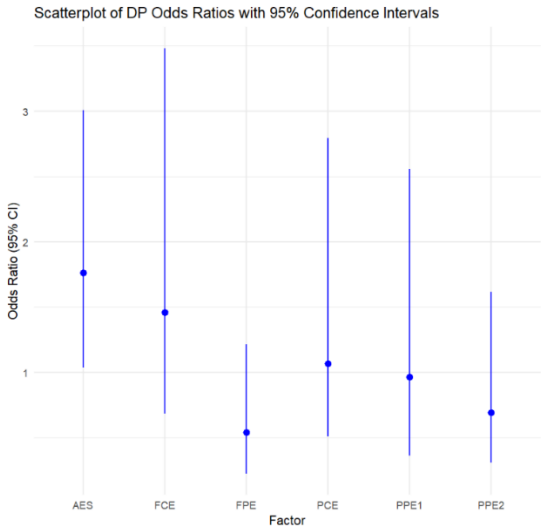
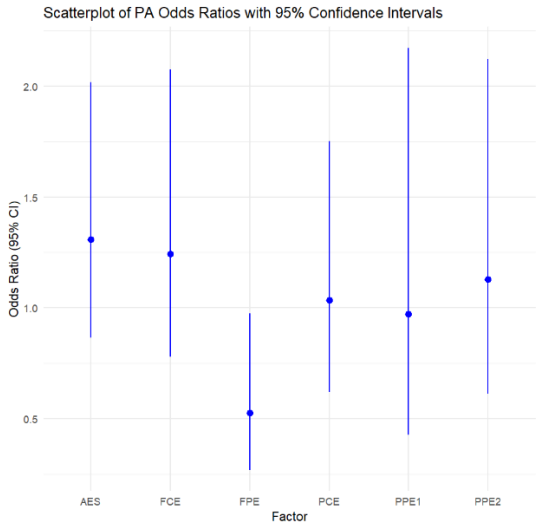


Figure 3.3. Scatterplot of Odds Ratios for the Personal Achievement subscale of the 'All Variables Model'



H. Post-estimation Exploration

To better understand how the combination of campus climate factors, as well as the addition of URM and FGCS terms interacting with said factors, improve the model, post-estimation exploration was completed. This involved a linktest and the Hosmer-Lemeshow test. This helps to ensure that the models accurately represent the relationship between predictor variables and an outcome. When the p-value of the Hosmer-Lemeshow test exceeds 0.05, it implies that a logistic regression model provides a good fit to the data, and there is no strong indication that additional predictors or patterns are needed to explain the observed outcomes. The Hosmer-Lemeshow test p-value for the 'All Variables Model' for the EE subscale was 0.815, for the DP subscale it was 0.787, and for the PA subscale it was 0.565.

The Hosmer-Lemeshow test p-values for the 'All Variables Model' were high, exceeding 0.05, which implies that the logistic regression model provides a good fit to the data, and there is no strong indication that additional predictors or patterns are needed to explain the observed

outcomes. However, it is essential to interpret a p-value above 0.05 cautiously for the Hosmer-Lemeshow test. While it indicates that there is no significant evidence against the null hypothesis of adequate model fit, it does not necessarily mean that the model is perfect or that it captures all relevant relationships in the data.

Despite the Hosmer-Lemeshow test indicating the model a good fit to the data, the notion that the model might not capture all relevant relationships in the data first arose when it became evident that the significant relationships that are present in the 'All Variables Model' and the 'Backwards Selection Model', are not consistently significant throughout all the models. The pre-selection model did not show any significant relationships despite including both terms. This includes the AES variable of the DP subscale and the FPE variable of the PA subscale. Significance emerged again for these same relationships for the interaction model with the addition of a significant relationship for the PPE2 term for the PA subscale (p-value = 0.027). This is to say, I am cautious in interpreting the significance of these relationships. It is a possibility that this inconsistency is a result of none of the models fitting the data well due to violations of logistic regression assumptions. For instance, logistic regression assumes that the relationship between the independent variables and the logit of the dependent variable should be linear. It is also possible that the phenomenon is due to the presence of another kind of relationship where one variable accentuates the other variable's relationship in some way, such as the value of AES being dependent on the value of FPE or vice versa.

To explore this relationship further, histograms were created plotting the frequency of campus climate variable score by MBI score for both significant relationships. For the AES variable, although the frequency of AES scores for high DP sub-scores is normally distributed, the frequency of AES scores is right skewed for low DP sub-scores. For the FPE variable, the

frequency of FPE scores is left skewed for both high and low PA sub-scores (Figure 4). This is further evidence that the AES variable of the DP subscale and the FPE variable of the PA subscale violate the assumptions of logistic regression leading to poor fit of the models.

Figure 4. Histograms of Maslach Burnout Inventory-Student Survey Sub-Score Outcome by Factor for Significant Relationships

I. Interaction Model Output

Having conducted post-estimation exploration for the ‘All Variables Model’ and integrating significant interaction terms to form the 'Interaction Model', significance and goodness-of-fit testing were performed on this final model.

The ORs for the additional interaction terms were 0.25 for the PPE1:FGCS term, 4.25 for the PPE2:FGCS term, and 1.17 for the AES:FGCS:URM, of the EE subscale (Table 11). In the interaction model, as in the other models, there were no significant ORs for the EE subscale and thus these ORs will not be interpreted.

For the DP subscale, interaction term ORs were 2.81 for the AES term, 0.35 for the AES:FGCS term, and 1.52 for the FCE:FGCS term. The ORs for AES term (p-value = 0.004), as well as AES:FGCS (p-value = 0.021) and FCE:FGCS (p-value = 0.033) terms for the DP subscale were significant. The OR for the AES:FGCS term can be interpreted as each additional point on the AES score is associated with a 65% decrease in the odds of a respondent having a high DP sub-score, holding other variables constant. However, because this variable is part of an interaction, the effect on the odds on having a high DP sub-score may vary depending on FGCS status. The OR for the FCE:FGCS term can be interpreted as the odds of having a high DP sub-score are predicted to grow about 1.52 times larger for each additional point on the FCE score, holding other variables constant. However, because this variable is part of an interaction, the effect on the odds on having a high DP sub-score vary depending on FGCS status.

For the PA subscale, interaction term ORs were 1.48 for the FPE:URM term, 0.65 for the PPE2:URM term, and 1.10 for the FPE:FGCS term. For the PA subscale, the ORs for the FPE (p-value = 0.003) and PPE2 (p-value = 0.027) terms, as well as the FPE:URM (p-value = 0.032) and PPE2:URM (p-value = 0.018) terms, were significant. The OR for FPE:URM term can be interpreted as the odds of having a high PA sub-score are predicted to grow about 1.48 times larger for each additional point on the FPE score, holding other variables constant. However, because this variable is part of an interaction, the effect on the odds of having a high PA sub-score vary depending on URM status. The OR for PPE2:URM term can be interpreted as each additional point on the PPE2 score is associated with a 35% decrease in the odds of a respondent having a high PA sub-score, holding other variables constant. However, because this variable is part of an interaction, the effect on the odds on having a high PA sub-score may vary depending on URM status. Lastly, the OR for FPE:FGCS term can be interpreted as the odds of having a

high PA sub-score are predicted to grow about 1.10 times larger for each additional point on the FPE score, holding other variables constant. However, because this variable is part of an interaction, the effect on the odds on having a high PA sub-score vary depending on FGCS status.

Table 11. Odds Ratios for the 'Interaction Model'

Factor	EE OR (95% CI)	DP OR (95% CI)	PA OR (95% CI)
PCE	0.95 (0.55-1.80)	0.91 (0.41-2.46)	0.95 (0.55-1.66)
AES	1.07 (0.66-1.70)	2.81 (1.44-5.94)*	1.30 (0.84-2.06)
FPE	0.8 (0.41-1.58)	0.58 (0.24-1.33)	0.26 (0.10-0.62)*
FCE	0.86 (0.50-1.52)	1.30 (0.58-3.17)	1.23 (0.74-2.13)
PPE1	0.97 (0.35-2.66)	0.74 (0.27-2.04)	0.59 (0.22-1.49)
PPE2	0.63 (0.27-1.45)	0.78 (0.34-1.88)	3.00 (1.17-8.29)*
AES:FGCS		0.35 (0.13-0.82)*	
FCE:FGCS		1.52 (1.05-2.31)*	
PPE1:FGCS	0.25 (0.05-0.92)		
PPE2:FGCS	4.25 (1.08-23.50)		
AES:FGCS:URM	1.17 (0.91-1.64)		
FPE:URM			1.48 (1.06-2.24)*
PPE2:URM			0.65 (0.42-0.91)*
FPE:FGCS			1.10 (0.94-1.30)
Emotional exhaustion (EE), depersonalization (DP), professional achievement (PA), perceptions of the campus environment (PCE), academic environment stress (AES), feelings of the program environment (FPE), feelings about the campus environment (FCE), perceptions of the program environment (PPE), underrepresented minority (URM), first-generation college student (FGCS)			
*Significant at p<0.05.			

IV. Discussion

This study utilized factor analysis, descriptive statistics for both campus climate variables and the Maslach Burnout Inventory (MBI-SS) sub-scores, and logistic regression to explore the relationship between institutional-level variables and MBI subscale scores. Regression models were extended to include potential interaction terms.

This study found that 33.33% of respondents had high-level emotional exhaustion, 15.69% of respondents had high-level depersonalization, and 54.9% of respondents had high-level reduced personal achievement. This study also found that academic environment stress, which reflected stress caused by the classroom environment and instructor relationships, has a positive correlation with depersonalization. This indicates that higher levels of stress related to the academic environment are correlated with increased feelings of depersonalization among nursing students. Depersonalization manifests as a lack of interest in lessons and clinical activities. It was also found that being a FGCS has a multiplicative effect on this relationship suggesting that FGCS status exacerbates the challenges related to a lack of interest in lessons and clinical activities within the context of the academic environment.

Finally, this study determined that feelings of the program environment, which reflected personal feelings of the environment of the nursing program, including peers, faculty, and staff, was found to have a negative relationship with professional achievement, although low personal achievement represents a positive screen for burnout on this subscale. Meaning, when students perceive the program environment more negatively, their sense of professional achievement tends to decrease. Personal achievement, also known as low professional efficacy, manifests as the feeling of incompetence in completing nursing tasks. It was also found that belonging to a URM had a multiplicative effect on this relationship, suggesting that URM status exacerbates the challenges related to feelings of incompetence in completing nursing tasks within the context of the program environment.

Comparing the findings of this study to the literature, it is notable that respondents reported higher MBI sub-scores for all three MBI subscales. This contrasts with the findings of McKee-Lopez et al., who reported that 22% of students experienced moderate to high levels of

emotional exhaustion, 24% experienced moderate to high levels of depersonalization, and 37% experienced moderate to high levels of reduced personal achievement.[21] However, it's important to acknowledge that McKee-Lopez et al. treated burnout as a categorical variable, whereas in this study, it was treated as a binary variable, thus limiting direct comparability between the two studies.

The literature review had found that risk factors for burnout include lack of sleep, the impact of the pandemic on sleep, the impact of the pandemic on physical activity, as well as adverse childhood events.[20,21] The findings of this study would add academic environment stress and feelings of the campus environment to potential risk factors for burnout. This study did not address protective factors or interventions to prevent burnout.

From the MBI score distribution, it was determined that despite having lower CC scores than the non-URM subgroup, the URM subgroup had disparately high MBI scores. However, these disparities were not found to be statistically significant. This lack of significance may indicate a genuine absence of differences between the subgroups, but it's also possible that the sample size was insufficient to detect any distinctions. Additionally, unaccounted variables in the analysis might be influencing the association between CC scores and MBI scores, potentially obscuring true differences. Therefore, it is essential to consider these factors and conduct further research to better understand the relationship between CC scores and MBI scores in different demographic subgroups.

There was evidence of significant interaction between the campus climate terms and the URM and FGCS terms. Additionally, the ‘Interaction Model’, which included these pre-selected interaction terms, yielded statistically significant ORs. This included the AES:FGCS (p-value = 0.021) terms for the DP subscale and the FPE:URM (p-value = 0.032) terms for the PA subscale,

as previously mentioned. Additional interactions were observed: one between feelings of the campus environment and being a FGCS for the DP subscale (p-value = 0.033), and another involving perceptions of the program environment (specifically, sensitivity, supportiveness, and integration) and being from a URM for the PA subscale (p-value = 0.018). However, the significance of these relationships has more limited evidence, as they only became significant with the introduction of the FGCS and URM terms. Additional research into the interaction between URM and FGCS status and campus climate factors is needed.

Alternatively, the presence of significant interaction between the campus climate terms and the URM and FGCS terms may be because the URM and FGCS variables are more relevant for predicting burnout among nursing students than campus climate variables. The original URM study, from which the data for this study was obtained, sought to identify factors predicting exhaustion, burnout, and stress among graduate health professional students more broadly, with a focus on the experiences of students who are FGCS and/or URM. The study revealed that fewer URM students felt adequately supported in their program, with many expressing the need for additional support, particularly concerning their well-being, from staff and faculty members. Additionally, URM and FGCS status showed a positive correlation. The relationship between URM and FGCS status and burnout among graduate nursing students, specifically, represents an area for future research.

Large amounts of residual deviance suggests that the models do not fit the data well. Specifically, it indicates that the models are unable to explain a significant portion of the variance in the response variable. This could be due to several reasons including that the models may be missing important predictor variables that are related to the response variable. Another reason that the models might not fit the data well is that logistic regression assumes that the

relationship between the predictors and the log odds of the response is linear. For future research, alternative methods better suited to the data might include machine learning techniques, capable of effectively handling nonlinear relationships and identifying complex patterns and interactions among various institutional factors influencing burnout. Alternatively, qualitative approaches such as interviews, focus groups, or observations may be more appropriate, as they can offer in-depth insights into individuals' lived experiences within institutions and elucidate how specific factors contribute to burnout from their perspectives. Combining quantitative and qualitative methods can provide a comprehensive understanding of institutional factors influencing burnout, with quantitative analyses identifying patterns and associations, and qualitative data providing context and explanations for these findings.

A. Implications for Theory

The findings of this study add to the evidence base confirming the aforementioned conceptual model. Originally proposed by Maslach et al., the MBI, which is both a measurement tool and a conceptual model, is composed of the emotional exhaustion, depersonalization, and a sense of low personal achievement dimensions.

When applying this model to the current study, I found that academic environment stress, which reflected stress caused by the classroom environment and instructor relationships, has a positive relationship with depersonalization. This indicates that higher levels of stress related to the academic environment are correlated with increased feelings of depersonalization among nursing students. Depersonalization manifests as a lack of interest in lessons and clinical activities. This finding confirms that weak relationships amongst students and between students and professors or hospital preceptors is a cause of depersonalization. It was also found that being a FGCS has a multiplicative effect on this relationship suggesting that FGCS status exacerbates

the challenges related to a lack of interest in lessons and clinical activities within the context of the academic environment.

Feelings of the program environment, which reflected personal feelings of the environment of the nursing program, including peers, faculty, and staff, was found to have a negative relationship with professional achievement, although low personal achievement represents a positive screen for burnout on that subscale. Meaning, when students perceive the program environment more negatively, their sense of professional achievement tends to decrease. Personal achievement, also known as low professional efficacy, manifests as the feeling of incompetence in completing nursing tasks. It was also found that belonging to a URM had a multiplicative effect on this relationship, suggesting that URM status exacerbates the challenges related to feelings of incompetence in completing nursing tasks within the context of the program environment.

Ghods et al. explored the concept of burnout in nursing students, specifically, and found that the concept of incompatible learning style was an additional dimension that was not a component of Maslach's original model.[39] Incompatible learning style, when preferred methods for acquiring knowledge, skills, and attitudes, are not used, can lead to disappointment and educational failure while reducing motivation. This fourth dimension was indicated by qualitative data collected during individual semi-structured interviews which aimed to identify the dimensions of academic burnout in nursing students and its influential factors. Additionally, Ghods et al. identified eight sub-categories of the four dimensions. These dimensions and subcategories are described below.[39]

Exhaustion: Due to academic pressure and activity load, including academic assignments and clinical work pressure.

- Academic assignments: Pressure to memorize difficult abbreviations and acronyms, especially challenging at the start of the academic program.

- Clinical work pressure: Pressure from condensed internship plans and being considered as staff during hospital internships.

Depersonalization: Psychological adaptation to heavy academic and workload, resulting in a lack of interest in lessons and clinical activities.

- Theoretical lessons: Decreased motivation, attention, and understanding for theoretical content.

- Clinical activities: Lack of motivation for clinical placements due to patients' disregard for students' time and preceptors' inefficiency.

Low professional efficacy: Feelings of incompetence in completing nursing tasks, leading to inadequacy in patient care and a lack of educational progress.

- Inadequacy in patient care: Feelings of failure and fear of consequences from inefficacy in caring for patients.

- Lack of educational progress: Resulting in low grades and feelings of inefficacy.

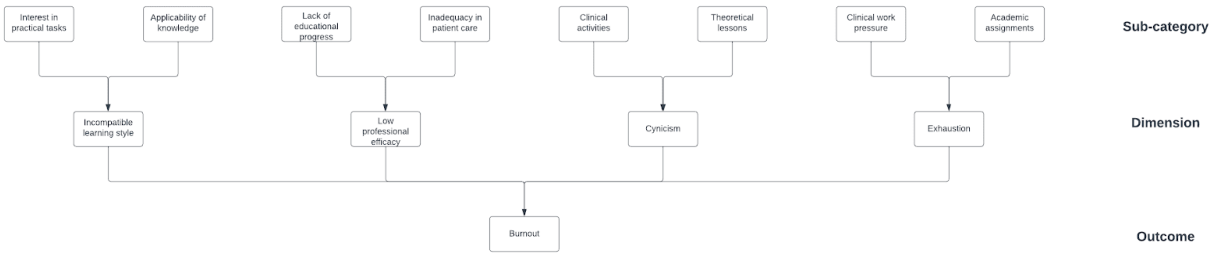
Incompatible learning style: Discrepancy between preferred learning styles and educational methods, leading to disappointment, educational failure, and reduced motivation.

- Interest in practical tasks: Desire for practical applications of knowledge.

- Applicability of knowledge: Impact of studies on job expectations.

Figure 5 displays a visual representation of the three dimensions of the MBI modified with the additional incompatible learning style dimension and sub-categories.

Figure 5. Modified Conceptual Model



Although outside the scope of this study, these four dimensions can be critically appraised individually based on validity, reliability, relevance, specificity, and utility, to gain a deeper understanding of their effectiveness in assessing burnout among nursing students and informing efforts to mitigate its impact. This dataset did not have the capacity to explore any of the sub-categories of the MBI dimensions proposed by Ghods et al.. Similarly, Ghods et al.'s proposed additional fourth dimension, incompatible learning style, characterized as a lack of planning and commitment to educational progress mainly resulting in low grades and therefore feelings of inefficacy, could also not be explored with this dataset.

Additional interactions were observed: one between feelings of the campus environment and being a FGCS for the depersonalization dimension, and another involving perceptions of the program environment (specifically, sensitivity, supportiveness, and integration) and being from a URM for the personal achievement dimension. However, the significance of these relationships has more limited evidence, as they only became significant with the introduction of the FGCS and URM terms. Additional research into the interaction between URM and FGCS status and campus climate factors is needed.

B. Implications for Nursing Programs

Nursing programs need to be aware of the impact of academic environment stress and feelings of the program environment on nursing students' burnout. They should develop and

implement preventive strategies aimed at reducing stressors within the academic environment and improving the environment of the nursing program. Specifically, nursing programs need to consider how relationships between students, as well as between students and professors or hospital preceptors can be improved upon. The recommendation to improve the environment of the nursing program, including peers, faculty, and staff, is perhaps too broad to have any practical implications but addressing how students can cope with their feelings about the program environment may be a more realistic prevention method. For example, nursing programs should integrate stress management and resilience-building skills into their curriculum.[27–29] This can empower nursing students with the tools they need to cope effectively with stressors encountered during their education and future careers. For instance, the University of Vermont implemented the Benson-Henry Institute Stress Management and Resiliency Training (SMART) program, an eight-week stress management and resiliency training program, into their curriculum for fourth-year baccalaureate nursing students and saw statistically significant decreases in their students stress, anxiety, and depression levels.[40] Similarly, peers, faculty, and staff may need to be trained in recognizing the signs of burnout among nursing students to facilitate early intervention. The literature review did not find any training programs that are currently being tested, implemented, or regularly used in nursing programs that aim to enhance recognition of burnout symptoms in others.

Encouraging a culture of self-care and well-being within the nursing profession is essential. Policies and programs that prioritize mental health support and promote a healthy work-life balance for nursing students and professionals alike should be advocated for. Nursing programs can advocate for increased resources and support for mental health services targeting nursing students. Similarly, programs can enact policy changes to address systemic stressors

within educational institutions. These changes may include revising the curriculum, implementing initiatives to alleviate financial stress among nursing students, ensuring adequate support and supervision during clinical rotations, and implementing regular feedback mechanisms to solicit input from students. Programs should develop diversity and inclusivity initiatives as well as support services for their more vulnerable students, which may include students from URM and FGCS. Further research into the specific stressors within the academic and program environment, as well as other factors contributing to burnout that were not measured in this study such as sleep, time spent on homework or studying for exams, age, ACEs, depression, anxiety, or stress, and their impact on burnout among nursing students is needed.[20,21,24]

The findings from the literature review also showed a need for evidence-based interventions such as training or curriculums in nursing programs that increase awareness of stress and build resilience to mitigate the impact of stress, prevent burnout, and support nursing students. Although this study did not directly address an intervention, the findings imply the need to address the issue of burnout among nursing students in similar ways. McKee-Lopez et al. demonstrated a need for faculty to be educated on burnout among students.[5] Additionally, the findings of this study point to the need for the fostering of positive relationships between students and faculty in order to prevent burnout.

C. Strengths and Limitations

The original URM study paid special attention to the experiences of students who are URM and/or are FGCS with the authors taking the need for a representative sample into consideration during recruitment and data collection. A power analysis indicated that a sample size of 64 was necessary to detect medium effect sizes. With 153 nursing student respondents,

this requirement was met. However, the sample size was insufficient for detecting small effect sizes, which would necessitate a sample size of 394. As the data collection period for that study coincided with the onset of the COVID-19 pandemic, there could potentially have been an impact on the responses to questions about burnout and stress as students were asked to rate their feelings about exhaustion in terms of frequency during the week and stress in general terms. As some participants chose the "Other/Don't Know" option when selecting the type of institution they attended (minority serving or predominantly white), the original URM study was not able to precisely measure the effect of institution type. For this reason, I could only account for URM status and not institution status. Considering this study is on institution-level factors, accounting for institution status would have been valuable. Additionally, 95.42% of the respondents identified as female. Although this is in line with the nursing student population generally, it may hide differences between male and female nursing students both in terms of campus climate score and MBI score distributions that may be present in the population.

As previously noted, this study's generalizability is constrained by its focus solely on graduate nursing students, thereby limiting its applicability to the wider nursing student population. Nevertheless, the study's findings hold relevance beyond this specific demographic due to shared elements such as core curriculum, clinical exposure, professional standards, faculty expertise, interdisciplinary collaboration, and clinical practice expectations, which are characteristic across various levels of nursing education.

V. Conclusion

This study found that higher levels of stress related to the academic environment are correlated with increased feelings of depersonalization among graduate nursing students and that FGCS status exacerbates this relationship. It was also found that when students perceive the program environment more negatively, their sense of professional achievement tends to decrease and that URM status exacerbates this relationship.

Nursing programs should develop and implement preventive strategies aimed at reducing stressors within the academic environment and improving the environment of the nursing program. This might include the integration of stress management and resilience-building skills into their curriculum, as well as the training of peers, faculty, and staff in recognizing the signs of burnout among nursing students to facilitate early intervention. Policies and programs that address systemic stressors within educational institutions, prioritize mental health support, and promote a healthy work-life balance for nursing students and professionals alike should be advocated for. Programs should develop diversity and inclusivity initiatives as well as support services for their more vulnerable students, which may include students from URM and FGCS.

Future research avenues should delve into several key areas. There is a need to validate whether URM respondents exhibit a higher prevalence of high MBI scores. Exploring the interplay between URM and FGCS status alongside institutional-level factors and burnout among nursing students could shed further light on this issue. It is essential to investigate specific stressors within the academic and program environment, along with other unmeasured factors contributing to burnout among nursing students. In addition, employing alternative methods better suited to the complexities of the data and incorporating qualitative approaches could provide invaluable insights. Qualitative methods, in particular, could offer a nuanced

understanding of how various factors contribute to burnout from the students' own perspectives, complementing quantitative analyses.

By addressing factors that contribute to burnout among nursing students, a healthier and more resilient nursing workforce can be created, ultimately improving quality of care and the efficiency of the healthcare system.[8]

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