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Profiles of Military Medical Students' Well-being, Burnout, and Retention

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ABSTRACT

Background:

Well-being concerns among medical students are more prevalent than their age-matched peers in the United States. It remains unknown, however, if individual differences in well-being exist among U.S. medical students serving in the military. In this study, we sought to identify profiles (i.e., subgroups) of well-being in military medical students and examine the associations between these well-being profiles and burnout, depression, and intended retention in military and medical fields.

Methods:

Using a cross-sectional research design, we surveyed military medical students and then conducted latent class analysis to explore profiles of well-being, and applied the three-step latent class analysis method to assess predictors and outcomes of well-being profiles.

Results:

Heterogeneity in well-being was identified among the 336 military medical students surveyed, portraying medical students' falling into three distinct subgroups: High well-being (36%), low well-being (20%), and moderate well-being (44%). Different subgroups were associated with different risks of outcomes. Students in the subgroup of low well-being were at the highest risk of burnout, depression, and leaving medicine. In contrast, students in the moderate well-being group were at the highest risk of leaving military service.

Conclusions:

These subgroups may be clinically important as burnout, depression, and intention to leave medical field and/or military service occurred with varying likelihoods among medical students across the different well-being subgroups. Military medical institutions may consider improving recruitment tools to identify the best alignment between students' career goals and the military setting. Besides, it is crucial for the institution to address diversity, equity, and inclusion issues that may lead to alienation, anxiety, and a sense of wanting to leave the military community.

INTRODUCTION

Military medicine relies on undergraduate medical education to produce a reliable and steady stream of new clinicians to support the total force. As a result, factors that impact the readiness of medical students are of critical importance to the longevity of total force health. Unfortunately, it is well-documented that the high demands of learning throughout medical school put medical learners at risk for well-being problems, emotional distress, and burnout.[1–3] Although medical students in general start medical school with quite positive well-being,[4] research suggests that, as a result of attending medical school, poor well-being is more prevalent among medical students than their age-matched peers in the United States.[5] In addition, prior research has found that well-being problems among medical students can result in alcohol abuse, suicidal intention, depression, and intention to drop out of their medical programs.[4,6,7] The professional ramifications also include detrimental effects on ethical conduct and compromised patients' access to medical care.[1,4]

Prior well-being research has primarily investigated well-being as either a total score or average score, which reduces all attributes of well-being to a single score. This approach could be problematic because it ignores the individual differences in medical students' well-being and heterogenous experiences that may exist under the umbrella term of well-being. For example, among an array of well-being indicators, one medical student may have primarily experienced anxiety and burnout but not experienced other well-being problems, such as depression or physical illness. In contrast, another medical student may have experienced well-being problems (such as physical illness and sleep problems) but had the same or very similar overall well-being score as the first student. Thus, two students with different profiles cannot be distinguished by a single score; what is more, the institutional support services needed by each student may be notably different.

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Despite evidence showing that low well-being among medical students leads to impaired learning, depression, and intention to drop out,[7] most of this work has been conducted in nonmilitary samples using a total score approach, which largely ignores the differences in profiles of student experience. Moreover, research on military medical students is relatively lacking. Although prior work suggests that military medical students are less depressed than nonmilitary medical students, military medical students are still at high risk of low well-being and burnout.[8] Additionally, low well-being is found to be a significant predictor of retention problems in the medical field.[8] Thus, it remains to be seen if well-being problems contribute to retention problems in military physicians.

One's decision to leave the military is likely the result of multiple factors, including changes in personal or career goals; however, lacking adaptive well-being may influence one's intention to leave both military service and/or the medical field. It is possible that some profiles of well-being are more likely to influence one's intention to leave the military (e.g., experiencing anxiety may be more impactful than physical illness–both of which are common well-being indicators). Therefore, understanding military medical students' well-being profiles could be important in identifying more tailored interventions for subgroups of medical students.

To date, the only study examining profiles of well-being among medical students has revealed a significant heterogeneity in profiles of well-being in a Canadian sample of medical students.[9] Across the four indicators of mental health assessed (i.e., emotional well-being, social well-being, psychological well-being, and resilience), three distinctive subgroups/profiles were identified, including an overall low well-being group (14%), a moderate well-being group (58%), and a high well-being group (29%). It remains unknown if similar profiles, or subgroups, of well-being experiences exist in medical students serving in the military, and how these different profiles of well-being may contribute to different risk levels of students' burnout, depression, and retention issues in the military forces. Therefore, in this study, we sought to explore individual differences in well-being profiles among U.S. military medical students using latent class analysis (LCA). The use of a person-centered approach (i.e., LCA) is suitable for this inquiry to identify subgroups/profiles that portray the heterogenous aspects of well-being among military medical students.[10] Three research questions guided the current study. (1) How many distinctive subgroups of military medical students' well-being can be identified? (2) To what extent do demographic factors (i.e., age, gender, ethnicity, prior military service, seniority) predict the various well-being subgroups? (3) Do students with different well-being subgroups have distinguishable outcomes in depression, burnout, and intended retention in military and medical fields? Findings from this study are a first step in helping to better serve this military student population.

METHODS

Study Participants and Procedures

This study was part of the larger Long Term Career Outcome Study conducted at the F. Edward Hébert School of Medicine, USUHS. As the United States' only federal medical school, USUHS matriculates approximately 170 medical students annually. In September 2019, all military medical students from USUHS were invited to participate in this study ($N = 678$). The data collection period span across approximately 8 weeks (from September 16, 2019 to November 15, 2019). During the 8 weeks, the research team sent the reminders every 2 weeks, resulting in a total of three reminders in addition to the initial email invitation.

Measures

Well-being measure

Medical students' well-being was measured using the Medical Student Well-being Inventory (MSWBI).[11] This instrument covers multiple aspects of well-being, including burnout (two items), depression (one item), stress (one item), fatigue (one item), and quality of life (both mental and physical, two items). For example, "During the past month, have you often been bothered by feeling down, depressed, or hopeless?" Participants rated their experiences on each item using a dichotomous response scale (Yes = 1; No = 0).

Outcome measures

Four outcomes of well-being were measured in this study: Overall rating on burnout, depressive symptoms, intention to leave the military, and intention to leave the medical field. The overall burnout was assessed by one item that asked participants to rate their current level of burnout based on their own definition on a five-point Likert-type response scale ranging from "1 = I enjoy my work. I have no symptoms of burnout" to "5 = I feel completely burned out and often wonder if I can go on. I am at the point where I may need some changes and may need to seek some sort of help." In previous work, this item was found to be highly correlated with the Maslach Burnout Inventory for Physicians.[12]

Medical students' depression was measured using the Depressive Symptom Scale.[13] The adapted scale included seven items that asked participants to rate "over the past two weeks, how often have you been bothered by any of the following problems" on a four-point frequency response scale, ranging from not at all = 1 to nearly every day = 4. A sample item included "little interest or pleasure in doing things." We calculated an average score for each participant, with higher scores indicating more depressive symptoms.

Military medical students' intentions to leave the medical field and to leave military service were each measured using single items. Both items employed a five-point, Likert-type response scale (not at all likely = 1 to definitely = 5).

Demographic variables

Predictors of latent classes assessed included gender from matriculation data (Female = 1, Male = 2), age (age at matriculation), medical school year (MS1 = 1 to MS4 = 4), ethnicity, and prior services in military (Yes = 1, No = 0).

Statistical Analysis

We conducted LCA to explore subgroups of medical students' well-being. Latent class analysis is a model-based cluster analysis technique. We used it to place military medical students into latent classes, or subgroups, based on their responses to the set of items assessing well-being.[14] The derived subgroups show qualitatively different traits for students falling into the same profile or subgroup. Latent class analysis used an exploratory multivariate analysis approach because there is no *a priori* specification of the number or subgroups that emerge. We made decisions of model selection based both on model fit indices and empirical evidence. In this study, we would expect to see at least two groups—one group reflecting overall high well-being as well as one group reflecting overall low well-being based on prior empirical evidence.[9] Models were estimated in Mplus Version 8 using full information maximum likelihood estimation with robust standard errors.[15] The full information maximum likelihood approach adjusts for missing data under the Missing at Random assumption by allowing subjects who have data on at least one of the well-being measures to be included in the analysis.[16]

To explore our first research question, we specified models of varying numbers of subgroups. To determine the optimal solution of the best-fitting model, we used commonly accepted fit indices (e.g., Lo–Mendell–Rubin likelihood ratio test [LMR], Akaike's information criterion [AIC], Bayesian information criterion [BIC], correct model probability [cmP], see details and criteria under Table II notes).[10,14] Furthermore, we applied the three-step LCA method to include covariates and distal outcomes.[16] The three-step approach helps to ensure the emergence of latent classes is not unintentionally affected by the inclusion of covariates or distal outcomes in the model.[16,17] Through this three-step analysis phase, we explored our second and third research questions. To answer our second research question, we identified factors of demographic predictors (i.e., gender, ethnicity, prior military services, and year in medical school) and modeled their ability to predict medical students' falling into a specific subgroup of well-being. To aid in the simplicity of result interpretation, ethnicity was recoded into a dummy category (Ethnically minority groups = 1, Others = 2). To address our third question, we modeled how well the well-being subgroups predicted outcomes on depression, burnout outcomes, and intention to leave military and medical fields.

RESULTS

Latent Classes of Medical Students' Well-being

A total of 336 students (out of 693 overall students) responded and comprised the current study sample. Among the study sample ($N = 336$), there were 43% female, 87% White, 6% Black, 5% Latinx, 1% Native American, 1% multiethnicities, and 39% who had prior military service. Table I shows the descriptive statistics of key characteristics for the study sample. The response rate ranged from 46% to 56% across the 4 years of medical cohorts. On average, the participants took about 7 minutes to finish the survey (median = 410 seconds); most participants completed the survey within 6 minutes (mode = 345 seconds). The reliability (Cronbach alpha) in the current sample was 0.67 for the MSWBI scale and 0.80 for the depression scale and the constructs validity of both scales hold well.

TABLE I. Descriptive Statistics for Key Variables in the Study

Variable	*N*	% within current sample	*M* (SD)	Range	
				Potential	Actual
Categorical					
Gender					
Female	149	46			
Male	165	51			
Medical School Year					
MS1	70	21			
MS2	89	28			
MS3	80	25			
MS4	82	25			
Ethnicity					
White		87			
African American		6			
Hispanic		5			
Native American		1			
Multiethnicity		1			
Prior service in military					
Yes	125	39			
No	189	58			
Continuous					
Age			24 (3.87)		20-40
Well-being			1.29 (0.26)	1-2	1-2
Burnout			2.25 (0.70)	1-5	1-5
Depression			1.52 (0.50)	1-4	1-3.71
Intention to leave military			2.06 (1.01)	1-5	1-5
Intention to leave medicine			1.27 (0.60)	1-5	1-4

MS1= Medical School Year 1. The percentage of the medical school year showed the composition percentage of each class in the current sample.

Table II shows all model fit indices for models from one class to seven classes. The LCA fit indices are not all in congruence regarding what the best-fitting model is (see Table II). Thus, in addition to fit indices, we also determined the viability of model results for each model based on consistency with prior research,[9] as well as the substantive meaningfulness and interpretability of the LCA results.[18] The three-class solution was chosen as the best model. Figure 1 depicts the

TABLE II. Fit Indices of Class Enumeration from Class 1 to Class 7

Model (*K*-class)	LL	Npar	AIC	CAIC	BIC	saBIC	AWE	LRTS	BF (k, $k+1$)	cmP(k)
1-class	−988.324	6	1,988.65	2,016.93	2,010.93	1,991.90	2,063.21	–	0.000	0.000
2-class	−887.446	13	1,800.89	1,862.17	1,849.17	1,807.94	1,962.45	201.76	12,772.693	1.000
3-class	−876.903	20	1,793.81	1,888.08	1,868.08	1,804.65	2,042.36	21.09	111,866.874	0.000
4-class	−868.530	27	1,791.06	1,918.33	1,891.33	1,805.70	2,126.60	16.75	7,103,263.038	0.000
5-class	−864.308	34	1,796.62	1,956.88	1,922.88	1,815.05	2,219.15	8.44	4,945,876.808	0.000
6-class	−859.724	41	1,801.45	1,994.71	1,953.71	1,823.68	2,310.97	9.17	41,995,155.287	0.000
7-class	−857.279	48	1,810.56	2,036.82	1,988.82	1,836.59	2,407.08	4.89	–	0.000

To determine the optimal solution of the best-fitting model, we used commonly accepted fit indices, including the Bayesian information criterion (BIC), Akaike's information criterion (AIC), consistent Akaike's information criterion (CAIC), sample-size adjusted BIC (saBIC), approximate weight of evidence criterion (AWE), where lower values indicate better fit. Two likelihood-based indices were used, including the Lo–Mendell–Rubin likelihood ratio test (LMR) and the Bootstrap likelihood ratio test (BLRT), in which significant *P* values of LMR–aLRT indicate that the model with *k* classes has better fit to the data than a model with *k*-1 classes. We also assessed the approximate correct model probability (cmP), where a cmP value closer to 1 indicates the actual probability of Model A being the correct model relative to a set of J models under consideration.[9,13]

item probability plot of the best model. The item probability plot shows the probability that the military medical students in a given subgroup experienced a particular type of well-being, and how well each well-being item differentiated the emergent subgroups from one another.

Among the study sample, there were 36% ($N = 108$) of military medical students who were low on all of the indicators impacting well-being and thus represent a high well-being (labeled high well-being). The second subgroup comprised military medical students who had experienced a moderate to high level of worries or feeling irritated but were relatively low on items of feeling depressed, feeling burnout, as well as physical health issues such as falling asleep in traffic and/or having physical health interfered with workability (labeled moderate well-being, 44%, $N = 132$). The third subgroup consisted of military medical students who reported the lowest well-being. These students had experienced a variety of aspects impacting well-being such as feeling depressed, burnout, having emotional problems, and feeling that things are piling up without being able to overcome them. Unlike the other two subgroups, these students also experienced moderate trouble with physical health issues that interfered with workability (labeled low well-being, 20%, $N = 63$).

Predictors of Well-being Class Memberships among Medical Students

To examine what predicts medical students' falling into a specific class membership, we examined three-step LCA in which medical school year, gender, participants' age, and prior military service were assessed as a predictor of class membership via a multinomial logistic regression framework. The results indicated that both gender and medical year were significant predictors of well-being classes, whereas age, ethnicity, and prior service were not. Compared to both Year 1 and Year 4 students, Year 3 students are more likely to be in both the low well-being group (compared to MS1: logit = 1.908, $P = .003$; compared to MS4: logit = 0.358, $P < .001$) and the moderate well-being group (compared to MS1: logit = 1.023, $P = .048$; compared to MS4: logit = 0.921, $P < .001$). Compared to Year 4 students, Year 1 students were more likely to be in the high well-being group (logit = −1.55, $P = .014$). In addition, female military medical students, compared to male military medical students, were more likely to be in the moderate well-being group as opposed to being in the high well-being class (logit = 1.007, $P = .007$).

Well-being Classes Membership Predicting Burnout, Depression, and Intention to Leave

We applied a three-step LCA model to assess how students' well-being class memberships are associated with their burnout, depression, intention to leave the military, and intention to leave the medical field. Table III showed the omnibus test results on the four outcomes derived from the wald tests,

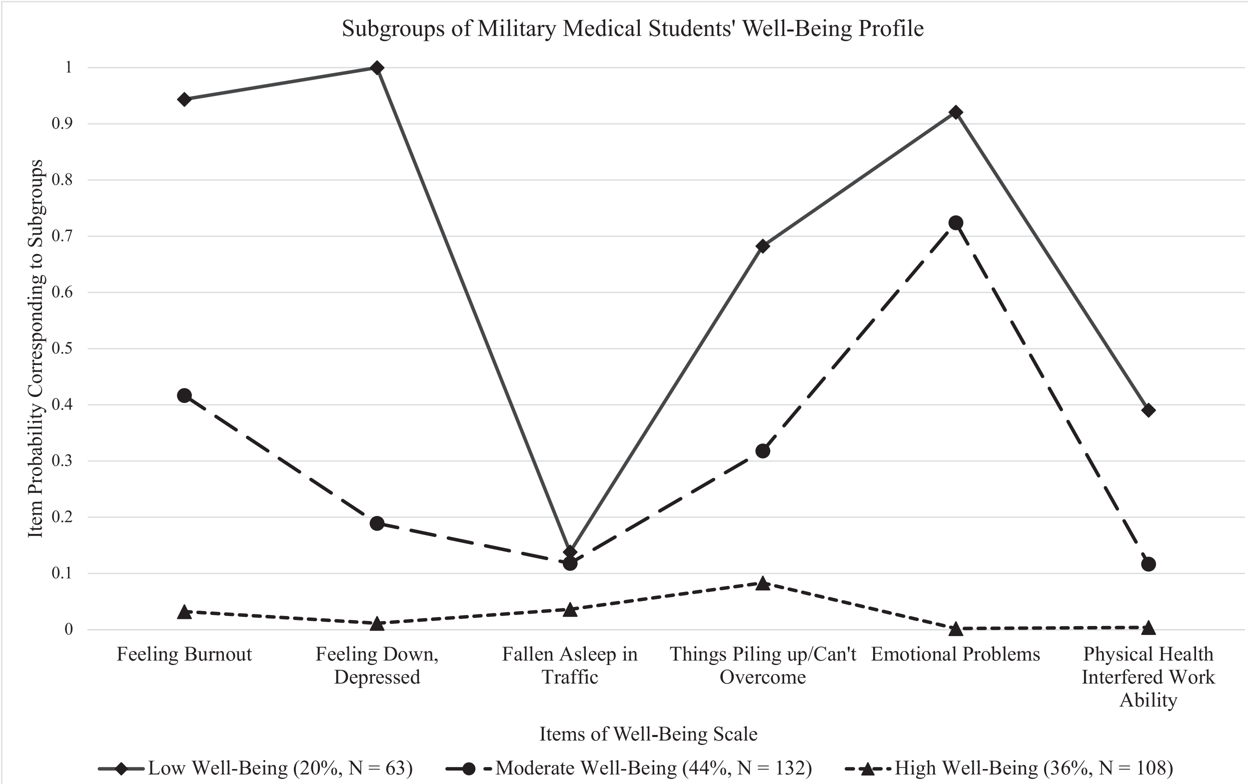

FIGURE 1. Well-being item probability plot of the best model.

TABLE III. Outcomes of Military Medical Students in Different Well-being Classes

	Burnout Mean (SE)	Depression[e] Mean (SE)	Intention to leave military Mean (SE)	Intention to leave medicine Mean (SE)
Class 1—Low well-being	3.185 (0.08)[a]	2.174 (0.09)[a]	2.09 (0.20)[a&b]	1.51 (0.14)[a]
Class 2—Moderate well-being	2.227 (0.05)[b]	1.535 (0.03)[b]	2.22 (0.10)[a]	1.25 (0.05)[a]
Class 3—High well-being	1.781 (0.04)[c]	1.151 (0.02)[c]	1.66 (0.11)[b]	1.11 (0.04)[b]
Wald test	207.512 ($P < .001$)	201.357 ($P < .001$)	11.871 ($P = .003$)	13.066 ($P = .001$)

The means in the same column that shared the same superscript letter (a, b, or c) are not significantly different from each other.
[e]Given that depression was measured using existing scales and that one item was dropped from the original scale during data collection, to verify if the latent factor of depression still holds well with the current six-item model and with our military student sample, we tested the structure of the scale using a one-factor confirmatory analysis (CFA). Confirmatory analysis is a commonly used modeling technique to test whether the underlying construct of a survey based on data is consistent with researchers' understanding of the nature of the construct before data collection. The results showed that the one-factor CFA model with the six-item of depression scale fit the data well, χ^2 (9) = 19.089, $P = .12$, Comparative Fit Index (CFI) = 0.988, Tucker-Lewis Index (TLI) = 0.981, Root Mean Square Error of Approximation (RMSEA) = 0.040, $P = .64$. Additionally, the one-factor model of MSWBI (well-being measure) also fit the data well (χ^2 (9) = 12.514, $P = .185$, CFI = 0.991, TLI = 0.985, RMSEA = 0.036, $P = .65$), indicating the two measures are valid with the current military medical student sample and with the current item structures.

which were all significant. The follow-up pairwise comparisons were shown in Table III and Figure 2.

Students in the low well-being group, compared to the high well-being group, experienced significantly more burnout, depression, and stronger intention to leave the medical field. Students in this group also showed significantly worse burnout and depressive symptoms compared to those in the moderate well-being group. When compared to students in the high well-being group, medical students in the moderate well-being group also reported significantly more burnout and depressive symptoms.

In comparing subgroups, unique differences emerged between the intention to leave the military versus the medical field. Both the low well-being group and the moderate well-being group showed significantly stronger intentions to leave the medical field, when compared to the high well-being group. However, students in the moderate well-being group showed the strongest intention to leave the military among the three groups. On the other hand, students in the low well-being group did not significantly differ from the other two groups in terms of intention to leave the military.

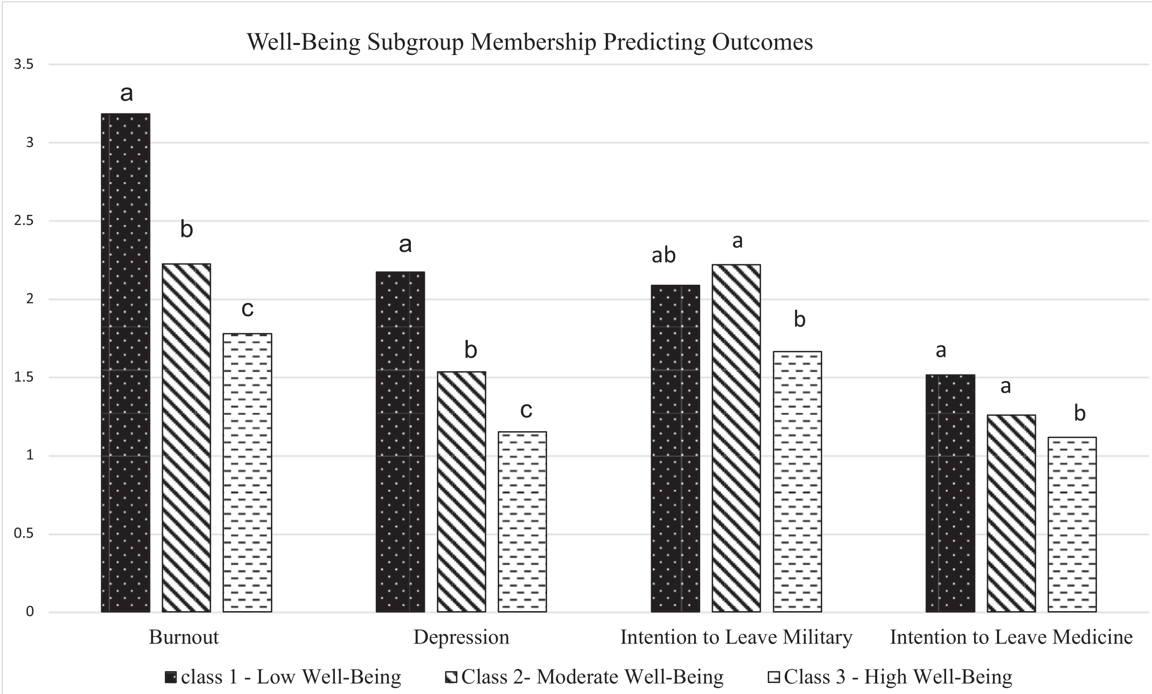

FIGURE 2. Outcomes of military medical students in different well-being classes (subgroups). The means in the same variable that shared the same superscript letter are not significantly different from each other.

DISCUSSION

The current study is among the first to study the heterogeneity of well-being among medical students worldwide,[9,19] and is also the first study to explore well-being subgroups of U.S. military medical students. More specifically, heterogeneity in well-being was identified, portraying military medical students' falling into the following three distinct subgroups in the study sample: High well-being (36%), low well-being (20%), and moderate well-being group (44%). These subgroups may be clinically important as burnout, depression, and intention to leave the medical field and/or military service occurred with varying likelihoods among medical students across the different well-being subgroups.

Taking a closer look at the subgroups, we found that military medical students in the overall low well-being group experienced the highest burnout and depressive symptoms. Military medical students in this group showed the strongest intention to leave the medical field. However, the low well-being students did not report a significant likelihood of leaving the military. Rather, students in the moderate well-being group showed the highest likelihood of leaving military service after graduation compared to the other two groups. Thus, the large proportion of military medical students in the moderate well-being group (44%) is concerning. Besides, the moderate well-being group did not significantly differ from those in the low well-being group to leave the medical field (i.e., they did not have significantly stronger intentions to stay in the medical field). Given the overall positive well-being score (less than three in total), students in the moderate well-being group may not be easily recognized as a population of students who need help, especially when using traditional approaches (using overall or average score).[10] This finding suggests that it may be important to investigate the profiles of well-being experiences of medical students, as opposed to simply examining overall averages. Although the traditional cut-off score approach is likely to identify the low well-being group, the approach of examining profiles/subgroups can help to identify the moderate well-being group who may be at the risk of leaving both the military and medical fields. This group may warrant additional institutional support.

Our findings stress the importance that well-being scores should be viewed as a spectrum with subgroups as opposed to an all or none phenomenon. Our findings also showed that medical school year and gender might predict well-being subgroup classification. This finding echoes prior research showing that the stress and burnout after entering medical schools culminated around the Year 3 mark as they strive to complete both clinical clerkships and the United States Medical Licensing Examination (USMLE) STEP 1 test.[20] Additionally, although both genders are equally represented in both low and high well-being groups, female students were more likely to be present in the moderate well-being group, echoing a prior meta-analytic report using a civilian sample.[21] Other factors not included in this study may also play an important role in predicting the well-being group. Prior research noted that students' well-being is also predicted by learning environment factors such as the amount of support from faculty and staff, grading system, and quality of peer collaboration.[4] Future research scrutinizing how subgroups of well-being are predicted by multidimensional factors situated with the learning environment is warranted.

The training of future military physicians takes a great deal of time and resources. The identified well-being subgroups among medical students suggest that intervention and prevention in medical education may need to be tailored. Given the number of learners in the moderate well-being group that would not be detected by simply viewing the overall well-being score, medical schools may wish to consider screening and possibly prevention strategies that may help prevent these students from progressing into the low well-being group. Furthermore, although some military medical students in the moderate well-being group may be identified through several intervention mechanisms available at the institution, they may not be consistently recognized as a group associated with a higher risk for retention concerns. Note that this association may be mutual: It is possible that students express a higher intent to leave the military because of their well-being; it is also possible that students in the moderate well-being group felt anxious because they have recognized the misalignment with a career in the military. The implication of this study is 3-fold. Student services may take heed to the retention concerns for medical students showing possible signs of specific emotional concerns, such as feeling anxious and irritable. Further, military medical institutions may consider improving recruitment tools to identify the best alignment between students' career goals and the military setting. Besides, it is crucial for the institution to address diversity, equity, and inclusivity issues that may lead to alienation, anxiety, and a sense of wanting to leave the military community.

One limitation of the current study is that we did not assess how subgroups may be different from year to year because of the low sample size collected in each medical school year. Future studies with multisites and thus a bigger sample size can scrutinize the nuance in changes of well-being across different medical school years. However, given that USUHS is the only military medical school in the United States, the uniqueness of the school context will be different from other institutions hosting military students (e.g., through Health Professional Scholarship Program (HPSP) programs). Although one could potentially include the HPSP students at other institutions, other confounding factors across different school contexts may need to be addressed. An alternative is to extend the current findings with a sequential mixed-design, adding a qualitative portion to explore why military students falling in the middle group—the moderate well-being group—are more likely to leave the military and how the institution can best support students falling into this group to address issues of military force retention and readiness. In addition, the study was collected during a quite broad period (8 weeks) and caution needs to be taken with interpreting the results because of potential sampling bias (e.g., one student may take the survey prior to an exam while another student takes it after an exam). Furthermore, future research needs to consider collecting a more comprehensive range of demographic factors such as marital status, living arrangements, commuting distance, and prior behavioral health diagnosis history that may be associated with military medical students' well-being.

Our findings speak to the importance of developing a tailored approach of intervention practices and student support strategies that are conducive to improving the well-being of students in different well-being subgroups and thus protect the workforce. Interventions such as mindfulness training were found to have some effects in relieving medical students' stress levels.[22,23] Other researchers argued the importance of deconstructing resilience and the necessity of building a holistic support system,[24] including establishing a wellness curriculum, making accessible the help resources for medical students at risk, and training staff and faculty for the purpose of enhancing a positive learning environment.[25]

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CONFLICT OF INTEREST STATEMENT

None declared.

REFERENCES

1. Almeida T, Kadhum M, Farrell SM, Ventriglio A, Molodynski A: A descriptive study of mental health and wellbeing among medical students in Portugal. Int Rev Psychiatry 2019; 31(7–8): 574–8.
2. Farrell SM, Kadhum M, Lewis T, Singh G, Penzenstadler L, Molodynski A: Wellbeing and burnout amongst medical students in England. Int Rev Psychiatry 2019; 31(7–8): 579–83.
3. Jacobs R, Lanspa M, Kane M, Caballero J: Predictors of emotional wellbeing in osteopathic medical students in a COVID-19 world. J Osteopath Med 2021; 121(5): 455–61.
4. Dyrbye L, Shanafelt T: A narrative review on burnout experienced by medical students and residents. Med Educ 2016; 50(1): 132–49.
5. Brazeau CM, Shanafelt T, Durning SJ, et al: Distress among matriculating medical students relative to the general population. Acad Med 2014; 89(11): 1520–5.
6. Jackson ER, Shanafelt TD, Hasan O, Satele DV, Dyrbye LN: Burnout and alcohol abuse/dependence among U.S. medical students. Acad Med 2016; 91(9): 1251–6.
7. O'Neill LD, Wallstedt B, Eika B, Hartvigsen J: Factors associated with dropout in medical education: a literature review. Med Educ 2011; 45(5): 440–54.
8. Gulec M, Bakir B, Ozer M, Ucar M, Kilic S, Hasde M: Association between cigarette smoking and depressive symptoms among military medical students in Turkey. Psychiatry Res 2005; 134(3): 281–6.
9. McFadden T, Fortier M, Sweet SN, Tomasone JR: Physical activity participation and mental health profiles in Canadian medical students: latent profile analysis using continuous latent profile indicators. Psychol Health Med 2021; 26(6): 671–83.
10. Nylund KL, Asparouhov T, Muthén BO: Deciding on the number of classes in latent class analysis and growth mixture modeling: a Monte Carlo simulation study. Struct Equ Model 2007; 14(4): 535–69.

11. Dyrbye LN, Szydlo DW, Downing SM, Sloan JA, Shanafelt TD: Development and preliminary psychometric properties of a well-being index for medical students. BMC Med Educ 2010; 10: 8.
12. Rohland BM, Kruse GR, Rohrer JE: Validation of a single-item measure of burnout against the Maslach Burnout Inventory among physicians. Stress Health 2004; 20(2): 75–9.
13. Beck AT, Guth D, Steer RA, Ball R: Screening for major depression disorders in medical inpatients with the Beck Depression Inventory for Primary Care. Behav Res Ther 1997; 35(8): 785–91.
14. Masyn KE: Measurement invariance and differential item functioning in latent class analysis with stepwise multiple indicator multiple cause modeling. Struct Equ Model 2017; 24(2): 180–97.
15. Muthen LK, Muthen BO: *Mplus User's Guide*. 7th ed., *Muthén & Muthén*; 2012:19982006.
16. Asparouhov T, Muthén B: Auxiliary variables in mixture modeling: three-step approaches using M plus. Struct Equ Model 2014; 21(3): 329–41.
17. Nylund-Gibson K, Grimm R, Quirk M, Furlong M: A latent transition mixture model using the three-step specification. Struct Equ Model 2014; 21(3): 439–54.
18. Muthén B: Statistical and substantive checking in growth mixture modeling: comment on Bauer and Curran (2003). 2003.
19. Mobaderi T, Salehi M, Roudbari M: Application of latent class modelling in students' life skills: the case of Iran University of Medical Sciences. Shiraz E Med J 2020; 21(2): 1–6.
20. Strowd RE, Lambros A: Impacting student anxiety for the USMLE Step 1 through process-oriented preparation. Med Educ Online 2010; 15(1): 4880.
21. Puthran R, Zhang MW, Tam WW, Ho RC: Prevalence of depression amongst medical students: a meta-analysis. Med Edu 2016; 50(4): 456–68.
22. de Vibe M, Solhaug I, Tyssen R, et al: Mindfulness training for stress management: a randomised controlled study of medical and psychology students. BMC Med Educ 2013; 13: 107.
23. Warnecke E, Quinn S, Ogden K, Towle N, Nelson MR: A randomised controlled trial of the effects of mindfulness practice on medical student stress levels. Med Educ 2011; 45(4): 381–8.
24. Akinla O, Hagan P, Atiomo W: A systematic review of the literature describing the outcomes of near-peer mentoring programs for first year medical students. BMC Med Educ 2018; 18(1): 98.
25. Teodorczuk A, Thomson R, Chan K, Rogers GD: When I say … resilience. Med Educ 2017; 51(12): 1206–8.