From Fit to At-Risk: Latent Profiles of Health and Behavior Among First-Year Mexican American College Students

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Abstract

The first year of college is pivotal for establishing lifelong health habits, yet many Mexican American students experience challenges during this transition. Using data from 285 first-year students at three Hispanic-Serving Institutions in Texas, we performed latent profile analysis (LPA) to explore groups of behavioral and physical health indicators. Four profiles were identified: (1) Moderate Risk Behavior—healthy body composition but high intake of alcohol and fast-food; (2) Multidimensional High Risk—poor sleep, high body fat, and high substance use; (3) Health-Optimal Active—active lifestyle, low-risk behaviors, and good sleep quality; and (4) Physically Inactive but Lean—low activity with lean body composition but irregular dietary habits. The *Multidimensional High Risk* and *Moderate Risk Behavior* profiles showed less favorable health patterns, whereas the *Health-Optimal Active* profile reported the most favorable health outcomes. Notably, psychological distress remained high even in "lean" groups without clinical weight risks. Findings call for subgroup-specific health interventions that prioritize behavioral patterns over a weight-based paradigm in this underserved population.

Keywords: Mexican American students, health behavior, latent profile analysis, self-rated health, psychological distress, first-year college students

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Introduction

The first year of college is a major life transition during which young adults begin making independent decisions and establishing daily routines that shape their long-term health behaviors (Romm et al., 2022). Many students struggle to maintain healthy habits during this period, with disrupted sleep, irregular meals, and increased substance use often used to manage stress (Cameron & Rideout, 2022; Jao et al., 2019). These patterns can negatively affect physical and mental well-being (Cameron & Rideout, 2022; Jao et al., 2019).

For Hispanic American students, especially those of Mexican descent who represent a growing share of U.S. undergraduates (de Brey et al., 2019), this transition can be especially complex. In addition to academic adjustment, many face cultural expectations, family demands, and financial strain, often within environments where culturally responsive support is lacking (Castillo et al., 2008). These challenges are linked to disparities in physical activity, diet, and substance use (Hu et al., 2011).

Most prior research examines health behaviors in isolation, despite their tendency to occur. Person-centered approaches, such as latent profile analysis, are well-suited to identify behavioral patterns (Jao et al., 2019; Romm et al., 2022). Nonetheless, few studies have applied this approach to first-year Mexican American college students.

The present study draws insights from two complementary frameworks. Pender's Health Promotion Model emphasizes that engagement in health-promoting behaviors, such as physical activity, adequate sleep, and balanced nutrition, supports perceived health and psychological well-being (Pender, 2011). The stress-vulnerability framework adds that exposure to multiple behavioral and environmental stressors can increase susceptibility to poor health outcomes, particularly during transitional life stages such as the first year of college. Together, these perspectives suggest that patterns of behavior, rather than isolated habits, may more meaningfully shape student health. Accordingly, the present study identifies behavioral health profiles among first-year Mexican American college students and examines their associations with self-rated health and psychological distress.

Methods

Participants and procedures

Participants were first-year college students recruited from three Hispanic-Serving Institutions (HSIs) in the South-Central region of Texas during the Fall 2022 semester. Recruitment occurred through presentations during freshman orientations and required first-year courses, where students were invited to participate. Data collection occurred during a one-hour lab visit. Participants received a fitness tracker (AGPTEK Fitness Tracker, Model F1 Pro) as compensation. All procedures were approved by the Institutional Review Board at participating universities. Because recruitment occurred in large group settings, the total number of students exposed to recruitment materials was not recorded. To provide context, total freshman enrollment in 2022 was approximately 1,093, 1,099, and 5,770 across the participating institutions. The initial recruitment sample included 307 students. Analyses were restricted to students who self-identified as Mexican American, yielding a final analytic sample of 285 first-year students. Descriptive statistics are based on the final analytic sample ($n = 285$). Participants had a mean age of 18.51 years ($sd = 1.22$), and 55.05% identified as female. Race and ethnicity were assessed using separate survey items; approximately one-third of participants reported their race as White. About one-third of parents held an associate degree or higher. Most were U.S.-born (88.85%) and spoke English at home (93%).

Measurement

Self-rated physical and mental health were each measured using a single-item Likert scale (poor to excellent) and dichotomized such that responses of "poor" or "fair" were coded as poor health. Depression, anxiety, and stress were measured using the 21-item Depression Anxiety Stress Scale (DASS-21) (Lovibond & Lovibond, 1995) with good internal consistency in this sample, as indicated by high Cronbach's alpha values (depression $\alpha = 0.98$; anxiety $\alpha = 0.78$; stress $\alpha = 0.85$; total scale $\alpha = 0.93$).

Alcohol-related problems were assessed using the 18-item Rutgers Alcohol Problem Index (RAPI) ($\alpha = 0.78$) (White & Labouvie, 1989). Tobacco use was assessed with a self-report item asking whether participants had used tobacco products. Tobacco was defined as cigarettes, cigars, e-cigarettes or vaping products, and chewing tobacco. Sleep quality was evaluated using adapted items from the *Pittsburgh Sleep Quality Index* (PSQI), including sleep quality, duration, latency, medication use, daytime dysfunction, and sleep efficiency; items were recoded following PSQI conventions, with higher scores indicating poorer sleep quality (Buysse et al., 1989). Physical activity was assessed using both objective and self-reported indicators. Participants wore a wrist-worn fitness tracker (AGPTEK F1 Pro; AGPTEK, China) for one week to record step counts. The device uses a photoplethysmography (PPG) sensor and triaxial accelerometer. Prior research supports the general validity of wearable devices for physiological monitoring during low-to-moderate intensity activity (Wallen et al., 2016). At the end of the week, participants reported daily step counts from device records. Self-reported physical activity was assessed by frequency and duration of vigorous and moderate exercise, converted to metabolic equivalent (MET) minutes/week (1 MET = 3.5 ml O_2/kg/min) and categorized as inactive (0–599), low (600–2,999), moderate (3,000–5,999), or vigorous (≥6,000; capped at 28,800). Dietary behaviors were assessed through weekly frequency of fast-food consumption and breakfast (0 = none, 6 = every day) and average daily caloric intake (kcal). Participants completed three-day food records with portion guidance, and caloric intake was analyzed using Diet Power® software (version 4.4; DietPower Inc., USA). Standardized written instructions, including portion size estimation guidelines, were provided to enhance the accuracy and completeness of dietary records. Height (m) was measured using a wall stadiometer (Novel Products, USA), and body mass (kg), percentage body fat, and fat mass (kg) were assessed using a bioelectrical impedance analyzer (InBody 520; InBody Co., Ltd., Seoul, South Korea), which has demonstrated acceptable validity and reliability (Kyle et al., 2004).

Analysis

Latent Profile Analysis (LPA) identified subgroups based on health-related behavioral and biophysical indicators. Missing data were low (less than 5%) and handled using full information maximum likelihood (FIML), keeping all available information from each participant rather than applying listwise deletion. Raw descriptive means for behavioral indicators and health outcomes by profiles and for the overall sample are provided in Appendix Tables A1 and A2. For visualization purposes, profile means were subsequently standardized (z-scores) to generate the heatmap shown in Figure 1. Model selection was guided by the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), sample-size adjusted BIC (ABIC), entropy values, and the Lo–Mendell–Rubin Likelihood Ratio Test (LMR-LRT) (Table 1) (Nylund et al., 2007). Profiles with less than 5% of the sample were excluded for model stability (Elliott et al., 2020). Multivariate regressions were performed to examine associations between latent profile membership and health outcomes, including self-rated physical and mental health and psychological distress (e.g., depression, anxiety, and stress) (Figure 2).

Results

A four-profile solution was selected based on fit indices (lowest AIC, BIC, and ABIC values, a significant LMR-LRT p = .03, entropy = 0.81), indicating strong classification accuracy (Table 1). Although the five-class model had comparable entropy, it did not improve fit or interpretability.

LPA revealed four distinct behavioral profiles. Standardized z-scores (Figure 1) indicated that physical activity, sleep quality, and caloric intake were among the indicators

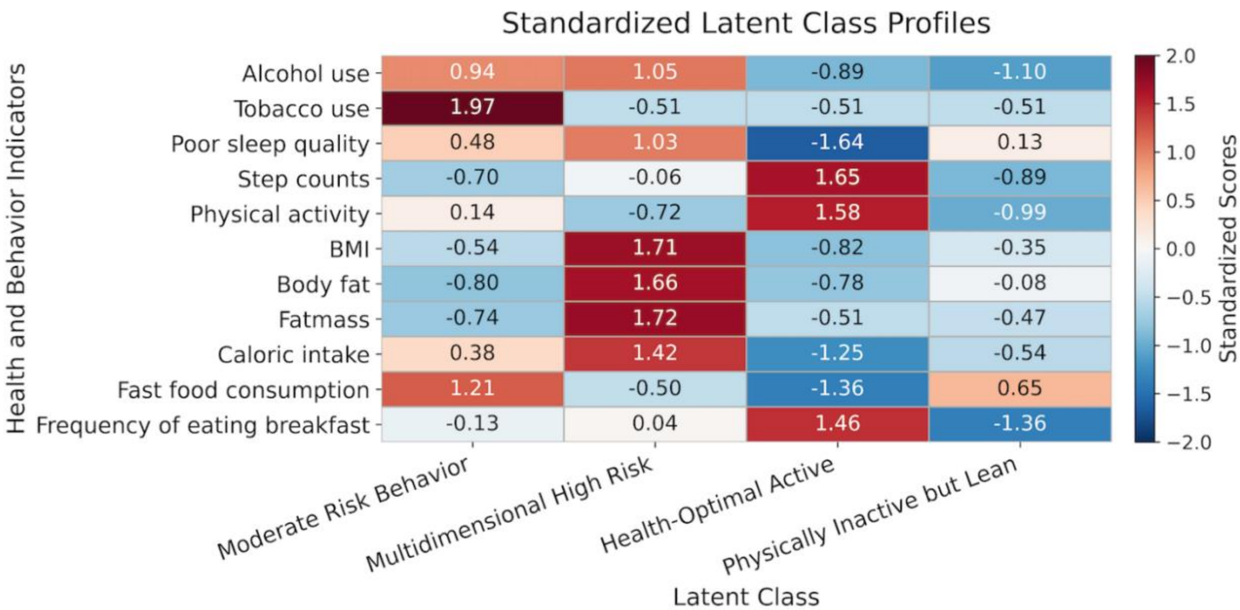
Table 1
Model Fit Information Used in Selecting the Four-Profile Solution

Model	Log-Likelihood	AIC	BIC	ABIC	LMR-LRT p-value	Entropy
1-Class	–10815.68	21675.37	21759.67	21689.87	—	—
2-Class	–10657.74	21383.49	21513.77	21405.91	0.01	0.72
3-Class	–10657.55	21395.11	21548.38	21421.49	0.12	0.74
4-Class	–9517.90	19123.80	19292.40	19152.83	0.03	0.81
5-Class	–9903.53	19891.06	20052.00	19918.77	0.22	0.78

Note. Log-Likelihood, AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), ABIC (sample-size adjusted BIC), LMR-LRT *p*-value (Lo–Mendell–Rubin Likelihood Ratio Test), and Entropy are reported for each model. Lower AIC, BIC, and ABIC values indicate better fit; higher entropy values indicate better class separation.

Figure 1

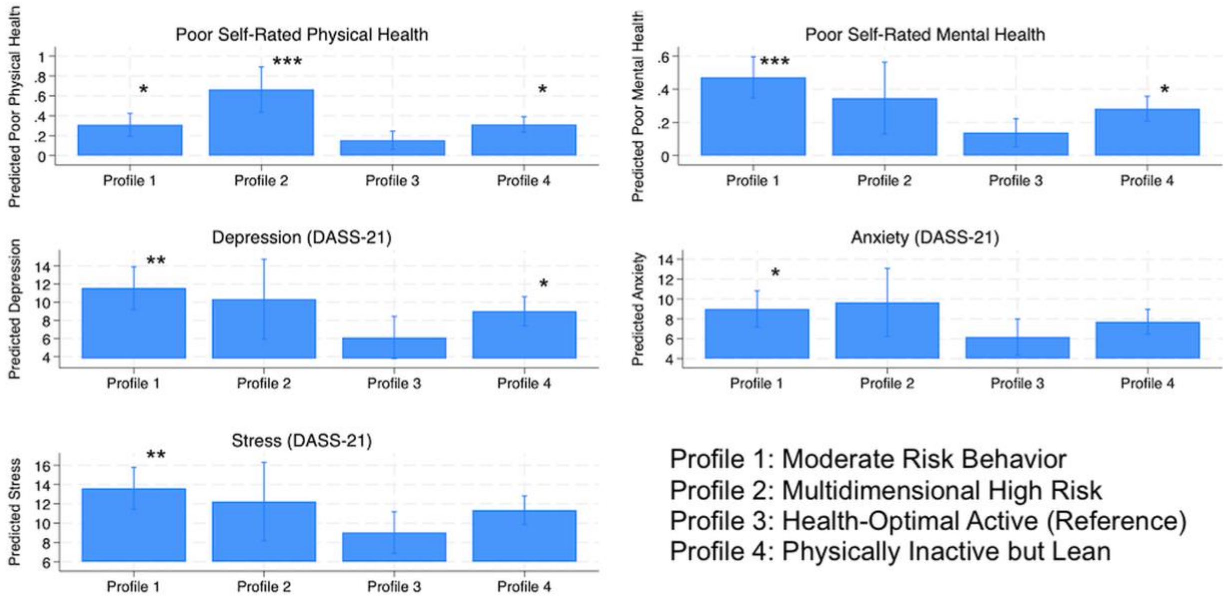
Heatmap Displaying Standardized Health and Behavior Indicators Across Identified Profiles



Note. Values represent standardized deviations (z-scores) of the model-estimated latent profile means from the overall sample mean for each indicator, calculated as: *(profile mean − overall sample mean) / overall sample standard deviation.* These values allow comparison across variables measured on different scales. Positive values indicate that the profile mean is above the sample average, and negative values indicate values below the sample average. Appendix Table A1 reports raw descriptive means based on observed data within assigned profiles. Minor differences between the heatmap and Appendix Table A1 reflect the distinction between model-estimated profile means and observed group averages. Warmer colors indicate higher standardized values, and cooler colors indicate lower values. Percent body fat was included as the primary body composition indicator in the latent profile analysis; BMI and fat mass are presented for descriptive comparison to illustrate consistent body composition patterns across profiles.

Figure 2

Predicted Health Outcomes by Latent Behavioral Health Profile Among First-Year Mexican American College Students



Note. Error bars represent 95% confidence intervals. Asterisks indicate statistically significant differences from the reference group (the *Health-Optimal Active* profile): *p<.05, ** p<.01, ***p<.001. All values are based on multivariate models adjusting for age, gender, parental education, nativity (U.S.-born), language use at home, and on-campus residence.

that most clearly distinguished the profiles. The *Moderate Risk Behavior* profile (n = 65, 23%) had relatively healthy body composition and moderate physical activity, but elevated alcohol use and tobacco use, and the highest fast-food consumption. The *Multidimensional High Risk* profile (n = 20, 7%) emerged as the most health-compromised group, characterized by elevated body composition, poor sleep quality, and high alcohol problems, and the highest caloric intake. In contrast, the *Health-Optimal Active* profile (n = 65, 23%) exhibited the most health-protective pattern, with high physical activity and step count, good sleep quality, minimal substance use, and favorable dietary behaviors and body composition. The *Physically Inactive but Lean* group (n = 135, 47%), the largest subgroup, was characterized by low physical activity and irregular eating, despite lean body composition.

Profiles differed significantly in self-rated health and psychological distress (Figure 2). The *Health-Optimal Active* group consistently showed the lowest predicted probability of poor self-rated physical and mental health. The *Multidimensional High Risk* profile showed the highest probability of poor self-rated physical health. The *Moderate Risk Behavior* profile exhibited higher predicted probabilities of poor self-rated health and elevated depression, anxiety, and stress compared to the reference group (i.e., *Health-Optimal Active* group).

Results from the DASS-21 subscales revealed that anxiety and stress scores were highest in both the *Moderate Risk Behavior* and *Multidimensional High Risk* profiles, and lowest in the *Health-Optimal Active* reference group. The *Physically Inactive but Lean* profile showed moderate levels across health outcomes. Although the *Multidimensional High Risk* group exhibited a greater mental health burden, these differences did not reach statistical significance, likely reflecting limited statistical power due to the small subgroup size (n = 20, 7%).

Discussion

This study identified four distinct behavioral health profiles among first-year Mexican American students, highlighting the clustering of health behaviors and their associations with health outcomes, ranging from a high-functioning, physically active group to a high-risk group with multiple behavioral vulnerabilities.

Students in the *Health-Optimal Active* group stood out as a resilient subgroup, with high physical activity, good sleep, favorable body composition, and low substance use (Pender, 2011). Our findings echo earlier research positively linking physical activity and sleep quality with better physical and mental health among college students (Irish et al., 2015; Peach et al., 2016).

The *Multidimensional High Risk* group, though small, showed the most compromised overall health profile, especially in the physical domain. Their mental-health indicators were elevated but not extreme, suggesting that clustering of risky behaviors may primarily affect physical functioning. The clustering of risky behaviors reflects behavioral comorbidity, where combined risks amplify physiological strain beyond any single factor alone (Champion et al., 2018; Ogbu et al., 2025; Warren et al., 2020).

The *Moderate Risk Behavior* profile adds an interesting layer of nuance. These students had generally healthy body composition and moderate activity levels, but higher alcohol and fast-food consumption, and slightly greater caloric intake. Even this moderate clustering of unhealthy behaviors was tied to elevated stress, depression, and poorer self-rated health, underscoring that "moderate risk" carries meaningful health implications.

The *Physically Inactive but Lean* group warrants attention. Despite lean body composition, low physical activity and irregular eating patterns suggest underlying vulnerabilities that are not captured by body weight alone. Research on the "metabolically unhealthy normal weight" phenotype indicates that individuals with normal weight may still experience adverse metabolic and psychological outcomes (Stefan, 2020). Sedentary behavior and stress-related processes associated with muscle loss and metabolic vulnerability may further contribute to these risks (Booth et al., 2012). Consistent with this literature, this group showed elevated depression and poorer self-rated health, challenging the common assumption that leanness is an indicator of good health (Penney & Kirk, 2015).

Limitations

This study has several limitations. First, we cannot establish causal relationships between health profiles and outcomes with its cross-sectional design. Second, self-report was used for some measures (e.g., sleep, diet, and substance use), which could be skewed by recall or social desirability bias. Although physical activity was assessed using a fitness tracker, step counts were self-reported from device displays rather than directly extracted from device memory or application data, which may introduce potential reporting or transcription errors. Third, although the sample was selected from three Hispanic-Serving Institutions, findings may not apply to the general population of Mexican American students or other Hispanic subgroups. Finally, despite the inclusion of multiple behavioral and physiological indicators, other factors, such as stress coping, social support, and acculturation, were not evaluated. Future research should explore these dimensions using longitudinal, multi-site approaches.

Implications for Health Behavior Research

The findings highlight the value of person-centered approaches for moving beyond single-health behavior models (Short & Mollborn, 2015). The identification of a *Physically Inactive but Lean* subgroup illustrates that weight-based indicators alone may overlook behavioral and mental health risks. Intervention should prioritize modifiable behaviors, such as physical activity, sleep quality, and dietary regularity, rather than body composition alone (Penney & Kirk, 2015). Tailored interventions are also needed across subgroups. Students in the *Multidimensional High Risk* and *Moderate Risk Behavior* profiles may benefit from integrated public health programs that simultaneously address nutrition, sleep hygiene, and substance use rather than targeting each behavior alone. Reinforcing physical activity and sleep quality as protective leverage points can inform low-cost, scalable campus interventions, while efforts for the *Physically Inactive but Lean* group should focus on increasing daily activity and regular eating patterns.

Consistent with the stress-vulnerability framework (Ingram & Luxton, 2005), the co-occurrence of academic, social, and developmental stressors during the first year may amplify the impact of even moderate behavioral risk among this population (Beiter et al., 2015). Early, targeted intervention during the transition period may help reduce long-term health disparities and support resilience in this underserved group.

Discussion Questions

How might cultural values and familial and institutional contexts influence the formation of distinct health behavior profiles among first-year Mexican American college students? Do students in "High-Risk" profiles show a downward trajectory in academic performance over four years, or do some students maintain academic performance despite “unhealthy” behavioral clustering?

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