Identifying response trends across mental health help-seeking beliefs in first-year engineering students using Latent Class Analysis (LCA)

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Introduction

Traditional variable-centered quantitative methods that are often used in engineering education research, such as regressions and correlations, struggle to adequately represent the beliefs of engineering students who do not fall into the majority, typically cisgender White men [1]. Using person-centered quantitative methods, researchers can avoid superficial characterizations of groups and issues caused by assumptions of population homogeneity [2, 3]. Therefore, in this methods paper we apply latent class analysis, a person-centered analysis method, to identify underlying subgroups that share similar beliefs about seeing help for their mental health.

Latent Class Analysis

Latent class analysis (LCA) is a person-centered analysis method that uses a probability-based assignment approach to identify hidden classes, or population subgroups, based on the means of a set of provided categorical indicator variables [4]. Latent class analysis determines these classes by assuming local independence, meaning that within each latent class, it is assumed that the observed categorical indicator variables are not related to each other. In other words, it assumes that within each latent class, the relationships between observed indicator variables are fully explained by the latent class itself. Consequently, classes are formed such that the observations within each latent class resemble each other but differ from the observations within other latent classes [5]. There is still much debate about best practices for performing latent class analysis; there are no widely agreed-upon processes for selecting indicator variables, selecting final class models, or reporting appropriate statistics [6].

Latent class analysis is especially useful when the relationship between predictor variables and outcomes is inconsistent. For example, consider a hypothetical scenario in which students take an introductory engineering course with a pass/fail outcome, and every student has 3 categorical predictors of success: attendance, peer collaboration, and math skills, each with strong, mid, and poor categories. Variable-centered analyses, like regression, may show that stronger attendance, collaboration, and math skills predict passing the course. However, variable-centered analysis methods fail when there are different types of students for whom the same predictor variable might strongly predict success for one type but not another. Person-centered methods, such as latent class analysis, can reveal for whom and under what conditions these predictors matter.

For a hypothetical group of high-performing independent learners, success could be most strongly predicted by math skills, with attendance and peer collaboration having a weak effect on their pass/fail outcomes. However, poor attendance and weak peer collaboration could be devastating for a group of highly social learners. There could also be a hypothetical group of disengaged students whose pass/fail outcome is only weakly related to all 3 predictor variables. By identifying which predictors matter for which groups, we can consider differences in student needs when we design interventions. Some groups might benefit significantly from interventions designed to boost participation, and some may not. Additionally, there may be groups whose pass/fail outcomes are not highly correlated with any single predictor and require intervention in multiple areas to succeed.

We chose LCA preferentially over other types of person-centered analyses, such as cluster analyses, because LCA provides probabilities of likely class assignment, rather than seeking to assign individuals to classes explicitly. LCA is an appropriate mixture modeling technique for single time point studies with discrete indicator variables [6]. Our assumptions include that latent traits exist among students that are determinant on groups of students with differing help-seeking intentions; in the absence of a theoretical model of these groupings, LCA allows for empirical and exploratory definitions of latent classes of people.

Integrated Behavioral Model

This paper uses latent class analysis to determine subgroups of first-year engineering students based on their beliefs about seeking professional treatment for mental health distress. Discovering group-specific needs is crucial for the design of interventions that can effectively encourage students to seek help for mental health distress. To identify what best predicts students' intentions to seek professional help, we applied the Integrated Behavioral Model (IBM), an empirically supported theoretical framework (Figure 1) [7].

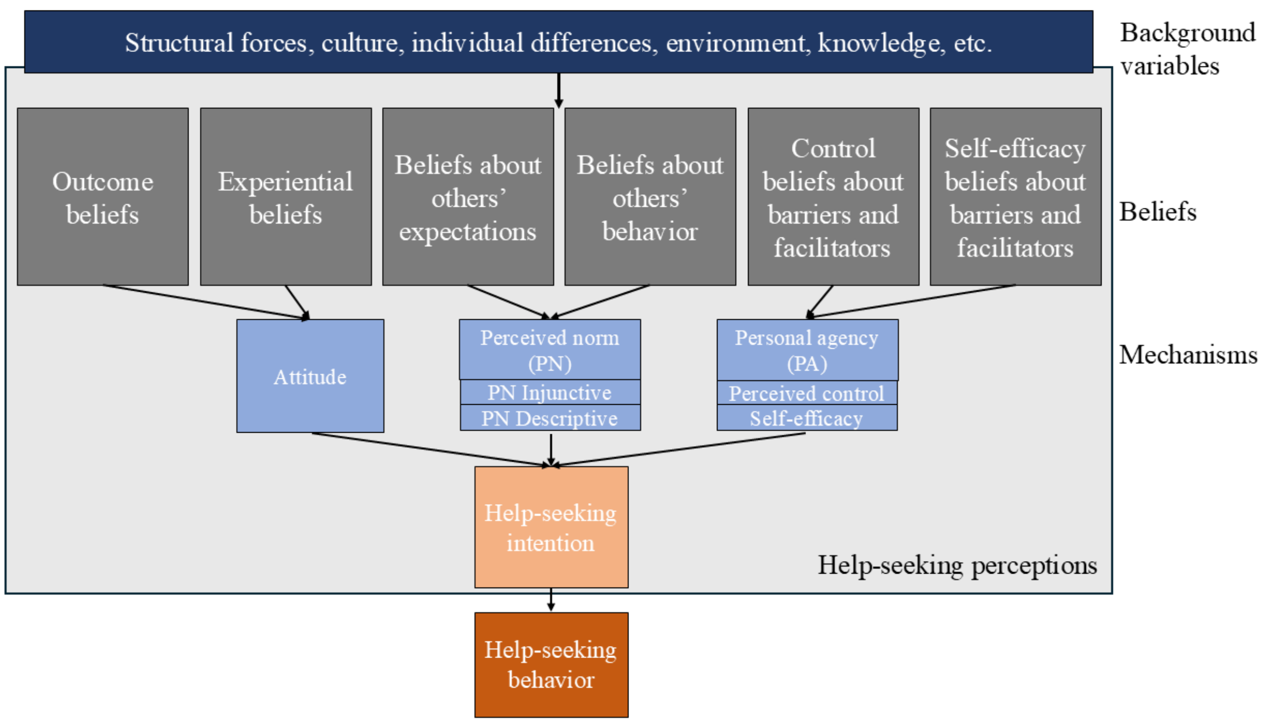

Figure 1: Background variables, beliefs, and mechanisms that drive mental health help-seeking, according to the Integrated Behavioral Model

When it is applied to mental health help-seeking, the IBM dictates that intention to seek help drives help-seeking behavior. The IBM also dictates that 3 help-seeking mechanisms (attitude, perceived norms, and personal agency) inform intention to seek professional mental health treatment. Attitude refers to an individual's positive or negative evaluation of the idea of seeking help for themselves, and it is informed by the outcome and experiential beliefs of the individual. Outcome beliefs are an individual's anticipated positive or negative outcomes of help-seeking behavior, and experiential beliefs are an individual's emotional response to the idea of seeking help. Perceived norm, which can be divided into injunctive and descriptive categories, is an individual's perception of the social approval of mental health related help seeking based on their beliefs about how those people who are important to them feel about seeking help. Perceived norm injunctive refers to the individual's perceptions about the expectations of important people or groups in their life, and perceived norm descriptive refers to the individual's beliefs about what important people or groups in their life would do if they were experiencing a mental health concern. The third help-seeking mechanism, personal agency, encompasses an individual's perceptions about whether they do or do not believe that they have the resources and power to seek professional mental health treatment. Personal agency can be represented by: 1) self-efficacy, which is defined as an individual's beliefs about their ability to seek help considering the individual's perceptions of help-seeking facilitators and barriers, and 2) perceived control, which is defined by an individual's perceptions about their control of their mental health help seeking considering the individual's perceptions of help-seeking facilitators and barriers.

The Current Study

A previous analysis of the data set used in this study was conducted using variable-centered analysis methods [8]. This analysis found that help-seeking intention was significantly correlated with all 5 of the mental health help-seeking mechanisms ($p < 0.001$), with the following bivariate correlation coefficients: attitude (0.575), perceived norm injunctive (0.786), perceived norm descriptive (0.674), self-efficacy (0.413), and perceived control (0.217). The previous investigation also determined, using linear regression, that the attitude, perceived norm injunctive, and perceived norm descriptive items were significantly predictive of mental health help-seeking intention ($p < 0.05$), having standardized regression coefficients of 0.24, 0.52, and 0.16, respectively. Perceived control and self-efficacy were found to have standardized regression coefficients of -0.03 and 0.07, respectively, and they were not determined to be significantly predictive of help-seeking intention due to their failure to account for incremental variance in mental health help-seeking intention [8]. The goal of the present study is to explore the use of person-centered analysis methods to find previously hidden subgroups within the dataset and identify differences between the subgroups.

Methods

Sample

After IRB approval, a total of 467 first-year engineering students were recruited to participate in the study. The participating students were assigned to complete the survey for their mandatory first-year engineering course at a large public university. Students were first given a cover letter detailing the purpose of the survey and then were given the option to participate. Student assignment grades were not affected by their participation in the study. Students were not incentivized to finish the entire survey and were informed that they had the option to skip questions at any time. Students were asked to provide their name, email address, and course section number in order to receive course credit for the assignment. To protect student privacy, faculty overseeing the courses were not informed which students chose to participate, and all personal identifying information was removed from the dataset following the assignment deadline. The demographic information of the study participants can be found below (Table 1).

Table 1: Demographic information for first-year engineering students who participated in this study (N = 467)

Demographic Group	N	%
Gender Identity		
Male	348	74.5%
Female	112	24.0%
Nonbinary	7	1.5%
Race/Ethnicity		
White	361	77.3%
Biracial	13	2.8%
Black	19	4.1%
Hispanic/Latine	35	7.5%
Asian American/Asian	36	7.7%
Middle Eastern/Arab/Arab American	4	0.9%
American Indian Or Alaskan Native	4	0.9%
Jewish	6	1.3%
Sexual Identity		
Heterosexual	401	85.9%
LGBQ+	56	12.0%

There is no widely agreed-upon sample size requirement for latent class analysis, but previous research has indicated that common fit statistics perform adequately when N ≈ 300–1000. Models that use fewer indicators and sufficiently well-separated classes may still produce acceptable results with a sample size of less than 300 [9].

Measures of Help-Seeking Mechanisms and Help-Seeking Intention

Five mental health help-seeking mechanisms (attitude, perceived norm injunctive, perceived norm descriptive, self-efficacy, and perceived control) were assessed in accordance with the IBM using the process described in the previous variable-centered analysis [8]. In brief, participants were asked to report their beliefs about mental health help-seeking using a 7-point Likert scale. Responses ranged from 1 to 7, with 1 being a more negative perception regarding a mental health help-seeking mechanism and 7 being a positive perception.

Analysis

Beginning with a single-class model, we tested models with 1 to 7 classes using the help-seeking mechanism scores dictated by the IBM (attitude, perceived norm injunctive, perceived norm descriptive, self-efficacy, and perceived control) as indicators to investigate mental health help-seeking intention as a distal outcome. All analyses were conducted using M*plus* 8.11 using full information maximum likelihood (FIML) and a large number of random starts (>500) [10]. The output for each model was examined to check that the log-likelihood value was sufficiently replicable and to ensure that global maxima had been established [9].

To discern the ideal number of latent classes to describe the observed data, the following items were considered:

- The number of sample members in each class must be greater than 50. [6]
- All classes must contain greater than 5% of the sample. [1, 6]
- Entropy must be greater than 0.80. [11]

- Sample-adjusted Bayesian information criterion (SABIC) should be considered. Smaller values of SABIC are preferred. [1, 12, 13]
- Bayesian information criterion (BIC) should be considered. Smaller values of BIC are preferred. [1, 14, 15, 16]
- The smallest average latent posterior probability should be considered. The value must exceed 0.80. A value between 0.80 and 0.90 may be acceptable if other fit criteria are met. A value greater than 0.90 is ideal. [6, 17, 18]
- The interpretability of the model should be considered. [6]

After the best model was identified, the estimated mean help-seeking intention score and the estimated mean help-seeking mechanism scores were calculated and plotted for each class.

Results & Discussion

A summary of the fit statistics for each of the models is provided below (Table 2).

Table 2: Fit indices and other relevant information generated by the comparison of models with 1 to 7 classes

# of classes	BIC	SABIC	Entropy	Smallest average latent posterior probability	Minimum # of sample members	% Class 1	% Class 2	% Class 3	% Class 4	% Class 5	% Class 6	% Class 7
2	7600.3	7406.7	0.769	0.906	171	36.6	63.4	-	-	-	-	-
3	7485.9	7193.9	0.808	0.902	125	26.8	35.5	37.7	-	-	-	-
4	7535.4	7145.0	0.835	0.886	77	25.3	37.9	20.3	16.5	-	-	-
5	7620.5	7131.7	0.843	0.873	64	19.5	30.4	16.5	19.9	13.7	-	-
6	7721.2	7134.0	0.872	0.879	28	19.5	29.8	21.2	16.9	6.0	6.6	-
7	7849.4	7163.8	0.865	0.847	27	8.1	28.7	21.4	16.9	5.8	6.9	12.2

The process outlined in the methods section was used to assess the ideal number of classes for this dataset. The 6- and 7-class models do not have a minimum of 50 sample members in each class, suggesting they should not be used [6]. Entropy must be greater than 0.80 [11], so the 2-class model was eliminated from the remaining options, leaving the 3, 4, and 5-class models. The 3-class model has the lowest BIC and the best class separation (according to the smallest average latent posterior probability). However, the 3-class model ranks third out of the remaining models for SABIC and entropy. The 5-class model has the lowest SABIC and the highest entropy but ranks third out of the remaining models for BIC and class separation. The 4-class model had the second-best values for BIC, SABIC, entropy, and class separation. Because each of these models demonstrated they could potentially be acceptable models, they advanced to the next stage of analysis and were plotted (Figures 2, 3, and 4) so that we could assess their potential for interpretation.

The 3-class model clearly shows 3 groups of students with varying beliefs about seeking professional mental health treatment (Figure 2).

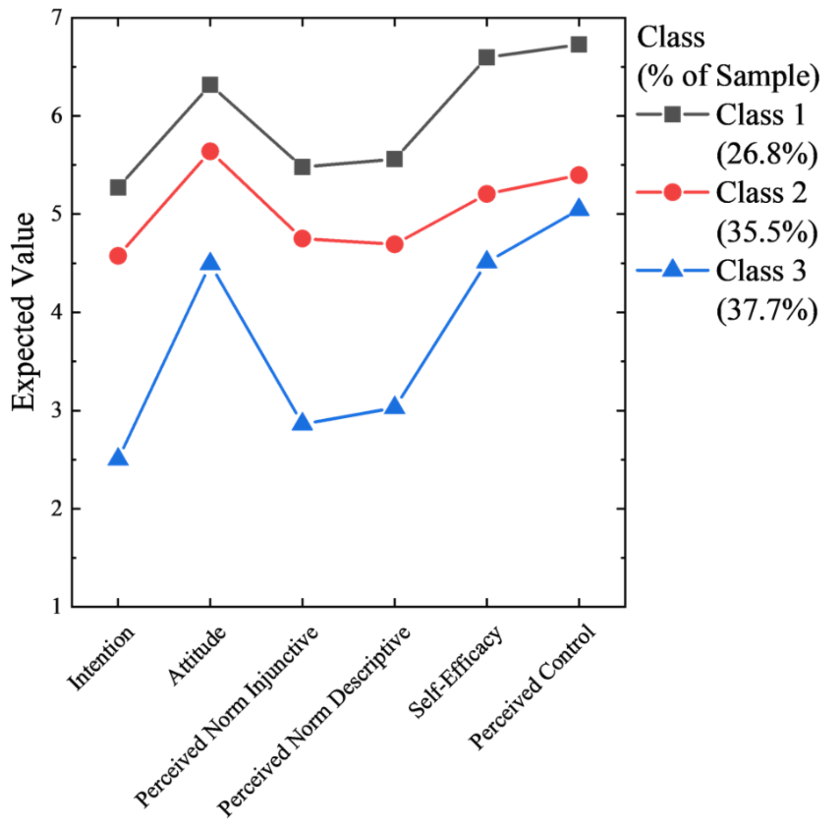

Figure 2: Estimated means for help-seeking mechanisms and intention for the 3-class model

The estimated means for Class 3 appear to be less favorable across all mental health help-seeking mechanisms and help-seeking intention when compared to Classes 1 and 2. The estimated means for Class 1 were higher for all help-seeking mechanisms as well as intention. Intention was not used as an indicator variable (i.e., intention was not involved in the formation of the classes). Rather, the IBM dictates that help-seeking intention is an outcome of the help-seeking mechanisms. It is clear in Figure 2 that the help-seeking mechanisms seem to have a direct impact on help-seeking intention.

With the addition of a new class (Class 4), shown in Figure 3, the importance of using person-centered analyses is highlighted.

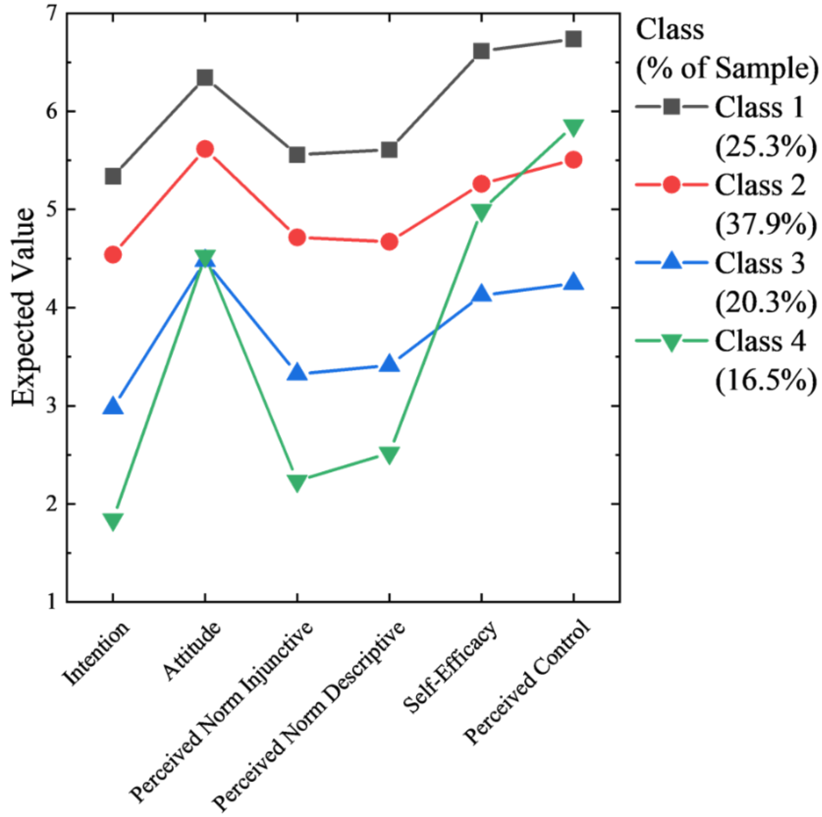

Figure 3: Estimated means for help-seeking mechanisms and intention for the 4-class model

In this model, Class 4, characterized by very low intention and perceived norms, low attitude, mid-self-efficacy, and mid-perceived control, was not observed previously using variable-centered analysis methods [8]. This is because the regression employed in the previous investigation could not sufficiently account for population heterogeneity. This means that there is a subgroup of the studied first-year engineering students who are unlikely to intend to seek help for a mental health concern despite believing that they would have the power and resources to do so. Further, this new subgroup with especially low intention (Class 4) has, on average, a nearly identical estimated mean for attitude as the class with the second-lowest intention (Class 3), but Class 4 has a more negative evaluation about whether people who are important to them would support their seeking professional help for mental health.

Similarly to the 4-class model, the 5-class model showcases a new class of students who report more positive attitudes and beliefs about personal agency relative to their beliefs about perceived norms.

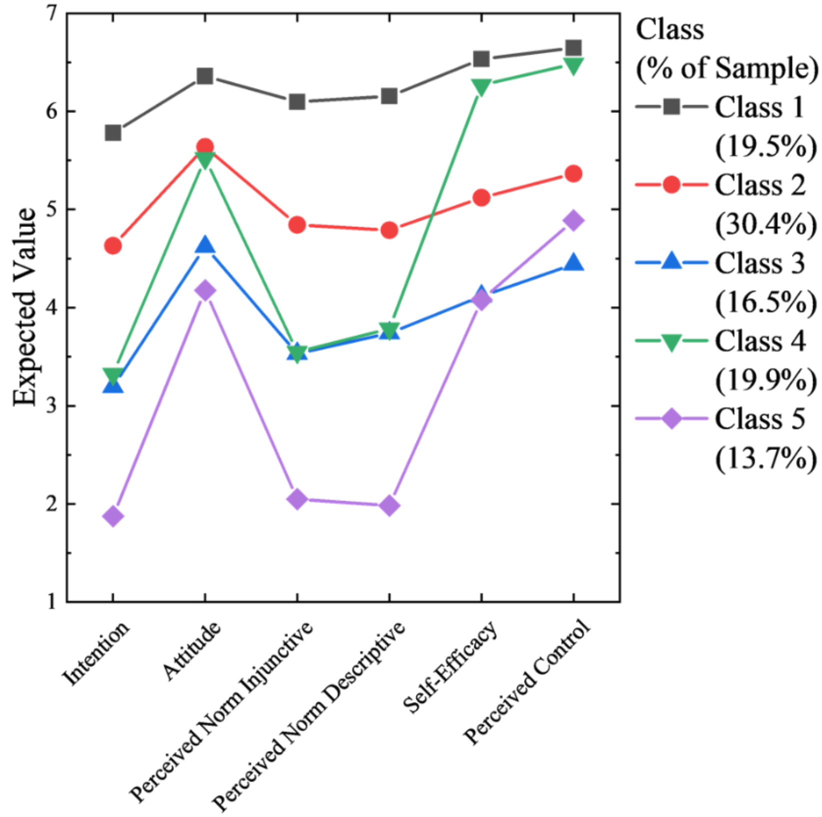

Figure 4: Estimated means for help-seeking mechanisms and intention for the 5-class model

In the previously conducted variable-centered analysis that this paper serves to extend, the mental health help-seeking mechanisms that were most predictive of mental health help-seeking intention were the perceived norm items (injunctive and descriptive). Looking at the beliefs of Class 4 and Class 5 (Figure 4), a portion of the sample may be especially contributing to the predictive power of the perceived norm items. The perceived norm items are especially predictive of intention for Classes 4 and 5, and comparatively, the personal agency items seem to be much less predictive of help-seeking intention. For Classes 1, 2, and 3, it appears that the personal agency items might be stronger predictors of help-seeking intention than they are for Classes 4 and 5.

A summary of the characteristics of the classes for the models with 3, 4, and 5 classes can be found below (Table 3).

Table 3: Qualitative comparison of each class using the 3-, 4-, and 5-class models.

	Class 1	Class 2	Class 3	Class 4	Class 5
3-class model	High intention and help-seeking perceptions	Mid-intention and help-seeking perceptions	Low intention and help-seeking perceptions	-	-
4-class model	High intention and help-seeking perceptions	Mid-intention and help-seeking perceptions	Low intention and help-seeking perceptions	Very low intention and perceived norms, low attitude, mid personal agency	-
5-class model	High intention and help-seeking perceptions	Mid-intention and help-seeking perceptions	Low intention and help-seeking perceptions	Low intention and perceived norms, mid attitude, high personal agency	Very low intention and perceived norms, low attitude and personal agency

Limitations and Future Directions

Latent class analysis presents great potential for applications in mental health help-seeking intervention design due to its ability to discover latent subgroups. Although previous research using linear regression found that personal agency (self-efficacy and perceived control) was not significantly predictive of help-seeking intention [8], the results of person-centered analysis suggest that personal agency may be a stronger predictor for some groups than others. Awareness of these subgroups and their specific needs is critical for the success of these interventions; by identifying class-specific differences in student subgroups, we can create intervention strategies that deliver targeted support.

While latent class analysis has demonstrated its capability to offer new perspectives compared to variable-centered analysis methods, it also has limitations. One such example is the sample size requirements of latent class analysis, which may pose a problem for some researchers. Additionally, there is no widely agreed-upon process for model selection, and previous investigations have shared conflicting findings about which fit statistics are the most accurate [9]. There are also limitations because of the probabilistic nature of latent class analysis, namely, the possibility of incorrect class assignments and the inability of latent class analysis to determine exactly how many sample members are in each class [6].

Future directions for this research could involve using latent class analysis to identify key differences between classes, including differences in the specific mental health help-seeking beliefs that form the larger evaluations of mental health help-seeking.

Conclusions

We employed latent class analysis (LCA) to analyze whether hidden subgroups of students that share similar beliefs about mental health help-seeking were prevalent in this data set. Using person-centered analysis revealed grouped students into 3 categories—low-intention, mid-intention, and high-intention—based on responses to attitude, perceived norms, and personal agency items. A 4-class model revealed an additional subgroup with low help-seeking intention, splitting them into those with low and high perceived control and confidence. This suggests that some first-year engineering students feel capable of seeking help but may avoid professional treatment despite significant mental health issues. These findings highlight the importance of person-centered analysis in identifying diverse mental health belief groups, which can guide targeted interventions for engineering students.

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