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Mitigating Ceiling Effects in a Longitudinal Study of Doctoral Engineering Student Stress and Persistence

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Abstract

Aim/Purpose	The research reported here aims to demonstrate a method by which novel applications of qualitative data in quantitative research can resolve ceiling effect tensions for educational and psychological research.
Background	Self-report surveys and scales are essential to graduate education and social science research. Ceiling effects reflect the clustering of responses at the highest response categories resulting in non-linearity, a lack of variability which inhibits and distorts statistical analyses. Ceiling effects in stress reported by students can negatively impact the accuracy and utility of the resulting data.
Methodology	A longitudinal sample example from graduate engineering students' stress, open-ended critical events, and their early departure from doctoral study considerations demonstrate the utility and improved accuracy of adjusted stress measures to include open-ended critical event responses. Descriptive statistics are used to describe the ceiling effects in stress data and adjusted stress data. The longitudinal stress ratings were used to predict departure considerations in multilevel modeling ANCOVA analyses and demonstrate improved model predictiveness.
Contribution	Combining qualitative data from open-ended responses with quantitative survey responses provides an opportunity to reduce ceiling effects and improve model

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performance in predicting graduate student persistence. Here, we present a method for adjusting stress scale responses by incorporating coded critical events based on the Taxonomy of Life Events, the application of this method in the analysis of stress responses in a longitudinal data set, and potential applications.

Findings: The resulting process more effectively represents the doctoral student experience within statistical analyses. Stress and major life events significantly impact engineering doctoral students' departure considerations.

Recommendations for Practitioners: Graduate educators should be aware of students' life events and assist students in managing graduate school expectations while maintaining progress toward their degree.

Recommendations for Researchers: Integrating coded open-ended qualitative data into statistical models can increase the accuracy and representation of the lived student experience. The new approach improves the accuracy and presentation of students' lived experiences by incorporating qualitative data into longitudinal analyses. The improvement assists researchers in correcting data with ceiling effects for use in longitudinal analyses.

Impact on Society: The method described here provides a framework to systematically include open-ended qualitative data in which ceiling effects are present.

Future Research: Future research should validate the coding process in similar samples and in samples of doctoral students in different fields and master's students.

Keywords: doctoral students, attrition, persistence, stress, longitudinal survey, SMS survey, ceiling effects, qualitative

INTRODUCTION

Self-report rating scales remain a cornerstone of large-scale longitudinal psychological research. However, survey data can suffer from "ceiling effects" that occur when participant scores remain at the highest limit of the scale (Everitt, 2002; Feng et al., 2019; Hessling et al., 2004), which eliminates measurement of variance and estimation beyond the upper limit of the scale (Cramer & Howitt, 2004; Liu & Wang, 2021). These ceiling effects can lead to problematic non-linearity or underestimated parameters in regression and incorrect model selection (Wang et al., 2008). Some treatments of data allow statistical correction for ceiling effects or alternative analysis methods to resolve ceiling effects (Fitzmaurice et al., 2004; Wang et al., 2008). However, multiple research methods and the inclusion of qualitative data may provide an alternative participant-centric correction for ceiling effects in which open-ended text-entry items are incorporated into the quantitative data analysis. Centering participant experience focuses on corrections to better represent participants than statistical corrections, which only address normality and distribution concerns. In this paper, data from a longitudinal weekly measurement of stress in doctoral engineering education contexts demonstrates the opportunity to correct ceiling effects in a stress measure in data using qualitative data. In our proposed method, the qualitative data allows participants to describe events or perspectives that demonstrate the inadequacy of the scale limit to be incorporated into the quantitative metrics, thereby more fully representing participants' lived experiences. The demonstration of the method includes the longitudinal stress measure adjusted with text-based critical events responses as the predictor for a semester-end measure of degree completion confidence. While this research focuses on a stress measure, the method presented in this paper will be valuable for scholars using scales prone to ceiling effects across disciplines, including psychology, education, and health.

LITERATURE REVIEW

CEILING EFFECTS AS A METHODOLOGICAL LIMITATION

In quantitative psychological and educational research, ceiling effects occur when self-report survey scores cluster either at or near the highest possible value on a scale with a similar floor effect when scores cluster at the lowest value (Feng et al., 2019; Hessling et al., 2004). A ceiling effect may indicate accurate scores, such that they represent the actual clustering of individuals near the top of a scale (i.e., high scores on an exam), or the ceiling effect may indicate truncation of scores where individuals' accurate scores would be beyond the highest measure (i.e., in a sample of individuals with high stress). In either case, ceiling effects represent a distortion of the data that defies the normality assumption in many commonly used statistical analyses. Data with ceiling effects exhibit non-normally distributed data due to a reduction of variance, which leads to reduced reliability and validity, poor model fit, incorrect model selection, or Type I error (Austin & Brunner, 2003; Fan & Hancock, 2012; Hessling et al., 2004; Uttl, 2005; Vogt, 2005; West et al., 1995). Ceiling effects continue to be noted as problematic for researchers in pre and post-test evaluation of self-efficacy, anxiety, and physical rehabilitation, factor identification, human development studies (Feng et al., 2019; Schweizer et al., 2019; Singh, et al., 2021; Skoda et al., 2021; van Woerkom & Meyers, 2019). The problems of ceiling and floor effects affect statistical methods differently, with transformed data working well but inconsistently based on specific ceiling and floor effects and types of transformation (Šimkovic & Träuble, 2019). Liu and Wang (2021) describe data with ceiling effects as "censored data," such that the only available information about the true value of data is that it lies near or above the ceiling value. Ceiling effects cause meaningful limitations on the interpretation of data and statistical analysis.

Although literature and textbooks identify ceiling effects as problematic, sources often remain silent on what to do about ceiling effects (Liu & Wang, 2021). Traditional corrections for ceiling effects focus on data transformations (e.g., square root, log, or inverse) that may bring the data closer to normality. More recent approaches vary based on the type of analysis, such as non-parametric tests, and others utilize item response theory, which relates an individual item measurement to other measures of the construct of interest for that respondent. Liu and Wang (2021) provide a few examples of corrections available for ceiling effects, such as Tobin's (1958) Tobit model and applications (Wang et al., 2008), or Bayesian estimation (Piccinin et al., 2013).

Despite available numerical correction options, most studies simply acknowledge ceiling effects without addressing them in the analysis plan: In a limited review of ceiling effects in t-tests and ANOVAs, Liu and Wang (2021) found that 57% of articles in their sample with t-tests and 70% of those with ANOVA treated the ceiling or floor effect as if the value were an accurate value, simply ignoring the effect within the statistical analyses, while the remaining researchers dealt with ceiling/floor effects by discarding the extreme scores or by transforming the data to resemble normally distributed data. While each of these methods for addressing ceiling effects may hold merit and prove effective in handling the numerical data, it can be argued that each of these strategies ignores both the participants' intention and the inaccuracy of the scale to capture the true value of the participant on a given construct. However, over-reliance on statistical manipulation of data may be a disservice to *science,* writ large, researchers' needs, and participant representation. Researchers need methods for handling ceiling effects that can simultaneously improve the accuracy and representation of participants' experiences. We offer that ceiling effects represent the limit of quantitative data to represent the full range of human experience. Qualitative research offers a potential solution to this conundrum, as qualitative data benefits from no similar restriction or censoring of participants' experiences.

Therefore, this paper aims to establish a method by which novel applications of qualitative data in quantitative research can resolve ceiling effect tensions for educational and psychological research while continuing to center the participant experience in a constructivist way, even in quantitative survey-based methods. To demonstrate, we engage with a practical example of our method applied to longitudinal survey data from a project that seeks to investigate engineering doctoral students' departure considerations from the doctorate, which we consider to be any early departure before the attainment of the degree. In this demonstration, we address the ceiling effects identified when measuring stress as a predictor of doctoral engineering students' beliefs that they will complete their degrees. To motivate the context in which this study is conducted and the research design, we offer a short overview and literature-based justification of the project.

Justification of Exemplar Study: Doctoral Departure and Stress

Doctoral students leaving their programs before degree completion represents a major problem across higher education. The departure of highly skilled, knowledgeable, talented, and otherwise capable individuals is a loss to the workforce, universities, funding agencies, faculty members, and the students themselves. Literature often refers to students leaving without their doctoral degree as attrition; we prefer the student and person-centered nomenclature of early departure to avoid the negative connotations of loss or failure associated with attrition. Previous research has demonstrated the importance of multiple factors in graduate student persistence across all fields, including satisfaction with the graduate experience, beliefs about self-efficacy in professional success, and differences between experiences and expectations in graduate education (Hardré et al., 2019). In Science, Technology, Engineering, and Mathematics (STEM) fields, the problem has been researched from multiple viewpoints in an attempt to meet federal goals and industry needs for doctoral-level researchers who can address the needs of 21st-century problems (National Academies of Sciences, Engineering, and Medicine, 2018). Within engineering doctoral departure research, specific factors include poor advisor experiences, support networks, life balance, costs, and changing goals (Berdanier et al., 2020); and race and gender-based discrimination (Bahnson et al., 2022; Burt et al., 2018, 2019; McGee et al., 2019). However, early departure rates in engineering are not as high as in other disciplines in the social sciences and humanities, partly because of consistent and relatively high funding of graduate students and a relatively short time to degree completion. However, departure rates remain high, between 24% and 36% for men and women, respectively, and even higher for racially underrepresented groups (Sowell et al., 2008, 2015). For example, in engineering, the ten-year completion rate for Ph.D. students hovers between 50% and 64% (Sowell et al., 2015). Further, 70% of engineering doctoral students frequently consider leaving their doctoral program without a degree (Bahnson & Berdanier, 2023), indicating students' distress, regardless of whether they decide to persist or depart from their programs.

While some census-level research tracks degree completion (National Science Board [NSB], & National Science Foundation [NSF], 2020), the data available do not indicate decisions for attrition. Further, most existing early departure research uses qualitative or cross-sectional methods (Bean, 1981, 1983; Hardré et al., 2019; Litalien & Guay, 2015; Mendoza et al., 2014; Pauley et al., 1999; Tinto, 1988), thereby limiting causal inference based on participants' persistence or departure considerations and decisions. Without accurate modeling of departure considerations and decisions, administrators will be unable to address high attrition, continuing a trend toward poor preparation of an educated, diverse, and robust workforce (National Academies of Sciences, Engineering, and Medicine, 2018; Nerad, 2004).

During graduate school, some students experience critical events that alter their worldviews on remaining in graduate school, which have been shown to lead to departure considerations and eventual early departure (Lott et al., 2009; Zerbe et al., 2023). While many life experiences can be critical events for students (Zerbe et al., 2022), many factors influence departure considerations, including advisor and peer relationships, discrimination, and employment opportunities (Artiles & Matusovich, 2020; Bahnson et al., 2022; Berdanier et al., 2020; Lott et al., 2009; Sallai et al., 2023; Zerbe et al., 2023). In other students, more general dissatisfaction and unhappiness build with no identifiable critical event leading to departure.

One potential cause of unspecified distress may come from chronic stress, an often-cited problem for graduate students that leads them to consider departure and to eventually leave their program (Hyun et al., 2007; Lipson et al., 2016). Stressors change as students advance through the degree program (Ampaw & Jaeger, 2012; Kiley, 2009), with marginalized students experiencing additional stress and hardships in graduate school (Posselt, 2018; Thomas et al., 2007). With longitudinal repeated-measures methods, variation in a measured variable, such as stress, provides the necessary data for assessing outcome associations. However, chronic stress common for graduate students (Evans et al., 2018) and unanticipated geopolitical, sociocultural, and pandemic-related stress (i.e., invasion of Ukraine, January 6th insurrection, and Omicron Covid-19 variant) can lead to ceiling effects in stress measures limiting the value and accuracy of a tested model.

Longitudinal Doctoral Stress and Departure Study Design and Methods

An NSF-funded national longitudinal survey of graduate engineering students has been launched to address gaps in understanding engineering doctoral student attrition (Jwa & Berdanier, 2022) to investigate departure considerations and the events which lead to departure without the doctoral degree, employing SMS (text message) based survey methods. SMS-text survey distribution began on January 17th, 2022, to ensure most students had returned from winter break, and will continue at least through August 2022.

Recruitment and Participants

Following IRB approval, we sent a recruitment e-mail to the top 50 engineering Ph.D. granting programs in the U.S. (The American Society for Engineering Education [ASEE], 2020). The e-mail included a link to our Qualtrics screening survey, which collected graduate experience information, recent departure considerations, demographic information, and contact details. The consent and participant recruitment information emphasized that the survey duration would require a year of sustained participation. From a total of 3,495 prospective participants, 200 engineering doctoral students enrolled at research-intensive universities were selected for the initial wave of participation. In the screening survey, 44% of respondents (n = 1545) consented to SMS (text-based) survey participation and were Ph.D. students. Selected participants met stratified sampling to include representation by gender (101 women, 96 men, 2 non-binary, and 1 another gender), domestic (n = 151; 54% women and 44% men), and international students (n = 49; 38% women and 59% men). Recruitment priority was given to those with high departure considerations and participants from backgrounds considered at higher risk for early departure (Black or African American, Native American or First Nations, Latino/a/x, or Pacific Islander). Asian (n = 40) and White (n = 42) students were randomly selected based on gender, their doctoral program stage, and those considering departure. International students were randomly selected from those who had often or sometimes considered leaving their doctoral program.

Survey Instrument, Items, and Data Collection

Longitudinal SMS (text-message) data collection methods assist researchers in collecting frequent measures while eliminating the need for special software or participant training. Further, participants find SMS-text surveys easier to use than web-based surveys (Kuntsche & Robert, 2009), potentially increasing response rates. However, the ease and convenience of SMS-text surveys is offset by the need to limit the number and type of questions to manage costs and maintain response rates. Each one- and two-way text message with each participant incurs costs for the research team. To manage costs, survey items must have a clear theoretical and phenomenon focus (Kuntsche & Robert, 2009) without the opportunity for similar items or reverse-coded items.

Substantial survey design, cognitive interviewing with participants, and pilot testing prefaced SMS data collection (Jwa & Berdanier, 2022). Clarity of questions was discussed and tested through pilot testing and cognitive interviews with pilot participants. In our pilot study following 5 graduate engineering student participants who represented different backgrounds and engineering disciplines, we tested our deployment software and conducted cognitive interviews on timing of surveys (reducing the survey from 5 times per week to 3 times per week, per participant feedback on survey fatigue); and revisions on ambiguities to ensure maximum clarity for our participants. For example, when we asked about the stress, "Today, the stress I'm experiencing is overwhelming," two volunteers from the pilot study thought that it wasn't sure whether we wanted them to consider stress from outside of the graduate program or only pertaining to academics. The question was revised by adding "related to graduate school and/or life." Based on their feedback, we also honed language to avoid excessively priming our participants about attrition, such that the question "Today, I am confident in my ability to complete my degree" is framed positively (indirectly measuring attrition considerations). As the survey items were honed, we reached convergence where all participants interpreted the questions in the same way, and each question represented a critical aspect of our theoretical framework, thus achieving a reasonable standard of theoretical content validity. Because we are inherently limited by cost per SMS text message and the need for high survey response, we could not classically assess reliability based on similar questions or reverse coded questions. The instrument is designed to assess dynamic and changing perceptions in our participants, such that test-retest reliability is not the goal: Stress one day will not be the same as stress another day. We want to capture the dynamics over time as their circumstances affected their stress and attrition considerations, such that construct validity is the most important indicator of quality for us.

May 2022						
Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
1	2	3	4	5	6	7
Reminder email	**Daily Survey @ 3PM**		**Daily Survey @ 3PM**		**Weekly Survey @ 3PM**	
8	9	10	11	12	13	14
Reminder email	**Daily Survey @ 3PM**		**Daily Survey @ 3PM**		**Semesterly Survey @ 3PM**	
15	16	17	18	19	20	21
Reminder email	**Daily Survey @ 3PM**		**Daily Survey @ 3PM**		**Monthly Survey @ 3PM**	
22	23	24	25	26	27	28
Reminder email	**Daily Survey @ 3PM**		**Daily Survey @ 3PM**		**Weekly Survey @ 3PM**	
29	30	31	June 1	June 2	June 3	June 4
Reminder email	**Daily Survey @ 3PM**		**Daily Survey @ 3PM**		**Weekly Survey @ 3PM**	

Figure 1: Example month (May, 2022) of data collection

Data collection began on January 17th, 2022, using Qualtrics software to send individual SMS surveys to participants' cell phone numbers thrice weekly. Survey distribution is automated using the secure survey software platform, Qualtrics. The SMS text survey distributed on Mondays, Wednesdays, and Fridays includes two items. The first item measures stress: Today, the stress I'm experiencing related to graduate school and/or life is overwhelming. The second item measures degree completion attitudes: Today, I am confident I will complete my degree objective (e.g., M.S. or Ph.D.). Participants respond to each item on a scale from 1 (Strongly disagree) to 7 (Strongly agree). Each week, an SMS text on Friday directs participants to a Qualtrics survey with additional items (Figure 1), which collects other data related to funding, advisor relationships, peer support, and degree progress data, among other facets. All questions were based in literature, theory, and piloted with cognitive interviews to ensure validity. The full survey is provided in Appendix A. We allow participants until 12 am on the following survey day to respond. Participants receive compensation monthly ($10/month) if they do not miss more than two of the "daily" surveys or one weekly survey in that calendar month. In addition, participants who complete the semester are entered in a drawing to receive one of three $50 gift cards.

The authors' institutional review board (IRB) approved all data collection procedures. Study materials are available upon request to the authors. Longitudinal data collection is ongoing at the time of this writing.

DATA ANALYSIS

To mitigate the methodological challenge presented by ceiling effects found in the stress measure, as will be demonstrated in the Results section, we focus on the Friday stress assessment: *Today, the stress I'm experiencing related to graduate school and/or life is overwhelming*; the weekly open-ended critical events item: *Have you experienced stressful events related to graduate school and/or life this week?,* and the semester-end degree completion confidence item: *At this point, I am confident that I can complete my program of study (e.g., M.S., Ph.D.).* For this analysis, we use the data collected from January 17th, 2021, to May 13th, 2021.

The results are presented in three parts. First, we describe the ceiling effects found within the original data. Second, we describe the development of our method to adjust the stress rating and present the resulting adjusted data. Third, the results from the multilevel modeling ANCOVA analyses demonstrate the change in explained variance resulting from the systematic adjustment of the stress construct.

Preliminary descriptive statistics were conducted in SPSS with specific attention toward assessing ceiling effects in the stress variable. Multilevel modeling in SAS was used to assess the repeated stress measures associated with students' belief they will complete their doctoral degree. In the multilevel modeling framework, a null analysis is a preliminary analysis conducted to verify sufficient variability at Level 1, and Level 2 exists to warrant additional analyses (Raudenbush & Bryk, 2002). The null or fully unconditional model, in which no variables are included except the intercept, will demonstrate the amount of variation in stress scores with the individual student compared to the variation in stress scores between individuals. Following the null analysis, a second analysis tests the relationship to the dependent variable by including it in an ANCOVA. In these analyses, each step (null and ANCOVA) is conducted twice: first on the original data and then on the adjusted data. ANCOVA is conducted twice to measure the change in variance explained when life events are used to adjust the stress scores in the second ANCOVA.

RESULTS

IDENTIFICATION OF CEILING EFFECTS

Initial descriptive analyses identified potential ceiling effects for the stress item. For example, individual participants scored high, with 18 (13%) participants' mode at 7 (strongly agree) for the seventeen

Friday time points at which stress measures were collected. In addition, some weeks had excessively high scores: In 11 of 17 weeks, the 7 (strongly agree) response option was at or over 15% by participants. Kurtosis provides another indication that the data may have ceiling effects when kurtosis exceeds ± .07 (Table 1). Of the weekly stress scores, 16 of 17 weeks demonstrated platykurtic distribution, with kurtosis below -.07. Figure 2 shows the histogram of the least platykurtic measure, and Figure 3 shows the most platykurtic measure. Together, Figures 2 and 3 illustrate the extreme ceiling effect quantitatively.

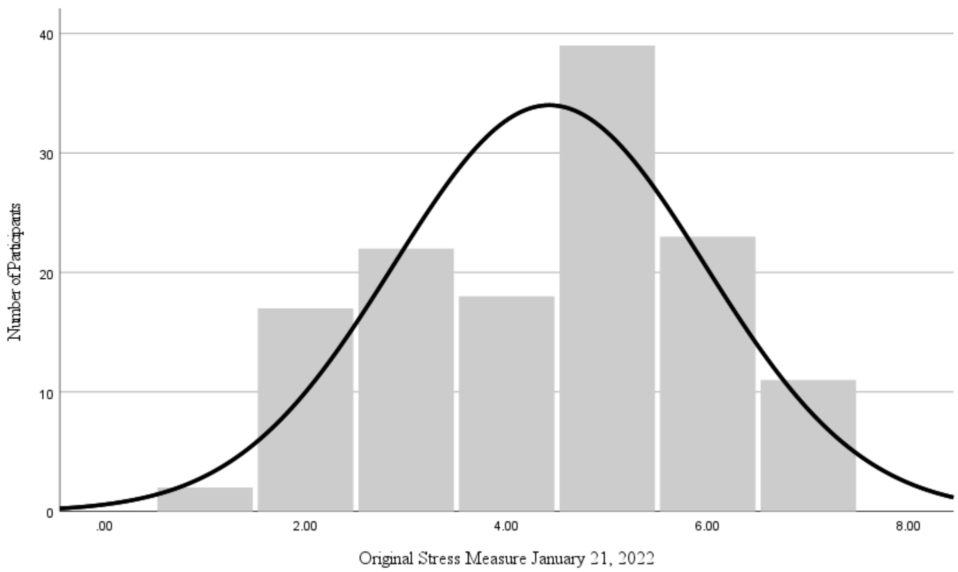

Figure 2: Histogram of Original Stress Measure from January 21st, 2022

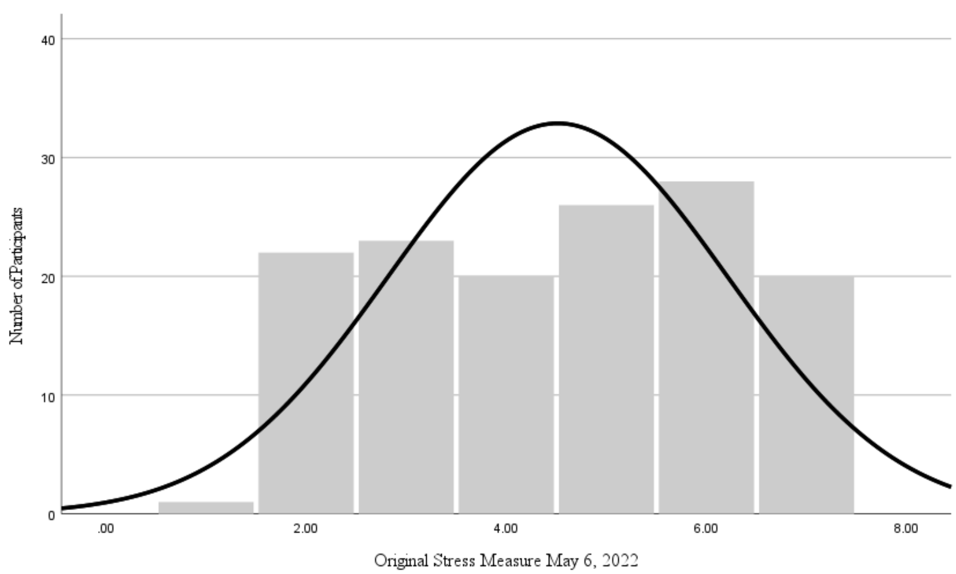

Figure 3: Histogram of Original Stress Measure from May 6th, 2022

We first turned to content analysis of the open-ended stress question on each weekly survey to interpret the ceiling effect. However, upon reviewing these text responses, the ceiling effect in the scale seemed to censor participants' ability to rate their stress experiences each week accurately. Participants strongly agreed (7) with the stressful events measure while reporting qualitatively distinct stressful events on the Friday open-ended survey item. For instance, one participant's 7 ratings included the experience, "I have a difficult experimental setup, and it has been a struggle to get it to work." The following week again rated a 7 for "Grandpa died of COVID." Another participant had the following weeks rated as a 7 on the stress measure: first, "My latest simulation results disagrees with the trend of the rest.... so something, somewhere is wrong... And idk [I don't know] what."; and then the following week, "I had a medical emergency and surgery this week. Also, Ukraine got invaded, effecting (sic) a co-worker." In addition to having ceiling effects in the quantitative data, the open-ended qualitative data also demonstrated the inadequacy of the survey-based responses to the stress item in representing participants' lived experiences, particularly over time.

Table 1: Descriptive statistics for original stress variables.

Weekly Measure	N	Range	Min, Max	M	SD	Skewness (*SE*)	Kurtosis (*SE*)
January 21st	132	6	1, 7	4.42	1.55	-0.21, (0.21)	**-0.87, (0.42)**
January 28th	140	6	1, 7	4.23	1.58	-0.07, (0.21)	-0.67, (0.41)
February 4th	139	6	1, 7	4.35	1.59	-0.22, (0.21)	**-0.88, (0.41)**
February 11th	142	6	1, 7	4.46	1.58	-0.21, (0.20)	**-0.88, (0.40)**
February 18th	142	6	1, 7	4.33	1.57	-0.25, (0.20)	**-0.86, (0.40)**
February 25th	138	6	2, 7	4.51	1.66	-0.07, (0.21)	**-1.08, (0.41)**
March 4th	142	6	1, 7	4.32	1.64	-0.12, (0.20)	**-1.02, (0.40)**
March 11th	141	6	1, 7	4.35	1.72	0.00, (0.20)	**-1.13, (0.41)**
March 18th	141	6	1, 7	4.32	1.73	-0.12, (0.20)	**-1.05, (0.41)**
March 25th	141	6	1, 7	4.16	1.65	0.08, (0.20)	**-1.00, (0.41)**
April 1st	139	6	1, 7	4.4	1.67	-0.19, (0.21)	**-1.00, (0.41)**
April 8th	141	6	1, 7	4.57	1.54	-0.13, (0.20)	**-0.79, (0.41)**
April 15th	142	6	1, 7	4.63	1.67	-0.32, (0.20)	**-0.96, (0.40)**
April 22nd	143	6	1, 7	4.44	1.67	-0.11, (0.20)	**-1.06, (0.40)**
April 29th	139	6	1, 7	4.5	1.62	-0.16, (0.21)	**-0.96, (0.41)**
May 6th	140	6	1, 7	4.51	1.70	-0.11, (0.21)	**-1.21, (0.41)**
May 13th	142	6	1, 7	4.29	1.81	-0.01, (0.20)	**-1.19, (0.40)**
Note: Bold indicates excess kurtosis > -.70.							

Reviewing these and similar examples in the data, we realize our data provides a much richer source of stressful life events than we had planned when designing the original survey. We expected life events like relationship problems, moving house, and even the death of family members, in addition to academic events like coursework, dissertation work, and advisor relationship stress. In addition to these expected events, our participants continued dealing with COVID-19 and the (at-the-time new) Omicron variant, major U.S. political strife, and global conflict leading to the Russian invasion of Ukraine and the ensuing geopolitical and economic fallout of the war in Europe.

The realization that our stress measure was not accurately capturing participants' lived experiences indicated a need to explore additional options for integrating the qualitative responses into our quantitative analyses beyond a traditional mixed methods treatment of using qualitative data to offer context to the quantitative trends. Since the stress measure is one of the main longitudinal repeated measures in the project, we began to seek solutions to identify opportunities to better represent our participants within the data used for quantitative analyses rather than just seek solutions to handle the non-normality caused by ceiling effects in the data.

Stress Construct Adjustment Using Longitudinal Qualitative Data

To take a participant-centric approach to handle ceiling effects in the quantitative data, we used the longitudinal qualitative data collecting weekly accounts of participants' critical events to develop an adjustment for the stress construct following a variation on processes for translating qualitative data into quantitative data. However, as a research group with substantial qualitative research efforts and constructivist philosophies, we experienced significant tension in this activity. Our goal in developing and employing the method described here focuses on ensuring that the quantitative data represents our participants' experiences as accurately as possible. This tension guided our reasoning and care in planning, executing, and evaluating our adjustment of the weekly stress variable.

To most accurately incorporate longitudinal qualitative data into the longitudinal quantitative data, we employed a modified version of the Life Events Taxonomy (Haimson et al., 2021; Table 2) to serve as an a priori codebook. This taxonomy provides a wide range of critical life events that require some level of readjustment when experienced. The researchers who established this taxonomy assessed the amount of life adjustment required to handle each life event through quantitative analyses of individuals' ratings of each event. The ratings of that taxonomy range from 1 to 100, with 100 representing the most adjustment possible to be required and 1 the least adjustment required. Each life event has a life adjustment score for the event happening to the individual (self) or to someone close to them (close tie).

Table 2: Frequency and Adjustment Values for Taxonomy of Life Events

Life transition / event	Participants Experienced (n)		Adjustment to Stress Rating (+)	
	self	close tie	self	close tie
Health	2	4		
serious physical illness diagnosis	20	12	82.72	75.55
serious physical illness survival	2	1	73.76	62.31
serious injury, accident, or physical ailment	38	9	76.53	72.22
car or motorcycle accident	4	2	64.58	56.39
got violently attacked (including sexual assault)	1		75	96.67
mental health struggles or diagnosis	30		79.09	70.88
recovery from mental health struggles	1		71.71	63.31
major surgery	4	2	68.06	63.12
hospitalization	3	5	64.59	61.31
pregnancy			77.31	68.57
pregnancy loss			89.44	93.33
abuse (including sexual abuse)	2		80	79.44
suicide attempt	1	1	80	80.59
physical fitness milestone			45.54	26.84
change in sleeping habits	19		49.53	32.22
change in eating habits			47.01	37.91
Financial	2			
paid off debt	1		40.34	27.19
major financial difficulty	13		76.31	67.23

Life transition / event	**Participants Experienced (n)**		**Adjustment to Stress Rating (+)**	
	self	**close tie**	**self**	**close tie**
major financial gain			46.25	37.84
personal property damaged or stolen	6	1	46.01	30.23
Relocation	5			
move within same town/city	14		55.14	45.92
move to different town/city within same state	2		59.14	50.55
move to a different state	2		74.05	60.42
move in with family	1		65.83	54.05
lost home / became homeless	1		73.33	54.69
major travel	8	2	36.88	35.14
Relationships	16	1		
began serious romantic relationship	2		63.79	48.84
ended serious romantic relationship	20	1	76.28	58.86
engagement		1	55.56	44.49
ended engagement			70	53.33
marriage		2	59.68	48.79
relationship became abusive	1		71.54	65
serious argument with neighbor or friend	24		49.2	40.99
Family Relationships	10			
gave birth / became a parent			90.66	59.04
parenting difficulties	1	1	70.74	54.63
serious argument with relative	3		53.85	51.08
family betrayal			67.64	64.44
Death	2	1		
death of spouse			100	71.04
death of child			98.57	71
death of parent	3		89.31	78.33
death of pet	4		64.99	46.39
death of a friend	1		69.91	56.57
death of a loved one	3		80.25	71.29
death of extended family member	2	1	59.69	62.91
Career	12			
started a new job, same type of work	1		59.04	47.66
change in responsibilities at work	20		52.33	43.74
significant success at work			46.79	41.53
troubles at work	18		60.14	50.58
workplace discrimination or harassment	3	2	70.93	58.41
voluntary job loss (e.g., quit)		1	64.3	48.25
involuntary job loss (e.g., fired)	1	1	84.56	64.18
became a business owner / entrepreneur			58.87	50.85
retirement			76.32	53.12
unable to find work	1		66.32	59.92
Education				
graduated college		1	51.12	41.09
started graduate school			61.43	43.33
graduated graduate school	1		75.71	30.26

Life transition / event	Participants Experienced (n)		Adjustment to Stress Rating (+)	
	self	close tie	self	close tie
transferred to a different school			65.28	48.54
left school (without graduating)		1	54.77	32.14
Lifestyle Change				
change in physical habits			51.06	40.29
change in responsibilities in personal life	3		65.73	52.66
new pet	3		37.3	29.94
Identity				
identified sexual preference			50.32	57.65
change in political beliefs			44.44	29.66
change in religious/spiritual beliefs or practices	2		57.82	46.5
Societal				
natural disaster	6		57.08	52.07
pandemic*	27		73.14	73.71
war*	1		47.14	45.00
major political event that had personal impact	5		53.54	43.69
met a celebrity			13.87	23.35
Notes: Categories of life events and value adjustments adapted from the Life Events Taxonomy (Haimson et al., 2021); * Pandemic and War were not robustly rated in the original Taxonomy. Here we have used ratings developed when assessing the added items.				

The first and second authors used the Life Events Taxonomy to code 20 participants' weekly responses and determined critical life events needed to be added to the taxonomy. Participants' responses often fit the specific context of graduate (engineering) education requiring the addition of several academic-specific events to the taxonomy. Academic-specific critical events were required to contextualize participants' experiences as graduate students (see Table 3). The coders focused coding on the source of stress rather than relying on a more straightforward content analysis. For example, open-ended responses may include a single sentence linking advisor relationships, dissertations, and family health issues. By focusing on the stress event, the code can more accurately reflect students' specific issues rather than simply adding multiple codes to cover every topic mentioned. The codes developed represent a shared interpretation of the meaning of events in participants' lives such that our constructivist epistemology remained represented in the quantitatively coded data. The same researchers used the finalized codebook to code the remaining participants' responses independently. Each researcher coded the data independently, then compared codes to discuss differences before coming to a consensus on the appropriate codes for each open-ended response.

To determine the level of adjustment for each added item, 16 engineering doctoral students rated the items on the same life adjustment scale used for the original Life Events Taxonomy (rating from 1 to 100). The students represented a range of engineering disciplines (i.e., mechanical, industrial, or civil and environmental). Students identified as international students (n = 7) and U.S. citizens or permanent residents (n = 9); women (n = 9) or men (n = 7); white (n = 5), Latinx/Hispanic (n = 3), Black (n = 2), or Asian (n = 6). These students were not previously involved in the project and were studying at one of three research-intensive universities in the United States. Each engineering student rated each event for life adjustment as if they had personally experienced the event (self) and the life adjustment if the event was experienced by someone close to them (close tie; Appendix B). The average of these 12 students' scores for each event was used as the life adjustment value for each added item (Table 3).

Table 3: Frequency, Adjustment Values, and Definitions for Added Life Events

Life transition / event	Participants Experienced (n)		Adjustment to Stress Rating (+)		Event Definition/Description
	self	close tie	self	close tie	
Advisor Issues	85		68.00	46.00	Any mention of frustration, disagreement, or argument with research, dissertation advisor; critical feedback; communication problems
Prelim/Quals	48	2	59.00	40.00	Any mention about prelim or qual exams or candidacy
Dissertation	13		64.33	47.00	Any mention about dissertation or thesis
Lab Equipment and Experiments	74	1	56.71	37.14	Experiment failure, equipment failure, access to equipment or resources, poor results
Graduate student life	240		58.43	39.71	General stressors and responsibilities of being a graduate student, balancing competing responsibilities, feelings of inadequacy
Ex- relationship	6		39.00	21.57	Issues related to dealing with a former relationship
Coursework	92		53.43	35.29	Pressure related to coursework
Publications	5		46.43	25.71	Any mention of journal paper submission or conference paper submission
International Student Issues	2		62.83	54.14	Issues specifically experienced by international students, visa, homesickness, culture shock, (not including discrimination experiences)
Funding for Domestic Students	2		62.40	54.50	Loss or lack of funding
Funding for International Students	1		86.20	67.33	Loss or lack of funding, in extreme case also lack TA/RA opportunity forcing someone to leave country

Life transition / event	Participants Experienced (n)		Adjustment to Stress Rating (+)		Event Definition/Description
	self	close tie	self	close tie	
University Structure Problems	18		44.43	34.43	Any mention of problems with program, department, or university regulations or responsiveness.
Teaching	3		53.50	30.33	Teaching responsibilities
Notes: Categories of life events and value adjustments adapted from the Life Events Taxonomy (Haimson et al., 2021).					

Given the differences in the stress item scales from the longitudinal survey (1 to 7) and the Life Event Taxonomy (1 to 100), we recoded the weekly stress item to meet the 1 to 100 scale (1 = 1; 2 = 16.667; 3 = 33.332; 4 = 50; 5 = 66.667; 6 = 83.332; 7 = 100). The semester-end item assessing participants' beliefs in their ability to finish their degree was similarly recoded on the same 1 to 100 scale. The Life Events Taxonomy and our Academic Events Taxonomy were used to adjust the stress rating for each week when participants reported stressful events. The adjustment was accomplished by adding the life adjustment value (Tables 2 and 3) to the stress item for the week the life/academic event was reported.

The resulting adjusted data set demonstrates a reduction in the ceiling effects compared to the original data. For example, rather than 18 participants with the extreme mode (7), 13 had a mode of 100 (the equivalent of 7 on the original scale), and 6 had modes greater than 100 with the highest mode at 158.43. The change in modes demonstrates a major extension of the right tail in the data. Similarly, kurtosis was reduced (Table 4). Of the weekly stress scores, 8 of 17 (compared to 16 of 17 in the original data) demonstrated leptokurtic distribution, with kurtosis above .07. Figure 4 shows the adjusted January 21st data histogram as compared to Figure 2 of the original data.

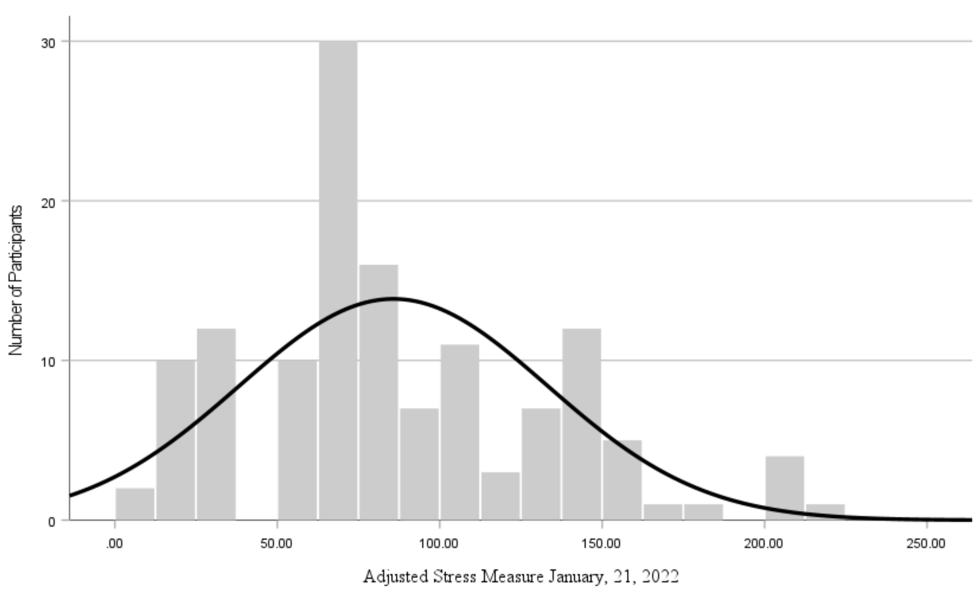

Figure 4: Histogram of Adjusted Stress Measure from January 21st, 2022

Table 4: Descriptive statistics for adjusted stress variables

Adjusted Weekly Measure	Range	Min, Max	M	SD	Skewness (*SE*)	Kurtosis (*SE*)
January 21st	217.49	1, 218.49	86.79	45.76	0.59, (0.20)	0.27, (0.40)
January 28th	257.29	1, 258.29	88.78	51.55	0.61, (0.20)	0.01, (0.40)
February 4th	268.19	1, 269.19	73.69	48.74	1.19, (0.20)	**2.24, (0.40)**
February 11th	238.59	1, 239.59	71.05	41.46	0.82, (0.20)	**1.33, (0.40)**
February 18th	210.52	1, 211.52	71.30	43.11	0.89, (0.20)	**0.88, (0.40)**
February 25th	178.53	16.67, 195.19	72.63	41.47	0.57, (0.20)	-0.27, (0.40)
March 4th	243.29	1, 244.29	68.42	43.57	1.05, (0.20)	**1.67, (0.40)**
March 11th	197.47	1, 198.47	67.97	42.45	0.79, (0.20)	0.39, (0.40)
March 18th	180.82	1, 181.82	66.37	40.67	0.51, (0.20)	-0.39, (0.40)
March 25th	225.4	1, 226.4	67.30	44.88	1.02, (0.20)	**1.01, (0.40)**
April 1st	171.22	1, 172.22	64.51	35.12	0.47, (0.20)	0.19, (0.40)
April 8th	214.14	1, 215.14	72.60	42.90	0.94, (0.20)	**0.87, (0.40)**
April 15th	177.54	1, 178.54	71.90	38.48	0.45, (0.20)	-0.14, (0.40)
April 22nd	214.14	1, 215.14	68.50	44.06	1.05, (0.20)	**0.99, (0.40)**
April 29th	164.09	1, 165.09	69.72	38.53	0.52, (0.20)	-0.15, (0.40)
May 6th	243.35	1, 244.35	71.08	44.11	1.05, (0.20)	**1.63, (0.40)**
May 13th	160.86	1, 161.86	67.43	42.18	0.48, (0.20)	-0.62, (0.40)
Note: Bold indicates excess kurtosis > .07.						

Similarly, Figure 5 shows the adjusted May 6th data compared to the original data in Figure 3. However, the most kurtic measure became February 4th (Figure 6) and the least kurtic (Figure 7). The adjusted data set continues to demonstrate several non-normal measures; however, the overall dataset no longer demonstrates a ceiling effect.

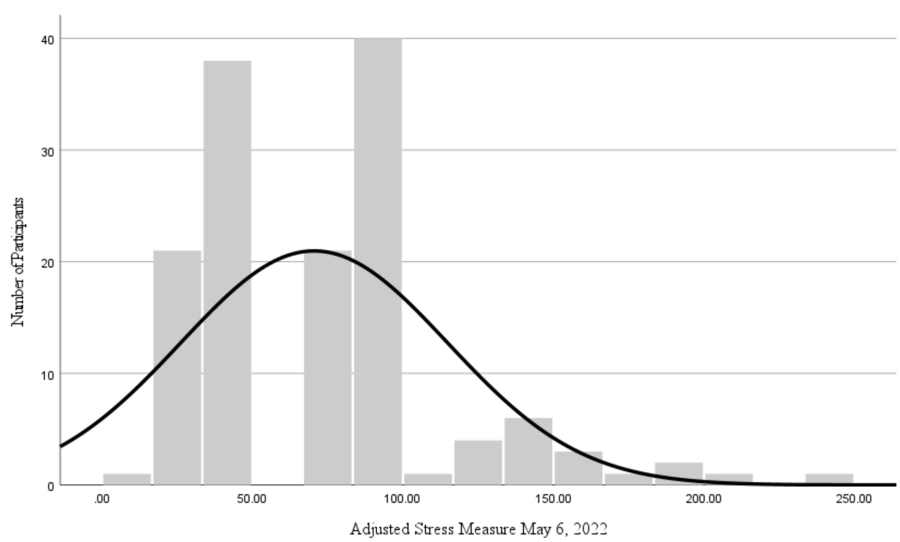

Figure 5: Histogram of Adjusted Stress Measure from May 6th, 2022

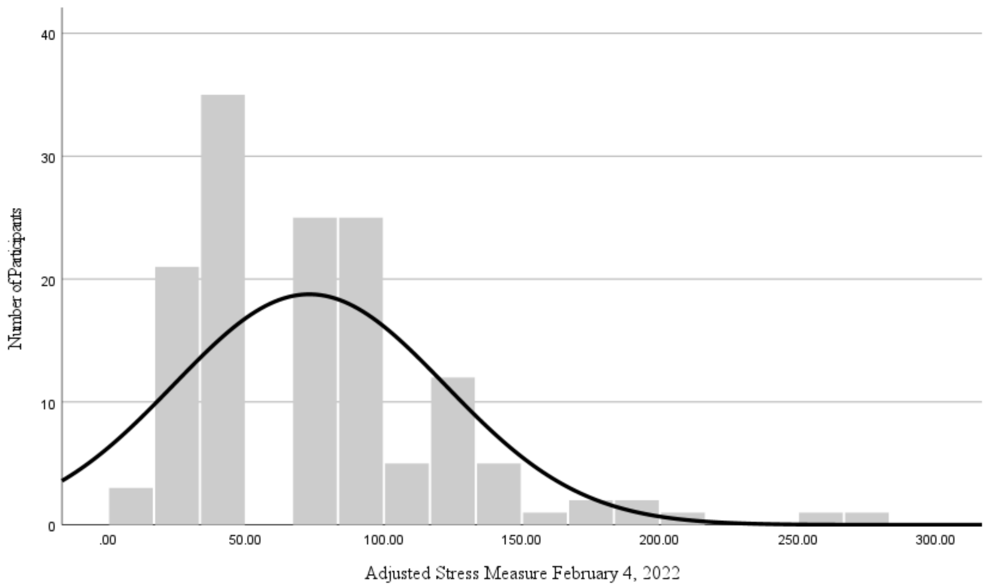

Figure 6: Histogram of Adjusted Stress Measure from February 4th, 2022

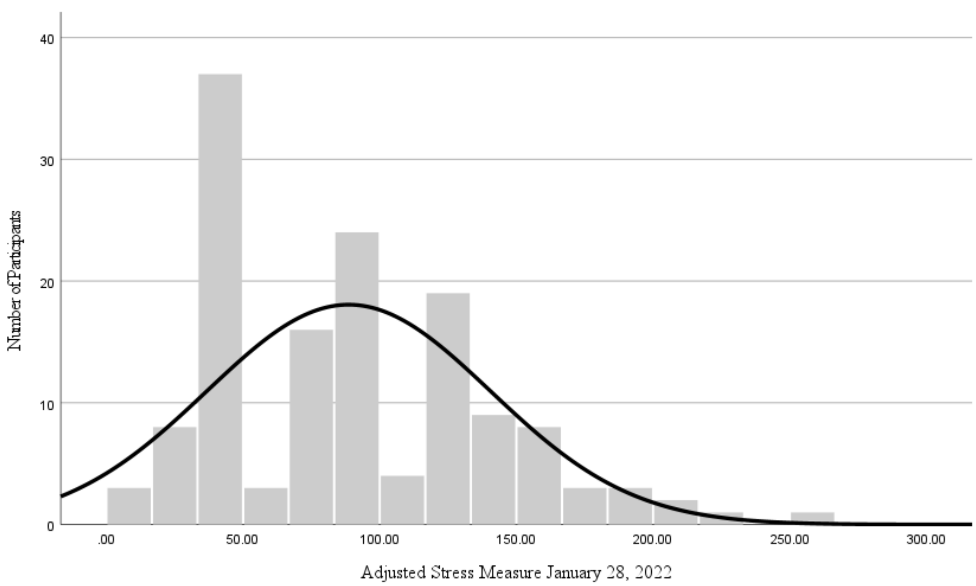

Figure 7: Histogram of Adjusted Stress Measure from January 28th, 2022

In preparation for the multilevel modeling, the weekly stress variables in the original and adjusted data were restructured into long format such that each participant has multiple rows, each row with one time point. Figures 8 and 9 show the histogram of the restructured long stress variable. Similar to the individual weekly measures, the original data demonstrates a platykurtic tendency with ceiling effects. However, the adjusted data demonstrates a leptokurtic tendency with no ceiling effects.

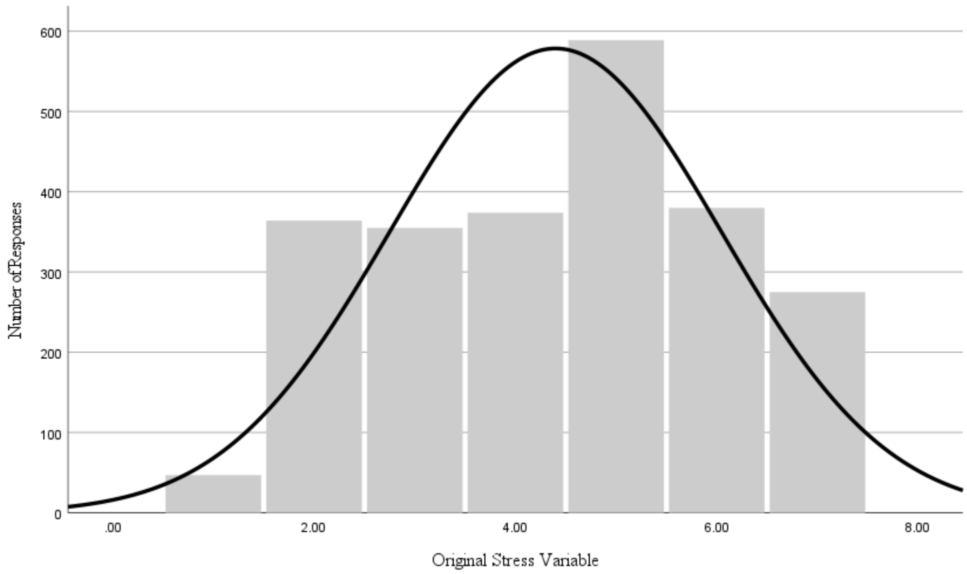

Figure 8: Histogram of Original Long Stress Measure

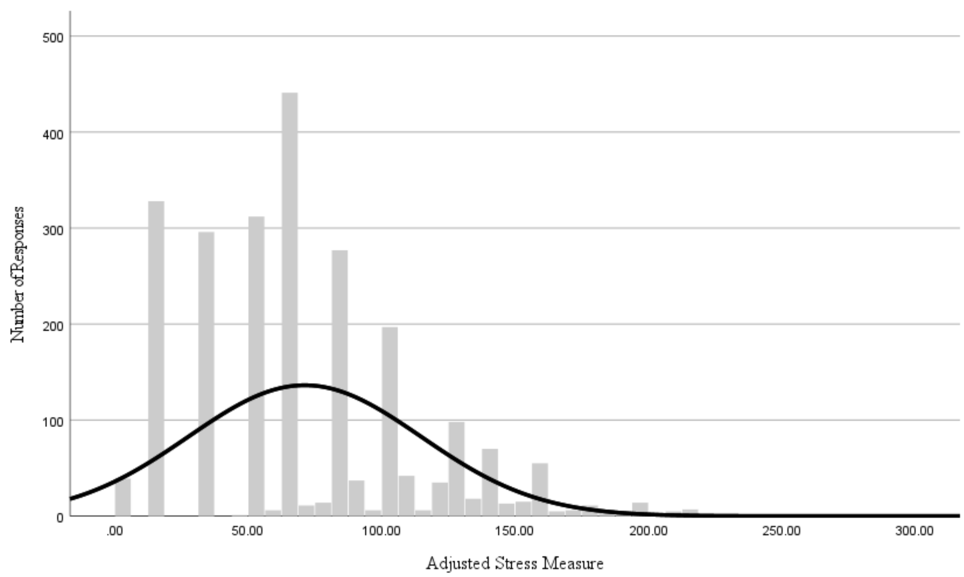

Figure 9: Histogram of Adjusted Long Stress Measure

Using Multilevel Modeling ANCOVA to Compare Variance Between Original and Adjusted Data

To understand whether and how the adjusted scale—which mitigates ceiling effects—can explain variance between participants, multilevel model ANCOVAs were performed on both the original (non-adjusted) data and the adjusted model. Applied to the original data, the null model indicated that 52% of the variability in the returning variable was within individuals ($\sigma = 1.41$, $z = 33.47$, $p < .001$) and 48% was between individuals ($\tau00 = 1.30$, $z = 7.91$, $p < .001$). Significant variance within and between individuals warrants further analysis. Following the null model, a one-way ANCOVA with random effects model estimated the relationship between stress ratings and returning variable. On average, student ratings of stress significantly associated with lower completion beliefs and explained 47% of the variation in completion beliefs ($\gamma 10 = -0.18$, $t = -2.95$, $p = .004$, $R2 = .47$).

Pertaining to the adjusted data, the null model indicated that 68% of the variability in the returning variable was within individuals ($\sigma = 1296.70$, $z = 33.48$, $p < .001$) and 32% was between individuals ($\tau 00 = 608.13$, $z = 7.47$, $p < .001$). Significant variance within and between individuals warrants further analysis. A one-way ANCOVA was run to re-estimate the relationship between adjusted stress ratings and completion beliefs. On average, student ratings of stress were significantly associated with lower completion beliefs and explained 31% of the variation in completion beliefs ($\gamma 10 = -0.19$, $t = -2.29$, $p = .023$, $R2 = .31$).

Comparing the two models demonstrates that the adjustments for stressful life events reduced the explained variance of the model, decreasing 16% from 47% to 31% of the explained variance. From the literature, we posit that the adjusted model likely represents a more accurate representation of the actual impact of stress—of all types, not just academic stress--on degree completion beliefs, as will be discussed.

DISCUSSION

The results from this work advance research in doctoral retention and methods in a few ways. First, we discuss how our method demonstrates a reduction of ceiling effects and provides a higher utility value to the understanding of stress in the context of doctoral student stress and attrition. Secondly, we discuss the value of our method to adjust psychological measures using qualitative data as a technique for researchers to integrate qualitative data into studies in ways that add substantial value to research.

In our data, as in many other survey-based studies, ceiling effects reflect a limitation of participant responses, adversely affecting model selection due to non-linearity or poor estimation of regression parameters (Wang et al., 2008). The ANCOVA of the original data likely represents an overestimation of the explanatory power of stress on degree departure considerations or some level of Type I error in the estimation due to the presence of a ceiling effect (Austin & Brunner, 2003). Alternative data analysis approaches (Fitzmaurice et al., 2004; Staus et al., 2021; Wang et al., 2008) provide strictly quantitative solutions to ceiling effect limitations. In our adjusted data model, the combination of quantitative and qualitative data provides an alternative to strictly statistical manipulation for correcting for ceiling effects while providing the benefit of integrating participants' life experiences into the quantitative model. As demonstrated here, the improvement in quantitative modeling can better reflect theory while providing a more accurate model of participants' experiences.

The original data model and the adjusted data model both support existing literature which connects the stress experienced with student departure considerations. For example, the field is aware that chronic and excessive stress in graduate education directly impacts students and their plans to continue or leave their graduate programs (Berdanier et al., 2020; Cornér et al., 2017; Hardré et al., 2019; Noel et al., 2022; Stillwell et al., 2017). Our study showed that the adjusted scale reduced the explained variance in participants' departure consideration mechanisms compared to the original model. While this reduction in explained variance from the original model to the adjusted model may be interpreted as bad thing, we posit that the revised model provides a more realistic estimation of the influence of stress on departure considerations, providing space for other constructs to be added to more sophisticated models of early departure in the future, rather than trying to explain early departure solely through the lens of stress.

Indeed, through theory and literature on doctoral education, although chronic stress in graduate school is significant and meaningful, we know from the literature that many other constructs significantly impact considerations to depart or remain in engineering graduate study, including advisor and peer relationships, non-academic events, gender and race-based discrimination, costs, and employment opportunities (Artiles & Matusovich, 2020; Bahnson et al., 2022; Berdanier et al., 2020; Lott et al., 2009; Sallai et al., 2023; Zerbe et al., 2023). Further, most studies of stress in doctoral programs focus on academic stress (e.g., Cornér et al., 2017; Cornwall et al., 2019; Pyhältö et al., 2012), or a systems-level understanding of stress related to career attainment after graduate school (e.g., Bekkouche et al., 2022), instead of also capturing pressures from life outside of the academy. One of the affordances of an adjusted stress scale is to account for the pressures that graduate students are facing in all areas of their lives, not just immediate academic deadlines or advisor conflicts. We know from the literature that these outside forces affect student well-being (e.g., Grady et al., 2014; Noel et al., 2022), but to date, these have not been able to be understood in terms of departure considerations or accounted for in surveys. The change in explained variance demonstrates the practical utility of the adjusted stress measures in this model. Stress should significantly predict departure considerations, but it should not explain a majority of the variance.

Another dominant value added to the literature is the demonstration of a method to reduce ceiling effects in practice. The demonstrated method allows quantitative researchers to represent participant experience in statistical analyses better. While ceiling effects are often noted in quantitative studies, with overwhelming clustering of survey responses at the high end of the scale, few studies have proposed methods by which to handle the ceiling effects. The methods that have been promoted to handle ceiling effects typically focus on making the data appear to reach normality so that traditional statistical techniques can be used, but we argue in this study that the goal of human subjects research should not be to make the data look normal but rather to understand the human experience better. In this sense, in our approach, the goal was not "to make the data look normally distributed," instead, the goal was to make sure that we were best capturing all the stressors that are influencing our participants during their graduate experiences, to understand how these pressures influence departure considerations. We offer the integration of qualitative methods in a novel application of methods as a participant-centric, constructivist solution to representing participants in quantitative data. This philosophy has, to date, not been offered as an alternative in handling ceiling effects in quantitative data in the past and represents a substantial value add to the quantitative research community.

Limitations and Future Work

As with all research, some limitations that motivate future work must be noted. Primarily, quantifying qualitative experiences remains a practice requiring significant care and consideration. Researchers must be able to justify the quantification as an accurate reflection of the qualitative experience. As a research team of predominantly qualitative researchers, this issue was top of mind throughout the coding, quantification, and analysis process. However, the ability to represent participants' experiences more accurately in quantitative analyses offsets our concerns.

The analyses presented in this paper include only one semester of data collection. The strength of the larger project lies in the multi-semester data collection and observation of actual departure, continuation, or degree completion. Future analyses with additional data may indicate that additional nuance is needed in the stress measure adjustment to predict degree outcomes accurately. For instance, we did not use the Monday or Wednesday stress ratings in these analyses. Inclusion and adjustment of additional days require significant evaluation and testing to ensure any change accurately reflects student experiences. For instance, should life events from Friday be carried forward to adjust the following Monday and Wednesday? Or should adjustment be only to the day the open-ended item was posed, as we did in these analyses? These and other questions require thought and testing to determine expansions or limitations on how this adjustment method should be applied.

Another limitation reflects the time-intensive nature of coding open-ended responses over a large and growing data set. Additional participants were recruited to the initial sample of 200 participants in January 2022 to extend the study for a second year, presenting a vast set of open-ended and individual experiences that must be coded to be utilized in the quantitative model proposed. We plan to leverage natural language processing (NLP) automation to code and quantify open-ended responses. In this process, the coded open-ended items will be used to train an NLP algorithm as it codes the next data set, employing a human-in-the-loop method where the program identifies passages that cannot be coded for the human to code, and the human spot-checks coded passages for accuracy. Both human-involved steps hone the NLP algorithm.

In addition, as we progress through a larger funded mixed methods project, we plan to include other measures from the survey (i.e., funding, advisor relationship) to improve models of early departure and further capture the complexity of departure considerations and decisions within graduate engineering. Other graduate fields may find similar longitudinal research helpful in investigating the causes of excess attrition, particularly in other STEM fields.

Applications to Other Domains that Suffer from Ceiling Effects

In an immediate application of the mitigation of ceiling effects in stress measures, the extension, and use of the Life Events Taxonomy to code and quantify open-ended stress or critical life events may be immediately helpful for researchers studying the impact of stress on a wide variety of contexts employing both stress and critical events. More broadly, though, using open-ended qualitative responses to ensure accurate survey quantification in the face of ceiling effects represents an opportunity for various psychological measures to improve predictive models. Ceiling effects in scales such as the Suicide Intervention Response Inventory (Neimeyer & Bonnelle, 1997) may be overcome by including specific life event triggers from coding open-ended questions during screening.

We propose additional areas of research and application that could benefit from an advanced treatment of ceiling or floor effects. Many surveys include open-ended questions, which are often left unanalyzed due to their brevity (single-word responses) or the volume of responses. The 'knee-jerk reaction' of adding an open-ended item to surveys reflects the reality that we feel – even if we do not acknowledge it – that a survey alone often cannot completely measure constructs of interest.

One practical application could help understand and study user or customer satisfaction ratings. The seemingly ubiquitous 1- or 5-star ratings that require reading the comment sections to understand the value and reality of the rating could be alleviated. Businesses may find utility in systematically integrating open-ended comments with customer ratings. For example, developing a consumer taxonomy could allow businesses to systematically contextualize low ratings in the lived experience of consumers and the implications for the business. In this example, does the 1-star rating represent product-related problems, non-product-related problems (i.e., shipping), or physical harm? To implement this, business analytics could create a product taxonomy and 'life impact' scores for open-ended comments.

Another practical application revolves around individual performance reviews, ratings, or other merit-based metrics. In this application, the equity and justice of formally integrating qualitative comments into the quantitative measure may drastically improve the accuracy of performance metrics. For instance, numerical ratings may not be able to distinguish between the highest (and lowest) performers in preparation for increased compensation or promotion. Women and People of Color often receive lower performance ratings than their white or male peers (Biernat et al., 2012; Castilla, 2012) despite the unpaid labor of women and People of Color (i.e., mentoring, representing minorities, committee participation). One specific application of merit-based ratings in the university context is students' rating of teachers and teaching effectiveness using surveys that include open-ended items for students to provide specific comments. However, evidence demonstrating these ratings have little relation to a students' learning (Kreitzer & Sweet-Cushman, 2022). Women and People of Color face sexist and racist name-calling, comments, and abusive language, demonstrating a clear bias in qualitative comments (Kreitzer & Sweet-Cushman, 2022; Lindahl & Unger, 2010; Wallace et al., 2020). Other comments reflect the students' perceptions of the class experience rather than any real evaluation of teaching or learning (Abrami, 2001; Arreola, 2004; Linse, 2017). A taxonomy of student comments and weights could integrate student comments improving the utility of the ratings and helping administrators more effectively award merit-based promotions and raises.

Conclusion

This paper presented a method to mitigate ceiling effects in longitudinal survey data by integrating longitudinal qualitative data to create an adjusted scale. In our context, we investigated the ceiling effects present in a longitudinal study of stress and departure considerations in doctoral engineering students. We found that an adjusted stress measure, which was expanded using participants' qualitative data, more accurately represents the lived experience of our participants and better represents how stress explains variance in departure considerations, providing a more sophisticated utility value of our scale. This approach offers a participant-centric and constructivist approach to handling ceiling effects, which to date has not been proposed in the methods literature, which is more often concerned with correcting data to approach normality (Liu & Wang, 2021). With the opportunity to be extended into many other domains limited by ceiling and floor effects, the method described here holds the potential to integrate qualitative open-ended items into quantitative models to predict outcomes better. Reducing ceiling effects through adjusted stress measures improves the accuracy of the statistical analyses and more accurately represents the lived experiences of participants.

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APPENDICES

APPENDIX A: LONGITUDINAL SURVEY FREQUENCY AND ITEMS

Distribution	Theme	Item
Daily	Degree completion confidence	Today, I am confident I will complete my degree objective (e.g., MS or PhD).
	Perceived stress	Today, the stress I'm experiencing related to graduate school and/or life is overwhelming.
Weekly	Advisor relationship	This week, I am satisfied with my relationship with my advisor.
	Support network	This week, I feel well-supported by the people I interact with at my university.
	Belongingness	This week, I feel I belong in my discipline.
	Quality of Life and Work	*This week, I like the work I do as a graduate student.* *This week, I am satisfied with the quality of work.*
	Stressful events	Have you experienced stressful events related to graduate school and/or life this week? [Yes/No] Yes-> Could you describe the event(s)?
	Degree completion confidence	Today, I am confident I will complete my degree objective (e.g., MS or PhD).
	Perceived stress	Today, the stress I'm experiencing related to graduate school and/or life is overwhelming.
Monthly	Intention to dropout	In the past month, how often did you consider leaving your program?
	Goals	This past month, I felt that I was on the right track to meet my future goals.
	Cost	This past month, I felt that pursuing an advanced degree was worth the costs (e.g., effort, time, money, psychological costs).
	Motivation	This past month, I felt what I have studied got along with my values (e.g., curiosity, ambition, success).
Semesterly	Productivity perception	In the last four months, I felt successful.
	Self-efficacy / or degree completion confidence [very similar with daily question]	At this point, I am confident that I can complete my program of study (e.g., MS, PhD).
	Advisor relationship	At this point in my program, I consider my advisor a mentor.

Distribution	Theme	Item
	Support network	In the last four months, I felt well-supported by people in my network outside the university.
	Degree status	Are there any new changes to your degree objectives (check all that apply)? Which option best describes your graduation?
	Perception by others	(Who answer yes, leaving at the degree status) I am worried what others will think about my decision to change my degree objective.
	Critical events	A "critical event" can be defined as an important occasion, event, or milestone related to graduate school and/or personal life that causes a re-evaluation of worldview or goals. Critical events can be either positive or negative. From your point of view, in the last four months, did you experience any "critical events" that affected your degree objectives (e.g., altercations with labmates, switching advisors, achieved academic milestones, getting married, having a baby)? • If yes, please tell us about any critical events from these four months that affected how you consider your degree objectives.
Semesterly (Only for first year students)	Expectation vs. experiences	At this point, I feel that my experiences are well-matched with the expectations I had for graduate school before I started the program.
	Commitment	I am sure that this graduate program is the right place for me.
	Support network progress	At this point, I feel that I'm developing a healthy social life (or network) in or out of school.
	Advisor status	At this point, have you found a research advisor to oversee your graduate work?
	Funding status	At this point, do you have financial support within the university/department (e.g., research assistant, teaching assistant, grants, scholarships, etc.)? How aligned is your funding with your professional goals?

APPENDIX B: LIFE TRANSITION SCALE WITH ADDITIONAL ITEMS FOR SCORE DEVELOPMENT

Throughout life, everyone experiences events that impact their lives positively and negatively. These life events can be thought of on a scale from 1 to 100 with 100 being the biggest impact possible. For instance, a serious physical illness diagnosis might be an 83, while traveling might be only a 37. In addition, people around us can experience life events that impact us as well. For example, if you were arrested, the rating might be 77, but if some-one close to you was arrested it might only be 50. Below, you will see an existing list of life events and established ratings for self and close tie. These are provided as references for additional life events we would like you to rate from 1 to 100 on their impact on life.

EXAMPLE Life transition / event	EXAMPLE Average social readjustment required	
	self	close tie
Health		
serious physical illness diagnosis	82.72	75.55
serious physical illness survival	73.76	62.31
serious injury, accident, or physical ailment	76.53	72.22
car or motorcycle accident	64.58	56.39
mental health struggles or diagnosis	79.09	70.88
recovery from mental health struggles	71.71	63.31
major surgery	68.06	63.12
hospitalization	64.59	61.31
pregnancy	77.31	68.57
suicide attempt	80	80.59
began heavily using drugs or alcohol	75.15	72.36
drug / alcohol overdose	50	76.67
change in sleeping habits	49.53	32.22
change in eating habits	47.01	37.91
Financial		
major financial difficulty	76.31	67.23
major financial gain	46.25	37.84
claimed bankruptcy	44.17	57.41
personal property damaged or stolen	46.01	30.23
Relocation		
move within same town/city	55.14	45.92
move to different town/city within same state	59.14	50.55

Enter a number from 1 to 100 on how much adjustment each event requires in life.

Life Transition/Event to Rate	Social readjustment required	
	Rating (1 - 100)	
	self	close tie
Health		
pandemic		
war		
move to a different country as a refugee		
advisor issues		
prelim/quals		
dissertation		
lab equipment and experiments		
graduate student life		
ex- relationship		
coursework		
publications		
international student issues		
funding for domestic students		
funding for international students		
university structure problems		
teaching		

move to a different state	74.05	60.42
move to a different country	64	59.75
major travel	36.88	35.14
Relationships		
began serious romantic relationship	63.79	48.84
ended serious romantic relationship	76.28	58.86
engagement	55.56	44.49
ended engagement	70	53.33
serious argument with neighbor or friend	49.2	40.99
Family Relationships		
gave birth / became a parent	90.66	59.04
parenting difficulties	70.74	54.63
serious argument with relative	53.85	51.08
family betrayal	67.64	64.44
Death		
death of spouse	100	71.04
death of child	98.57	71
death of parent	89.31	78.33
death of pet	64.99	46.39
death of a friend	69.91	56.57
death of a loved one	80.25	71.29
death of extended family member	59.69	62.91
Career		
started first job	66.41	50.43
change in responsibilities at work	52.33	43.74
promotion	38.86	33.16
significant success at work	46.79	41.53
troubles at work	60.14	50.58
workplace discrimination or harassment	70.93	58.41
Education		
started graduate school	61.43	43.33
graduated graduate school	75.71	30.26
transferred to a different school	65.28	48.54
left school (without graduating)	54.77	32.14
denied entry into school	76.67	30
Societal		
natural disaster	57.08	52.07
major political event that had personal impact	53.54	43.69
met a celebrity	13.87	23.35

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