The Reliability of Psychology Instructor's Evaluations

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Abstract

Background: Student evaluations of teaching are regularly used within college classrooms to gauge effectiveness of instruction, provide evidence for administrative decision making, and inform instructors of course feedback. Teaching evaluations are thought to be a reliable measure, but few studies have explored their reliability over time.

Objective: We investigate over 30 years of teaching evaluations to determine the reliability of teaching evaluations across course, instructor, and time.

Method: A large dataset of student evaluations of teaching was examined for reliability of evaluations within the same or different semester, course, and instructor. We then used these estimates to determine the stability of reliability estimates over time and tried to predict reliability using student ratings of instructor fairness.

Results: Instructors teaching the same course multiple times within the same semester showed the highest reliability estimates. The reliability of instructor's evaluations showed a small decrease over time. We found the impact of a validity measurement on reliability.

Conclusion: Student evaluations of teaching appear reliable for instructors teaching the same courses within the semester, with decreasing reliability across time.

Teaching Implications: Evaluations should be carefully considered given the context of the semester received and potentially paired with other measures of teaching effectiveness.

Keywords: reliability, teaching effectiveness, fairness, grading, evaluations

The Reliability of Psychology Instructor's Evaluations

In the United States, college and university psychology professors are evaluated to varying degrees on research productivity, service, and teaching effectiveness. These dimensions are often used for high-stakes administration decisions, including hiring, retention, promotion, pay, and tenure (Freishtat, 2014; Hornstein, 2017; Spooren et al., 2013; Stroebe, 2020). Depending on the institution, a major failure of one of these evaluative dimensions could jeopardize a professor's position within the department; thus, professors are urged to maintain high standards of research, service, and teaching. Indeed, the vast majority of the 9,000 professors polled by the *American Association of University Professors* believed the teaching evaluative dimension should be taken as seriously as research and service (Flaherty, 2015). The consequences of teacher effectiveness may motivate collegiate faculty into actively considering the quality of their classroom.

Teaching effectiveness can be defined as the degree to which student achievement is facilitated (i.e., how much have students learned in a particular course, P. A. Cohen, 1981). Generally, assessments of teaching effectiveness come from student evaluations of teaching (SETs) or the course itself (e.g., "Student Opinion of Instruction," "Students Opinion of Teaching Effectiveness," "Students Evaluation of Faculty," "Overall Course Ratings," "Instruction Rating," P. A. Cohen, 1981; Flaherty, 2020). Often these metrics are described as evaluating the quality of the individual or course (Gillmore et al., 1978; Marsh, 2007) by gauging multiple facets of teaching, such as an instructor's proficiency in communication, organization, presentation, and grading (Hattie & Marsh, 1996).

Given the use of SETs in administrative decisions, both the reliability and validity of these measures should be demonstrated to ensure their utility. Psychology instructors, in particular, have both a vested interest and skill set to evaluate the quality of measurement. Psychologists are trained to varying degrees to evaluate and assess measurement through their training in psychometrics (APA Task Force on Psychological Assessment and

Evaluation, 2020). If these evaluations are used to make high-stakes decisions that will alter a professors' career and standing within the workplace, it is important to be skeptical and scrutinize the decision metrics used. We are not the first to explore if SETs are reliable and valid measures of teaching effectiveness, but our approach makes a unique contribution by analyzing over 30 years of SET data to address this question in a more compelling way.

Reliability

Past investigations of SETs concluded they are reliable measures (Arubayi, 1987; Marsh & Roche, 1997). Contemporary reviews have explored the reliability of SETs when controlling for various factors. For example, Benton and Cashin (2014) found SETs collected from the same class to be internally consistent when teaching effectiveness was assessed through several items. Even so, other data suggest that instructor, course, and student factors each contribute meaningfully to the variance of student evaluation ratings, which can influence their reliability (Feistauer & Richter, 2017). This result suggests SET ratings may be reliable over time if the aspects of a classroom remain constant. However, few data have explored the interactions of time with validity variables or how it affects reliability among SETs in relation to perceived fairness specifically. Little research investigating the reliability of SETs has collected evaluations beyond two time points (e.g., two semesters or less). There are some notable exceptions of longer periods of data being collected for SETs in Boring et al. (2016), Marsh (2007), and Fan et al. (2019) and, our study extends this work by examining the reliability patterns of 30 years of SET data with respect to various moderating influences that may affect both reliability and validity of SETs.

Validity

Sheehan's (1975) review of instructor evaluation literature found such measures contained multiple potentially biasing factors. These include (1) student demographics: gender, class, age, previous achievement, (2) class type: subject matter, size, degree requirements, and (3) instructor qualities: gender, rank, gender-match to student, etc. Decades later, studies still show that sexism (MacNell et al., 2015; Mitchell & Martin, 2018), racism (Smith & Hawkins, 2011), and biases in general pervade students' evaluations today in both traditional courses and possibly online ones as well (Heffernan, 2022; O'Sullivan et al., 2014; Rovai et al., 2006; Zheng et al., 2023). Individual factors may also yield some influence on SET ratings, including instructors' cultural background (Fan et al., 2019), attractiveness (Felton et al., 2008; Wright, 2000), position ranking (Johnson et al., 2013), and students' expected grade from the course (Chen et al., 2017; Crumbley et al., 2001; Marks, 2000). Biasing factors may even include the volume of the instructor's voice and how legible their instructor's writing is (W. E. Becker et al., 2012). Concerningly, Stroebe (2020) highlighted the danger of an incentive system tied to student ratings; specifically, instructors may be incentivized to be a less effective teacher (e.g., grade leniently, choose to teach courses based on student interest, etc.) rather than challenge students critically to boost their SET ratings.

Concerns of bias raised decades ago have not dissipated over time (Boring et al., 2016; Dunn et al., 2014; Hornstein, 2017; Uttl et al., 2017). Recent meta-analyses suggest SETs may be entirely unrelated to material learned (Uttl et al., 2017), and potentially biasing aspects cannot be altered due to their complex interactions (Boring et al., 2016). While students' ratings may show some utility in indicating to their peers which classes to pursue and which professor to take (Stankiewicz, 2015), this usefulness may come at the cost of the professor's self-efficacy (Boswell, 2016). While SETs are conceptually valuable towards gaining insight on teacher effectiveness or course quality, the many outstanding issues suggest they may not be valid measures. Even so, some researchers argue that the complete removal of SETs from administrative consideration is the wrong course of action (Benton & Ryalls, 2016). A more appropriate solution may be to utilize multiple measures of teaching effectiveness simultaneously (eclass observation by another instructor of the same material, peer reviews of course curriculum Benton & Young, 2018; Berk, 2018; Esarey & Valdes, 2020; Kornell & Hausman, 2016). However, the cost of implementing a more accurate, multi-pronged approach may be unrealistic given a university's budget and expectations of the instructor. Instead, we may be able to potentially control for some biasing or moderating factors with additional items on the SET questionnaire, and our study explores the aspect of perceived fairness in grading.

Perceived Fairness

Extant research broadly supports that SETs are influenced by students grades. Intriguingly as pointed out by Wright (2000), students' expectations of their final grades may not affect their SET ratings nearly as much as their perceived fairness of their grades or the grading process that produced them. For this reason, some psychology instructors may feel pressured into reducing the rigor of their course for the sake of attaining higher SET ratings (Greenwald & Gillmore, 1997; Marks, 2000). However, professors who are consistent, accurate, unbiased, and correctable in their grading may receive high SET ratings regardless of how much a student learns or what his/her final grade turns out to be (Horan et al., 2010; Leventhal, 1980). Students' grades may predict their SETs only so much as students perceive the grading processes as fair (Tata, 1999).

Students' perceptions of fairness may be more akin to comprehensive assessments of the instructor rather than face-value judgments of their expected grade. Perceived fairness may also play a multifactorial role in its influence on SETs. Tripp et al. (2019) found that students' perceived fairness of their instructors' grading processes affected their perceived fairness of their assigned grade, which then related to instructors' SETs. Additionally, *perceived fairness of the course* workload and difficulty may be inversely related to *perceived fairness of the grading process* as a challenging professor may be thought of as less fair (Marks, 2000). Access to grading criteria, frequency of feedback, and proactive instruction are other aspects of grading thought to explicitly affect perceived fairness (Pepper & Pathak, 2008). Therefore, the perceived fairness of those aspects must also be considered when determining the impact of perceived fairness on SET ratings, especially when different professors teach the same course or teach multiple courses in the same semester. The validity and reliability of SETs may then partially hinge on the consistency of students' perceptions of fairness.

The Current Study

The current study is similar in scope to recent work (Boring et al., 2016; Fan et al., 2019) in its analysis of teacher evaluations collected over an extensive period. Boring et al. (2016)'s investigation on both French instructors and U.S. teaching assistants' gender ranged across five years. Similarly, Fan et al. (2019)'s investigated the topic across seven years. Their utilization of multi-sections has been described as the gold standard for researching students' ratings. However, it is important to continue to assess the reliability and usefulness of SETs as the types of students, student expectations, teaching pedagogy, grading practices, and university administrative decisions change and evolve over time.

We believe the current study contributes to the literature in several ways. When compared to the next largest study on SETs (Fan et al., 2019),we collected and analyzed three decades worth of data between 1987 and 2018 within an American population (vs seven years from 2010 - 2016 from an Australian population). Second, we investigated psychology instructors and their courses specifically focusing on teaching of psychology (vs academic disciplines in general). Last, our dataset is publicly available online following best open science practices (Wilkinson et al., 2016). We believe this openness will provide value to psychology educators overall, and SET researchers specifically, by allowing future analyses to explore the richness of this extensive dataset.

We aimed to analyze the reliability of students' ratings provided the *same* or *different* (i) instructor, (ii) course type, and/or (iii) semester of enrollment. This separation is paired with testing reliability over more than 30 years of data, extending previous work into new areas. We examined the impact of a potential validity variable on the reliability of ratings using perceived fairness of grading.Therefore, we sought to explore the following research questions:

1) What is the reliability of student evaluations?
2) Are student evaluations reliable across time?
3) Is the average level of perceived fairness of the grading in the course a moderator of reliability in student evaluations over time?
4) Does the average variability in instructor fairness rating moderate reliability of student evaluations over time?

The following was pre-registered as a secondary data analysis at: https://osf.io/czb4f. The manuscript, code, and data can be found on our Open Science Framework page at: https://osf.io/k7zh2/ or GitHub: https://github.com/doomlab/Grade-Lean. This manuscript was written with the *R* packages *papaja* (Aust et al., 2022), *rio* (J. Becker et al., 2021), *dplyr* (Wickham et al., 2020), *nlme* (Pinheiro et al., 2017), *ggplot2* (Wickham, 2016), *MuMIn* (Bartoń, 2020), *ppcor* (Kim, 2015), and *effectsize* (Ben-Shachar et al., 2020).

Method

Data Source

The archival study was conducted using data from the psychology department at a large Midwestern public university. We used data from 2898 undergraduate, 274 mixed-level undergraduate, and 42 graduate psychology classes taught from 1987 to 2018 that were evaluated by students using the same 15-item instrument. Faculty followed set procedures in distributing scan forms no more than two weeks before the conclusion of the semester. A student was assigned to collect the forms and deliver them to the departmental secretary. The instructor was required to leave the room while students completed the forms. In the last several years of evaluations, online versions of these forms were used with faculty encouraged to give students time to complete them in class while they were outside the classroom. The average sample size before moving online was 25.13 (SD = 25.45) students, while the average sample size after moving online was 15.17 (SD = 25.51).[1] Courses

[1] Only a few semesters of online evaluation data are present in this dataset.

generally ranged from 10 to 30 for undergraduate courses with the exception of introduction to psychology which was converted into a large scale 300-person format. Graduate courses enrollment depended on the size of the program but was generally 5 to 10 students.

SET Questionnaire

The questionnaire given to students can be found at https://osf.io/4sphx. These items were presented with a five-point scale from 1 (*strongly disagree*) to 5 (*strongly agree*). The ratings were averaged for each course across students, and the sample size for each rating was included.

Reliability

The specific formula for reliability is described in planned analysis. The reliability scores were generally created by comparing the overall instructor evaluation question: "The overall quality of this course was among the top 20% of those I have taken." of each instructor to every other instructor, controlling for sample size of the ratings. The pairwise combination of instructors in the dataset allowed us to create reliability scores for the same or different combinations of instructor, course, and semester of enrollment. These values were created in Research Question 1 and used for the rest of the analyses.

Fairness

We used the question of "The instructor used fair and appropriate methods in the determination of grades." The average rating of fairness for each course was calculated, as well as the standard deviation of fairness to examine variability in perceptions of fairness (i.e., large standard deviations mean that students disagree on fairness, while smaller values indicate more agreement).

Planned Analyses

The evaluations were filtered for those with at least fifteen student ratings for the course (Rantanen, 2012). We performed a robustness check for the first research question by running the same analyses again to ensure the results were the same for different sample sizes. We used the data when the sample size was at least $n = 10$ up to $n = 14$ (i.e., on all evaluations with at least 10 ratings, then at least 11 ratings, etc.) to determine if the reliability estimates are stable at lower sample sizes. We first screened the dataset (two evaluation questions, sample size for course) for accuracy errors (obvious typos in the data), linearity (a linear relationship of the variables), normality (normal distributions for the errors), and homoscedasticity (an even spread of errors for the criterion variable at all parts of the independent variable). The data were assumed to not have traditional "outliers", as these evaluations represent true averages from student evaluations. If the linearity assumption failed, we considered potential nonparametric models to address non-linearity. Deviations from normality were noted but the large sample size should provide robustness for any violations of normality. If the errors appeared to be heteroscedastic, we used bootstrapping to provide estimates and confidence intervals.

This data was considered structured by instructor, meaning that each instructor had multiple courses across multiple years (i.e., repeated measures data); therefore, all analyses below were coded in *R* using the *nlme* package (Pinheiro et al., 2017) to control for correlated error of instructor as a random intercept in a multilevel model. Multilevel models allow for analysis of repeated measures data without collapsing by participant (i.e., each instructor/semester/course combination can be kept separate without averaging over these measurements, Gelman, 2006). Random intercept models are regression models on repeated data that structure the data by a specified variable, which was instructor in this analysis. Therefore, each instructor's overall average rating score was allowed to vary within the analysis, as ratings would be expected to differ from instructor to instructor. In traditional regression models, the intercept represents the grand mean of all of the data, which would ignore differences in instructor. By including this intercept, we were able to allow the intercept to vary by instructor, and then measure the impact of the independent variables on the ratings or reliability. Figure 1 this analysis might look visually for research question 1. In each of the analyses described below, the number of students providing ratings for the course was included as a control variable to even out differences in course size as an influence in the results. This variable was planned to be excluded if the models did not converge (i.e., did not mathematically find an answer). The criterion variable and predictors varied based on the research question, and these are described with each analysis below.

Research Question 1

In this research question, we examined the reliability of student evaluations on the overall rating and separately on the fairness rating. We calculated eight types of reliability using course (same or different) by instructor (same or different) by semester (same or different). Therefore, if instructor 1 taught two sections of PSY 101 in Fall 2010, this combination would be considered same course, same instructor, and same semester. If we compare instructor 1's PSY 101 Fall 2010 course to instructor 1's PSY 101 Spring 2011 course, this combination would be the same instructor, same course, and different semester. The criterion variable was the first question average for course 1 with a predictor of the comparison question average for course 2, and both sample sizes as control variables (first sample size course 1, comparison sample size course 2). Instructor code was used as the random intercept for both ratings (i.e., two instructor random intercepts, first course 1 instructor and comparison course 2 instructor). The value of interest was the standardized regression coefficient for the fixed effect of the overall rating question from this model.[2].

The standardized regression coefficient was considered "reliability", much in the same way that test-retest reliability is calculated. For each instructor by semester by course combination, the scores for each course are compared and the correlation, controlling for sample size is calculated. We considered these scores as our measure of reliability as they represent the match between instructor ratings for each SET question: instructors who get the same scores will have high correlations (i.e., higher reliability), while instructors with

[2] The formula was question 1 average for course 1 ~ question 1 average for course 2 + sample size course 1 + sample size course 2 with a random intercept for instructor

scores that vary a lot will have lower correlations (i.e., lower reliability). Given that the large sample size will likely produce “significant” p-values, we used the 95% confidence interval to determine which reliability values were larger than zero on the smaller end of the confidence interval and to compare reliability estimates to each other to see if their confidence intervals overlapped.

For this question, we might expect that the mismatch in combinations (i.e., different courses, instructors, or semesters) should have lower reliability because the students, instructor, or material is varied between the SET ratings. Therefore, the non-match conditions should be a good comparison to determine if the match conditions do show reliability. Traditional interpretations of reliability via test-retest correlations indicate that scores above .40 are considered fair (Cicchetti, 1994; Fleiss, 2011). Thus, we could suggest that correlations higher than non-match conditions and above .40 indicate reliability for instructor SET ratings.

Research Question 2

We used the reliability values for the same instructor, same course, and both same/different semesters calculated as described in RQ1 at each time point difference between semesters. For example, the same semester would create a time difference of 0. The next semester (Spring to Summer, Summer to Fall, Fall to Spring) would create a time difference of 1. We used the time difference as a predictor variable (i.e., fixed effect) to predict reliability for the overall rating of the course question.[3] We used the coefficient of time difference and its confidence interval to determine if there was a linear change over Time (i.e., if the confidence interval does not include zero, this change was more than chance). Finally, we plotted the changes over time to examine if this effect was non-linear in nature and discussed implications of the graph.

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[3] The formula was reliability ~ time difference for that reliability calculation with a random intercept for instructor.

Research Question 3

Using the analysis from RQ 2, we then added the average rating for the fairness question as the moderator with time to predict reliability.[4] Moderation implies an interaction of the change over time and the average fairness scores. For example, we might expect that instructors that are perceived as less fair show larger reliability change over time, while instructors who are perceived as fair do not show any change over time. Fairness was calculated as the average of the fairness question for all courses involved in the reliability calculation for that instructor and time difference. Therefore, this rating represented the average perceived fairness of grading at the time of ratings. If this interaction effect's coefficient did not include zero, we performed a simple slopes analysis to examine the effects of instructors who were rated at average fairness (i.e., the instructors who students perceive as the normal level of fairness), one standard deviation below average (i.e., instructors who are perceived below normal fairness), and one standard deviation above average (i.e., instructors who are perceived above normal fairness, J. Cohen et al., 2003).

Research Question 4

Finally, we examined the average standard deviation of fairness ratings as a moderator of time to predict reliability[5] This variable represented the variability in perceived fairness in grading from student evaluations, where small numbers indicated relative agreement on the rating of fairness and larger values indicated a wide range of fairness ratings. The variability in fairness ratings was calculated in the same way as the mean fairness, which was only for the instructor and semester time difference evaluations that were used to calculate the reliability estimate. This research question was assessed the same way as RQ3. We may expect that instructors who vary a lot in their fairness scores (i.e., sometimes they are

[4] The formula was reliability ~ standardized semester time difference × standardized average fairness scores with a random intercept for instructor.

[5] The formula was reliability ~ standardized semester time difference × standardized variability in fairness scores with a random intercept for instructor.

perceived as fair, other times not as fair, thus, higher standard deviations) would show a change in reliability scores over time because of their fluctuations in perceived fairness. However, instructors who are consistently rated as a certain level of fairness (i.e., no variability in fairness, low standard deviations) may see no change in reliability over time.

Results

Data Screening

The overall dataset was screened for normality, linearity, homogeneity, and homoscedasticity using procedures from Tabachnick et al. (2019). Data generally met assumptions with a slight skew and some heterogeneity. The complete anonymized dataset and other information can be found online at https://osf.io/k7zh2. This page also includes the manuscript written inline with the statistical analysis with the *papaja* package (Aust et al., 2022) for interested researchers/reviewers who wish to recreate these analyses. The bootstrapped versions of analyses and robustness analysis can be found online on our OSF page with a summary of results. We originally planned to bootstrap all analyses; however, the compute time for research question 1 was prolonged due to the size and complexity of the multilevel models. We therefore did not bootstrap that research question. These analyses suggest robust results for research question 1 (i.e., the results did not change with smaller sample sizes included) and for all other research questions the results are equivalent showing that the heteroscedasticity did not influence our findings.

Descriptive Statistics

3214 evaluations included at least 15 student evaluations for analysis. Table 1 portrays the descriptive statistics for each course level including the total number of evaluations, unique instructors, unique course numbers, and average scores for the two rating items. Students additionally projected their course grade for each class ($A = 5$, $B = 4$, $C = 3$, $D = 2$, $F = 1$), and the average for this item is included for reference. Overall, 231 unique instructors and 70 unique courses were included in the analyses below across 94 semesters.

Research Question 1

Each individual evaluation was compared to every other evaluation resulting in 5163291 total comparisons. Eight combinations of ratings were created by comparing every course to each other using instructor (same, different), course (same, different), and semester (same, different) on both the overall and fairness evaluation ratings separately. One of the individual ratings was used to predict the comparison rating (i.e., question 1 was used to predict a comparison question 1 for the same instructor, different instructor, same semester, different semester, etc.), and the number of ratings (i.e., rating sample size) per question were used as fixed-effects covariates. The instructor(s) were used as a random intercept to control for correlated error and overall average rating per instructor (see "Planned Analyses for a comprehensive explanation above). The effects were then standardized using the *parameters* package (Lüdecke et al., 2023). The data was sorted by year and semester such that"predictor" was always an earlier semester predicting a later semester's scores, except in cases of the same semester comparisons. Therefore, positive standardized reliability scores indicate that scores tend to go up over time, while negative scores indicate that scores tend to go down over time.

As shown in Figure 2, reliability was highest when calculated on the same instructor in the same semester and within the same course for both overall rating and fairness. These reliability scores were both approximately .50, suggesting fair reliability for the same instructor in the same semester in the same course. This reliability was followed by the same instructor, same semester, and different courses which was approximately .12. Next, the reliability for same instructor, same course, and different semesters was greater than zero but usually overlapped in confidence intervals with the same instructor, same semester, and different courses. Interestingly, the same instructor with different courses and semesters showed a non-zero negative relationship, indicating that ratings generally were lower for later semesters in different courses.

For different instructors, we found positive non-zero readabilities when they were at least calculated on the same semester or course. These values were very close to zero, generally in the .01 to .05 range. The reliabilities that were calculated on different courses, semesters, and instructors include zero in their confidence intervals. While many of these reliability correlations were non-zero, the results suggest that only the same semester, same course, and same instructor would be considered reliable given the strength of the scores (~ .50) and the overlap in all other correlations. Exact values can be found in the online supplemental document with the robustness analysis in .csv format. Robustness analyses revealed the same pattern and strength of results for evaluation reliabilities when sample size for evaluations was considered at n = 10, 11, 12, 13, and 14.

Research Question 2

The reliabilities were then filtered to only examine course and instructor matches to explore the relation of reliability across time. This reliability was calculated separately for each instructor and semester difference (i.e., the time between evaluations, zero means same semester, one means the next semester, two means two semesters later, etc.). The ratings were filtered so that at least 10 pairs of ratings were present for each instructor and semester difference combination (Weaver & Koopman, 2014). Of 36084 possible matched instructor and course pairings, 30728 included at least 10 pairings, which was 1009 total instructor and semester combinations.

The confidence interval for the effect of semester difference predicting reliability did not cross zero as our criterion for the smallest effect of interest, b = -0.004, 95% CI [-0.005, -0.003], $R^2 = .04$. The coefficient, while small, represents a small effect of time on the reliability of instructor ratings. As shown in Figure 3, reliability appears to decrease across time.

Research Question 3

The confidence interval for the interaction of semester time difference and average fairness did cross zero, b = -0.001, 95% CI [-0.007, 0.005], R^2 = .04. Therefore, there was no effect of the interaction of average fairness with semester differences in predicting reliability. Similarly, average fairness did not predict reliability overall, b = -0.041, 95% CI [-0.226, 0.143].

Research Question 4

The confidence interval for the interaction of variability of fairness and semester time difference did cross zero, b = -0.010, 95% CI [-0.022, 0.002], R^2 = .05. The variability of fairness also did not predict reliability overall, b = 0.291, 95% CI [-0.091, 0.672].

Discussion

Interpreting the Results

This investigation measured the reliability of SETs by calculating the reliability of evaluations across psychology instructors, semesters, and courses. Our first research question asked what the reliability of SETs was given the instructor, course, or semester. Our data showed that SETs of the same instructor within the same course and same semester were the most reliable [rs ~ .50 — 75th percentile of known psychology correlations; Lovakov and Agadullina (2021)], followed by those collected from students enrolled in the same course, with the same instructor, but in different semesters (rs ~ .12 — 25th percentile of known psychology correlations). Given previous suggestions on test-retest reliability, our results suggest that only the same instructor, course, and semester combinations would be considered fair reliability (Cicchetti, 1994; Fleiss, 2011).

Our second question investigated if instructors' SETs became more reliable with increasing years of teaching experience; stated simply, we explored if experience across time matters. We extended previous meta-analyses on reliability to show that reliability appears to slightly, but significantly, decrease over time — a new finding in comparison to the work of Marsh (2007). Given the small size of this effect, reliability would decrease approximately .06 points in the time normally designated for tenure and/or promotion (i.e., -.004 x 3 semesters x 5 years). This small decrease may not impact the administrative process, but it is worth considering that decreases in reliability could be expected.

Last, we explored the relationship of a variable that we believed potentially impacts the validity of SETs: perceived fairness in grading. Perceived fairness did not appear to impact reliability scores, nor did it moderate with time to predict reliability scores. While variability in perceived fairness is found across and within instructor ratings, this variability also did not impact reliability information. In other words, our data does not support that instructors perceived as fair have higher or lower reliability of their SETs. Further, it did not seem to matter if all students agreed the instructor was fair (low variability in perceived fairness) or if they disagreed (high variability in perceived fairness) when predicting the reliability of SETs.

This study extends previous work with several new strengths (Benton & Cashin, 2014; Benton & Ryalls, 2016; Marsh, 2007; Zhao & Gallant, 2012). The data included in this manuscript represents over 30 years of SETs and was analyzed for reliability within and across courses, semesters, and instructors, thus providing new insights into the expected level of reliability in different calculation scenarios. Sensitivity and bootstrapped analyses show that these results are robust even with a smaller number of evaluations used, supporting and extending work by Rantanen (2012). Further, we investigated the impact of validity variables on reliability, not just the overall validity of SETs based on various potential biases.

What should psychology instructors and administrators do with SETs?

Benton and Young (2018) provide a comprehensive checklist of ways to assess teaching and interpret evaluations considering the long history of validity questions for SETs. Here, we add that it is important to understand that reliability will vary by course and semester as instructor variability is usually expected. It is tempting to think that the same instructor teaching the same course should reliably get the same SET ratings; however, we should consider that instructors will grow and change over time, which may contribute to lessened reliability across time along with impeding biases. Potentially, as suggested by a reviewer, reliability could decrease over time as instructors try new course formats and take risks with course material. Further, facets of the different courses taught likely contribute to the lessened reliability between courses taught by the same instructor (e.g., required statistics courses versus elective courses). As Benton and Young (2018).[6]

These considerations are of special importance given the recent and growing adoption of alternative grading practices. As some professors and institutions move away from traditional grading structures, the criteria by which students evaluate their psychology instructors may also shift. To this point, ungrading is a burgeoning alternative approach to learning that emphasizes intrinsic motivation and equity on the part of students and focuses on the priorities of the instructor on the provision of direction, comments, and resources (Blum, 2020; Johanesen et al., 2023). Recent investigations of ungrading implemented in classrooms found that students reported improved ability to focus on learning (Kalbarczyk et al., 2023) and enjoyed their classroom experiences more than under a traditional grading system (Johanesen et al., 2023). Psychology instructors also may be able to focus more on the goals of their teaching rather than expending time on the construction of tasks, deadlines, and examinations (Ko, 2021). Although these benefits yield positive student regard for their learning environment, Guberman (2021) notes ungrading requires instructors to provide evidence of student learning and achievement via other outcomes. Thus, the instructor may lose some influence over the student and their learning which may affect students' perceptions of the instructor and subsequent SET ratings. However, a reduction in teacher-student interaction may also warp other aspects of SET rating separate from grading (i.e., openness, perceived fairness, difficulty, etc.). Blum (2020) noted the proliferation of

[6] Variables such as race, age, and gender were not available in our dataset to ensure anonymity.

ungrading in educational settings in 2020; as more psychology instructors incorporate elements of alternative grading practices like ungrading into their course structures, SET reliability may need to be reassessed.

Conclusion

While this study provides valuable evidence about SET reliability, it only includes the SET ratings of one department, and our descriptive statistics suggest these ratings were often collected at ceiling on a 1 to 5 Likert-type scale. Moreover, SETs are always biased by the students who are in class or fill out the online survey — information about missing student perceptions are never recorded. Last, SET analyses can be limited by the instruments used - in this manuscript, all items come from the same rating scale used by students. The concerns about the validity of SETs are still relevant, and it may be that reliability is interesting but not altogether useful if the scores are not valid representations of teaching effectiveness. However, open-ended feedback, paired with SET scores, are often a beneficial gauge for instructors to reflect on new practices or how a semester progressed. As universities struggle to balance demands of higher education cost and student enrollment, teaching effectiveness may be a critical target for administrators to ensure student engagement and retention. These results suggest that SETs can be reliable indicators of teaching effectiveness, but likely only within the same courses and semester. Thus, a multifaceted approach to assessing instructor effectiveness and improvement is a more appropriate measurement tool for long-term evaluations of instruction, given the limitations of university size and funding (Benton & Young, 2018).

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Table 1

Descriptive Statistics of Included Courses

Statistic	Undergraduate	Mixed	Master's
N Total	2898	274	42
N Instructors	223	40	10
N Courses	41	21	8
Average N Ratings	34.39	21.15	21.10
Average Overall	3.94	4.01	3.72
SD Overall	0.55	0.59	0.67
Average Fairness	4.46	4.50	4.19
SD Fairness	0.35	0.38	0.55
Average Grade	4.26	4.52	4.41
SD Grade	0.33	0.27	0.34

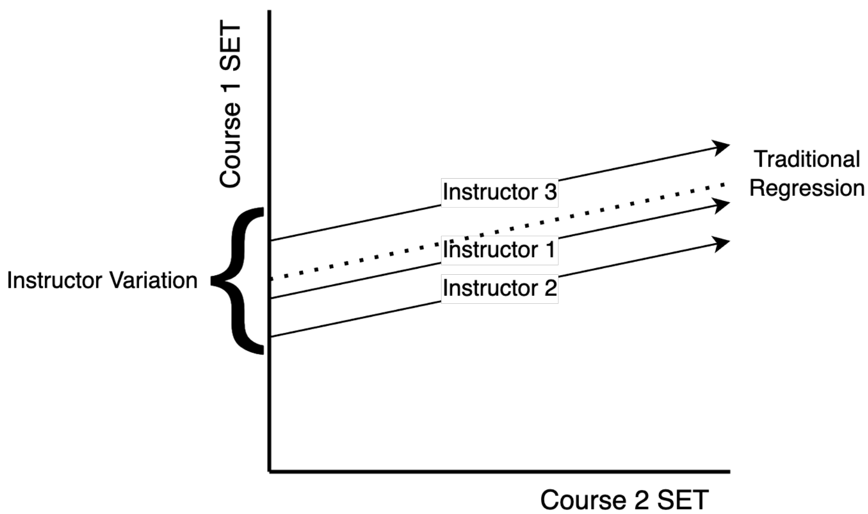

Figure 1

An example of Research Question 1 including random intercepts for instructor. Each instructor shows a different overall course average score where the regression line crosses the y-intercept. The traditional regression analysis (the dotted line) ignores differences in instructor by averaging over instructor.

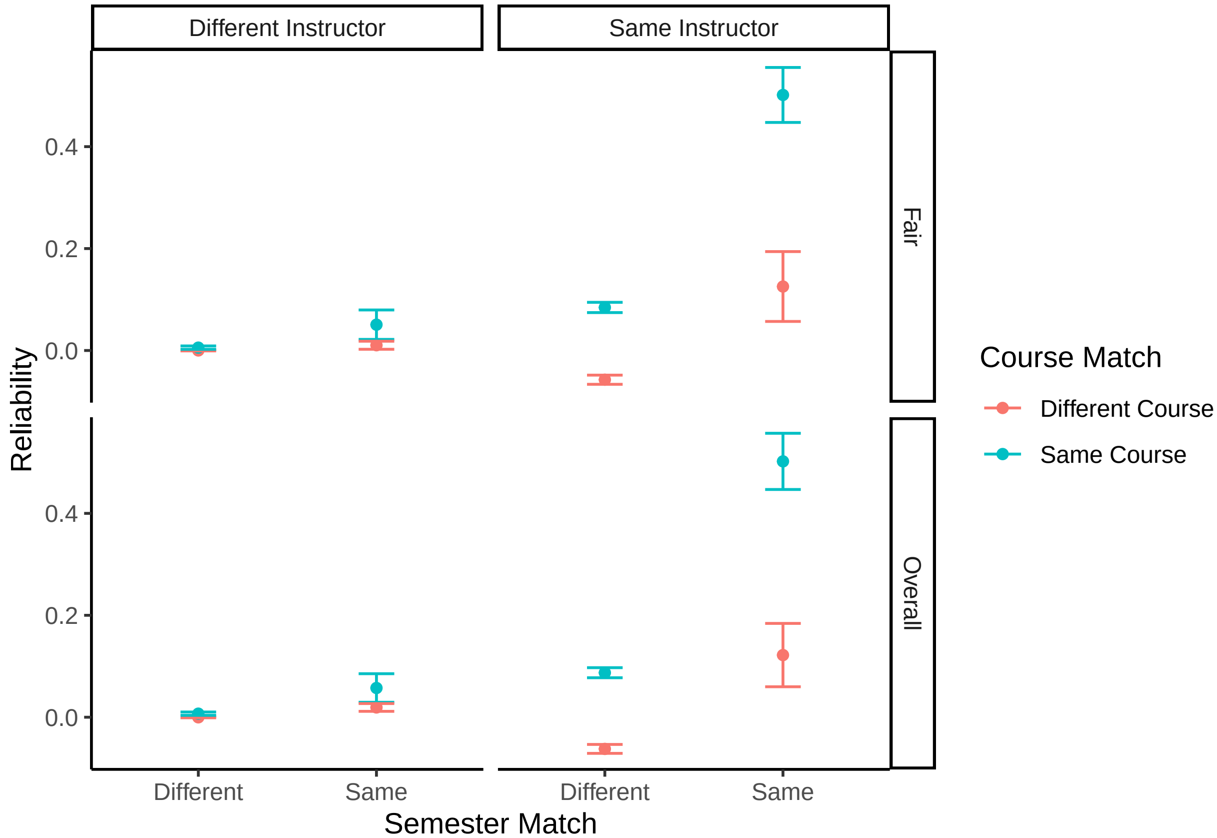

Figure 2

Reliability estimates for instructor, course, and semester combinations.

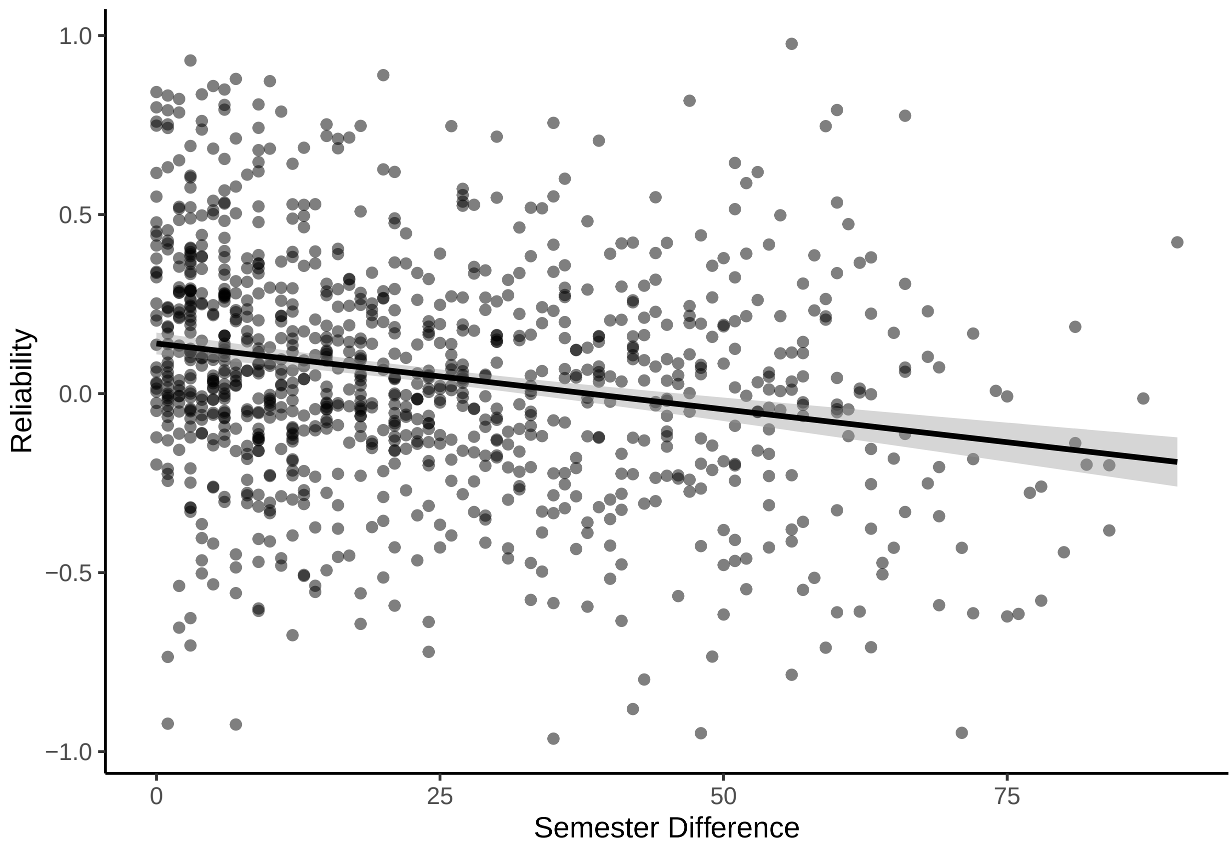

Figure 3

Reliability estimates for same instructor and course across time.