Perceived Grading and Student Evaluation of Instruction

2 Abstract

- We analyzed student evaluations for 3,585 classes collected over 20 years to determine
- 4 stability and evaluate the relationship of perceived grading to global evaluations, perceived
- <sup>5</sup> fairness, and appropriateness of assignments. Using class as the unit of analysis, we found
- <sub>6</sub> small evaluation reliability when professors taught the same course in the same semester,
- <sup>7</sup> with much weaker correlations for differing courses. Expected grade and grading related
- 8 questions correlated with overall evaluations of courses. Differences in course evaluations on
- expected grades, grading questions, and overall grades were found between full-time faculty
- and other types of instructors. These findings are expanded to a model of grading type
- questions mediating the relationship between expected grade and overall course evaluations
- with a moderating effect of type of instructor.
- 13 Keywords: Student evaluation, teacher evaluation, perceived grading, reliability

## Perceived Grading and Student Evaluation of Instruction

Student evaluations of professors are a typical practice, but their validity and reliability 15 has been disputed. The impact of student evaluations on professor advancement can be great 16 and often acts as a deciding factor in professor promotion, demotion, coursework choice, 17 tenureship, or to inform access to certain funding opportunities. Some suggest that there are 18 variables that result in improving evaluations, such as giving higher grades (Greenwald & 19 Gillmore, 1997; Isely & Singh, 2005; Krautmann & Sander, 1999). Student evaluations are also influenced by likability, attractiveness, and dress (Buck & Tiene, 1989; Gurung & 21 Vespia, 2007; Hugh Feeley, 2002). Further, 20 years ago, Neath (1996) suggested twenty tongue-in-cheek tips in which professors may bolster their evaluations from students. These suggestions have no relationship with research supported instructional methods or further learning retention among the student body, such as being a male professor and only teaching only male students. In more recent research, Boring, Ottoboni, and Stark (2016) confirms that student evaluations of teaching are biased against female instructors, and the authors 27 conclude student evaluations are more representative of the students' grading expectations and biases rather than an evaluation of objective instructional methods. All together, these findings elicit the argument that student evaluations are not necessarily measuring whether the instructional methods of professors are sound, rather student evaluations of instruction 31 are measuring whether or not the instructor met the students' expectations of their performance in the classroom, in addition to the instructor meeting pre-existing biases. 33

However, this finding does not imply that an instructor can simply raise grades to meet expectations (Centra, 2003; Marsh, 1987; Marsh & Roche, 2000), instead one should consider the effect of "perceived grading". We operationally define perceived grading as the students' perceptions of assignment appropriateness, grading fairness, and the expected course grade at the time the evaluations are being completed. Social psychology theory would support that students with low perceived grading perceptions may reduce cognitive dissonance and engage in ego defense by giving low evaluations in turn (Maurer, 2006), subsequently
resulting in decreased validity and reliability of the proposed construct, professor instruction.
We argue both social psychology theory and the evidence from student evaluations supports
that higher perceived grading can lead to better student evaluations of instruction. For
example, Salmons (1993) provided causal evidence of lowered student evaluations due to
expected grades. In her study of 444 students completing faculty evaluations at two separate
points in a semester, students who expected to get Fs significantly lowered their evaluations
while students who expected to receive As and Bs significantly raised their evaluations
(Salmons, 1993). This theory and evidence from student evaluation leads us to further argue
student evaluations of professors are biased towards their expected grade and the perceived
fairness of the grading system, rather than the actual instructional methods used over the
course of a semester.

Much of the literature on student evaluations involves diverse and complex analyses

(e.g., Marsh (1987)) and lacks social-psychological theoretical guidance on human judgment.

To expect that student evaluations would not be influenced by expected grade would

contradict a long-standing history of social psychology research on cognitive dissonance,

attribution, and ego threat. As we know, failure threatens the ego (Miller, 1985) and

motivates us to find rationales to defend the ego. Further, Kenworthy, Miller, Collins, Read,

and Earleywine (2011) found guilt as a significant correlate of dissonance which may be

illuminated in this study by the guilt of under-performing from a student's own expectations.

Failing students, or those performing below personal expectations, would be expected to

defend their ego by attributing low grades to poor teaching or unfair evaluation practices

(Maurer, 2006). One common strategy involves diminishing the value of the activity (Miller

& Klein, 1989), which would result in lowered perceived value of a course.

Similarly, Cognitive Dissonance Theory (Festinger, 1957) predicts that people who experience poor performance but perceive themselves as competent will experience

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dissonance, of which they can reduce through negative evaluations of the instruction
(Maurer, 2006). Attribution research (Weiner, 1992) also supports the argument that among
low achievement motivation students, failure is associated with external attributions for
cause, and the most plausible external attribution for the student in the evaluation context
is the quality of instruction and grading practices. Although arguments regarding degree of
influence are reasonable, the position that they are not affected is inconsistent with existing
and established theory. Thus, it is not surprising that the majority of faculty perceive
student evaluations to be biased by perceived grading and course choice (Marsh, 1987).

Blackhart, Peruche, DeWall, and Joiner (2006) analyzed 167 psychology classes in a multiple regression analysis and found the two most significant predictors of instructor ratings were average grade given by the instructor and instructor status (teaching assistant 76 or ranked faculty). Because of the limited number of classes, the power of the analysis was limited. However, in addition to the concern regarding the relationship between grades and global course evaluations, it was found that teaching assistants were rated more highly than ranked faculty. This finding raises additional questions on validity student evaluation of instructional quality. We must either accept that the least trained and qualified instructors 81 are actually better teachers, or we must believe this result suggests that student evaluations have given us false information on the quality of instruction via their perceptions of grading. 83 Research from DuCette and Kenney (1982) and Ellis, Burke, Lomire, and McCormack (2003) also showed medium to large correlations between expected grade and course ratings. However, these studies did not consider the predictive relationship for instructors across different courses and semesters, which was one aim of the current study. Using nearly twenty years of data from a large midwestern university, the following research questions were examined:

1) If ratings are, in fact, valid measures of instructor attributes, it should be expected that ratings would have some stability across semesters and specific courses. If variation

were due to instructor attributes and not the course they are assigned, we would expect ratings to be most stable across two different courses during the same semester. We would expect these correlations to decline somewhat for the same course in a different semester, since faculty members may improve or decline with experience. However, if they are reliable and stable enough to use in making choices about retention, their stability should be demonstrated across different semesters, as well. Therefore, in the current study, we first sought to establish if ratings are reliable for instructors across courses and semesters. This analysis was conducted by calculating all possible correlations between each average course rating in the dataset to examine course (same/different) by semester (same/different) by instructor (same/different) reliability.

- 2) After examining reliability, we sought to show that items on instructor evaluations were positively correlated, demonstrating that overall course evaluations are related to perceived grading ratings from the students.
- 3) Given the proposed differences in ratings by instructor type (Blackhart et al., 2006), we examined a moderated mediation analysis to portray the expected relationship of the variables across instructor type. First, for the mediation analysis, we hypothesized that expected grade predicted overall course rating, with perceived grading ratings mediating that relationship. With this analysis, we would demonstrate that evaluations are not merely a measure of expected grade, but also influenced by grading system used in the course (i.e., students with higher grades likely perceive grading to be more fair/appropriate, which then influences their ratings of the course). This mediation was expected to be moderated by instructor type, as previous research has shown that different types of instructors (teaching assistants, ranked faculty) appear to receive different ratings overall.

116 Method

The archival study was conducted using data from the psychology department at a large Midwestern public university. We used data from 4313 undergraduate, 397 mixed-level undergraduate, and 687 graduate psychology classes taught from 1987 to 2016 that were evaluated by students using the same 15-item instrument. The graduate courses were excluded from analyses due to the ceiling effects on expected grades. 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.

We focused upon the five items, which seemed most pertinent to the issues of perceived grading and evaluation. We were most interested in how grades related to global course evaluation and grading/assignment evaluations. These items were presented with a five-point scale from 1 (strongly disagree) to 5 (strongly agree):

- 1) The overall quality of this course was among the top 20% of those I have taken.
- 2) The examinations were representative of the material covered in the assigned readings and class lectures.
  - 3) The instructor used fair and appropriate methods in the determination of grades.
- 4) The assignments and required activities in this class were appropriate.
- 5) What grade do you expect to receive in this course? (A = 5, B, C, D, F = 1).

135 Results

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All data were checked for course coding errors, and type of instructor was coded as
graduate teaching assistant, per-course faculty, full-time instructors, and tenure-track faculty.
Graduate teaching assistants were generally assigned to teach lower-level introductory
courses (Introduction to Psychology, Statistics for Psychology, Research Methods

laboratories), and these students were interviewed and hired by the faculty supervising those courses. Graduate students were generally in their second year of the masters program in the department, and levels of supervision varied by course and supervisor.

This data was considered structured by instructor; therefore, all analyses below were 143 coded in R using the nlme package (Pinheiro, Bates, Debroy, Sarkar, & Team, 2017) to 144 control for correlated error of instructor as a random intercept in a multilevel model. 145 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 the repeated data that structure the data by a specified variable, which was 149 instructor in this analysis. Therefore, each instructor's average rating score was allowed to 150 vary within the analysis, as ratings would be expected to be different from instructor to 151 instructor. In each of the analyses described below, the number of students providing ratings 152 for the course was included as a control variable to even out differences in course size as an 153 influence in the results. The dependent variable and predictors varied based on the research 154 question, and these are described with each analysis below. 155

The overall dataset was screened for normality, linearity, homogeneity, and homoscedasticity using procedures from Tabachnick and Fidell (2012). Data generally met assumptions with a slight skew and some heterogeneity. This data was not screened for outliers because it was assumed that each score was entered correctly from student evaluations. The complete dataset and other information can be found online at http://osf.io/jdpfs. This page also includes the manuscript written inline with the statistical analysis with the *papaja* package (Aust & Barth, 2017) for interested researchers/reviewers who wish to recreate these analyses.

## 64 Reliability of Instructor Scores

Reliability of ratings of instructors can be inferred by the consistency of ratings across 165 courses and semester, assuming that we infer there is a stable good/poor instructor attribute 166 and that these multiple administrations of the same question are multiple assessments of 167 that attribute. A file was created with all possible course pairings for every instructor, 168 semester, and course combination. Therefore, this created eight possible combinations of 169 matching v. no match for instructor by semester by course. Multilevel models were used to calculate correlations on each of the eight combinations controlling for response size for both 171 courses (i.e., course 1 number of ratings and course 2 number of ratings) and random intercepts for instructor(s). The independent variable was the question rating for one 173 instructor/semester/course combination, while the dependent variable was the same question 174 rating for a second combination. The target variable of interest was therefore the correlation 175 between these two ratings, after adjusting for individual differences due to instructor 176 (random intercepts) and course size (control variable). Correlations were calculated 177 separately for each of the target questions listed above. 178

The overall pattern of the data was the same for each of the eight combinations, and 179 these were averaged for Table 1. The complete set of all correlations can be found online. 180 Given that the large sample size would bias statistical significance based on p-values, we 181 focused on the size of the correlations. The correlations were largest for the same instructor 182 in the same semester and course, followed by the same instructor in the same semester with 183 a different course and the same instructor in a different semester with the same course. The first shows that scores are somewhat reliable (i.e.,  $rs \sim .45$ ) for instructors teaching two or more of the same class at the same time. The correlations within instructor then drop to rs 186  $\sim .09$  for the same semester or same course. All other correlations are nearly zero, with the 187 same semester, same course, and different instructor as the next largest at  $rs \sim .05$ . Given 188 these values are still low for traditional reliability standards, these results may indicate that 189

student demand characteristics or course changes impact instructor ratings.

## 91 Correlations of Evaluation Questions

In this analysis, we correlated each of the five relevant evaluation questions, as the
above analysis indicated reliability for each item across time, but not their relation to each
other. The multilevel models for this analysis included course size as an adjustor variable,
one evaluation item as the independent variable, and a separate evaluation item as the
dependent variable. Again, these included the instructor as a random intercept to control for
differences in average ratings. This analysis was on the original dataset where each
semester/course/instructor combination was only compared to the matching
semester/course/instructor combination (i.e., ratings are correlated only on the exact same
course, semester, and instructor), rather than the special dataset created above for reliability.

Table 2 presents the inter-correlations for the five relevant evaluation questions. The 201 partial correlation (pr) is the standardized coefficient from the multilevel model analysis 202 between items while adjusting for sample size and random effects of instructor. The raw 203 coefficient b, standard error, and significance statistics are also provided. We found class 204 expected grade was related to class overall rating, exams reflecting the material, grading 205 fairness, and appropriateness of assignments; however, these partial correlations were 206 approximately half of all other pairwise correlations. The correlations between grading 207 related items were high, representing some consistency in evaluation, as well as the overall 208 course evaluation to grading questions. 209

## 210 Moderated Mediation

We proposed a mediation relationship between expected grade, perceived grading, and overall course grades that varies by instructor type. Figure 1 demonstrates the predicted

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relationship between these variables. We hypothesized that expected course grade would impact the overall course rating, but this relationship would be mediated by the perceived grading in the course, which was calculated by averaging questions about exams, fairness of grading, and assignments. Therefore, as students expected to earned higher grades, their perception and ratings of the grading would increase, thus, leading to higher overall course scores. This relationship was tested using traditional and newer approaches to mediation (Baron & Kenny, 1986; Hayes, 2017) wherein the following steps were examined:

- 220 1) The c path: Expected grade was hypothesized to predict overall course rating.
- 2) The a path: Expected grade was hypothesized to predict perceived grading.
- 3) The b path: Perceived grading was expected to predict overall course rating, adjusting for expected grade in the same model.
  - 4) The c' path/mediation: Expected grade's prediction of overall course rating should diminish when including perceived grading in the same model. In this step, the confidence interval of the indirect effect (i.e., the amount of mediation) was calculated by bootstrapping the analysis 1000 times. If the confidence interval of the indirect effect did not include zero, we concluded that mediation occurred.

All categorical interactions were compared to ranked faculty. Each step of the model is
described below, as independent and dependent variables change based on the path analyzed.
Because significant interactions were found, we calculated each group separately to portray
these differences in path coefficients. Tables 3 and 4 provide all regression statistics for
predictor variables in the overall and separated models. All regressions were analyzed with
multilevel models including course size as the adjustor variable and instructor as the random
intercept.

c Path. First, expected grade was used to predict the overall rating of the course, along with the interaction of type of instructor and expected grade. The expected grade positively predicted overall course rating, p < .001, wherein higher expected grades was related to higher overall ratings for the course (b = 0.542). A significant interaction between type and expected grade rating was found for instructors versus faculty. When examining Figure 1, we find that instructors (b = 0.836) have a stronger relationship between expected grade and overall course rating than faculty (b = 0.537, interaction p < .001), while per-course (b = 0.605, interaction p = .329) and teaching assistants (b = 0.510, interaction p = .643) were not significantly different than faculty on the c path coefficient.

Expected grade was then used to predict the average of the grading related 245 questions, along with the interaction of type of instructor. Higher expected grades were 246 related to higher ratings of appropriating grading (b = 0.360, p < .001), and a significant 247 interaction of faculty by per-course (p = .001) and faculty by instructors (p < .001) were 248 found, but not faculty by teaching assistants (p = .384). Faculty (b = 0.359) have a much 249 weaker relationship between expected grade and average ratings of grading than per-course 250 (b = 0.505), and instructors (b = 0.562), while faculty were equal to teaching assistants in 251 this path (b = 0.407). 252

B and C' Paths. In the final model, expected grade, average ratings of grading, 253 and the two-way interactions of these two variables with type were used to predict overall 254 course evaluation. Average rating of perceived grading was a significant predictor of overall 255 course rating (b = 1.098, p < .001), indicating that a perception of fair grading was related 256 positively to overall course ratings. An interaction between per-course faculty and fair 257 grading emerged, p < .001, wherein faculty (b = 1.097) had a less positive relationship than 258 per-course (b = 1.426), while teaching assistants (b = 1.265), interaction p = .102 and 259 instructors (b = 1.144, interaction p = .256) were not significantly different coefficients. 260

The relationship between expected grade and overall course rating decreased from the original model (b = 0.148, p < .001). However, the interaction between this path and per-course (p < .001) and teaching assistants (p = .031) versus faculty was significant, while faculty versus instructors' paths were not significantly different (p = .513). Faculty

relationship between expected grade and overall course scoring, while accounting for ratings of grading was stronger (b = 0.142) than per-course (b = -0.109) and teaching assistants (b = -0.010), but not that of instructors (b = 0.194).

Mediation Strength. We then analyzed the indirect effects (i.e., the amount of mediation) for each type of instructor separately, using both the Aroian version of the Sobel test (Baron & Kenny, 1986), as well as bootstrapped samples to determine the 95% confidence interval of the mediation (Hayes, 2017; Preacher & Hayes, 2008) due of the criticisms on Sobel. For confidence interval testing, we ran 1000 bootstrapped samples examining the mediation effect and interpreted that the mediation was different from zero if the confidence interval did not include zero.

For teaching assistants, we found mediation significantly greater than zero, indirect = 0.51 (SE = 0.09), Z = 5.39, p < .001, 95% CI[0.33, 0.68]. Per-course faculty showed mediation between expected grade and overall course rating, indirect = 0.72 (SE = 0.10), Z = 9.43, p < .001, 95% CI[0.55, 0.93]. Instructors showed a similar indirect mediation effect, indirect = 0.64 (SE = 0.05), Z = 10.34, p < .001, 95% CI[0.54, 0.75]. Last, faculty showed the smallest mediation effect, indirect = 0.39 (SE = 0.02), Z = 14.39, p < .001, 95% CI[0.35, 0.44], wherein the confidence interval did not include zero.

282 Discussion

These findings appear to indicate that faculty ratings are only somewhat reliable, with lower correlations (or no correlation) between semester and course iterations of teaching.
Only the same instructor, in the same semester with the same course showed a medium correlation, while all others were practically zero. The individual items appeared to be correlated, with the strongest inter-item correlations between perceived grading items.
Mediation analyses showed that expected grade was positively related to overall course

ratings, although this relationship was mediated by the perceived grading in the course.

Therefore, as students have higher expected grades, the perceived grading scores increase,
and the overall course score also increases. Moderation of this mediation effect indicated
differences in the strength of the relationships between expected grade, grading questions,
and overall course rating, wherein faculty generally had weaker relationships between these
variables.

Because the study was not experimental, causal conclusions from this study alone need to be limited. However, Salmons (1993) provides some evidence of the causal direction of student ratings of instructors and expected grades. She had 444 students complete faculty evaluations after 3-4 weeks of classes, and again after 13 weeks. Students who expected to get Fs significantly lowered their evaluations while students who expected to receive As and Bs significantly raised their evaluations.

It is compelling that the correlations suggest that we can do a better job of 301 understanding global ratings, perception of exams, fairness, and appropriateness of 302 assignments based upon the grade students expected as compared to relating these ratings 303 using ratings for the same course in a different semester or ratings for a different course in 304 the same semester for instructor (i.e., correlations between items in the same semester are higher than reliability estimates across the board). It is very likely that these correlations with expected grade are suppressed by the loading of scores at the high end of the scale for 307 course ratings and expected grade. Generally, evaluation items reflect scores at the high end of the 1-5 scale even when items are intentionally constructed to move evaluators from the 309 ends. The item, "The overall quality of this course was among the top 20% of those I have 310 taken" is conspicuously designed to move subjects away from the top rating. 311

Evidence suggests that student evaluations are influenced by likability, attractiveness, and dress (Buck & Tiene, 1989; Gurung & Vespia, 2007; Hugh Feeley, 2002) in addition to leniency and low demands (Greenwald & Gillmore, 1997). One must question whether a factor like instructor warmth, which relates to student evaluation (Best & Addison, 2000), is really fitting to the ultimate purposes of a college education. In a unique setting where student assignments to courses were random and common tests were used, Carrell and West (2010) demonstrated that teaching strategies that enhanced student evaluations led to poorer performance in subsequent classes. With the sum of invalid variance from numerous factors being potentially high, establishment of a high positive relationship to independent measures of achievement is essential to the acceptance of student evaluations as a measure of teaching quality.

The influence of perceived grading on teacher evaluations is far more detrimental to 323 the quality of education than the biased evaluations themselves. It is unlikely that good teachers, even if more challenging, will get bad evaluations (i.e. evaluations where the 325 majority of students rate the course poorly). Good teachers are rarely losing their positions 326 due to low quality evaluations. But Marsh (1987) found that faculty perceives evaluations to 327 be biased based upon course difficulty (72%), expected grade (68%), and course workload 328 (60%). If one's goal is high merit ratings and teaching awards, and the most significant 329 factor is student evaluations of teaching, then putting easier and low-level questions on the 330 test, adding more extra credit, cutting the project expectations, letting students off the hook 331 for missing deadlines, and boosting borderline grades would all be likely strategies for 332 boosting evaluations. 333

Effective teachers will get positive student ratings even when they have high
expectations and do not inflate grades. But, many excellent teachers will score below
average. It is maladaptive to try to increase a 3.90 global rating to a 4.10, because it often
requires that the instructor try to emphasize avoidance of the lowest rating (1.00) because
these low ratings in a skewed distribution have in inordinate influence on the mean. This
effort of competing against the norms is likely to lead to grade inflation and permissiveness
for the least motivated and most negligent students. Some researchers (Ellis et al., 2003;

Greenwald & Gillmore, 1997) argue that student evaluations of instruction should be
adjusted on the basis of grades assigned. However, there are problems with such an
approach. The regression values are likely to differ based upon course and many other
factors. In our research and in research by DuCette and Kenney (1982), substantial variation
in correlations was found across different course sets. Establishing valid adjustments would
be problematic at best. Further, such an approach would punish instructors when they
happen to get an unusually intelligent and motivated class (or teach an honors class) and
give students the grades they deserve. Student evaluations are not a proper motivational
factor for instructors in grade assignment, whether it is to inflate or deflate grades.

It would seem nearly impossible to eliminate invalid bias in student ratings of 350 instruction. Yet, they may tell us a teacher is ineffective when the majority give poor ratings. 351 It is the normative, competitive use that makes student evaluations of teaching subject to 352 problematic interpretation. This finding is especially critical in light of recent research that 353 portrays that student evaluations are largely biased against female teachers, and that 354 student bias in evaluation is related to course discipline and student gender (Boring et al., 355 2016). Boring et al. (2016) also examine the difficulty in adjusting faculty evaluation for bias 356 and determined that the complex nature of ratings makes unbiased evaluation nearly 357 impossible. Stark and Freishtat (2014) further explain that evaluations are often negatively 358 related to more objective measures of teaching effectiveness, and biased additionally by 359 perceived attractiveness and ethnicity. In line with the current paper, he suggests dropping 360 overall teaching effectiveness or value of the course type questions because they are 361 influenced by many variables unrelated to actual teaching. Last, they suggest the distribution and response rate of the data are critical information, and this point becomes particularly important when recent research shows that online evaluations of teaching experience a large drop in response rates (Stanny & Arruda, 2017). Our study contributes to 365 the literature of how student evaluations are a misleading and unsuccessful measure of 366 teaching effectiveness, especially focusing on reliability and the impact of grading on overall 367

questions. We conclude that it may be possible to manipulate these values by lowering 368 teaching standards, which implies that high stakes hiring and tenure decisions should 369 probably follow the advice of Palmer, Bach, and Streifer (2014) or Stanny, Gonzalez, and 370 McGowan (2015) in implementing teaching portfolios and syllabus review, particularly 371 because a recent meta-analysis of student evaluations showed they are unrelated to student 372 learning (Uttl, White, & Gonzalez, 2017).

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 $\label{thm:constructor} \begin{tabular}{ll} Table 1 \\ Correlations for Instructor, Semester, and Course Combinations \\ \end{tabular}$ 

Instructor	Semester	Course	b	SE	df	t	p
Different Instructor	Different Semester	Different Course	001	.000	10144295	-3.580	.013
Different Instructor	Same Semester	Different Course	.006	.002	152801	2.906	.048
Different Instructor	Different Semester	Same Course	.008	.001	517353	6.236	.027
Different Instructor	Same Semester	Same Course	.054	.010	6265	5.402	< .001
Same Instructor	Different Semester	Different Course	038	.003	108849	-13.130	< .001
Same Instructor	Same Semester	Different Course	.095	.020	1872	4.659	< .001
Same Instructor	Different Semester	Same Course	.090	.004	55057	21.769	< .001
Same Instructor	Same Semester	Same Course	.446	.023	1401	19.631	< .001

 $\label{eq:table 2} Table \ 2$   $t \ Statistics \ for \ Inter-item \ Relationship$ 

Coefficient		b	SE	df	t	p
Overall to Exams		.828	.014	4447	60.813	< .001
Overall to Fair	.606	.903	.016	4447	57.837	< .001
Overall to Assignments	.675	.999	.016	4447	63.251	< .001
Overall to Expected Grade		.597	.022	4447	27.167	< .001
Exams to Fair		.751	.012	4447	61.387	< .001
Exams to Assignments	.615	.700	.014	4447	50.425	< .001
Exams to Expected Grade	.311	.416	.018	4447	23.066	< .001
Fair to Assignments		.715	.011	4447	63.912	< .001
Fair to Expected Grade		.438	.016	4447	27.865	< .001
Assignments to Expected Grade		.404	.015	4447	26.913	< .001

 $\label{eq:table 3} t \ Statistics \ for \ Moderated \ Mediation$ 

DV	IV	b	SE	df	t	p
Overall Course	Expected Grade	0.542	0.026	4336	20.650	< .001
Overall Course	Teaching Assistant	-0.096	0.081	191	-1.187	.237
Overall Course	Per-Course	0.018	0.076	191	0.235	.815
Overall Course	Instructor	-0.198	0.109	191	-1.814	.071
Overall Course	EG X TA	-0.049	0.105	4336	-0.464	.643
Overall Course	EG X PC	0.077	0.079	4336	0.976	.329
Overall Course	EG X IN	0.255	0.060	4336	4.234	< .001
Average Grading	Expected Grade	0.360	0.017	4336	21.790	< .001
Average Grading	Teaching Assistant	0.083	0.044	191	1.860	.064
Average Grading	Per-Course	0.060	0.041	191	1.441	.151
Average Grading	Instructor	-0.049	0.059	191	-0.839	.403
Average Grading	EG X TA	0.056	0.064	4336	0.870	.384
Average Grading	EG X PC	0.167	0.049	4336	3.403	.001
Average Grading	EG X IN	0.173	0.038	4336	4.556	< .001
Overall Course	Expected Grade	0.148	0.020	4332	7.537	< .001
Overall Course	Teaching Assistant	-0.198	0.045	191	-4.388	< .001
Overall Course	Per-Course	-0.056	0.041	191	-1.354	.177
Overall Course	Instructor	-0.133	0.058	191	-2.286	.023
Overall Course	Average Grading	1.098	0.019	4332	58.334	< .001
Overall Course	EG X TA	-0.173	0.080	4332	-2.164	.031
Overall Course	EG X PC	-0.299	0.063	4332	-4.714	< .001
Overall Course	EG X IN	0.034	0.051	4332	0.654	.513
Overall Course	AG X TA	0.142	0.087	4332	1.634	.102
Overall Course	AG X PC	0.359	0.061	4332	5.922	< .001
Overall Course	AG X IN	0.061	0.054	4332	1.136	.256

 $\label{eq:table 4} Table \ 4$   $t \ Statistics \ for \ Individual \ Mediations$ 

Group	DV	IV	b	SE	df	t	p
Teaching Assistant	Overall Course	Expected Grade	0.510	0.092	219	5.534	< .001
Teaching Assistant	Average Grading	Expected Grade	0.407	0.049	219	8.326	< .001
Teaching Assistant	Overall Course	Expected Grade	-0.010	0.077	218	-0.126	.900
Teaching Assistant	Overall Course	Average Grading	1.265	0.084	218	15.017	< .001
Per-Course	Overall Course	Expected Grade	0.605	0.071	425	8.536	< .001
Per-Course	Average Grading	Expected Grade	0.505	0.040	425	12.640	< .001
Per-Course	Overall Course	Expected Grade	-0.109	0.051	424	-2.163	.031
Per-Course	Overall Course	Average Grading	1.426	0.049	424	28.991	< .001
Instructor	Overall Course	Expected Grade	0.836	0.054	504	15.511	< .001
Instructor	Average Grading	Expected Grade	0.562	0.035	504	15.967	< .001
Instructor	Overall Course	Expected Grade	0.194	0.044	503	4.375	< .001
Instructor	Overall Course	Average Grading	1.144	0.045	503	25.230	< .001
Tenure Track	Overall Course	Expected Grade	0.537	0.027	3185	19.817	< .001
Tenure Track	Average Grading	Expected Grade	0.359	0.017	3185	20.722	< .001
Tenure Track	Overall Course	Expected Grade	0.142	0.021	3184	6.891	< .001
Tenure Track	Overall Course	Average Grading	1.097	0.020	3184	56.152	< .001

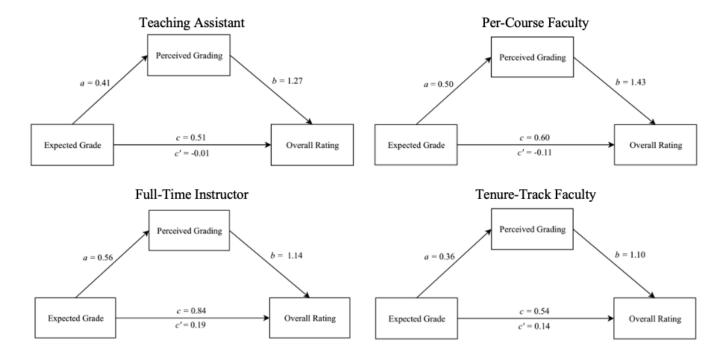


Figure 1. Mediation models for moderated mediation analysis indicating mediation effects for each type of teacher. Expected grading indicates student entered grade expected in the course, perceived grading is an average score of fairness, appropriateness, and exam grading questions, and overall rating indicates the omnibus rating for a course.