Sociocognitive Approach to the Validity of Teaching Assessment Instruments.

Roberto Daniel Cáceres-Bauer (1), Pilar Rodríguez Morales (2), Mario Luzardo Verde (3).

(1) Instituto Nacional de Evaluación Educativa, Montevideo, Uruguay. Orcid:0000-0002-8047-872X

(2) Centro Universitario Regional del Este, Universidad de la República, Maldonado, Uruguay. Orcid: 000-0003-1929-4961

(3) Faculty of Psychology, Universidad de la República, Montevideo, Uruguay. Orcid: 0000-0002-9360-2806

Author note

Correspondence concerning this article should be addressed to Roberto D. Cáceres-Bauer, Instituto Nacional de Evaluación Educativa (INEEd), Av. Italia 6201, Montevideo, State ZIP 11500, Uruguay. Email: rcaceres@ineed.edu.uy. ORCID: 0000-0002-8047-872X

Abstract.

The present study investigates the construct validity of Student Evaluation of Teaching (SET) questionnaires using a sociocognitive approach and rater-mediated assessment methods. The study employed many-facet Rasch measurement (MFRM) and a SET questionnaire to evaluate the quality of teaching in medical courses, accounting for the variability resulting from rater severity and item difficulty. The Central Model of Student Perception (CSP) is a theoretical framework employed to analyze socio-cognitive factors influencing student responses. The findings indicate that students possess the capacity to differentiate between the measured dimensions and correctly interpret the questionnaire items. However, the severity of their responses exhibits considerable variability. The study suggests that SET questionnaires can yield valuable information regarding teaching quality, but only if appropriate instrument design, administration protocols, and data collection and analysis methods are used. The CSP, along with advanced analysis methods like MFRM, provides a flexible approach for evaluating and researching teaching quality.

Keywords: teaching evaluation, student perceptions, social cognition, construct validity, psychometrics.

1. Introduction

Student evaluation of teaching (SET) questionnaires are employed in academic institutions worldwide for various purposes, including the provision of feedback to educators and the enhancement of pedagogical practices (Abrami et al., 1990; Brown, 2011; Hativah, 2019; 2014; Seldin, 2006). They are also used for managerial and administrative decision-making (Arreola, 2007; Cáceres, 2018; Cáceres-Bauer et al., 2024; Madichie, 2011; Marsh et al., 2019, 2007, 1997, 1987; Seldin, 2006; Theall and Franklin, 2001). Furthermore, they have been employed to examine students' perceptions and satisfaction with the quality of teaching and the relationship between teaching and learning (Cáceres, 2018; Cáceres-Bauer et al., 2024; Marsh et al., 2007; Marsh, 1987; Theall et al., 2001).

In general, rigorously developed and validated student evaluations of teaching (SET) questionnaires are more reliable and valid measures of teaching quality than other information sources (Aleamoni, 1999; d'Apollonia & Abrami, 1997; Benton & Cashin, 2013; Hativah, 2019, 2014; Marsh, 2007, 1987; Marsh & Roche, 1997; Ogbonnaya, 2014; Renaud & Murray, 2005; Theall et al., 2001; Zhao & Gallant, 2012). However, validity can be undermined by faulty instruments, improper administration, or flawed data collection and analysis (Arreola, 2007; Benton et al., 2013; Franklin & Theall, 1990; McKeachie, 1997; Spooren et al., 2013; Theall et al., 2001).

Recent research focuses on biases in student perceptions as a source of SET invalidity. Some studies find that SET scores are biased and their validity compromised (Heffernan, 2022; Kreitzer & Sweet-Cushman, 2021; Mitchell & Martin, 2018; Radchenko, 2020; Uttl & Smibert, 2017; Young et al., 2009). Other studies report no practically significant biases in SET scores

(Benton & Cashin, 2013; Centra, 2003, 2009; Hativa, 2019; Marcham et al., 2020; Marsh, 1987; Punyanun-Carter & Carter, 2015; Remedios & Lieberman, 2008).

Controversy also exists about the relationship between SET scores and proxies for learning. Moderate positive correlations between SET and final course grades appear in multi-section studies and meta-analyses (Cohen, 1981; Feldman, 1997; Onwuegbuzie et al., 2009). Positive associations have also been reported between SET and students' self-assessments of skill development (Braun & Leidner, 2009; Stapleton & Murkison, 2001). Other studies report no correlation between SET and learning outcomes (Mohanty et al., 2005; Stark-Wroblewski et al., 2007; Uttl et al., 2017).

Advancing understanding of contradictory findings on SET validity requires theoretical and methodological progress (Hativa, 2019; Theall & Franklin, 2001; Marsh, 1980; Marsh & Roche, 1997; Spooren et al., 2013). Many studies still struggle to capture the complexity of student perception and the response process (Cáceres-Bauer et al., 2024; Cáceres, 2018; d'Apollonia & Abrami, 1997; Klimoski & Donahue, 2013; Theall et al., 2001; Van Wyk et al., 2003). Social cognitive psychology, which addresses person perception, offers a promising framework to enrich research on how students evaluate teaching (Bierhoff, 2012; Hamilton & Stroessner, 2020; Higgins et al., 2022).

A number of educational-psychology constructs—attitudes, metacognition, self-efficacy, expectations, and attributions—are self-perceptual and have been widely studied to explain how students engage in learning (Brophy & Good, 1986; Bandura, 2023; Flavell, 2019; Marsh & Shavelson, 1985; Shuell, 1986). Socio-cognitive motivational theories clarify how these constructs interact with instruction to facilitate learning (Arreola, 2007; Bandura, 2023; Elliot et al., 2017; Ryan & Deci, 2017; Schunk et al., 2014). These perspectives can inform research on SET by elucidating how students form judgments of teaching quality.

Recent emphasis on student-perception biases as a source of measurement invalidity has not been matched by adequate methods to account for student effects on SET scores. Suitable rater-mediated assessment methods exist to model rater influence and to diagnose and control bias (Bond & Fox, 2020; Eckes, 2023; Engelhard & Wind, 2017).

The many-facet Rasch measurement (MFRM) framework addresses key methodological challenges in SET research (Eckes, 2023). From this viewpoint, student evaluations of teaching are a form of rater-mediated assessment: student responses yield data to obtain objective measures of teaching effectiveness while accounting for variability and potential biases in student perception. Although MFRM offers important advantages, its application in this field remains limited (Borkan, 2017; Haladyna & Hess, 1994; Quansah, 2022).

Research on SET typically uses class- or teacher-level item score means (Gravestock & Gregor-Greenleaf, 2008; Hativa, 2019; Marsh, 2007, 1987; Marsh & Roche, 1997). Means reduce random error but may not address the ordinal scale of responses, the absence of a suitable unit of analysis, or multiple contributing influences (Eckes, 2023; Engelhard & Wind, 2017; Haladyna & Hess, 1994; Larson, 1979; Marsh & Groves, 1987; Whitely & Doyle, 1976). Using anonymous rather than anonymized data limits the examination of response patterns and the diagnosis and control of rating bias.

This paper uses a substantive-construct-validity approach focused on cognitive processes and mental representations from item responses (Embretson, 1994; Messick, 1995). It integrates person-perception, social-cognitive motivation, and rater-mediated assessment literatures

(Bandura, 2023; Bierhoff, 2012; Elliot et al., 2017; Hamilton & Stroessner, 2020; Higgins et al., 2022; Ryan & Deci, 2017; Schunk et al., 2014; Eckes, 2023; Engelhard & Wind, 2017).

This study aims to provide construct‑validity evidence for the meaning and intended inferences of SET measures (Cizek, 2020; Embretson, 2007; Mislevy, 2007; Newton & Shaw, 2014; Whitely, 1983). We apply a substantive-validity framework that is grounded in the Central Model of Student Perception (CSP; Cáceres-Bauer et al., 2024) and MFRM models. The CSP, the guiding model for this study, frames teaching perception with social‑cognitive theories and treats teaching's influence on learning through socio‑cognitive motivational theories (Cáceres‑Bauer et al., 2024; Cáceres, 2018).

Students' perception of teachers is a specific case of person perception studied in social cognitive psychology (Gilovich et al., 2023; Hamilton & Stroessner, 2020; Sutton et al., 2019). When evaluating teaching, the student assumes the role of observer while the teacher is both the observed and the provider of instruction. Because these roles overlap, student perception is distinctive: students both observe teachers' behavior and experience its effect on their learning. The facilitating effect of teaching increases the likelihood of learning and produces deeper, more meaningful learning outcomes (Arreola, 2007; Cáceres‑Bauer et al., 2024; Ryan & Deci, 2017). The Central Student Perception (CSP) model posits that SET are cognitively mediated by variables explaining this effect, drawn from socio‑cognitive motivational theories—for example, causal attributions, self‑efficacy, outcome expectations, intrinsic motivation, perceived self‑determination, goal orientations, and implicit theories of intelligence (Ames & Lau, 1979; Cáceres, 2018; Cáceres‑Bauer et al., 2024; Graham, 1991; Grimes et al., 2004; Svanum & Aigner, 2011; Wigfield et al., 1997)

The CSP describes cognitive processes in student perception using social cognitive psychology. Students use schemas about people, roles, and events—abstract representations that include attributes and their relations (Fiske & Taylor, 2021; d'Apollonia & Abrami, 1997). Schemas act as cognitive categories that guide information selection and processing and provide social prototypes of typical people and situations (Bierhoff, 2012). They also contribute to general impressions—organized cognitive representations of the perceiver about the perceived person (Bierhoff, 2012; Hamilton & Stroessner, 2020).

General impressions influence cognitive processing and can persist but may change when students encounter information they judge inconsistent. Implicit theories of students' ability may influence how they perceive their learning and its facilitating effects (Cáceres, 2018; Dweck & Molden, 2017) Likewise, implicit theories about teaching attributes or their relations shape perceptions of teaching; if inaccurate, they can cause biases or illusory correlations, whereas if accurate, they support correct inferences (Renaud & Murray, 2005). Social stereotypes—simplified generalizations shared about a group of people (e.g., gender)—can also affect students' perceptions and be a potential source of bias (Fiske & Taylor, 2021; Renström et al., 2021).

The CSP assumes students evaluate teaching based on perceived teaching characteristics and the facilitating effect they experience, while outlining cognitive mechanisms that may bias those perceptions. For SET to yield valid measures, conditions must allow perceptions of actual teaching quality and its impact to predominate. Under such conditions, students are likelier to rate more positively teachers whose behaviors and attributes produce a stronger facilitating effect. A student's general tendency to award lower scores is represented by a severity parameter: higher severity increases the probability of negative ratings.

The CSP posits that students form schemas about teaching and its relation to the facilitating effect they experience during instruction. These schemas help identify teaching characteristics, behaviors, and attributes that facilitate learning. Students' perceptions and experiences thus highlight certain teaching features as more effective

Mental representations let students identify cues for classroom-teaching attributes. Specific teacher behaviors and impressions are stored in long-term social memory. Responding to SET items activates those memory traces, which working memory processes through inference steps drawn from long-term memory to produce a response. When observers lack direct evidence, they use schema-based inferences that supply relevant attributes and relations.

This study proposes the following hypothesis: Students' perceptions of teaching characteristics and the facilitating effect they experience are the primary determinants of their evaluations of instruction. Thus, more positive student evaluations (less severe) are associated with a stronger facilitating effect or with perceiving teacher attributes and behaviors linked to that effect.

Applying the CSP and MFRM models allows assessment of the plausibility of this hypothesis via the following research questions:

RQ1. Can students differentiate the questionnaire's measured dimensions?

RQ2. Can students interpret the questionnaire items adequately?

RQ3. Do students use the item scoring scale consistently?

RQ4. Are there differences in students' severity when evaluating teachers?

RQ5. Do severity and item interpretation vary across instructors or occasions?

RQ6. Is the between- and within-course pattern of student and teacher measures consistent with the hypothesis?

RQ7. Are students' perceptions of teaching better explained by variation in instructional quality and facilitative effects than by biasing influences

2. Method

Data

The sample comprised responses from 3,243 students who evaluated 98 teachers across 10 courses in seven disciplines during the first three years of the medical degree at the University of the Republic (Uruguay). The study focuses on multi-section compulsory courses whose teachers follow identical programs, objectives, content, textbooks, and summative assessments; group sizes and contextual factors across sections are comparable. Student assignment to sections is independent of instructor identity: students are organized into groups that are then allocated to course sections. Summative assessments are standardized across sections, so grading leniency is equivalent within a course and can differ only between teachers of different multi-section courses. Participation by students and faculty was voluntary. Among teacher evaluations, 47% were for male instructors and 53% for female instructors. The overall student response rate was 71%. Questionnaires were administered online during the final two weeks of each course, before the final exam. A single randomized item order was used for all respondents, and access to the questionnaire was password-protected.

This study was approved by the Ethics Committee of the University of the Republic (approval no. 070153-000391-16). Written informed consent was obtained electronically via the study website before participants completed the questionnaire, which included a consent statement describing data-processing procedures. Students and teachers were informed of the evaluation objectives. The consent indicated that data would be anonymized, used only for formative feedback to improve teaching and learning, and not used for administrative decisions or summative teacher evaluation. It also stated that the data would support research on the validity of instruments assessing teaching and learning quality. Students additionally completed a socio-cognitive questionnaire on the course learning process; results from that instrument will be reported in a subsequent publication.

Instruments

The questionnaire comprised nine subscales measuring aspects of teaching quality (see Table 1) and 49 items scored on a five-point Likert scale: 1 = Strongly disagree; 2 = Disagree; 3 = Neither agree nor disagree; 4 = Agree; 5 = Strongly agree. Development procedures aimed to ensure content and face validity (Wainer & Braun, 2013). Content selection was informed by an extensive literature and instrument review. Experimental versions were examined for psychometric properties and factor structure and were rated by a sample of teachers for relevance; these data guided revisions that produced the version used here. The questionnaire was designed to measure dimensions similar to the Endeavor Instrument (Frey et al., 1975) and the Students' Evaluation of Educational Quality (SEEQ; Marsh, 1987), which have extensive international validity evidence (Coffey & Gibbs, 2001; Grammatikopoulos et al., 2014; Ibrahim, 2012; Lin et al., 1995; Marsh, 1981; Marsh et al., 1985; Watkins et al., 1987).

Analysis

MFRM analysis

The MFRM models generalize the Rasch model by assuming a unidimensional latent variable while incorporating multiple facets. These models account for rater severity and other facet effects and place all facet elements on a common, additive logit scale that is invariant under perfect fit. The MFRM estimates teacher quality while controlling for student severity and item difficulty. Analyses to fit the MFRM models and obtain item, student, and teacher measures were conducted using FACETS 64-bit (Many-Facet Rasch Measurement), Version 4.3.4 (Linacre, 2025). Other supplementary analyses were performed in R (R Core Team, 2025).

The estimation of measures in MFRM models is an iterative process that controls the influence of misfitting elements, which may distort scale calibration and diagnostic statistics (Cáceres, 2018; Crisan et al., 2017; Linacre, 2024b). It is also imperative to ensure that the level of connection among teachers, students, and items is sufficient, as inadequate connection may compromise the estimation of measures and fit statistics. Moreover, disconnected subsets may prevent proper specification of the measurement model (Engelhard, 1996; Linacre, 2024b). The iterative process continues until the measurement estimates stabilize and converge, maintaining adequate levels of connectivity (Cáceres, 2018).

The analysis and interpretation of MFRM results are based on a set of fit and diagnostic indices (Eckes, 2023; Linacre, 2024a). We evaluated model fit using Infit and Outfit mean-square statistics computed at the element and category levels and aggregated at the model level to provide an overall fit indicator (Bond et al., 2020; Wright & Stone, 1999; de Jong & Linacre, 1993). We also examined the observed proportion of absolute standardized residuals exceeding 2 (PRE_2) as an overall fit indicator. If the model fit were perfect, the standardized residuals would approximate a standard normal distribution (Wright & Stone, 1999); accordingly, a satisfactory PRE_2 is expected to be close to $PRE_2 = .046$.

The Rasch measurement approach is prescriptive in that it specifies an ideal of objective measurement and systematically identifies discrepancies between that ideal and observed data (Bond et al., 2020; Engelhard & Wind, 2017; Wright & Stone, 1999). Infit and outfit mean-square statistics are used to optimize measures and to examine item, rater, and ratee behavior; they also help identify items with problematic or inconsistent response patterns (Bond et al., 2020; Engelhard, 2012). Linacre (2024b) characterizes values between 0.50 and 1.50 as productive for measurement; values above 2.00 are likely to distort the measurement system, and values below 0.50 may yield spuriously high reliability estimates. These diagnostics target complementary aspects of model-data fit. The point-measurement correlation (r_{pm}) is a Rasch statistic that is used to evaluate if the measurement of an element is consistent ($r_{pm} \geq 0$) or contradicts ($r_{pm} < 0$) the overall meaning of the measure (Linacre, 2024b). The Many-Facet Rasch Model fixes item discrimination at 1; post hoc diagnostics compute Discrim to quantify any departures (Discrim = 1 indicates conformity; Linacre, 2024a). Another statistic used is the proportion of the variance of the observed scores explained by the model (*PVE*), which expresses how well the model explains the observed scores. The effect size defined from the *PVE* given in Linacre (2005, 2006) is 2% (small effect size), 13% (medium effect size), and 26% (large effect size). The proportion of the additional variance explained by introducing an interaction term (PVE_{INTER}) allows us to assess the importance of this term in explaining the observed scores. Likewise, the chi-square test with fixed effects (all zero) allows contrasting the hypothesis that the interaction terms all have zero measure, attributing the observed differences to estimation errors (Engelhard & Wind, 2017).

To test the invariance property, high linear correlation coefficients must be obtained between two complementary random subsamples, as well as between each of the subsamples and the full sample (Muñiz, 1997; Rupp & Zumbo, 2004).

Separation reliability (*SR*) is the ratio of the true variance to the observed variance of the element measures of a facet. It shows how reproducible the ordering is between the measurements of the elements of a facet. Its value varies between 0 and 1; the higher its value, the higher the reliability of the measurement. The ratio between the adjusted standard deviation (*SDA*) and the root mean square error (*RMSE*) defines the G-index, which expresses the reliability of the measurement as a function of the *RMSE* value (Wright & Stone, 1999). The strata index (*H*) is the number of distinct strata that can be measured with the data (Bond et al., 2020). In addition, the chi-square test with fixed (all equal) effects allows testing the null hypothesis that the elements of a facet have the same measure, attributing the observed differences to estimation errors (Linacre, 2024a; Engelhard & Wind, 2017).

As a complementary analysis, we estimated the proportion of variance attributable to within-course (*PVWC*) and between-course (*PVBC*) differences in latent measures derived from a Many-Facet Rasch Model (*MFRM*). To this end, we fitted mixed-effects models with courses treated as a random effect, using standard procedures for variance decomposition in hierarchical data structures (see Faraway, 2016). To account for heteroscedastic residuals, we fitted a linear mixed-effects model in nlme (Pinheiro et al., 2024, v. 3.1-166) with course as a random intercept and a group-specific residual variance structure (weights = varIdent(form = ~1 | course)), estimated by restricted maximum likelihood (REML). The dependent variables were teacher and student measures obtained from the MFRM calibration. We computed the intraclass correlation coefficient (*ICC*) to quantify the proportion of variance explained by course-level differences (*PVBC*), with the remaining variance interpreted as within-course variation (*PVWC*). For interpretive purposes, we adopted benchmarks proposed by Ferguson (2009): 4% (minimal), 25% (moderate), and 64% (large), acknowledging that these thresholds were originally developed for general effect size interpretation and are used here as heuristic guides. Using the same modeling approach, we also estimated the proportion of variance attributable to within- and between-teacher differences in student measures (*PVWT* and *PVBT*, respectively).

Categorization validity statistics are used to analyze whether subjects responding to the items consistently use the defined categories. For a larger category to reflect a larger value of the measured construct, it is necessary that the averages of the measures of the observations in the categories are ordered in an ascending order (Bond & Fox, 2007; Engelhard & Wind, 2017; Linacre, 2002). Another indicator of categorization validity is the analysis of Rasch-Andrich thresholds, which represent the points on the latent trait scale where a respondent has an equal probability of selecting one category or the next. When these thresholds follow a monotonic order aligned with the scoring categories, they indicate better functioning of the scale and higher measurement quality (Bond & Fox, 2007; Eckes, 2023). The quality of the scoring scale is also adequate if the separation between thresholds is at least 1 logits and less than 5 logits (Eckes, 2023; Linacre, 2002). Each category also has an expected Outfit value of 1. Values substantially greater than 1 indicate the presence of unexpected observations within that category. Outfit values are generally considered acceptable when they do not exceed 2 (Bond & Fox, 2007; Engelhard & Wind, 2017; Linacre, 2002). Additionally, a regular distribution of response frequencies across categories, without unobserved or unused categories, is taken as another sign of good rating scale functioning (Eckes, 2023; Linacre, 2002).

Dimensional Structure and Local Independence

The dimensional structure of the SET questionnaire was explored in two stages. First, an exploratory factor analysis (EFA) was performed on aggregated teacher-level mean item scores to identify putative latent dimensions and compare them with previous research. Second, unidimensionality within each subscale was examined using principal component analysis of Rasch residuals (PCAR). The EFA of teacher-level mean item scores followed current best-practice recommendations (Costello & Osborne, 2005; Goretzko et al., 2021; Hativa, 2019; Marsh, 1987; Marsh & Roche, 1997). EFA was implemented in R using the psych package (Revelle, 2024). This initial step enabled direct comparison with prior factor-analytic studies of related instruments (Frey et al., 1975; Marsh, 1987) and complemented subsequent Rasch-based analyses.

Next, unidimensionality of the putative subscales was evaluated using principal components analysis of Rasch residuals (PCAR; Bond et al., 2020; Boone et al., 2020; Linacre, 1998). Residuals were obtained from MFRM calibrations fitted separately for each subscale. The

PCAR and related residual diagnostics were conducted in R using the FactoMineR package (Lê, Josse, & Husson, 2008). An eigenvalue less than or equal to two for the first principal component (first Rasch contrast) of the standardized residuals indicates consistency with unidimensionality (Chou & Wang, 2010; Linacre, 1998, 2024b; Smith, 2002). If an eigenvalue greater than two is observed, the existence of extra dimensions can be identified by vertical stratification in the plot of the first principal component with respect to the Rasch measure (Bond et al., 2020; Boone et al., 2020; Linacre, 1998).

To assess violations of the model's local independence assumption, we estimated the raw residual correlation matrix for all item pairs following Yen (1984) and computed the adjusted residual-correlation statistic Q3* (Christensen et al., 2017) to identify local dependence. We adopted the cutoff Q3* > .20 following Christensen et al. (2017). We also examined the standardized residual correlation matrix and reported the maximum standardized-residual correlation r_{MAX} and the proportion of residual correlations exceeding the cutoff, $PCOR_x$, by subscale. For interpretation, correlations near r = .40 were considered low conditional dependence with minimal practical impact. Correlations at or above r = .70 indicate substantial shared residual variance ($r^2 \geq .49$), which may bias parameter estimates, inflate reliability indices, and compromise model fit (Linacre, 2024b).

MFRM models

Teachers, students and items measurement facets and the dummy facet courses were included in the models. The course's facet was used for the analysis of the interaction between students and courses. The measures of the dummy facet elements are set to a null value. The basic MFRM model is

$$ln[P_{nijk}/P_{nijk-1}] = B_n - D_i - C_j - F_{ki} \quad \textbf{(1)}$$

where

P_{nijk} = Probability that teacher n receives score k on item i for student j,

P_{nijk-1} = Probability that teacher n receives score k - 1 on item i for student j,

B_n = Quality of the teacher's teaching n,

D_i = Difficulty of item i,

C_j = Severity of student j,

F_{ki} = Difficulty of category k of the scale for item i relative to category k-1.

The following models were used to analyze interactions between facets:

$$ln[P_{nijk}/P_{nijk-1}] = B_n - D_i - C_j - F_{ki} - I_{nj} \quad \textbf{(2)}$$

where

I_{nj} = Interaction between element n of the teacher facet and element j of the student facet,

$ln[P_{nijk}/P_{nijk-1}] = B_n - D_i - C_j - F_{ki} - I_{ij}$ **(3)**

where

I_{ij} = Interaction between element i of the item facet and element j of the student facet,

$ln[P_{nijk}/P_{nijk-1}] = B_n - D_i - C_j - F_{ki} - I_{gj}$ **(4)**

where

I_{gj} = Interaction between element g of the course facet and element j of the student facet.

CSP and the MFRM framework

The application of item response theory (IRT) models and Rasch-based frameworks to the study of cognitive processes and mental structures is a well-established area of research (De Boeck & Wilson, 2004; Embretson, 2013; Mair & Hatzinger, 2007; Reynolds, 1994; von Davier & Carstensen, 2007). The MFRM family of models allows for the development of specific variants —such as the Linear Logistic Test Model (LLTM)—which relate item difficulty to the cognitive operations and structures required to respond to each item (Embretson, 2013; Linacre, 2024a; Mair & Hatzinger, 2007; Reynolds, 1994).

MFRM models facilitated the extension of this approach to the cognitive study of student perception. For instance, through explanatory MFRMs of student measures (Cáceres, 2018; De Boeck & Wilson, 2004). The MFRM model provides measures that characterize the influence on the observed scores of students, items, and teachers. The measurement of each student enables the characterization of the influence of their perception on the observed score. Conversely, the measurement of the teacher enables the identification of how the quality of their teaching influences the observed score. From a cognitive perspective, students' perceptions of instruction emerge from underlying cognitive processes and structures. We examine the influence of these processes and structures through MFRM models by analyzing patterns in measurements of teachers, students, items, and their interactions. The prevailing approach in MFRM models to analyze possible biases in assessment is the analysis of interactions (Eckes, 2023; Haladyna & Hess, 1994). The CSP facilitates the identification of anticipated patterns in teacher, student, and item measures, as well as their interactions, considering the mental processes and structures involved in student perception. The analysis of interactions in MFRM models also allows for the examination of potential changes in the quality of teachers' teaching or in student perception.

A first analytical focus is to examine whether observed patterns align with those expected if student evaluations primarily reflect variation in teaching quality and its facilitation effect or instead with patterns consistent with bias. This requires distinguishing between construct‑relevant and construct‑irrelevant variability. According to the CSP, accurate perceptions of teaching quality are indicated by the ability to distinguish teaching‑quality dimensions, correctly interpret scale items, consistently use scoring scales, and by specific patterns of variation in student severity. Perceptual biases may manifest in other patterns. In particular, certain interactions between teacher, student, and item measures may indicate differences in teaching facilitation, while others may signal distortions in student perception. The pattern of results across teaching-quality dimensions is central to deciding whether evaluations reflect valid perceptions or are distorted by irrelevant influences.

A second analytical focus is to identify and characterize specific cognitive factors relevant to student evaluations. For example, gender stereotypes may signal genuine assessment bias and thus require teacher-gender data. Using the MFRM, we can test whether gender stereotypes operate as potential bias. The CSP then helps interpret whether an observed MFRM interaction reflects bias or instead instructional differences or facilitative effects by examining patterns across teaching-quality dimensions. Combined with sociocognitive questionnaires, CSP and MFRM permit investigation of cognitive sources of specific bias and of students' learning processes and teachers' facilitating effects.

Another potential source of bias is students' mental schemas and implicit theories about teaching-quality dimensions and their relations. Using MFRM, we can derive measures to describe correlations among those dimensions and determine whether students' dimension-level correlations reflect underlying teaching-quality correlations or the semantic similarity of dimensions for the sampled students (Renaud & Murray, 2005). This analysis requires measuring semantic similarity among questionnaire items for the specific student population.

Application of the CSP to the present study

Instrument design, administration protocol, and student–teacher interaction shape the response process to a SET questionnaire. The evaluation's objectives must be explicit, and the administration structured to minimize irrelevant variance. Students' general impressions or social stereotypes can influence ratings more when there is insufficient observation. In such cases, students may infer unobserved attributes from their schemas about teaching attributes, which act as implicit theories about what is expected for an unobserved attribute, given other aspects that were observed. The adequacy of these inferences depends on schema quality and the associations they encode among teaching‑effectiveness dimensions (Cáceres‑Bauer et al., 2024). The CSP theoretical analysis supports the plausibility of the research hypothesis under the study conditions.

A socio-cognitive analysis of the student's role as evaluator and learner, conducted using the CSP, can assess the plausibility of the research hypothesis and identify expected patterns should the cognitive mechanisms outlined in the hypothesis exert a dominant influence on the students' questionnaire response process. This can be achieved by considering the expected patterns associated with each research question.

Expected pattern for RQ1

If students perceive and distinguish each dimension, dimensional‑structure analysis should recover nine dimensions, as expected. If students discriminate teaching quality levels within dimensions, MFRM analyses should show high SR for teacher measures and a significant chi-square test with fixed (all equal) effects. Conversely, if students form a global evaluation based on a single attribute (halo effects), one would expect fewer dimensions in student ratings (Bierhoff, 2012; Michela, 2022; Röhl & Rollett, 2021).

Expected pattern for RQ2

We expect students to interpret items correctly. If so, a high SR and a significant fixed-effects (all-equal) test for the item facet are expected. If students discriminate teacher effectiveness across questionnaire attributes and interpret items correctly, high r_{pm} values should appear, indicating consistency between item measures and the construct. At the student individual level, very low or negative r_{pm}, together with Infit and Outfit indicating poor fit, would signal inconsistent responding.

Expected pattern for RQ3

Students should correctly interpret items and discriminate levels of teaching effectiveness on each dimension; therefore, they are expected to use item scales consistently, and psychometric diagnostics of scale use should reflect this expectation.

Expected pattern for RQ4

According to the CSP, students may exhibit differences in their social cognition that explain differences in how they perceive and evaluate instruction and experience different facilitating effects. If the cognitive mechanism expressed in the research hypothesis dominates the students' response process, it is expected that measures of severity will exhibit high variability.

High SR values and statistically significant fixed effects tests manifest inter-student variability in severity. We expect the evaluations in this study to be subjective, yet informative. Therefore, we also expect teachers to have good levels of *SR*, statistically significant fixed effects tests (all equal), and high positive values of r_{pm} and *Infit* and *Outfit* values that show a good level of fit.

Expected pattern for RQ5

The study permits detection of deviations from a primary-effects MFRM model that the CSP explains via the facilitator effect. Such discrepancies can further substantiate the CSP, which generates forecasts based on specific cognitive processes and predicts interaction patterns.

Under our research hypothesis, the CSP posits that variation in facilitating effects and cognitive mediation may explain differences in severity. These discrepancies appear as interactions between the student facet and the teacher and item facets. Local severity can be measured with an MFRM that includes facet interactions. Student–teacher interactions reflect changes in students' perceptions of teachers; student–item interactions reflect changes in students' interpretations of items. This pattern produces a poorer fit for the student facet than for other facets and lower teacher invariance with respect to students. Additionally, teacher measures are expected to show lower invariance with respect to students than other facets. We therefore anticipate that the model will fit students less well than teachers and items.

To interpret student-teacher interactions as changes in student perception, it is essential to assess the stability of measures of teacher efficacy. Marsh's study, conducted over more than a decade, shows remarkable stability at the individual-teacher level despite substantial differences between teachers (Marsh, 2007; Marsh & Hocevar, 1991).

The CSP suggests that if students experience a facilitating effect that differs markedly from their typical interaction with a teacher, the local severity with the teacher would diverge from the global severity. If this cognitive mechanism is pervasive, interactions between student and teacher would be observed, with statistically significant tests and proportions of the variance explained of practical significance for interactions.

The CSP enables analysis of changes in item interpretation. Should a student alter their interpretation of an item on two separate occasions, this can be identified in the MFRM analysis as a student-item interaction. If the cognitive mechanism explaining this interaction is frequent, one would expect to find student-item interactions with statistically significant tests and proportions of the variance explained of practical relevance for interactions. However, the cognitive mechanism implied by the CSP differs from that underlying student–teacher interactions. More specific mechanisms of cognitive mediation can elucidate the student-item interaction. Since each subscale measures a specific attribute and level in a teacher, and students may experience varying facilitator‑effect levels under the CSP, we expect facilitator‑effect differences to relate more to student–teacher than to student–item interactions. To illustrate this point, consider a scenario in which the facilitating effect produced by a teacher on a student is very large. This student will tend to give higher scores on all items on a scale, consistent with the teacher's level on the teaching quality dimension considered and their facilitating effect. If this scenario recurs across many students, a significant teacher–student interaction should explain a meaningful portion of the observed score variance.

Conversely, a student-item interaction in this example would imply that the student tends to provide higher scores to the teacher on only some of the items on the scale. In this second case, the student shows a change in the interpretation of some of the items on the scale. These interpretive changes may reflect cognitive mechanisms linking them to the facilitating effect or mechanisms tied to potential biases (Cáceres‑Bauer, 2024). Additionally, no teacher–item interactions are expected because the hypothesis attributes systematic changes to student severity, which can only produce interactions among facets that involve students (Eckes, 2023; Linacre, 1994).

In summary, if students' perceptions primarily reflect the quality of the teacher's instruction and its facilitating effect under the conditions of this study: (a) the measures of teachers, students, and items (i.e., their primary effects) should account for a significant proportion of the variance in the observed scores; (b) teacher-student interactions are expected to occur to a magnitude explained by the facilitating effect of instruction; (c) the student-item interactions are expected to occur to a much more limited extent and are less likely; and finally (d) teacher–item interactions are not expected.

Expected pattern for RQ6

Applying the CSP enables the specification of expected patterns in the variance components of teacher and student measures, as estimated using the MFRM model. To this end, it is necessary to analyze the process of student response to the SET questionnaire, the design features of multi-section courses, and the conditions under which the questionnaire is administered. In addition, the application of the CSP supports the prediction of expected patterns under the research hypothesis and enables their comparison with expected patterns derived from alternative hypotheses, which may help explain students' responses to the SET questionnaire.

For this purpose, the patterns expected under the research hypothesis (validity hypothesis) are compared with other hypotheses that have been considered in previous research as plausible alternatives (Brockx et al., 2011; Gump, 2007; Marsh, 1997, 1987). First, the leniency hypothesis is considered, which argues that the main factors determining student evaluations of teaching are teachers' leniency in grading students, such that more lenient teachers are evaluated more highly. Second, the a priori variables hypothesis is considered, which argues that the main factors determining students' evaluations of teaching are prior characteristics of students and courses that are unrelated to teaching and learning. Both alternative hypotheses posit invalid measurement and biased student evaluations. In the leniency hypothesis, the bias is introduced by the teacher's leniency in grading students, while in the a priori variables hypothesis, the biases are introduced by a priori variables of students and courses.

Table 2 presents the arguments supporting the expected patterns under each hypothesis. Differences in the expected variance components for teacher and student measures reflect (a) which cognitive or contextual factors are hypothesized to dominate student evaluations and (b) how the constraints of multi-section course design affect those factors For example, according to the design of multi-section courses, differences in teacher leniency could be observed between different courses and not between different sections of the same course. Conversely, the design of multi-section courses may introduce some restrictions on the variability of teaching, but in different ways depending on the aspect considered. For example, in the courses considered in this study, aspects such as Tasks Proposed (TRPR), Workload and Difficulty (TRDF), and Evaluation (EVAL) were more strongly constrained in their variability within sections of the same course than aspects such as the Teacher's Enthusiasm and Communication Style (ENTC), the Teacher's Personal Relationship with Students (RELP), and Clarity, Planning, and Organization (CLOR). A distinct case is the value of teaching (VALR subscale), which is partly related to the specific role of the course in physician training and future professional practice—a disciplinary factor that may vary across courses but remain consistent within their sections. Other aspects related to the value of teaching, such as strategies for promoting motivation and interest, as well as the ability to challenge students or facilitate learning that constitutes an achievement in itself, may vary more among teachers of different courses than among teachers of sections of the same course. In general, factors such as the role of the course coordinator and their guidelines for teachers in each course section may affect the relationship between the proportion of variance in teacher measures within and between courses.

It is important to note that the SET questionnaire and its application protocol are designed to control for possible sources of construct-irrelevant variance. In other words, the aim is to ensure that the quality of the teacher's teaching and their facilitating effect are the dominant factors in the student's evaluation and that possible biases, such as the teacher's leniency in evaluating students, do not have a significant effect. Additionally, the MFRM allows measurement of teachers while controlling for item difficulty and student severity, thereby reducing bias and construct-irrelevant variance. For example, the SET questionnaire protocol requires administration prior to the final examination, meaning that students lack information about teacher leniency at the time of response, thereby minimizing the likelihood that this variable influences their perception. (see A2.d in Table 2). Additionally, the design of multi-section courses controls leniency within the course between different sections, so differences in teacher leniency are not expected to explain differences in intra-course teacher measures. Therefore, if this variable were the dominant factor in student perception, we would expect levels of variation in intra-course teacher measures that do not reach a level of practical significance (see A2.e in Table 2 and E2.1 in Table 3).

Table 3 presents the expected variance-component patterns for each hypothesis. The validity hypothesis uniquely predicts that the proportions of variance in intra-course and inter-course teacher measures will vary by SET questionnaire subscale (i.e., the teaching-quality aspect; see E1.2 in Table 3). In contrast, the leniency and a priori variables hypotheses predict invariant variance proportions across subscales (see E2.2 and E3.2 in Table 3, respectively). Furthermore, for the validity hypothesis, the proportion of variance in teacher measures within the course is expected to show moderate to large effects in all cases. Meanwhile, for the leniency and a priori variables hypotheses, the within-course variance of teacher measures is expected to fall short of a level of minimal practical significance (compare E1.1 with E2.1 and E3.1 in Table 3).

Expected pattern for RQ7

According to the CSP, a direct way to answer this question is to apply a SET questionnaire and another one to measure socio-cognitive variables and characterize the student's facilitator effect with a certain teacher (Cáceres-Bauer, 2024). If a negative correlation is found between the facilitating effect and the student's severity, this would imply that the cognitive mechanism dominating the students' response process is the one specified in the research hypothesis. A forthcoming paper will address this direct approach to providing evidence. In the present work, the plausibility of the research hypothesis is assessed by determining the expected patterns according to the CSP and the design conditions of the study. If a high level of consistency is found for the aforementioned patterns related to research questions one through six, it would provide sufficient evidence to conclude that the perception of teaching aligns with the dominant role of accurate perception and the facilitating effect experienced by students.

3. Results

Dimensional Structure

To address Research Question 1 (RQ1), we analyzed the dimensional structure of the SET questionnaire to assess whether students differentiate among its subscale dimensions. This section reports two complementary analyses used to evaluate the questionnaire's dimensional structure: an exploratory factor analysis (EFA) of teacher-level mean item scores followed by Rasch-based principal components analysis of residuals (PCAR).

Exploratory Factor Analysis.

Exploratory factor analysis (EFA) was performed using maximum likelihood extraction with an oblique quartimin rotation (BentlerQ) to allow correlated factors and to optimize a quartimin simplicity criterion. Adequacy diagnostics were satisfactory (N = 98; overall KMO = .93; Bartlett's test $\chi2(1,176) = 10,196.1$, $p < .001$). The results show a clear factor structure, with most items exhibiting high loadings in the expected dimensions; complete loading matrices and factor correlations are provided in Appendix E, and the factor solution is illustrated in Figure 1. Several criteria were used to determine the number of factors. The parallel analysis and the *VSS* criterion suggest at least three dimensions, while the adjusted *MAP*, *BIC*, and adjusted *BIC* criteria (Revelle, 2024) all suggest nine dimensions. The fit for the model with nine dimensions was acceptable (*RMSEA* = 0.09, 95% CI [0.08, 0.10]), and the overall reliability of the questionnaire was high (*Omega Total* = .99). No negative residual variances were detected; if present, negative residual variances would signal problems with the fitted model (Farooq, 2022). Given the extremely high reliability of the questionnaire and the high correlations between the scale factors, it is possible to observe some factor loading somewhat higher than 1, without such findings representing a problem with the fitted model (Babakus et al., 1987; Jöreskog, 1999). Figure 1 shows the factorial scheme obtained for the solution with nine factors.

Although the overall factor structure was robust, five items (5 of 49) exhibited some deviations from the primary pattern. In the Interaction/Discussion subscale (INTR), item INTR6 has a positive non-trivial weight in the ML4 dimension corresponding to the Personal Relationship subscale (RELP). Item INTR6 refers to the teacher's encouragement to foster interactions and discussions in a climate of respect and tolerance.

In the Evaluation subscale (EVAL), which refers to the quality of the evaluation performed by the teacher, six of the seven items of the scale present high positive factor loadings in the ML5 factor corresponding to the EVAL subscale, but the EVAL6 item has positive non-trivial factor loading in the ML9 factor corresponding to the Breadth /Depth subscale (APPR). In the EVAL subscale, items EVAL1 and EVAL7 present positive non-trivial factor loading in their corresponding factor, but also in factor ML8, corresponding to the Proposed Tasks subscale (TRPR). Item EVAL6 is related to the evaluation at the level of comprehension of the course content, while the APPR subscale is related to the breadth and depth of the teacher's teaching. Items EVAL1 and EVAL7 refer to the quality of the evaluation of assigned work and homework.

Unidimensionality Analysis

The unidimensionality of the questionnaire subscales was further studied using PCAR analysis. The results obtained are shown in Table 4. The TRDF, TRPR, and EVAL scales have eigenvalues less than 2, which means that the remaining variability in the residuals is consistent with the unidimensionality of these subscales. For subscales with eigenvalues greater than 2, it was necessary to analyze the presence of clustering or vertical stratification of the items in the Rasch measurement plot of the item vs. first Rasch contrast, which is also consistent with the unidimensionality of these subscales. Figure 1 shows the patterns found (without stratification) for the four subscales with higher eigenvalues, which is consistent with the unidimensionality of the subscales.

Facet Analysis.

The following subsections present results for the Item, Teacher, and Student facets and summarize how each facet contributes to the measurement system. Supporting diagnostics are reported in the appendices: the Overall Fit appendix documents a satisfactory global fit of each subscale to the MFRM; the Local Dependence appendix reports no practically relevant local dependencies that would compromise results; and the Invariance appendix shows acceptable levels of measurement invariance.

Item facet

To answer Research Question 2 (RQ2), an item analysis was conducted to evaluate the extent to which students interpret the questionnaire items correctly as a group. Table 5 presents the obtained measures, the standard error of measurement, and the fit statistics for each item. The Infit and Outfit values obtained for each item indicate a high level of fit to the model. The values of r_{pm} demonstrated consistency between the measures of each item and the construct measured by its scale for all items and subscales considered. Furthermore, the values of *Discrim* correspond to a satisfactory fit.

Table 6 presents the results of the reliability analysis for the item measures. The results of the fixed effects test (all equal) were found to be statistically significant in all cases. Table 6 presents the *G* values for each scale. In general, the results demonstrate that the item difficulty measures are highly reliable. The number of strata (H) for item difficulties reflects this high degree of measurement reliability. Additionally, a high *SR* value was identified, which is consistent with the values observed for the other indices.

Teacher facet

The teacher-facet analysis enabled us to assess both the validity and reliability of the teaching-quality measures and, building on our earlier analysis, to determine whether students differentiate among teaching-quality levels (Research Question 1 [RQ1]). Table 7 illustrates the distributions of the measures and the fit statistics for the teachers across each subscale. The distributions of the Infit and Outfit values for all subscales indicate an optimal level of fit. However, the fit found for the teachers is less optimal than that found for the items. This fact is evident when comparing the mean values and standard deviations found for the Infit and Outfit fit indices between the teacher and item facets. Conversely, the value of the mean and standard deviation of r_{pm} (Table 7) indicates a high level of consistency between the teachers' measures and the construct measured.

Table 8 presents the results of the reliability analysis of the teachers' measures. In all cases, the fixed effects (all equal) test yielded highly significant results. The reliability of the teachers' measures was found to be high, with levels ranging from those observed for the EVAL subscale (G = 5.75 and SR = .97) to those observed for the RELP subscale (G = 16.17 and SR = 1.00). Given these levels of reliability, the number of strata (H) for the teachers' measures ranged from eight (EVAL subscale) to approximately 22 (RELP subscale).

To address Research Question 6 (RQ6), we examined whether the pattern of variation in teacher measures—both between- and within-course—aligns with our research hypothesis. Table 9 summarizes the estimated variance components and their proportions at the between-course (*PVBC*) and within-course (*PVWC*) levels for each teaching-quality subscale.

PVWC exhibited a moderate to large effect size (*M* = .722, *SD* = .182; see Table 9), and the relative magnitudes of *PVBC* and *PVWC* varied by subscale. Specifically, *PVWC* substantially exceeded *PVBC* for the Personal Relationship (RELP), Clarity/Planning/Organization (CLOR), and Enthusiasm and Communication Style (ENTC) dimensions—dimensions less constrained by multi-section course design (see Table 9). In contrast, for the Workload/Difficulty (TRDF) and Evaluation (EVAL) subscales—where multi-section structures limit within-course variability—the *PVWC–PVBC* gap was markedly smaller (see Table 9). Although the VALR subscale (Value/Learning) exhibited moderate within-course variance (PVWC = .37), it was the only dimension in which between-course variance (PVBC = .63) surpassed within-course variance. These findings support our primary research hypothesis but diverge from the patterns predicted by the alternative leniency and a priori variable hypotheses.

Student facet

We examined the student facet to determine whether students differ in the severity with which they evaluate teachers (RQ4). The findings also provided evidence of students' consistency as evaluators, with further support from analyses presented elsewhere in this paper. Table 10 shows the distributions of the measures and the fit statistics for the students. The mean values of the Infit, Outfit, and r_{pm} for the students indicate satisfactory levels of fit, while a significant proportion of the students demonstrate acceptable levels of fit. However, the distributions of the fit measures indicate that some students exhibit deviations. The level of fit in the student facet is lower than that found in the item facets and the teacher facet.

Table 11 presents the reliability of the students' measures. The results of the fixed effects test (all equal) were found to be highly significant in all cases, indicating that there are differences in severity across the various subscales under consideration. The number of student severity strata ranged from four (H = 4.17; TRDF subscale) to five (H = 5.33; CLOR subscale). The results of the student severity measures unambiguously demonstrated the impact of the rater on the assessment process.

The analyses addressing Research Question 6 (RQ6) for teacher measures appeared at the close of the preceding Teacher Facet section. In this Student Facet section, we focus on student measures. Table 3 specifies the following expected variance-component patterns under the CSP for student measures (E1.3–E1.5):

- (E1.3) The proportion of within-course variance (*PVWC*) exceeds the proportion of between-course variance (*PVBC*) for all SET subscales.
- (E1.4) The relationship between *PVWC* and *PVBC* remains consistent across subscales.
- (E1.5) The mean *PVWC* is smaller than the mean within-teacher variance component (*PVWT*) for all subscales.

We next estimate *PVWC*, *PVBC*, and *PVWT* for each SET subscale and assess whether the observed patterns conform to these expected patterns.

Table 12 presents the estimated variance components and their proportions for student measures at the between-course (*PVBC*) and within-course (*PVWC*) levels across each teaching-quality subscale. For every subscale, *PVWC* consistently exceeded *PVBC*, confirming E1.3, and the *PVWC*-to-*PVBC* relationship remained uniform across subscales, supporting E1.4. Additionally, mean *PVBC* (M = .031, SD = .021) was lower than mean PVBT (M = .066, SD =

(.025) for the subscales, as predicted by E1.5 (see Table D1 in Appendix D). The size of PVBT indicates a nonnegligible proportion of variance attributable to teachers despite the student-assignment procedures used in multi-section courses. Together, these results demonstrate that student measures conform to the variance-component patterns anticipated in our theoretical analysis based on the CSP.

Interactions

To address RQ5, we analyzed interactions among facets to determine whether students' evaluation severity or their interpretation of questionnaire items changed under the study conditions and to assess whether the observed pattern matched that expected under our research hypothesis. Drawing on the CSP framework and our research hypothesis, we anticipated the following interaction pattern: (a) the main effects of teachers, students, and items would account for most of the variance; (b) teacher–student interactions would emerge when instructional facilitation significantly exceeded typical levels, manifesting consistently across all teaching-quality subscales; (c) student–item interactions would remain minimal even under those conditions; and (d) teacher–item interactions would be absent. Further theoretical detail is provided in the Expected Pattern for RQ5 subsection under the Application of the CSP to the Present Study section.

To evaluate these expectations, we analyzed the potential interactions among teacher, student, and item facets. Furthermore, a dummy facet with a null measure was introduced to facilitate investigation of teaching-level interactions at the course level. Table 13 presents a summary of the results of the interaction analysis. For each interaction under investigation, both the effect size and the statistical significance are presented. As illustrated in Table 13, the teacher-student interaction exhibited a higher percentage of variance explained in general (*M* = 17.02%, *SD* = 4.72%), followed by the course-student interaction (*M* = 10.47%, *SD* = 1.55%), which demonstrated a statistically significant result. The remaining interactions were not statistically significant, or the percentage of variance explained by the interaction was small. Even the teacher–student interaction effect was substantially smaller than the variance explained by the model's primary effects alone (*M* = 82.98%, *SD* = 4.72%).

Beyond the general pattern observed, a statistically significant interaction was identified for the measure derived from the TRPR subscale, explaining a percentage of the observed variance of practical significance. The student-item interaction for the measure derived from the TRPR subscale explained 16.62% of the variance and was found to be highly significant (p-value < .01). Conversely, the predicted interaction (teacher-student) for the EVAL subscale was not statistically significant and explained a smaller percentage of the observed variance than the interactions observed for all other subscales. Nevertheless, the course-student interaction for the EVAL subscale was found to be statistically significant.

Use of categories

We used categorization validity statistics within a Many-Facet Rasch framework to address Research Question 3 (RQ3), which asks to what extent students consistently apply the predefined item score categories. The mean of the observed measures demonstrated a monotonically increasing order for all subscales (Figure 3). The thresholds for all items within the subscales demonstrated adequate ordering and exhibited a monotonically increasing trend, as illustrated in Figure 4. A total of 98% of the thresholds were found to be greater than 1 and less than 5 logits. Only three items of the EVAL scale exhibited a distance between the initial two thresholds of less than one, while only one item of the RELP scale demonstrated a distance of slightly greater than five.

Figure 5 shows the frequencies of use of the categories. The response frequency distributions of the categories are unimodal, with the maximum frequency in category four (36 of 49 items) and category three (13 of 49 items). All categories are used for all items. The *Outfit* values for the categories of the subscale item scores show a good fit of the subscales to the model (Table 14).

4. Discussion

The study investigated whether student responses to the Student Evaluation of Teaching (SET) questionnaire primarily reflect variations in instructional quality and its facilitative effects rather than biases that compromise validity (Research Question 7). To address this question, we applied the central model of student perception (CSP; Cáceres-Bauer et al., 2024) and many-facet Rasch measurement (MFRM; Cáceres et al., 2018; Eckes, 2023) to examine the SET's internal structure and response processes underlying student ratings. Examining both sources of evidence is essential to construct validity research (American Educational Research Association et al., 2014; Embretson, 1994, 2013; Lissitz, 2009; Markus & Borsboom, 2024; Newton & Shaw, 2014). We also scrutinized instrument development procedures, assessed content validity, and implemented standardized administration protocols. Our findings aligned with CSP predictions, supporting the hypothesis that SET responses predominantly reflect instructional quality and its facilitative effects, with no compelling evidence that bias-driven response patterns influenced instructors' teaching-quality estimates derived from the MFRM analysis.

Evidence on Construct Validity

We evaluated the plausibility of the validity hypothesis with respect to Research Questions 1–7. The CSP-based analysis identifies the expected patterns when instructional quality and facilitative effects drive SET responses. We considered several alternative bias hypotheses and outlined methods to contrast them with the validity hypothesis. The following subsections offer three interrelated perspectives on construct validity—response processes, internal structure, and biases—and draw conclusions from the convergence of evidence across these lenses.

Evidence Based on Response Process.

First, we will discuss evidence from the response process, followed by complementary evidence from the instrument's internal structure. For RQ1 (students' ability to differentiate subscales), we expected nine coherent factors and robust teacher reliability in the MFRM; below, we assess whether EFA, PCAR, and MFRM results converge on that expectation.

Analyses of dimensional structure confirmed that students reliably differentiated among the candidate teaching quality dimensions. The EFA findings identified nine coherent factors with strong primary loadings in the intended dimension. The PCAR results support the unidimensionality of each subscale, indicating that no additional dimensions exist. The MFRM results for the teaching facet revealed no halo effect at the group level, satisfactory fit statistics, and satisfactory facet reliability indices (SR). These findings provide further evidence of the students' capacity to correctly interpret the items and discriminate between different levels of teaching quality. Collectively, these results support the validity hypothesis: the observed multidimensional signature and robust MFRM reliability are consistent with students' discrimination among teaching-quality dimensions and inconsistent with a halo-based account that would produce fewer dimensions and lower facet reliability (Bierhoff, 2012; Michela, 2022; Röhl & Rollett, 2021).

However, despite the overall convergent evidence, EFA flagged two items as potential indicators of another factor; nevertheless, all MFRM fit statistics and PCAR results indicated that those items functioned as intended within their respective subscales. One possible explanation for this discrepancy is that the EFA has a smaller capacity to control for the influence of student severity on teacher measures in relation to MFRM models. This scenario allows for the possibility that the factor structure suggested by EFA may be more susceptible to systematic distortions introduced by students' implicit theories about the relationship between teaching-quality dimensions (Larson, 1979; Renaud & Murray, 2005; Whitely et al., 1976).

For RQ2 (students' ability to interpret questionnaire items adequately), we expected high item-facet reliability (SR), a significant fixed-effects chi-square for the items facet, and high aggregate r_{pm}. The MFRM diagnostics met these expectations: item-facet SR was high, the fixed-effects (all-equal) test for items was statistically significant, and aggregate r_{pm} values indicated strong consistency between item measures and the intended construct. Taken together, these findings provide convergent support for RQ2: students largely interpret items as intended and produce reliable item measures.

With respect to RQ3 (students' ability to use item-score categories consistently), we expected ordered category functioning, well-spaced thresholds, and substantive use of all response categories. Category diagnostics broadly met these expectations: thresholds were ordered, and category distributions were unimodal, with category fit statistics indicating acceptable model fit. A minimal number of items displayed minor threshold spacing deviations. Overall, the pattern of findings supports the expected pattern under the validity hypothesis for RQ3.

In relation to RQ4 (differences in the severity with which students evaluate teachers), we expected inter-student variability in severity estimates, with student SR values and significant fixed-effects tests indicating subjective differences that are nevertheless informative; we also expected instructors to show satisfactory SR, positive r_{pm}, and acceptable Infit and Outfit if evaluation reliably reflected teaching quality. In line with the expected pattern for RQ4, the student facet exhibited substantial variability in severity estimates, indicating a subjective component in student evaluations; this variability is consistent with prior work (Borkan, 2017; Haladyna & Hess, 1994; Quansah, 2022). Instructor-level diagnostics showed satisfactory Infit and Outfit statistics, positive point-measure correlations (r_{pm}), and high separation reliability (*SR*) for instructor measures across all questionnaire subscales, and all fixed-effects chi-square tests for the subscales were statistically significant. Overall, the observed pattern for RQ4 is consistent with the validity hypothesis. These findings indicate that, although student evaluations contain subjective variance, they nonetheless provide valuable information about dimensions of teaching quality.

Evidence Based on Internal Structure.

After considering response-process evidence, we examined whether relationships among questionnaire items and components conformed to the construct underlying the proposed interpretation and use of the teaching-quality scores. This section interprets the reported findings as validity evidence based on internal structure and compares them with prior research.

Teaching quality was conceptualized as a multidimensional construct composed of nine related dimensions. Exploratory factor analysis (EFA) of mean item scores at the teacher level indicated that 44 of the 49 items had loadings of 0.50 or greater on their intended factor. Only two items had loadings below our cutoff of 0.32 on the target factor (INTR6 = 0.21; EVAL6 = 0.11). Item-level diagnostics (see Results/Table 5) indicated acceptable functioning for both items (INTR6: Infit = 1.02, Outfit = 0.99, r_{pm} = .74; EVAL6: Infit = 1.22, Outfit = 1.19, r_{pm} = .62). The PCAR results further indicated that these items functioned as intended within their respective subscales and supported the conclusion that each subscale operated correctly, with no evidence of extradimensions.

The pattern of factor loadings and interfactor correlations is broadly consistent with prior studies of related instruments that report nine strong factors (Marsh et al., 1985). Across factors, intercorrelations were generally large and positive, except for the Workload/Difficulty factor (ML3), which showed a small positive correlation with Value/Learning (ML2; r = 0.08) and small to moderate negative correlations with several other factors (range = −0.06 to −0.28). Squared, these coefficients indicate that ML3 explains less than 8% of the shared variance with each other factor, a magnitude similar to values reported for the Endeavor instruments (< 8%) and the SEEQ (< 5%) (Marsh et al., 1985).

Overall, MFRM analyses with primary effects presented satisfactory fit, providing evidence of adequate item performance and reliable teacher measures. These results align with previous studies reporting satisfactory fit for the model, the items, and instructor measures (Borkan, 2017; Haladyna et al., 1994).

Study of Biases

This subsection discusses potential sources of bias in student evaluations by combining interaction diagnostics from MFRM models with theory-driven expectations from the CSP. Interactions among facets (items, students, teachers) that are both statistically significant and of nontrivial effect size may indicate bias, but they can also reflect substantively meaningful differences in instructional quality or in facilitation effects on student learning.

Our approach proceeded in two steps. First, we used the CSP to derive an a priori pattern of expected interactions under the validity hypothesis—that students' perceptions of teaching characteristics and the facilitating effect they experience are the primary determinants of evaluations. Second, we derived predicted variance-component patterns for teacher and student measures under the validity hypothesis and two plausible alternatives previously discussed in the literature (leniency and a priori-variables hypotheses). These theoretical patterns guided the interpretation of observed MFRM interactions and variance components.

With respect to RQ5 (changes in the severity with which students evaluate instructors or in the interpretation of items), we expected: (a) primary effects of teachers, students, and items to account for most variance; (b) teacher–student interactions to emerge when instructional facilitation significantly exceeded typical levels, manifesting consistently across all teaching-quality subscales; (c) student–item interactions to be minimal; and (d) teacher–item interactions to be absent. The interaction analysis largely matched these expectations. Primary effects explained the bulk of variance (M = 82.98%, SD = 4.72% across subscales); the teacher–student interaction accounted for a modest but nontrivial proportion of variance (M = 17.02%, SD = 4.72% across subscales); the course–student interaction was smaller though statistically significant (M = 10.47%, SD = 1.55% across subscales); and the remaining interactions were small or nonsignificant (see Table 13). Overall, the observed pattern for RQ5 is consistent with the validity hypothesis: primary effects dominate, teacher–student interactions are limited, student–item interactions are minimal, and teacher–item interactions are absent. This pattern supports the view that variation in severity primarily reflects instructional facilitation rather than systematic bias.

Teacher–student interactions may help account for several features of student rater behavior observed in the MFRM analyses. First, such interactions may contribute to the lower overall fit of the student facet relative to the item and teacher facets. Second, they may explain why student ratings nevertheless provide meaningful information about teaching quality dimensions at the group level, even though some individual students show a poorer fit to a primary effects MFRM model. One plausible mechanism is that teacher–student interactions arise when instructional facilitation substantially exceeds typical levels, producing localized deviations while signaling genuine differences in teaching quality. If so, adequate fit at the teacher level would be expected, despite localized misfits at the student level. By contrast, if interactions primarily reflected systematic bias unrelated to instructional quality, we would not expect the same pattern of adequate fit at the teacher level.

Regarding RQ6 (whether the pattern of variation in teacher measures between and within courses matches the research hypothesis), we expected the validity hypothesis to produce subscale-specific variance patterns: substantial within-course variance (PVWC) across subscales, with PVWC and PVBC magnitudes varying by teaching-quality dimension in ways consistent with course design constraints; by contrast, the leniency and a priori-variables alternatives predict invariant variance proportions across subscales and negligible within-course teacher variance. The observed variance-component pattern largely matched the validity hypothesis. PVWC showed a moderate to large effect on average (M = .722, SD = .182; see Table 9), and the relative sizes of PVWC and PVBC varied by subscale as predicted: PVWC substantially exceeded PVBC for RELP, CLOR, and ENTC—dimensions less constrained by multi-section design—whereas the PVWC–PVBC gap was much smaller for TRDF and EVAL. Consistent with the hypothesis that variance proportions vary by subscale, VALR displayed moderate PVWC (0.37) and a larger PVBC (0.63), indicating greater between-course than within-course variance; however, this PVWC–PVBC relationship differs from that observed for several other subscales. Taken together, the observed pattern for RQ6 for teacher measures is consistent with the validity hypothesis: variance proportions differ across subscales in theoretically expected ways, and within-course teacher variance is generally substantial rather than negligible.

Conclusion for RQ7: Validity Versus Bias

The findings discussed above support the following group-level conclusions about the student response process.

1. With respect to RQ1, students were able to differentiate the nine dimensions measured by the SET questionnaire.
2. With respect to RQ2, students were able to interpret the questionnaire items as intended.
3. With respect to RQ3, students used the item response scale consistently.

   These conclusions (1–3) are consistent with the validity hypothesis and are unlikely under the leniency hypothesis and the a priori variables hypothesis.

4. With respect to RQ4, students differed substantially in the severity with which they evaluated instructors.
5. With respect to RQ5, the interaction analyses supported a pattern consistent with the validity hypothesis: (a) primary effects of teachers, students, and items accounted for most variance; (b) teacher–student interactions emerged only when instructional facilitation substantially exceeded typical levels and then manifested consistently across teaching-quality subscales; (c) student–item interactions were minimal; and (d) teacher–item interactions were absent.
6. With respect to RQ6, between- and within-course variation in student and teacher measures was consistent with the validity hypothesis and inconsistent with the leniency hypothesis and the a priori variable hypothesis.
7. With respect to RQ7, taken together (1–6), the results are more consistent with variation in instructional quality and facilitation effects than with biasing influences.

Concluding statement: Overall, these group-level results provide converging evidence in support of the validity hypothesis.

Implications

Our findings indicate that SET questionnaires can yield meaningful measures of teaching quality when grounded in a clear theoretical framework, rigorous instrument design, and appropriate analytic methods. The CSP clarifies the cognitive mechanisms through which teaching characteristics, facilitation of learning, and bias shape students' perceptions. Institutions seeking to improve teaching-evaluation systems should adopt standardized administration protocols and use multifaceted measurement models (for example, MFRM) to strengthen validity and support administrative and faculty-development decisions. Although teacher-level item mean scores in multisection courses partially control some sources of variation, they do not fully account for differences in student severity or other potential biases. The approach used in this study enables detection of practically relevant biases and provides improved control of those biases, thereby enhancing the interpretability of teacher measures.

Limitations and Future Directions

This study primarily examined whether the observed response patterns aligned with those expected if student evaluations were predominantly driven by instructional quality and its facilitative effects or, alternatively, by biases that could distort perception. However, one important aspect was not addressed: identifying and characterizing specific cognitive factors that may be crucial in student evaluations.

Another limitation is that the facilitatory effects of instruction were approached indirectly, using theoretical analysis and by predicting expected patterns under the assumption that the main influence on students' perceptions of instruction is teaching characteristics and facilitatory effects, or alternatively, is explained by hypotheses that posit biased perception.

To overcome these limitations, future designs could incorporate direct measures of facilitation and other socio-cognitive variables. According to the CSP, a complementary approach is to administer an SET questionnaire alongside an instrument that measures socio-cognitive variables and characterizes the student's facilitative response to instruction. Analysis of the relationship patterns between student and instructor measures on both questionnaires would provide an additional empirical test of the CSP's theoretical predictions and of potential bias.

Future research should explicitly investigate the influence of specific biases—such as gender stereotypes and the grading leniency—on SET responses, employing designs that isolate these factors. Simulation and modeling techniques could be used to test how distinct cognitive mechanisms generate characteristic MFRM patterns. The development of refined diagnostic criteria based on the measurement of facilitative effects would further enhance bias detection and strengthen the validity of SET instruments.

References

Abrami, P. C., D'Apollonia, S., & Cohen, P. A. (1990). Validity of student ratings of instruction: What we know and what we do not. Journal of Educational Psychology, 82(2), 219-231. https://doi.org/10.1037//0022-0663.82.2.219

Aleamoni, L. M. (1999). Student rating myths versus research facts from 1924 to 1998. *Journal of personnel evaluation in education*, *13*, 153-166.https://doi.org/10.1023/a:1008168421283

Ames, R., & Lau, S. (1979). An attributional approach to the validity of student ratings of instruction. Contemporary Educational Psychology, 4(1), 26-39. https://doi.org/10.1016/0361-476X(79)90024-9

American Educational Research Association, American Psychological Association, & National Council on Measurement in Education (Eds.). (2014). *Standards for educational and psychological testing*. American Educational Research Association. https://www.aera.net/publications/books/standards-for-educational-psychological-testing-2014-edition

Arreola, R. A. (2007). Developing a comprehensive faculty evaluation system: A guide to designing, building, and operating large-scale faculty evaluation systems (No Title). Jossey-Bass.

Babakus, E., Ferguson, C. E., & Jöreskog, K. G. (1987). The Sensitivity of Confirmatory Maximum Likelihood Factor Analysis to Violations of Measurement Scale and Distributional Assumptions. Journal of Marketing Research, 24(2), 222-228. https://doi.org/10.1177/002224378702400209

Bandura, A. (2023). *Social cognitive theory: An agentic perspective on human nature*. John Wiley & Sons.

Benton, S. L., & Cashin, W. E. (2013). Student ratings of instruction in college and university courses. In *Higher education: Handbook of theory and research: Volume 29* (pp. 279-326). Dordrecht: Springer Netherlands.

Bierhoff, H. W. (2012). Person perception and attribution.Springer Science & Business Media.

Boone, W. J., & Staver, J. R. (2020). Principal Component Analysis of Residuals (PCAR). Advances in Rasch Analyses in the Human Sciences, 13-24. https://doi.org/10.1007/978-3-030-43420-5_2. https://doi.org/10.1007/978-3-030-43420-5_2

Bond, T.G., & Fox, C.M. (2007). Applying the Rasch Model: Fundamental Measurement in the Human Sciences, Second Edition (2nd ed.). Psychology Press. https://doi.org/10.4324/9781410614575

Bond, T., Yan, Z., & Heene, M. (2020). Applying the Rasch Model: Fundamental Measurement in the Human Sciences (4th ed.). Routledge. https://doi.org/10.4324/9780429030499

Börkan, B. (2017). Exploring Variability Sources in Student Evaluation of Teaching via Many-Facet Rasch Model. Eğitimde ve Psikolojide Ölçme ve Değerlendirme Dergisi, 15–15. https://doi.org/10.21031/epod.298462

Braun, E., & Leidner, B. (2009). Academic Course Evaluation. European Psychologist, 14(4), 297-306. https://doi.org/10.1027/1016-9040.14.4.297.

Brophy, J., & Good, T. (1986). Teacher behavior and student achievement (3rd ed.). In M.C. Wittroch (Ed.), Handbook of research on teaching (pp. 328-375). Macmillan.

Brown, S. (2011). Bringing about positive change in the higher education student experience: a case study. Quality Assurance in Education, 19(3), 195-207. https://doi.org/10.1108/09684881111158027

Brockx, B., Spooren, P., & Mortelmans, D. (2011). Taking the grading leniency story to the edge. The influence of student, teacher, and course characteristics on student evaluations of teaching in higher education. Educational Assessment, Evaluation and Accountability, 23(4), 289–306. https://doi.org/10.1007/s11092-011-9126-2

Cáceres, R.(2018). Study of the response process to student evaluation questionnaires of teaching from the perspective of cognitive theories of motivation (Master's Thesis, University of the Republic). https://hdl.handle.net/20.500.12008/20054

Cáceres-Bauer, R., Rodríguez-Morales, P., Luzardo-Verde, M. (2024). Central and attributional models of student perception of teaching and their learning. Revista Digital de Investigación en Docencia Universitaria, 18(1), e1814. https://doi.org/10.19083/ridu.2024.1814.

Centra, J. A. (2009). Differences in responses to the student instructional report: Is it bias. Princeton: Educational Testing Service. https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=4145fb9109ac090cd280e0bb59d24b266c602071

Centra, J. A. (2003). Will teachers receive higher student evaluations by giving higher grades and less course work?. Research in higher education, 44(5), 495-518. https://doi.org/10.1023/a:1025492407752

Chou, Y.-T., & Wang, W.-C. (2010). Checking Dimensionality in Item Response Models With Principal Component Analysis on Standardized Residuals. Educational and Psychological Measurement, 70(5), 717-731. https://doi.org/10.1177/0013164410379322.

Christensen, K. B., Makransky, G., & Horton, M. (2017). Critical Values for Yen's Q3: Identification of Local Dependence in the Rasch Model Using Residual Correlations. *Applied Psychological Measurement*, *41*(3), 178-194. https://doi.org/10.1177/0146621616677520.

Cizek, G.J. (2020). Validity: An Integrated Approach to Test Score Meaning and Use.

Coffey, M., & Gibbs, G. (2001). The Evaluation of the Student Evaluation of Educational Quality Questionnaire (SEEQ) in UK Higher Education. Assessment & Evaluation in Higher Education, 26(1), 89-93. https://doi.org/10.1080/02602930020022318.

Cohen, P. A. (1981). Student Ratings of Instruction and Student Achievement: A Meta-analysis of Multisection Validity Studies. Review of Educational Research, 51(3), 281-309. https://doi.org/10.3102/00346543051003281.

Costello, A. B. & Osborne, J., (2005) "Best practices in exploratory factor analysis: four recommendations for getting the most from your analysis", Practical Assessment, Research, and Evaluation 10(1): 7. doi: https://doi.org/10.7275/jyj1-4868

Crişan, D. R., Tendeiro, J. N., & Meijer, R. R. (2017). Investigating the Practical Consequences of Model Misfit in Unidimensional IRT Models. Applied Psychological Measurement, 41(6), 439-455. https://doi.org/10.1177/0146621617695522.

d'Apollonia, S., & Abrami, P. C. (1997). Navigating student ratings of instruction. American Psychologist, 52(11), 1198-1208. https://doi.org/10.1037//0003-066x.52.11.1198

De Boeck, P., & Wilson, M. (Eds.). (2004). Explanatory Item Response Models. Springer New York. https://doi.org/10.1007/978-1-4757-3990-9

de Jong, J., and Linacre, J. (1993). Estimation methods, statistical independence and global t. Rasch Measurement Transactions, 7 (2), 296-297. https://www.rasch.org/rmt/rmt72n.htm

Dweck, C. S., & Molden, D. C. (2017). Their impact on competence motivation and acquisition. *Handbook of competence and motivation: Theory and application*, *2*, 135-154.

Eckes, T. (2023). Introduction to many-facet Rasch measurement: Analyzing and evaluating rater-mediated assessments. Peter Lang. https://www.peterlang.com/document/1359014

Elliot, A. J., Dweck, C. S., & Yeager, D. S. (Eds.). (2017). Handbook of competence and motivation: Theory and application. Guilford Publications. https://www.amazon.com/-/es/Andrew-J-Elliot-ebook/dp/B06XPTT2RC/

Embretson, S. (1994). Applications of cognitive design systems to test development. In Cognitive assessment: A multidisciplinary perspective (pp. 107-135). Boston, MA: Springer US. https://doi.org/10.1007/978-1-4757-9730-5

Embretson, S. E. (2007). Construct validity: A universal validity system or just another test evaluation procedure?. *Educational Researcher*, *36*(8), 449-455. https://doi.org/10.3102/0013189X07311600

Embretson, S. E. (Ed.). (2013). *Test design: Developments in psychology and psychometrics*. Academic Press. https://www.amazon.com/Susan-Embretson-ebook/dp/B01DUEH8P2

Engelhard, G. (1996). Evaluating Rater Accuracy in Performance Assessments. Journal of Educational Measurement, 33(1), 56-70. Portico. https://doi.org/10.1111/j.1745-3984.1996.tb00479.x

Engelhard Jr, G. (2012). Invariant Measurement: Using Rasch Models in the Social, Behavioral, and Health Sciences (1st ed.). Routledge. https://doi.org/10.4324/9780203073636

Engelhard, G., & Wind, S. A. (2017). Invariant Measurement with Raters and Rating Scales. Invariant Measurement with Raters and Rating Scales, 327-336. https://doi.org/10.4324/9781315766829-14

Faraway, J. J. (2016). Extending the Linear Model with R. Chapman and Hall/CRC. https://doi.org/10.1201/b21296

Farooq, R. (2022). Heywood cases: Possible causes and solutions. *International Journal of Data Analysis Techniques and Strategies*, *14*(1), 79-88. https://doi.org/10.1504/IJDATS.2022.121506. https://doi.org/10.1504/IJDATS.2022.121506

Feldman, K. A. (1997). Identifying Exemplary Teachers. In Effective Teaching in Higher Education: Research and Practice, 368.R.P. Perry and J.C. Smart (eds.), The Scholarship of Teaching and Learning in Higher Education: An Evidence-Based Perspective, 93-143.

Ferguson, C. J. (2009). An effect size primer: A guide for clinicians and researchers. *Professional Psychology: Research and Practice, 40*(5), 532–538. https://doi.org/10.1037/a0015808

Fiske, S. T., & Taylor, S. E. (2020). Social Cognition: From Brains to Culture. Sage. https://www.amazon.com/-/es/Susan-T-Fiske-ebook/dp/B0895ZBXJ9

Flavell, J. H. (2019). *Cognitive development* (Vol. 87). Antonio Machado Libros.

Franklin, J., & Theall, M. (1990). Communicating student ratings to decision makers: Design for good practice. New Directions for Teaching and Learning, 1990(43), 75-93. Portico. https://doi.org/10.1002/tl.37219904308

Frey, P. W., Leonard, D. W., & Beatty, W. W. (1975). Student Ratings of Instruction: Validation Research. American Educational Research Journal, 12(4), 435-444. https://doi.org/10.3102/00028312012004435.

Gilovich, T., Keltner, D., Chen, S., & Nisbett, R. E. (2023). Social psychology. WW Norton & Company. https://www.amazon.com/Social-Psychology-Sixth-Tom-Gilovich-ebook/dp/B0BMRZ6GX4

Goretzko, D., Pham, T. T. H., & Bühner, M. (2019). Exploratory factor analysis: Current use, methodological developments and recommendations for good practice. Current Psychology, 40(7), 3510-3521. https://doi.org/10.1007/s12144-019-00300-2.

Graham, S. (1991). A review of attribution theory in achievement contexts. Educational Psychology Review, 3(1), 5- 39. https://doi.org/10.1007/BF01323661

Grammatikopoulos, V., Linardakis, M., Gregoriadis, A., & Oikonomidis, V. (2014). Assessing the Students' Evaluations of Educational Quality (SEEQ) questionnaire in Greek higher education. Higher Education, 70(3), 395-408. https://doi.org/10.1007/s10734-014-9837-7

Gravestock, P., & Gregor-Greenleaf, E. (2008). Student course evaluations: Research, models and trends. Toronto: Higher Education Quality Council of Ontario. https://heqco.ca/wp-content/uploads/2020/03/Student-Course-Evaluations_Research-Models-and-Trends.pdf

Grimes, P. W., Millea, M. J., & Woodruff, T. W. (2004). Grades-Who's to blame? Student evaluation of teaching and locus of control. The Journal of Economic Education, 35(2), 129-147. https://doi.org/10.3200/JECE.35.2.129-147

Gump, S. E. (2007). Student Evaluations of Teaching Effectiveness and the Leniency Hypothesis: A Literature Review. Educational Research Quarterly, 30(3), 56-69. https://files.eric.ed.gov/fulltext/EJ787711.pdf

Haladyna, T., & Hess, R. K. (1994). The detection and correction of bias in student ratings of instruction. Research in Higher Education, 35(6), 669-687. https://doi.org/10.1007/bf02497081

Hamilton, D. L., Stroessner, S. N. (2020). Social Cognition: Understanding People and Events. United Kingdom: SAGE Publications.

Ḥaṭiva, N. (2019). *Student Ratings of Instruction: Can We Trust Them?*. Oron Publications. https://www.amazon.com/-/es/Nira-Hativa-ebook/dp/B07VR87SLL

Ḥaṭiva, N. (2014). Student ratings of instruction: A practical approach to designing, operating, and reporting. Oron Publications.

Heffernan, T. (2022). Sexism, racism, prejudice, and bias: A literature review and synthesis of research surrounding student evaluations of courses and teaching. *Assessment & Evaluation in Higher Education*, *47*(1), 144-154. https://doi.org/10.1080/02602938.2021.1888075

Higgins, E. T., Herman, C. P., & Zanna, M. P. (Eds.) (2022). Social Cognition: The Ontario Symposium Volume 1. Taylor & Francis. https://www.amazon.com/-/es/Tory-Higgins-ebook/dp/B0B8F17MQP/

Ibrahim, M. (2012). A Psychometric Evaluation of Two Teaching Effectiveness Scales. Journal of Sustainable Development, 5(7). https://doi.org/10.5539/jsd.v5n7p91

Jöreskog, K. G. (1999). How large can a standardized coefficient be. https://www.statmodel.com/download/Joreskog.pdf

Klimoski, R. J., & Donahue, L. M. (2013). Person perception in organizations: An overview of the field. *How people evaluate others in organizations*, 31-70. https://doi.org/10.4324/9781410600608-8.

Kreitzer, R. J., & Sweet-Cushman, J. (2021). Evaluating Student Evaluations of Teaching: a Review of Measurement and Equity Bias in SETs and Recommendations for Ethical Reform. Journal of Academic Ethics, 20(1), 73-84. https://doi.org/10.1007/s10805-021-09400-w. https://doi.org/10.1007/s10805-021-09400-w

Larson, J. R. (1979). The Limited Utility of Factor Analytic Techniques for the Study of Implicit Theories in Student Ratings of Teacher Behavior. American Educational Research Journal, 16(2), 201-211. https://doi.org/10.3102/00028312016002201.

Lê, S., Josse, J., & Husson, F. (2008). FactoMineR: An R package for multivariate analysis. Journal of Statistical Software, 25(1), 1–18. https://doi.org/10.18637/jss.v025.i01

Lin, W., Watkins, D., & Meng, Q. (1995). Students' Evaluations of University Teaching: A Chinese Perspective. Higher Education Research & Development, 14(1), 61-74. https://doi.org/10.1080/0729436950140106

Linacre, J. M. (1998). Detecting multidimensionality: which residual data-type works best?. Journal of outcome measurement, 2, 266-283. https://winsteps.com/a/Linacre-multidimensionality-residuals.pdf.

Linacre, J. M. (1994). *Many-faceted Rasch measurement.* https://www.winsteps.com/a/Linacre-MFRM-book.pdf

Linacre, J. M. (2002). Optimizing rating scale category effectiveness. *Journal of applied measurement*, *3*(1), 85-106.https://www.winsteps.com/a/Linacre-optimizing-category.pdf

Linacre, J. M. (2005). Fit to models: Rasch model vs. correlation model. Rasch measurement transactions, 19 (3), 1029. https://www.rasch.org/rmt/rmt193d.htm

Linacre, J. M. (2006). Data variance explained by Rasch measures. *Rasch Measurement Transactions*, *20*(1), 1045. https://www.rasch.org/rmt/rmt201.pdf.

Linacre, J. M. (2024a). A user's guide to facets rasch-model computer programs program manual 3.87.0. https://www.winsteps.com/a/Facets-Manual.pdf.

Linacre, J. (2024b). A user's guide to WINSTEPS® Ministep Rasch-model computer programs manual 5.7.0. https://www.winsteps.com/a/Winsteps-Manual.pdf

Lissitz, R. W. (Ed.). (2009). *The concept of validity: Revisions, new directions, and applications* [Kindle version]. Information Age Publishing. https://www.amazon.com/Concept-Validity-Robert-W-Lissitz-ebook/

Madichie, N. O. (2011). Students' evaluation of teaching (SET) in higher education: A question of reliability and validity. The Marketing Review, 11(4), 381-391. https://doi.org/10.1362/146934711X13210328715984

Mair, P., & Hatzinger, R. (2007). Extended Rasch Modeling: TheeRmPackage for the Application of IRT Models inR. Journal of Statistical Software, 20(9). https://doi.org/10.18637/jss.v020.i09

Marcham, C., Ade, A., Clark, P., & Marion, J. (2020). Bias and Trends in Student Evaluations in Online Higher Education Settings. Collegiate Aviation Review International, 38(2). https://doi.org/10.22488/okstate.20.100213.

Markus, K. A., & Borsboom, D. (2024). *Frontiers of test validity theory: Measurement, causation, and meaning* (2nd ed.) [Kindle version]. Routledge. https://www.amazon.com/dp/B0DPTM8HGV/

Marsh, H. W. (2007). Do university teachers become more effective with experience? A multilevel growth model of students' evaluations of teaching over 13 years. Journal of Educational Psychology, 99(4), 775-790. https://doi.org/10.1037/0022-0663.99.4.775

Marsh, H. W. (1987). Students' evaluations of University teaching: Research findings, methodological issues, and directions for future research. International Journal of Educational Research, 11(3), 253-388. https://doi.org/10.1016/0883-0355(87)90001-2

Marsh, H. W. (1981). Students' Evaluations of Tertiary Instruction: Testing the Applicability of American Surveys in an Australian Setting. Australian Journal of Education, 25(2), 177-193. https://doi.org/10.1177/000494418102500207

Marsh, H. W. (1980). Students' Evaluations of College/University Teaching: A Description of Research and an Instrument. https://eric.ed.gov/?id=ED197645

Marsh, H. W., Dicke, T., & Pfeiffer, M. (2019). A tale of two quests: The (almost) non-overlapping research literatures on students' evaluations of secondary-school and university teachers. Contemporary Educational Psychology, 58, 1-18. https://doi.org/10.1016/j.cedpsych.2019.01.011.

Marsh, H. W., & Groves, M. A. (1987). Students' evaluations of teaching effectiveness and implicit theories: A critique of Cadwell and Jenkins (1985). Journal of Educational Psychology, 79(4), 483-489. https://doi.org/10.1037//0022-0663.79.4.483

Marsh, H. W., & Hocevar, D. (1991). Students' evaluations of teaching effectiveness: The stability of mean ratings of the same teachers over a 13-year period. Teaching and Teacher Education, 7(4), 303-314. https://doi.org/10.1016/0742-051x(91)90001-6

Marsh, H. W., & Roche, L. A. (1997). Making students' evaluations of teaching effectiveness effective: The critical issues of validity, bias, and utility. American Psychologist, 52(11), 1187-1197. https://doi.org/10.1037//0003-066x.52.11.1187.

Marsh, H.W & Shavelson, R. (1985): Self-Concept: Its Multifaceted, Hierarchical Structure,Educational Psychologist, 20:3, 107-123. http://dx.doi.org/10.1207/s15326985ep2003_1

Marsh, H. W., Tourón, J., & Wheeler, B. (1985). Students' evaluations of university instructors: The applicability of American instruments in a Spanish setting. Teaching and Teacher Education, 1(2), 123-138. https://doi.org/10.1016/0742-051x(85)90011-3.

McKeachie, W. J. (1997). Student ratings: The validity of use. American Psychologist, 52(11), 1218-1225. https://doi.org/10.1037//0003-066x.52.11.1218

Messick, S. (1995). Validity of psychological assessment: Validation of inferences from persons' responses and performances as scientific inquiry into score meaning. American Psychologist, 50(9), 741-749. https://doi.org/10.1037//0003-066x.50.9.741

Michela, J.L. (2022): Toward understanding and quantifying halo in students' evaluation of teaching, Assessment & Evaluation in Higher Education. https://doi.org/10.1080/02602938.2022.2086965

Mislevy, R. J. (2007). Validity by Design. Educational Researcher, 36(8), 463-469. https://doi.org/10.3102/0013189x07311660.

Mitchell, K. M. W., & Martin, J. (2018). Gender Bias in Student Evaluations. PS: Political Science & Politics, 51(03), 648-652. https://doi.org/10.1017/s104909651800001x

Mohanty, G., Gretes, J., Flowers, C., Algozzine, B., & Spooner, F. (2005). Multi-Method Evaluation of Instruction in Engineering Classes. Journal of Personnel Evaluation in Education, 18(2), 139-151. https://doi.org/10.1007/s11092-006-9006-3

Muñiz (1997) Introducción a la teoría de respuesta a los ítems. Ediciones Pirámide.

Newton, P. E., & Shaw, S. D. (2014). *Validity in educational and psychological assessment* [Kindle version]. SAGE Publications Ltd. https://www.amazon.com/dp/B00KAY9ARK/

Ogbonnaya, U. I. (2014). Use of Survey Data to Evaluate Teaching: A Comparison of Self and Peer Evaluations of Teaching. *Mediterranean Journal os Social Sciences*, *5*. *https://doi.org/10.5901/mjss.2014.v5n9p370.* https://doi.org/10.5901/mjss.2014.v5n9p370

Onwuegbuzie, A. J., Daniel, L. G., & Collins, K. M. T. (2009). A meta-validation model for assessing the score-validity of student teaching evaluations. Quality & Quantity, 43(2), 197-209. https://doi.org/10.1007/s11135-007-9112-4.

Pinheiro J, Bates D, R Core Team (2024). nlme: Linear and Nonlinear Mixed Effects Models. R package version 3.1-166, <https://CRAN.R-project.org/package=nlme>.

Punyanunt-Carter, N., & Carter, S. (2015). Undergraduate Students' Perceptions of their Advisors: SocioCommunicative Style and Perceptions of Relational Satisfaction. Higher Learning Research Communications, 5(2), 14. https://doi.org/10.18870/hlrc.v5i2.188

Quansah, F. (2022). Item and rater variabilities in students' evaluation of teaching in a university in Ghana: application of Many-Facet Rasch Model. Heliyon, 8(12), e12548. https://doi.org/10.1016/j.heliyon.2022.e12548

R Core Team. (2024). *R: A language and environment for statistical computing* (Version 4.4.2) [Computer software]. R Foundation for Statistical Computing. https://www.R-project.org/

Radchenko, N. (2020). Student evaluations of teaching: unidimensionality, subjectivity, and biases. Education Economics, 28(6), 549-566. https://doi.org/10.1080/09645292.2020.1814997

Reynolds, C. R. (Ed.). (1994). Cognitive Assessment. Springer US. https://doi.org/10.1007/978-1-4757-9730-5

Remedios, R., & Lieberman, D. A. (2008). I liked your course because you taught me well: The influence of grades, workload, expectations and goals on students' evaluations of teaching. British Educational Research Journal, 34(1), 91-115. Portico. https://doi.org/10.1080/01411920701492043

Renaud, R. D., & Murray, H. G. (2005). Factorial Validity of Student Ratings of Instruction. Research in Higher Education, 46(8), 929-953. https://doi.org/10.1007/s11162-005-6934-6

Renström, E. A., Gustafsson Sendén, M., & Lindqvist, A. (2021). Gender Stereotypes in Student Evaluations of Teaching. Frontiers in Education, 5. https://doi.org/10.3389/feduc.2020.571287.

Revelle, W. (2024). *psych: Procedures for Psychological, Psychometric, and Personality Research*. Northwestern University, Evanston, Illinois. R package version 2.4.3, https://CRAN.R-project.org/package=psych.

Röhl, S., & Rollett, W. (2021). Student Perceptions of Teaching Quality: Dimensionality and Halo Effects. Student Feedback on Teaching in Schools, 31-45. https://doi.org/10.1007/978-3-030-75150-0_3

Rupp, A. A., and Zumbo, B. D. (2004). A note on how to quantify and report whether IRT parameter invariance holds: When pearson correlations are not enough. Educational and Psychological Measurement, 64 (4), 588-599. https://doi.org/10.1177/0013164403261051.

Ryan, R. M., & Deci, E. L. (Eds.). (2017). Self-Determination Theory: Basic Psychological Needs in Motivation, Development, and Wellness. https://doi.org/10.1521/978.14625/28806

Schunk, D. H., Meece, J. R., & Pintrich, P. R. (2014). Motivation in education: Theory, research, and applications. Pearson Higher Ed.

Seldin, P. (2006). Evaluating faculty performance: A practical guide to asses-sing teaching, research, and service. Anker Publishing Company. https://doi.org/10.1111/j.1467-9647.2009.00514.x

Shuell, T. J. (1986). Cognitive Conceptions of Learning. Review of Educational Research, 56(4), 411-436. https://doi.org/10.3102/00346543056004411

Smith Jr, E. V. (2002). Detecting and evaluating the impact of multidimensionality using item fit statistics and principal component analysis of residuals. *Journal of applied measurement*, *3*(2), 205-231. https://doi.org/10.1177/0013164410379322

Spooren, P., Brockx, B., & Mortelmans, D. (2013). On the Validity of Student Evaluation of Teaching. Review of Educational Research, 83(4), 598-642. https://doi.org/10.3102/0034654313496870

Stapleton, R. J., & Murkison, G. (2001). Optimizing the Fairness of Student Evaluations: A Study of Correlations between Instructor Excellence, Study Production, Learning Production, and Expected Grades. Journal of Management Education, 25(3), 269-291. https://doi.org/10.1177/105256290102500302.

Stark-Wroblewski, K., Ahlering, R. F., & Brill, F. M. (2007). Toward a more comprehensive approach to evaluating teaching effectiveness: supplementing student evaluations of teaching with pre-post learning measures. Assessment & Evaluation in Higher Education, 32(4), 403-415. https://doi.org/10.1080/02602930600898536.

Sutton, R., & Douglas, K. (2019). *Social psychology*. Bloomsbury Publishing. https://www.amazon.com/-/es/Robbie-Sutton-ebook/dp/B09HZCBTVP

Svanum, S., & Aigner, C. (2011). The influences of course effort, mastery and performance goals, grade expectancies, and earned course grades on student ratings of course satisfaction. British Journal of Educational Psychology, 81(4), 667-679. Portico. https://doi.org/10.1111/j.2044-8279.2010.02011.x

Theall, M., Abrami, P. C., & Mets, L. A. (2001). The student ratings debate: Are they valid? how can we best use them? Jossey-Bass

Theall, M., & Franklin, J. (2001). Looking for Bias in All the Wrong Places: A Search for Truth or a Witch Hunt in Student Ratings of Instruction?. New Directions for Institutional Research, 2001(109), 45-56. https://doi.org/10.1002/ir.3

Uttl, B., & Smibert, D. (2017). Student evaluations of teaching: teaching quantitative courses can be hazardous to one's career. PeerJ, 5, e3299. Portico. https://doi.org/10.7717/peerj.3299

Van Wyk, R., Boshoff, A. B., & Bester, C. L. (2003). Possible cognitive processes underlying competency assessment. SA Journal of Industrial Psychology, 29(3). https://doi.org/10.4102/sajip.v29i3.114.

von Davier, M., & Carstensen, C. H. (2007). Multivariate and Mixture Distribution Rasch Models. Springer New York. https://doi.org/10.1007/978-0-387-49839-3

Wainer, H., & Braun, H. I. (Eds.) (2013). Test Validity. Routledge. https://doi.org/10.4324/9780203056905

Watkins, D., Marsh, H. W., & Young, D. (1987). Evaluating tertiary teaching: A New Zealand perspective. Teaching and Teacher Education, 3(1), 41-53. https://doi.org/10.1016/0742-051x(87)90033-3.

Whitely, S. E., & Doyle, K. O. (1976). Implicit theories in student ratings. American Educational Research Journal,13(4), 241-253. https://doi.org/10.2307/1162387

Wigfield, A., Eccles, J. S., Yoon, K. S., Harold, R. D., Arbreton, A. J., Freedman-Doan, C., & Blumenfeld, P. C. (1997). Change in children's competence beliefs and subjective task values across the elementary school years: A 3-year study. Journal of Educational Psychology, 89(3), 451-469. http://dx.doi.org/10.1037/0022-0663.89.3.451

Wright, B., & Stone, M. (1999). Measurement Essentials 2nd Ed. WIDE RANGE. https://www.rasch.org/BTD_RSA/pdf/Best%20Test%20Design.pdf

Young, S., Rush, L., & Shaw, D. (2009). Evaluating Gender Bias in Ratings of University Instructors' Teaching Effectiveness. International Journal for the Scholarship of Teaching and Learning, 3(2). https://doi.org/10.20429/ijsotl.2009.030219

Zhao, J. & Gallant DJ. (2012) Student evaluation of instruction in higher education: exploring issues of validity and reliability, Assessment & Evaluation in Higher Education, 37:2, 227-235. http://dx.doi.org/10.1080/02602938.2010.523819

Acknowledgments

This research was developed within the framework of the R&D group "Núcleo de Investigación, Medición y Evaluación Educativa" (NIMEE) funded by CSIC (22620220100067UD) and received a doctoral grant from the National Agency for Research and Innovation of Uruguay.

Appendix A. Overall fit

Overall model fit was satisfactory across all subscales (see Table A1). Infit and Outfit statistics indicated acceptable fit and consistent randomness in response patterns, and the mean and standard deviation of standardized residuals approximated expected values for a perfect fit (M(*Z(Res))* ≈ 0; *SD(*ZRes) ≈ 1). Ratios of extreme absolute standardized residuals (PRE_2 ≈ 0.046) were near their expected values. The model accounted for a substantial portion of observed-score variance (*PVE* ≈ 60%), supporting the conclusion of satisfactory overall fit.

Table A1

Overall Fit Between Data and Model

	VALR	INTR	RELP	TRDF	CLOR	ENTC	APPR	TRPR	EVAL
Infit	0.99	1.00	0.99	1.00	0.99	0.99	0.99	0.99	1.00
Outfit	0.98	0.98	0.97	0.98	0.97	0.97	0.98	0.94	0.99
$M(Z_{Res})$	0.00	0.00	0.02	0.00	0.01	0.01	0.00	0.01	0.00
$SD(Z_{Res})$	0.98	0.98	0.94	0.99	0.96	0.96	0.97	0.95	0.99
PRE_2	.06	.06	.05	.06	.06	.05	.06	.07	.05
PVE	..9	.56	.64	.57	.62	.58	.58	.66	.53
N (Students)	2913	2874	2951	2907	2887	2889	3005	3051	2925
Prop.Excl.	.10	.11	.09	.10	.11	.11	.07	.06	.10

Note. Infit = infit mean-square*; Outfit* = outfit mean-square. $M(Z_{Res})$ = mean of standardized residuals*;* $SD(Z_{Res})$ = standard deviation of standardized residuals. PRE_2 = proportion of $|Z_{Res}| > 2$. *PVE = proportion of observed variance explained by the Rasch measure. N = number of students; Prop. Excl. = proportion of students excluded from estimation.*

Appendix B. Local Dependency Analysis

Table B1 reports $PCOR_x$, the maximum standardized-residual correlation (r_{MAX}), the item pairs producing r_{MAX} by subscale, and the adjusted residual-correlation statistic *Q3**. Observed *Q3** values indicate local dependence for CLOR, ENTC, and EVAL; these subscales exceed $r = .40$ but remain below $r = .70$. These results suggest moderate local dependence for the affected subscales, which is unlikely to have a practical impact on parameter estimates, reliability, or overall model fit. Invariance analyses of teacher and student measures (see Appendix C) similarly show that conditional dependence in these three subscales does not yield a practically significant effect. Likewise, the distribution of fit statistics does not indicate any meaningful impact of local dependence.

Table B1

Local Dependency Analysis.

Subscale	*Q3**	$PCOR_{.4}$	$PCOR_{.7}$	r_{MAX}	*Items*
VALR	.109	.100	.000	.428	VALR2,VALR3
INTR	.192	.133	.000	.527	INTR1, INTR2
RELP	.111	.800	.000	.556	RELP3,RELP5
TRDF	.150	.000	.000	.347	TRDF2,TRDF3
CLOR	.227	.357	.000	.622	CLOR1,CLOR2
ENTC	.226	.100	.000	.556	ENTC1,ENTC2
APPR	.083	.400	.000	.473	APPR4,APPR5
TRPR	.190	.000	.000	.332	TRPR1,TRPR2
EVAL	.381	.048	.000	.401	EVAL5, EVAL6

Note. $Q3^*$ = adjusted residual-correlation statistic for local dependence (Christensen et al., 2017). $PCOR_x$ = proportion of paired standardized-residual correlations exceeding cutoff x. r_{MAX} = maximum standardized-residual correlation; Items = item pair producing r_{MAX}. $Q3^* > .20$ indicates potential local dependence (Christensen et al., 2017). Standardized residuals near .40 reflect low dependence; values near .70 indicate substantial dependence likely to be of practical concern (Linacre, 2024).

Appendix C. Invariance

Table C1 reports invariance analyses for items, teachers, and students. Teacher measures were highly invariant relative to items across all subscales, whereas student measures showed slightly lower invariance relative to items. Item measures were strongly invariant relative to students. Teacher measures demonstrated the weakest invariance relative to students.

Table C1

Analysis of Measurement Invariance for Each Subscale

Subscale	r(x,y)	Student-Relative r(x, y)		Item-Relative r(x, y)	
		Items	Teachers	Students	Teachers
VALR	r(1,2)	.984 (1.000)	.649 (.669)	.869 (1.000)	.941 (1.000)
	r(1,C)	.996 (1.000)	.906 (.929)	.948 (1.000)	.980 (1.000)
	r(2,C)	.996 (1.000)	.895 (.918)	.978 (1.000)	.990 (1.000)
INTR	r(1,2)	.987 (.997)	.464 (.478)	.874 (1.000)	.924 (.948)
	r(1,C)	.997 (1.000)	.870 (.888)	.959 (1.000)	.976 (1.000)
	r(2,C)	.997 (1.000)	.782 (.798)	.971 (1.000)	.985 (1.000)
RELP	r(1,2)	.975 (.985)	.843 (.852)	.941 (1.000)	.993 (1.000)
	r(1,C)	.993 (1.000)	.964 (.969)	.973 (1.000)	.997 (1.000)
	r(2,C)	.994 (1.000)	.931 (.936)	.989 (1.000)	.999 (1.000)
TRDF	r(1,2)	.999 (1.000)	.326 (.338)	.838 (1.000)	.897 (.955)
	r(1,C)	1.000 (1.000)	.839 (.852)	.958 (1.000)	.976 (1.000)
	r(2,C)	1.000 (1.000)	.721 (.737)	.955 (1.000)	.971 (1.000)
CLOR	r(1,2)	.851 (.900)	.765 (.772)	.955 (1.000)	.990 (1.000)
	r(1,C)	.957 (.992)	.943 (.948)	.986 (1.000)	.997 (1.000)
	r(2,C)	.965 (1.000)	.903 (.907)	.987 (1.000)	.997 (1.000)
ENTC	r(1,2)	.982 (1.000)	.825 (.837)	.914 (1.000)	.980 (1.000)
	r(1,C)	.996 (1.000)	.980 (.985)	.981 (1.000)	.997 (1.000)
	r(2,C)	.995 (1.000)	.903 (.913)	.967 (1.000)	.992 (.997)
APPR	r(1,2)	.916 (.965)	.550 (.567)	.886 (1.000)	.945 (.980)
	r(1,C)	.987 (1.000)	.894 (.917)	.979 (1.000)	.991 (1.000)
	r(2,C)	.968 (1.000)	.826 (.848)	.956 (1.000)	.980 (1.000)
TRPR	r(1,2)	.804 (1.000)	.453 (.470)	.883 (1.000)	.955 (.989)
	r(1,C)	.927 (1.000)	.863 (.886)	.967 (1.000)	.988 (1.000)

	r(2,C)	.967 (1.000)	.818 (.843)	.969 (1.000)	.988 (1.000)
EVAL	r(1,2)	.996 (.996)	.305 (.316)	.851 (.995)	.895 (.942)
	r(1,C)	.999 (.999)	.658 (.674)	.970 (1.000)	.972 (1.000)
	r(2,C)	.999 (0999)	.0816 (.850)	.946 (1.000)	.974 (1.000)

Note. *r(x,y)* denotes the invariance coefficient (Pearson correlation) between subsamples *x* and *y* after splitting the secondary facet into two random subsamples. *r(1,2)* is the coefficient between random subsamples 1 and 2; *r(x,C)* is the coefficient between subsample *x* and the complete sample (*C*). Values in parentheses are attenuation-corrected correlations (Spearman correction using subsample reliabilities). Lower subsample connectivity can depress observed correlations; consequently, *r(1,C)* and *r(2,C)* may deviate more from *r(1,2)* than other pairwise coefficients

Appendix D. Between-Teacher and Within-Teacher Variance in Student Measures

Table D1 indicates a nonnegligible proportion of variance attributable to teachers despite the student-assignment procedures used in multi-section courses. Between-teacher differences in the distribution of student severity can bias student evaluation of teaching (SET) scores. These findings demonstrate the value of analytic approaches that adjust for student severity and item difficulty, such as the many-facet Rasch model (MFRM).

Table D1

Between-Teacher and Within-Teacher Variance in Student Measures

Subscale	sd_B	sd_W	sd_T	var_B	var_W	var_T	*PVBT*	*PVWT*
VALR	0.52	2.31	2.36	0.28	5.31	5.59	0.05	0.95
INTR	0.61	2.15	2.23	0.37	4.6	4.98	0.08	0.92
RELP	0.64	2.87	2.94	0.41	8.24	8.65	0.05	0.95
TRDF	0.65	2.01	2.11	0.42	4.02	4.44	0.09	0.91
CLOR	0.72	2.59	2.69	0.52	6.71	7.23	0.07	0.93
ENTC	0.71	2.25	2.36	0.5	5.06	5.56	0.09	0.91
APPR	0.83	2.34	2.48	0.69	5.47	6.16	0.11	0.89
TRPR	0.79	3.19	3.29	0.62	10.17	10.8	0.06	0.94
EVAL	0.42	1.7	1.75	0.17	2.9	3.07	0.06	0.94

Note. B = between-teacher component; W = within-teacher component; T = total variability. sd = standard deviation of student measure; var = variance of student measure; PVBT = proportion of variance between teachers; PVWT = proportion of variance within teachers.

Appendix E. Exploratory Factor Analysis Results: Loadings, Communalities, and Factor Correlations

Table E1.

Factor Loadings From Exploratory Factor Analysis of Teacher-Level Item Means

Item	ML1	ML2	ML3	ML4	ML5	ML6	ML7	ML8	ML9	h2	u2
VALR1	-0.08	**0.89**	-0.09	-0.15	0.12	0.04	0.16	-0.01	0.06	0.96	0.04
VALR2	-0.19	**0.92**	0.15	-0.02	-0.11	0.03	0.10	0.27	-0.01	0.95	0.05
VALR3	-0.14	**0.96**	-0.05	-0.12	0.04	0.06	0.17	0.01	0.03	0.96	0.04
VALR4	0.13	**0.78**	-0.14	0.11	-0.01	-0.03	-0.22	0.15	0.06	0.92	0.08
VALR5	0.00	**0.86**	-0.05	0.04	-0.01	-0.04	-0.06	0.04	0.19	0.96	0.04
INTR1	0.12	0.20	-0.18	-0.05	0.09	**0.91**	0.01	-0.17	-0.15	0.95	0.05
INTR2	-0.15	-0.05	0.06	-0.01	-0.12	**1.15**	0.06	-0.02	0.07	0.96	0.04
INTR3	0.28	0.07	0.04	0.27	-0.16	**0.46**	0.11	0.09	-0.09	0.97	0.03
INTR4	-0.08	0.22	-0.05	0.20	0.14	**0.38**	**0.36**	-0.18	0.02	0.87	0.13
INTR5	-0.02	0.14	-0.06	0.19	0.00	**0.63**	0.02	-0.02	0.09	0.96	0.04
INTR6	0.28	-0.12	0.03	**0.82**	-0.11	0.21	-0.12	-0.05	0.03	0.93	0.07
RELP1	-0.10	-0.01	0.03	**0.84**	0.16	-0.06	0.27	-0.10	0.01	0.97	0.03
RELP2	-0.13	-0.01	0.12	**1.02**	-0.22	0.04	-0.05	0.21	0.08	0.95	0.05
RELP3	0.05	0.00	0.00	**0.84**	-0.02	-0.11	0.16	0.08	0.01	0.98	0.02
RELP4	0.29	-0.22	-0.04	**0.57**	0.10	0.08	0.20	-0.01	-0.02	0.97	0.03
RELP5	**0.32**	-0.12	0.03	**0.81**	-0.07	-0.12	0.07	0.08	0.01	0.98	0.02
TRDF1	0.12	0.23	**0.89**	0.13	-0.09	-0.16	-0.09	0.14	0.05	0.87	0.13
TRDF2	0.11	-0.19	**0.94**	0.07	0.08	-0.04	-0.07	-0.11	0.09	0.86	0.14
TRDF3	-0.37	-0.18	**0.95**	0.09	0.02	0.11	0.21	0.00	0.03	0.83	0.17

TRDF4	**0.37**	**0.46**	**0.62**	0.04	0.22	0.11	-0.25	-0.36	-0.18	0.85	0.15
CLOR1	**1.04**	-0.03	-0.03	0.00	0.03	-0.06	0.04	-0.08	0.03	0.95	0.05
CLOR2	**1.05**	-0.07	-0.03	0.03	0.04	-0.12	0.06	-0.06	0.03	0.96	0.04
CLOR3	**0.79**	-0.02	0.02	-0.05	-0.01	0.05	0.24	0.00	0.00	0.96	0.04
CLOR4	**0.96**	-0.07	0.05	0.04	-0.02	-0.09	0.07	0.09	-0.01	0.95	0.05
CLOR5	**0.83**	-0.06	0.01	0.14	-0.10	0.14	-0.10	0.13	-0.01	0.94	0.06
CLOR6	**1.07**	-0.13	-0.05	0.15	0.16	-0.11	-0.02	-0.23	0.08	0.97	0.03
CLOR7	**1.06**	-0.21	-0.03	0.06	0.07	0.13	-0.04	-0.08	-0.03	0.94	0.06
CLOR8	**0.79**	-0.06	-0.01	0.07	0.02	0.04	0.04	0.05	0.05	0.96	0.04
ENTC1	0.03	0.10	-0.06	0.26	0.11	-0.05	**0.66**	-0.02	-0.03	0.97	0.03
ENTC2	0.13	0.02	-0.04	0.01	0.03	0.05	**0.81**	0.05	-0.07	0.99	0.01
ENTC3	-0.20	0.14	0.06	0.18	0.10	-0.08	**0.91**	-0.09	0.07	0.92	0.08
ENTC4	0.19	0.05	-0.04	-0.10	0.14	0.15	**0.77**	-0.13	-0.06	0.92	0.08
ENTC5	**0.46**	0.04	0.12	-0.36	-0.27	-0.03	**0.63**	**0.39**	0.09	0.94	0.06
APPR1	0.27	0.03	0.02	-0.11	0.11	0.23	0.09	0.00	**0.39**	0.91	0.09
APPR2	0.13	0.05	-0.02	-0.13	0.10	0.14	0.24	0.05	**0.45**	0.94	0.06
APPR3	0.01	0.16	0.06	0.15	0.08	-0.04	-0.11	-0.19	**0.96**	0.95	0.05
APPR4	0.11	0.06	0.07	-0.08	-0.02	-0.01	0.30	0.05	**0.65**	0.97	0.03
APPR5	0.20	0.04	0.16	-0.02	-0.18	0.17	0.10	0.12	**0.59**	0.93	0.07
TRPR1	-0.10	0.10	-0.07	0.15	0.00	0.05	-0.15	**0.80**	0.12	0.92	0.08
TRPR2	-0.01	0.09	0.01	0.02	0.01	-0.03	-0.04	**0.95**	0.01	0.95	0.05
TRPR3	-0.11	-0.03	0.01	0.13	-0.01	-0.03	0.13	**0.96**	-0.06	0.91	0.09
TRPR4	0.09	0.18	-0.03	0.09	-0.03	-0.04	-0.08	**0.92**	-0.15	0.95	0.05
EVAL1	0.27	-0.39	-0.01	0.05	**0.38**	0.15	-0.17	**0.46**	0.17	0.89	0.11
EVAL2	0.15	-0.09	-0.08	-0.07	**0.79**	0.02	-0.06	0.12	0.06	0.88	0.12
EVAL3	0.14	-0.05	0.14	0.09	**0.71**	-0.02	0.08	0.19	-0.14	0.86	0.14
EVAL4	-0.05	0.09	0.05	-0.20	**0.99**	-0.04	0.15	-0.09	0.06	0.88	0.12

EVAL5	0.17	0.05	-0.01	0.09	**0.40**	0.02	-0.30	0.30	0.28	0.87	0.13
EVAL6	0.03	0.04	0.17	0.25	0.11	-0.03	-0.20	0.30	**0.47**	0.74	0.26
EVAL7	-0.20	-0.05	0.07	0.08	**0.40**	-0.01	-0.05	**0.77**	-0.15	0.65	0.35

Note. The factor loadings in bold are equal to or greater than 0.32, indicating 10% or more of the variance overlaps with that of other items in the factor. Loadings equal to or greater than 0.50 are considered strong. According to Costelo et al. (2005), factors with three strong loaders are considered acceptable, and five strong loaders indicate a solid factor. ML1 to ML9 represent the factor loadings obtained from an exploratory factor analysis that utilized Bentler's oblique quartimin rotation (BentlerQ) on teacher-level item means; where h2 denotes communality and u2 denotes uniqueness. No negative residual variances were detected. Given the questionnaire's very high reliability and the strong correlations among factors, occasional factor loadings slightly greater than 1 may be observed and do not necessarily indicate a problem with the fitted model (Babakus et al., 1987; Jöreskog, 1999)

Table E2

Factor Correlation Matrix

	ML1	ML2	ML3	ML4	ML5	ML6	ML7	ML8	ML9
ML1	1.00	0.82	-0.06	0.80	0.69	0.87	0.87	0.82	0.86
ML2	0.82	1.00	0.08	0.56	0.57	0.79	0.58	0.70	0.70
ML3	-0.06	0.08	1.00	-0.17	-0.15	-0.12	-0.17	-0.28	-0.28
ML4	0.80	0.56	-0.17	1.00	0.62	0.77	0.86	0.74	0.74
ML5	0.69	0.57	-0.15	0.62	1.00	0.71	0.63	0.76	0.73
ML6	0.87	0.79	-0.12	0.77	0.71	1.00	0.77	0.82	0.87
ML7	0.87	0.58	-0.17	0.86	0.63	0.77	1.00	0.70	0.82
ML8	0.82	0.70	-0.28	0.74	0.76	0.82	0.70	1.00	0.81

ML9	0.86	0.70	-0.28	0.74	0.73	0.87	0.82	0.81	1.00

Note. ML1 to ML9 are factor loadings from an exploratory factor analysis using Bentler's oblique quartimin rotation (BentlerQ) of teacher-level item means

Table 1

Description of the SET Questionnaire

Subscale	Construct	Number of Items	Description of the construct
VALR	Value /Learning	5	The teaching is engaging and challenging, enhancing learning and understanding of relevant topics and preparing students for advanced levels.
INTR	Interaction/Discussion	6	Students are encouraged to engage in questioning, sharing ideas, applying concepts, discussing, and expressing critical thinking in a respectful and inclusive environment.
RELP	Personal Relationship	5	The teacher is friendly, approachable, respectful, attentive, willing to assist, and shows concern for the student's challenges.
TRDF	Workload/ Difficulty	4	This refers to the level of difficulty, workload, teaching pace, and time needed to comprehend the content.
CLOR	Clarity / Planning/ Organization	8	The teacher effectively communicates concepts through examples and illustrations, synthesizes them, and provides well-prepared materials, a clear work plan, and adherence to established objectives.
ENTC	Enthusiasm / Communication Style	5	The teacher is enthusiastic, dynamic and energetic, shows self-confidence, uses humor to enhance communication, and varies

			the speed and tone of his voice.
APPR	Breadth / Depth	5	The teacher provides examples, analyzes consequences, contrasts viewpoints, and shares recent research to help students understand the foundations and origins of ideas.
TRPR	Proposed Tasks	4	Homework assignments enhance understanding of topics, training, and skills, aligning with other course activities and providing significant value.
EVAL	Evaluation	7	The feedback is valuable, offering suggestions for improvement, self-assessment of learning, and progress reporting. Evaluations align with course objectives, focusing on important aspects, and assess comprehension with clear, unambiguous questions and problem wording.

Table 2

Arguments for Interpreting the Variance Components of the Measures Under Different Hypotheses

Argument 1	Argument 2	Argument 3
(A1.a) [Validity Hypothesis] The main determinants of students' evaluations of instruction are teaching characteristics and their facilitating effect on the student's learning.	(A2.a) [Leniency Hypothesis] The main determinants of students' evaluations of instruction are teacher leniency in grading students, in such a way that more lenient teachers are evaluated better.	(A3.a) [Prior Characteristics Hypothesis] The main determinants of students' evaluations of instruction are prior characteristics of students and courses, unrelated to instruction and learning.
(A1.b) [From (a) and MFRM] The teacher's measure reflects the characteristics of their teaching and the overall facilitating effect it has on students' learning.	(A2.b) [From (a) and MFRM] The teacher's measure reflects their level of leniency in grading.	(A3.b) [From (a) and MFRM] The teacher's measure reflects the overall conformity of students that depends on prior characteristics of students and courses, unrelated to teaching effectiveness.
(A1.c) [From (a) and MFRM] The student's measure reflects the overall characteristics of how they perceive and evaluate teaching.	(A2.c) [From (a) and MFRM] The student's measure reflects the overall characteristics of how they perceive and evaluate the teacher's leniency in grading.	|(A3.c) [From (a) and MFRM] The student's measure reflects global patterns in how they perceive and evaluate teachers, shaped by prior characteristics of students and courses unrelated to instruction and learning.
(A1.d) [From (A1.a) to (A1.c)] In order for the quality of teaching to influence students' perceptions of teachers, conditions must exist that allow them to perceive and discern differences in teaching quality among instructors.	(A2.d) [From (A2.a) to (A2.c)] In order for leniency in grading students to influence students' perceptions of teachers, conditions must exist that allow them to perceive and discern differences in leniency in grading among instructors.	(A3.d) [From (A3.a) to (A3.c)] In order for a priori variables of students and courses, unrelated to the quality of the teacher's teaching or its facilitating effect on learning, to influence the student's perception of the teacher, there must be a cognitive mechanism that allows these a priori variables to affect the student's perception and evaluation.

(A1.e) [From (A1.a) to (A1.d)] (i) To obtain at least a variance in teacher measures of minimal practical significance, a certain minimum level of variability in teaching quality among instructors is necessary. (ii) The greater the variability in teaching quality, the greater the variance in teacher measures.	(A2.e) [From (A2.a) to (A2.d)] (i) To obtain at least a variance in teacher measures of minimal practical significance, a certain minimum level of variability in leniency between instructors in grading students is necessary. (ii) The greater the variability in leniency between instructors in grading students, the greater the variance in teacher measures.	(A3.e) [From (A3.a) to (A3.d)] (i) To obtain at least a variance in teacher measures of minimal practical significance, a certain minimum level of variability in a priori student and course variables is necessary. (ii) The greater the variability in a priori student and course variables, the greater the variance in teacher measures.
(A.f) [From course design] (i) Students are first organized into groups, which are then allocated to different sections of each course independently of the instructor's identity. (ii) Teachers adhere to identical programs, learning objectives, content, textbooks, and summative assessments. (iii) Group sizes across sections are uniform, and contextual factors remain comparable within each multisection course.		
(A1.g) [From (A1.a) to (A1.e) and A.f] The proportions of within- and between-course variance in teacher measures reflect variation in teaching characteristics and their facilitatory effects, as well as the constraints imposed on teaching by multi-section course designs.	(A.2.g) [From (A2.a) to (A2.e) and A.f] The proportions of within- and between-course variance in teacher measures reflect variation in teacher leniency in grading students, as well as the constraints imposed on leniency in grading students by multi-section course designs.	(A3.g) [From (A3.a) to (A3.e) and A.f] The proportions of within- and between-course variance of teacher measures relate to prior characteristics of students and courses unrelated to instruction and learning and to constraints imposed by multi-section course designs on prior characteristics of students and courses.
(A1.h) [From (A1.a) to (A1.e) and A.f] The proportions of within- and between-course variance of student measures relate to the overall characteristics of how they perceive and evaluate teaching and to the assignment of students into groups and sections.	(A2.h) [From (A1.a) to (A1.e) and A.f] The proportions of within- and between-course variance of student measures relate to the overall characteristics of how they perceive and evaluate teacher leniency and to the assignment of students into groups and sections.	(A3.h) [From (A1.a) to (A1.e) and A.f] The proportions of within- and between-course variance of student measures relate to the global patterns in how they perceive and evaluate teachers, shaped by prior characteristics of students and courses unrelated to instruction and learning, as well as to the assignment of students into groups and sections.

(A1.i) [From (A1.a) to (A1.e) and A.f] The proportions of within- and between-teacher variance of student measures relate to the overall characteristics of how they perceive and evaluate teaching and to the assignment of students into groups and sections.	(A2.i) [From (A1.a) to (A1.e) and A.f] The proportions of within- and between-teacher variance of student measures relate to the overall characteristics of how they perceive and evaluate teacher leniency and to the assignment of students into groups and sections.	(A3.i) [From (A1.a) to (A1.e) and A.f] The proportions of within- and between-teacher variance of student measures relate to the global patterns in how they perceive and evaluate teachers, shaped by prior characteristics of students and courses unrelated to instruction and learning, as well as to the assignment of students into groups and sections.
Note.The measurements are assumed to be obtained using an many-facet Rasch measurement approach.		

Table 3

Expected Patterns Under Alternative Hypotheses

Expected patterns under the Validity Hypothesis	Expected patterns under the Leniency hypothesis	Expected patterns under the Prior Characteristics Hypothesis
(E1.1) The PVWC exceeds the minimum size effect for teacher measures across all subscales of the questionnaire, achieving a moderate to large effect size.	(E2.1) The PVWC is less than the minimal size effect and smaller than the PVBC for teachers' measures for all subscales of the questionnaire.	(E3.1) The PVWC is less than the minimal size effect and smaller than the PVBC for teachers' measures for all subscales of the questionnaire.
(E1.2) The relationship between PVWC and PVBC for teachers' measures depends on the subscale of the questionnaire.	(E2.2) The relationship between PVWC and PVBC for teachers' measures is uniform between subscales of the SET questionnaire.	(E3.2) The relationship between PVWC and PVBC for teachers' measures is uniform between subscales of the SET questionnaire.
(E1.3) The PVWC is greater than the PVBC for students' measures for all subscales of the questionnaire.	(E2.3) The PVWC is greater than the PVBC for students' measures for all subscales of the questionnaire.	(E3.3) The PVWC is greater than the PVBC for students' measures for all subscales of the questionnaire.
(E1.4) The relationship between PVWC and PVBC for students' measures is uniform between subscales of the SET questionnaire.	(E2.4) The relationship between PVWC and PVBC for students' measures is uniform between subscales of the SET questionnaire.	The relationship between PVWC and PVBC for students' measures is uniform between subscales of the SET questionnaire.
(E1.5) The mean PVWC is smaller than the mean PVWT for students' measures for all subscales of the SET questionnaire.	(E2.5) The mean PVWC is smaller than the mean PVWT for students' measures for all subscales of the SET questionnaire.	The mean PVWC is smaller than the mean PVWT for students' measures for all subscales of the SET questionnaire.

Note. PVWC = proportion of variance within courses; PVBC = proportion of variance between courses; PVWT = proportion of variance within teachers. Teacher and student measures were estimated using a many-facet Rasch measurement model. Expected patterns under each hypothesis reflect the most probable outcomes given the design of this study.

Table 4

PCAR Results for the SET Questionnaire Subscales

Subscale	PVE Rasch measure	PVE First contrast	PVE Rasch/PVE 1st Contr.	Eigenvalue First contrast
VALR	.59	.19	3.11	2.286
INTR	.56	.20	2.80	2.673
RELP	.64	.20	3.20	2.766
TRDF	.57	.17	3.35	1.613
CLOR	.62	.19	3.26	3.750
ENTC	.58	.20	2.90	2.380
APPR	.58	.21	2.76	2.558
TRPR	.66	.16	4.13	1.486
EVAL	.53	.11	4.82	1.639

Table 5

Measures and Fit Statistics for the Items

Items	*Measure*	*S.E.*	*Infit*	*Outfit*	r_{pm}	*Discrim*
VALR1	0.24	0.02	1.04	1.04	.77	0.95
VALR2	-0.37	0.02	0.94	0.91	.79	1.06
VALR3	0.04	0.02	0.95	0.93	.79	1.05
VALR4	-0.09	0.02	1.04	1.04	.76	0.95
VALR5	0.18	0.02	1.00	0.98	.78	0.99
INTR1	0.29	0.02	1.02	1.02	.76	0.98
INTR2	-0.04	0.02	0.93	0.91	.77	1.07
INTR3	-0.15	0.02	0.92	0.90	.77	1.08
INTR4	0.44	0.02	1.14	1.13	.73	0.85
INTR5	-0.11	0.02	0.96	0.94	.76	1.04
INTR6	-0.15	0.02	1.02	0.99	.74	0.99
RELP1	0.22	0.02	1.03	1.01	.77	0.93
RELP2	-0.5	0.02	0.95	0.91	.77	1.00
RELP3	0.00	0.02	0.93	0.89	.78	1.03
RELP4	0.38	0.02	1.12	1.14	.76	0.83
RELP5	-0.10	0.02	0.94	0.89	.78	1.02
TRDF1	-0.54	0.02	1.05	1.04	.75	0.94
TRDF2	0.21	0.02	0.93	0.91	.77	1.06
TRDF3	0.24	0.02	1.04	1.02	.75	0.97
TRDF4	0.09	0.02	0.98	0.97	.77	1.02
CLOR1	0.14	0.02	0.97	0.96	.79	1.02
CLOR2	0.15	0.02	0.97	0.95	.79	1.02
CLOR3	0.02	0.02	0.98	0.96	.79	1.01
CLOR4	-0.16	0.02	0.98	0.96	.78	1.01
CLOR5	-0.15	0.02	0.98	0.95	.78	1.01
CLOR6	0.09	0.02	0.98	0.96	.79	1.01
CLOR7	0.09	0.02	1.07	1.05	.78	0.93
CLOR8	-0.17	0.02	1.01	0.98	.78	0.99
ENTC1	-0.18	0.02	0.90	0.89	.75	1.10
ENTC2	-0.10	0.02	0.91	0.88	.75	1.09
ENTC3	0.90	0.02	1.06	1.05	.73	0.92
ENTC4	0.26	0.02	1.14	1.12	.72	0.84

ENTC5	-0.26	0.02	0.97	0.94	.73	1.02
APPR1	-0.04	0.02	1.00	0.99	.78	1.00
APPR2	0.15	0.02	1.01	1.01	.77	0.98
APPR3	0.13	0.02	1.02	1.02	.77	0.97
APPR4	0.00	0.02	0.94	0.92	.79	1.06
APPR5	-0.24	0.02	1.00	0.98	.77	0.99
TRPR1	0.00	0.03	0.95	0.91	.84	1.04
TRPR2	0.09	0.03	0.93	0.89	.85	1.05
TRPR3	0.03	0.02	1.13	1.08	.81	0.87
TRPR4	-0.11	0.02	0.95	0.89	.84	1.04
EVAL1	-0.27	0.02	0.86	0.85	.75	1.13
EVAL2	0.34	0.02	0.87	0.87	.76	1.13
EVAL3	-0.02	0.02	0.90	0.89	.74	1.09
EVAL4	0.83	0.02	1.02	1.03	.73	0.98
EVAL5	-0.42	0.02	0.96	0.95	.71	1.04
EVAL6	-1.01	0.02	1.22	1.19	.62	0.77
EVAL7	0.55	0.02	1.15	1.17	.68	0.84

Table 6

Reliability of the Subscales for the Items

Subscale	*SR*	*G*	*H*	Fixed Effects (*p-value*)
VALR	.99	9.85	13.46	.00
INTR	.99	13.87	18.83	.00
RELP	.99	12.75	17.33	.00
TRDF	.99	15.93	21.58	.00
CLOR	.97	5.63	7.84	.00
ENTC	.99	10.91	14.87	.00
APPR	.98	6.33	8.77	.00
TRPR	.88	2.66	3.88	.00
EVAL	1.00	31.91	42.89	.00

Table 7

Descriptive Statistics for the Teacher Facet for Each Subscale

		Measure	*S.E.*	*Infit*	*Outfit*	r_{pm}
VALR	*M*	2.29	0.16	1.11	1.11	.71
	SD	1.38	0.08	0.28	0.30	.16
	Q1	1.44	0.12	0.96	0.93	.69
	Q3	2.77	0.19	1.29	1.31	.78
INTR	*M*	2.18	0.14	1.13	1.12	.70
	SD	1.21	0.07	0.31	0.32	.16
	Q1	1.45	0.10	0.96	0.95	.67
	Q3	2.84	0.17	1.36	1.35	.76
RELP	*M*	3.71	0.18	1.09	1.08	.76
	SD	3.27	0.09	0.35	0.39	.09
	Q1	2.31	0.11	0.86	0.83	.72
	Q3	4.23	0.22	1.29	1.33	.82
TRDF	*M*	1.19	0.16	1.20	1.20	.72
	SD	0.96	0.08	0.31	0.32	.08
	Q1	0.60	0.11	1.02	0.98	.67
	Q3	1.74	0.19	1.37	1.39	.77
CLOR	*M*	3.05	0.13	1.09	1.09	.71
	SD	2.40	0.07	0.33	0.36	.19
	Q1	1.81	0.09	0.87	0.83	.67
	Q3	3.82	0.16	1.28	1.32	.79
ENTC	*M*	2.56	0.16	1.08	1.07	.70
	SD	2.57	0.08	0.32	0.34	.11
	Q1	1.44	0.10	0.88	0.86	.65
	Q3	3.18	0.19	1.27	1.28	.76
APPR	*M*	2.63	0.16	1.13	1.14	.68
	SD	1.32	0.08	0.31	0.33	.22
	Q1	1.77	0.11	0.90	0.90	.65
	Q3	3.67	0.19	1.32	1.32	.78
TRPR	*M*	2.67	0.20	1.19	1.15	.78
	SD	1.51	0.10	0.42	0.42	.10
	Q1	1.89	0.14	0.84	0.80	.73

	Q3	3.23	0.25	1.46	1.39	.85
EVAL	*M*	0.77	0.11	1.06	1.06	.68
	SD	0.72	0.05	0.25	0.25	.10
	Q1	0.45	0.08	0.88	0.88	.64
	Q3	1.09	0.13	1.25	1.25	.73

Note. *M* = mean; *SD* = standard deviation; *Q1* = first quartile; *Q3* = third quartile.

Table 8

Separation Reliability of the Teacher Facet for Each Subscale

	SR	*G*	*H*	Fixed Effects (*p-value*)
VALR	.98	7.54	10.39	. 00
INTR	.98	7.53	10.38	. 00
RELP	1.00	16. 17	21.90	. 00
TRDF	1.00	5.16	7.21	. 00
CLOR	1.00	15.83	21.44	. 00
ENTC	1.00	14.51	19.68	. 00
APPR	.98	7.20	9.93	. 00
TRPR	.98	6.69	9.25	. 00
EVAL	.97	5.75	8.00	. 00

Note. *SR* = separation reliability; *G* = G-index; *H* = strata.

Table 9

Between-Course and Within-Course Variance of Teacher Measures

Subscale	sd_B	sd_W	sd_T	var_B	var_W	var_T	*PVBC*	*PVWC*
VALR	0.98	0.75	1.23	0.96	0.56	1.51	.63	.37
INTR	0.60	1.03	1.19	0.36	1.07	1.42	.25	.75
RELP	0.55	3.03	3.08	0.30	9.17	9.47	.03	.97
TRDF	0.66	0.73	0.98	0.43	0.53	0.97	.45	.55
CLOR	0.68	2.08	2.19	0.47	4.33	4.79	.10	.90
ENTC	0.71	2.35	2.46	0.50	5.53	6.03	.08	.92
APPR	0.77	1.18	1.41	0.59	1.39	1.99	.30	.70
TRPR	0.72	1.16	1.36	0.52	1.35	1.86	.28	.72
EVAL	0.46	0.59	0.74	0.21	0.34	0.55	.38	.62

Note. B = between-course component; *W* = within-course component; *T* = total variability. *sd* = standard deviation of teacher measure; *var* = variance of teacher measure; *PVBC* = proportion of variance between courses; *PVWC* = proportion of variance within courses.

Table 10

Descriptive Statistics for the Student Facet for Each Subscale

		Measure	S.E.	Infit	Outfit	r_{pm}
VALR	*M*	0.00	0.70	0.98	0.98	.26
	SD	2.53	0.33	0.75	0.76	.40
	Q1	-1.50	0.42	0.51	0.48	.00
	Q3	1.65	0.85	1.30	1.33	.57
INTR	*M*	0.00	0.62	0.99	0.99	.28
	SD	2.41	0.34	0.75	0.75	.38
	Q1	-1.39	0.36	0.46	0.45	.00
	Q3	1.49	0.72	1.40	1.42	.60
RELP	*M*	0.00	0.85	0.95	0.95	.27
	SD	3.41	0.52	0.76	0.80	.39
	Q1	-1.96	0.47	0.46	0.43	.00
	Q3	1.72	0.97	1.14	1.16	.63
TRDF	*M*	0.00	0.69	0.98	0.97	.26
	SD	2.29	0.31	0.78	0.78	.45
	Q1	-1.35	0.44	0.43	0.42	.00
	Q3	1.32	0.87	1.40	1.41	.63
CLOR	*M*	0.00	0.64	0.95	0.95	.19
	SD	2.98	0.43	0.73	0.75	.41
	Q1	-1.77	0.35	0.49	0.45	.00
	Q3	-0.06	0.57	0.91	0.88	.10
ENTC	*M*	0.00	0.72	0.97	0.96	.26
	SD	2.73	0.45	0.73	0.74	.41
	Q1	-1.60	0.40	0.47	0.46	.00
	Q3	1.38	0.81	1.27	1.28	.59
APPR	*M*	0.00	0.72	0.95	0.95	.23
	SD	2.65	0.37	0.78	0.79	.42
	Q1	-1.52	0.42	0.44	0.43	.00
	Q3	1.57	0.83	1.26	1.28	.56
TRPR	*M*	0.00	0.90	0.91	0.91	.12
	SD	3.42	0.40	0.98	0.99	.47
	Q1	-2.22	0.55	0.03	0.03	.00
	Q3	2.25	1.25	1.00	1.02	.44
EVAL	*M*	0.00	0.49	0.97	0.97	.31
	SD	1.88	0.29	0.69	0.69	.35
	Q1	-0.92	0.30	0.43	0.44	.00
	Q3	0.09	0.45	0.86	0.86	.34

Note. *M* = mean; *SD* = standard deviation; *Q1* = first quartile; *Q3* = third quartile.

Table 11

Separation Reliability for the Student Facet for Each Subscale

	SR	*G*	*H*	Fixed Effects (*p-value*)
VALR	.91	3.11	4.47	.00
INTR	.91	3.25	4.67	.00
RELP	.92	3.28	4.71	.00
TRDF	.92	2.88	4.17	.00
CLOR	.93	3.75	5.33	.00
ENTC	.90	3.08	4.44	.00
APPR	.91	3.12	4.50	.00
TRPR	.92	3.32	4.76	.00
EVAL	.91	3.14	4.52	.00

Note. *SR* = separation reliability; *G* = G-index; *H* = strata.

Table 12

Between-Course and Within-Course Variance in Student Measures

Subscale	sd_B	sd_W	sd_T	var_B	var_W	var_T	*PVBC*	*PVWC*
VALR	0.2	2.41	2.42	0.04	5.8	5.84	0.01	0.99
INTR	0.46	2.23	2.28	0.21	5	5.21	0.04	0.96
RELP	0.32	3.11	3.13	0.1	9.67	9.77	0.01	0.99
TRDF	0.54	2.14	2.21	0.29	4.57	4.86	0.06	0.94
CLOR	0.41	2.75	2.78	0.16	7.56	7.72	0.02	0.98
ENTC	0.47	2.44	2.49	0.22	5.96	6.18	0.04	0.96
APPR	0.65	2.43	2.51	0.43	5.89	6.32	0.07	0.93
TRPR	0.38	3.3	3.32	0.15	10.86	11.01	0.01	0.99
EVAL	0.34	1.77	1.8	0.12	3.12	3.23	0.04	0.96

Note. *B* = between-course component; *W* = within-course component; *T* = total variability. *sd* = standard deviation of student measure; *var* = variance of student measure; *PVBC* = proportion of variance between courses; *PVWC* = proportion of variance within courses.

Table 13

Analysis of Interactions Between Facets for Each Dimension

	*C*S*		*C*I*		*T*I*		*T*S*		*S*I*	
	Var. Exp. (%)	Effects Fixed (p-value)	Var. Exp. (%)	Effects Fixed (p-value)	Var. Exp. (%)	Effects Fixed (p-value)	Var. Exp. (%)	Effects Fixed (p-value)	Var. Exp. (%)	Effects Fixed (p-value)
VALR	9.86	.00	0.57	.00	0.86	.00	18.52	.00	11.29	1.00
INTR	10.37	.00	0.76	.00	1.22	.00	19.13	.00	12.29	1.00
RELP	11.46	.00	0.32	.00	0.65	.00	20.19	.00	7.69	1.00
TRDF	10.63	.00	1.16	.00	1.61	.00	17. 27	.00	13.42	1.00
CLOR	9.78	.00	0.14	.00	0.66	.00	17.77	.00	9.37	1.00
ENTC	10.50	.00	0.35	.00	1.27	.00	19.89	.00	10.84	1.00
APPR	12.63	.00	0.39	.00	0.67	.00	21.86	.00	9.82	1.00
TRPR	11.84	.00	0.12	.00	0.39	1.00	11.50	.00	16.62	.00
EVAL	7.19	.00	1.12	.00	1.53	.00	7.07	0.74	30. 36	1.00

Note. *C* = curso; *T* = docente; *S* = estudiante; *I* = ítem; * = interacción; *Var. Exp.* (%) = porcentaje de varianza explicado por la interacción.

Table 14

Outfit for Item Categories

Items	*OUTFIT1*	*OUTFIT2*	*OUTFIT3*	*OUTFIT4*	*OUTFIT5*
VALR1	*1.30*	*1.20*	*1.00*	*1.00*	*1.10*
VALR2	*0.70*	*1.00*	*0.80*	*0.90*	*1.00*
VALR3	*0.80*	*1.10*	*0.90*	*0.80*	*1.00*
VALR4	*0.90*	*1.10*	*1.00*	*1.00*	*1.10*
VALR5	*0.70*	*1.30*	*0.90*	*0.90*	*1.00*
INTR1	*0.90*	*1.40*	*0.90*	*0.90*	*1.00*
INTR2	*0.90*	*1.00*	*0.90*	*0.80*	*1.00*
INTR3	*0.80*	*1.00*	*0.90*	*0.80*	*1.00*
INTR4	*0.80*	*1.50*	*1.20*	*1.00*	*1.10*
INTR5	*0.90*	*1.10*	*0.90*	*0.90*	*1.00*
INTR6	*1.20*	*1.10*	*0.90*	*0.90*	*1.10*
RELP1	*1.10*	*1.10*	*1.00*	*1.00*	*1.00*
RELP2	*1.00*	*1.00*	*0.90*	*0.90*	*1.00*
RELP3	*0.70*	*0.90*	*0.90*	*0.80*	*1.00*
RELP4	*1.00*	*1.30*	*1.20*	*1.10*	*1.10*
RELP5	*0.80*	*1.00*	*0.90*	*0.80*	*1.00*
TRDF1	*1.20*	*1.00*	*0.90*	*1.10*	*1.10*
TRDF2	*0.90*	*0.90*	*0.80*	*0.90*	*1.00*
TRDF3	*1.10*	*1.10*	*0.90*	*1.00*	*1.00*
TRDF4	*1.00*	*1.00*	*0.90*	*0.90*	*1.10*
CLOR1	*1.10*	*1.30*	*0.90*	*0.90*	*1.00*
CLOR2	*0.90*	*1.20*	*0.90*	*0.90*	*1.00*
CLOR3	*0.70*	*1.10*	*1.00*	*0.90*	*1.00*
CLOR4	*1.00*	*1.20*	*0.90*	*0.90*	*1.00*
CLOR5	*0.90*	*1.20*	*0.90*	*0.90*	*1.00*
CLOR6	*1.00*	*1.20*	*0.90*	*0.90*	*1.00*
CLOR7	*1.00*	*1.20*	*1.10*	*0.90*	*1.00*
CLOR8	*1.10*	*1.10*	*1.00*	*0.90*	*1.00*
ENTC1	*1.00*	*1.10*	*0.80*	*0.80*	*0.90*
ENTC2	*0.90*	*1.10*	*0.90*	*0.80*	*0.90*
ENTC3	*0.80*	*1.40*	*1.00*	*1.00*	*1.00*
ENTC4	*1.20*	*1.50*	*1.10*	*1.00*	*1.00*
ENTC5	*0.90*	*1.10*	*0.90*	*0.90*	*1.00*
APPR1	*0.70*	*1.10*	*0.90*	*0.90*	*1.00*
APPR2	*0.60*	*1.10*	*1.00*	*1.00*	*1.00*

APPR3	*0.60*	*1.20*	*1.00*	*1.00*	*1.00*
APPR4	*0.60*	*1.00*	*0.90*	*0.90*	*1.00*
APPR5	*1.00*	*1.10*	*0.90*	*0.90*	*1.00*
TRPR1	*1.10*	*0.80*	*0.80*	*0.90*	*1.10*
TRPR2	*0.90*	*0.80*	*0.90*	*0.90*	*0.90*
TRPR3	*0.90*	*1.10*	*1.10*	*1.10*	*1.10*
TRPR4	*0.90*	*0.80*	*0.90*	*0.80*	*1.00*
EVAL1	*0.80*	*0.80*	*0.80*	*0.90*	*1.00*
EVAL2	*0.80*	*1.00*	*0.80*	*0.90*	*0.90*
EVAL3	*0.80*	*0.80*	*0.80*	*1.00*	*1.00*
EVAL4	*1.00*	*1.20*	*1.00*	*0.91*	*0.91*
EVAL5	*0.70*	*0.90*	*0.90*	*1.00*	*1.00*
EVAL6	*0.80*	*1.00*	*1.10*	*1.20*	*1.40*
EVAL7	*1.20*	*1.40*	*1.10*	*1.00*	*1.10*

Note. Outfit values for categories of ordinal items analyzed with a many-facet Rasch model are generally considered acceptable when they do not exceed 2 (Bond & Fox, 2007; Engelhard & Wind, 2017; Linacre, 2002).

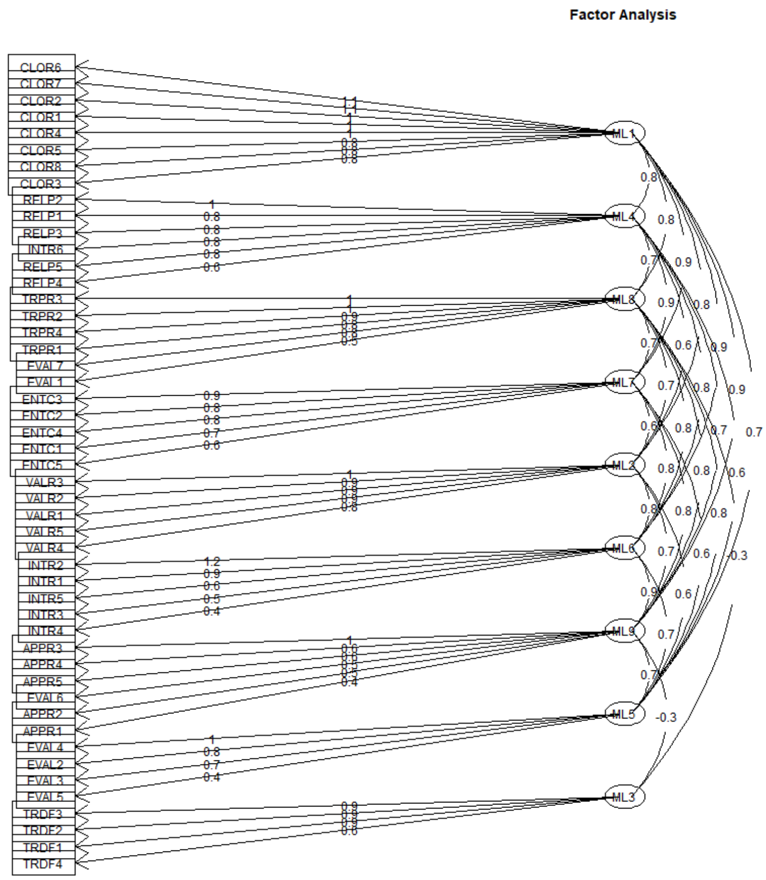

Figure 1.

Factor structure of the SET questionnaire (EFA)

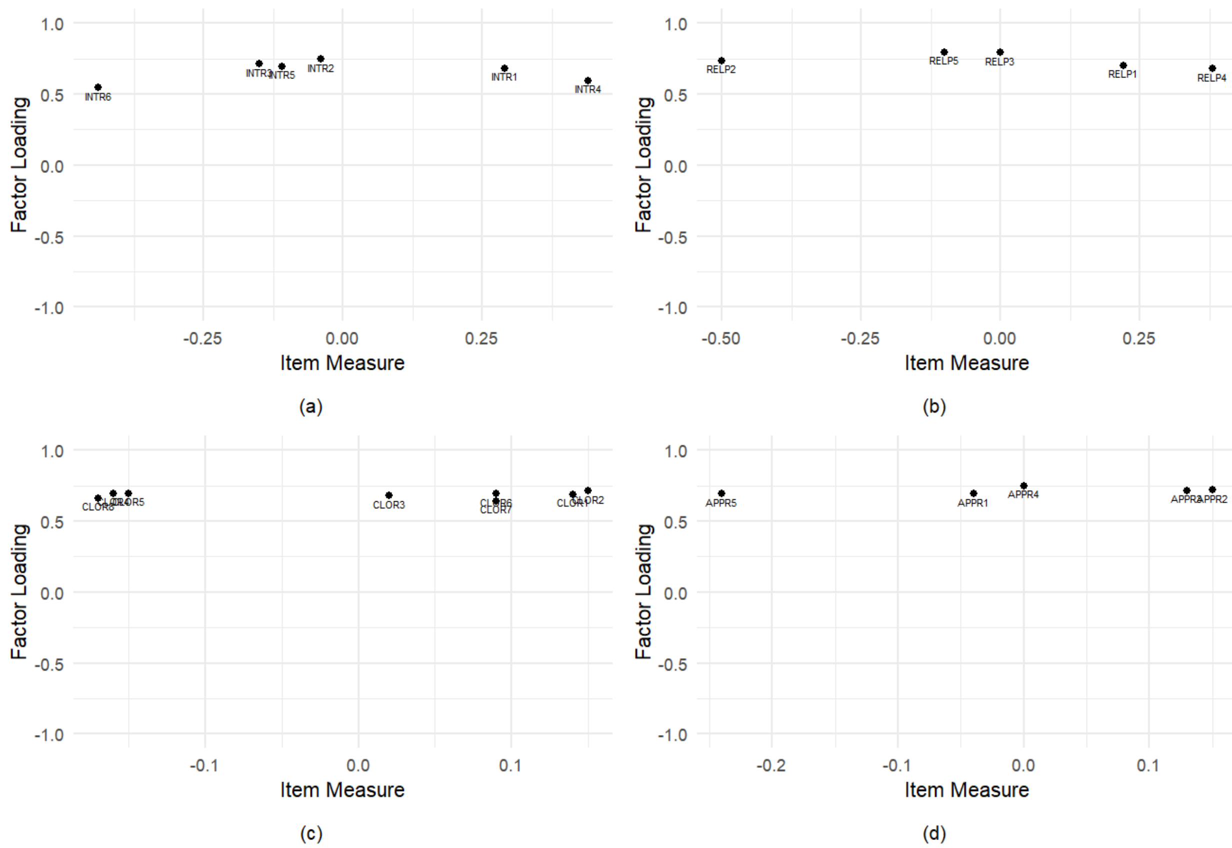

Figure 2

Item Measurement vs. First Contrast Weight

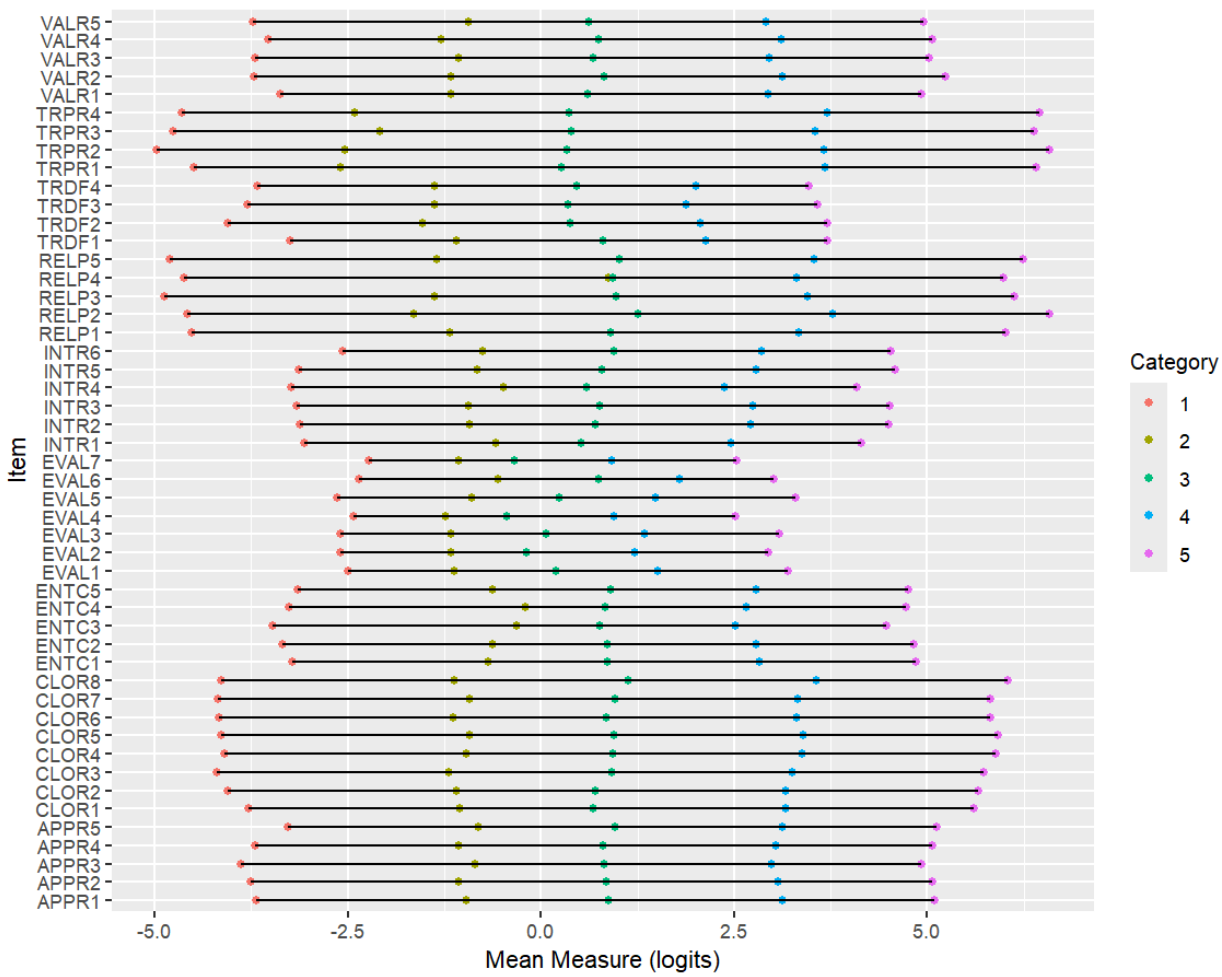

Figure 3

Average of measures for observations in each category.

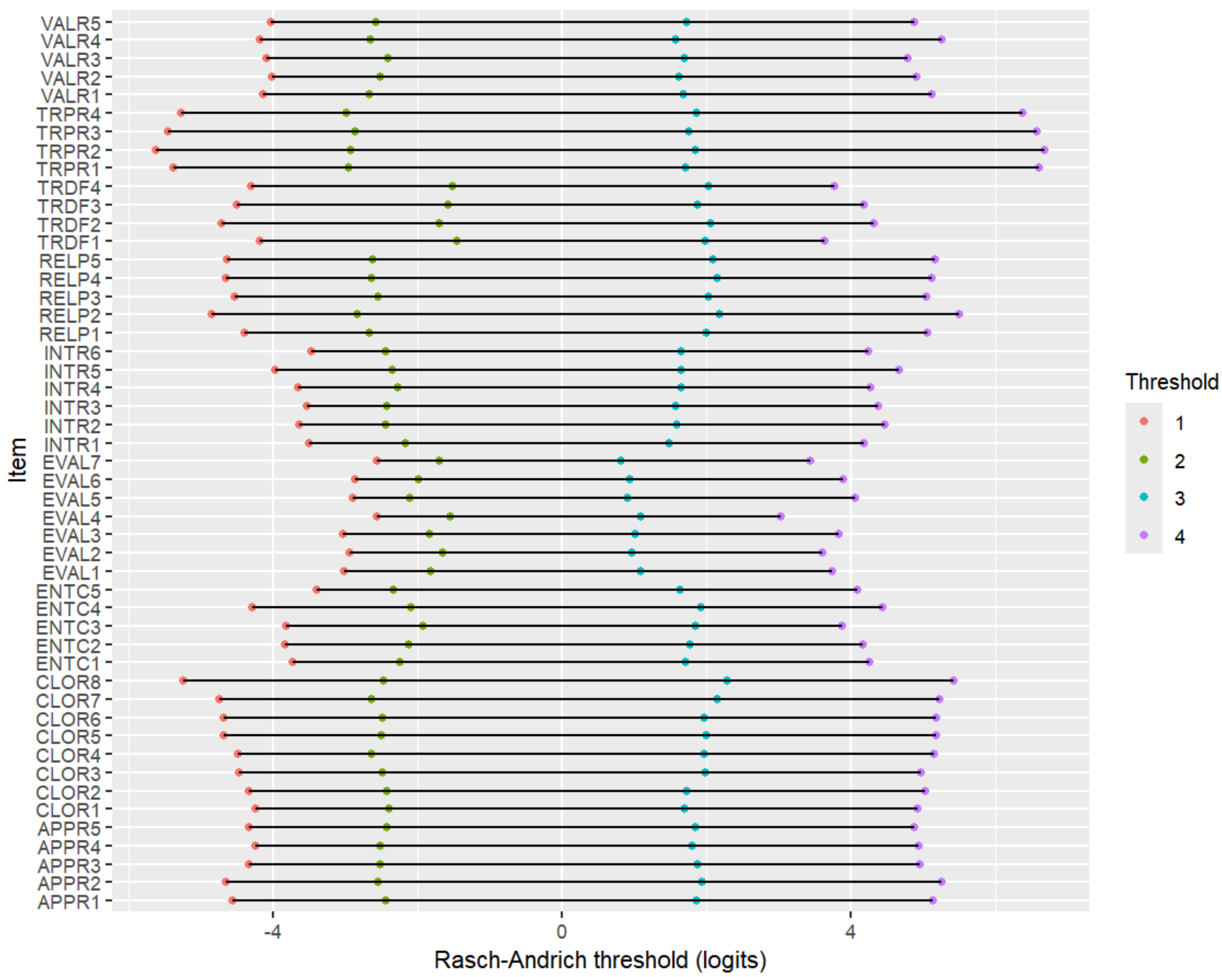

Figure 4

Item scale structure: Rasch-Andrich thresholds

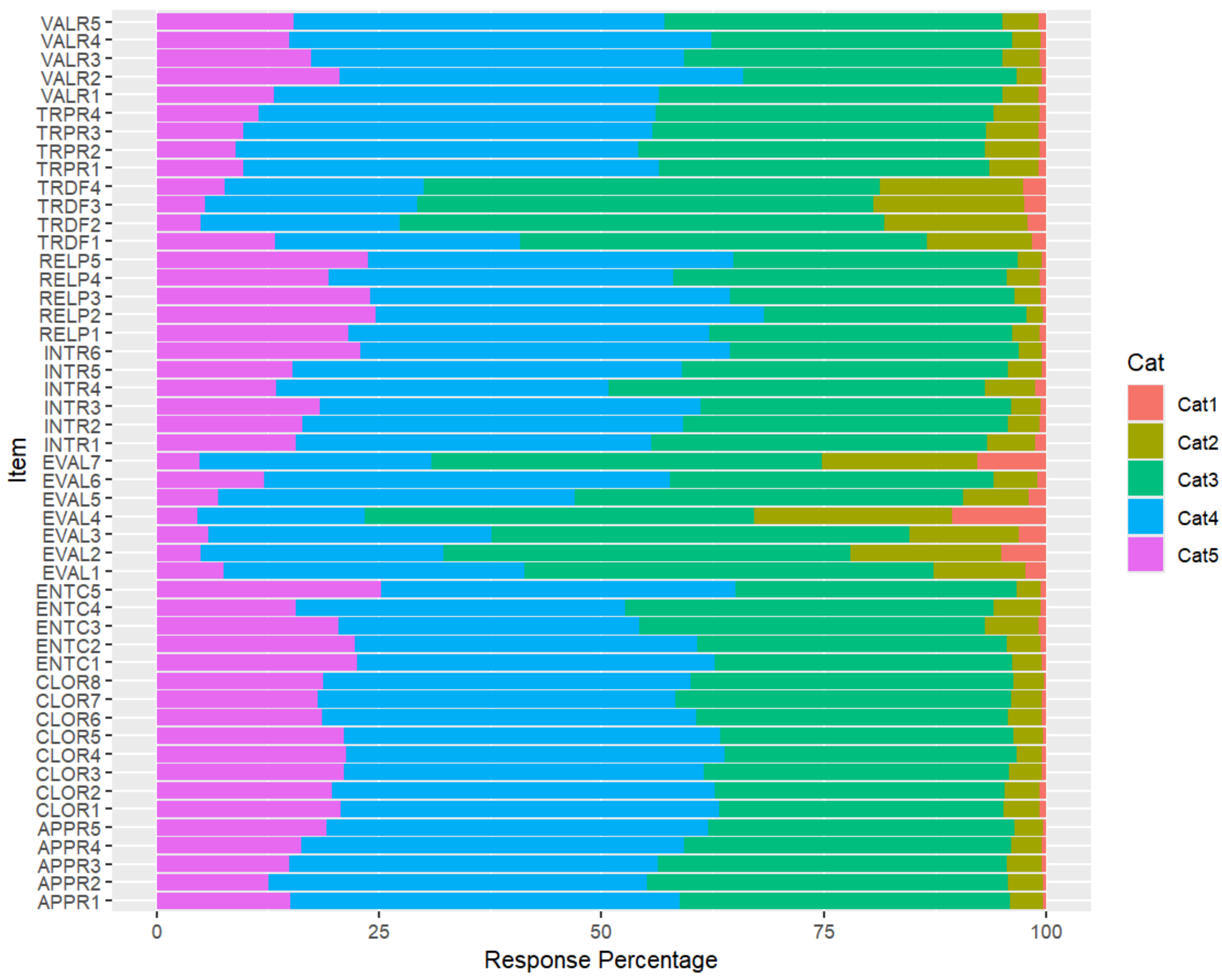

Figure 5
Frequency of use of categories for each item.