PRE-PRINT currently under review

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Disentangling objective characteristics of learning situations from subjective perceptions thereof, using an experience sampling method design

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Abstract

This article proposes a study design developed to disentangle the objective characteristics of a learning situation from individuals' subjective perceptions of that situation. The term 'objective characteristics' refers to the agreements across students, like when students agree that the lecture of Educational Psychology by teacher Cook this morning was objectively much more interesting than the lesson about Introduction to Scientific Writing by teacher Smith yesterday evening, because teacher Cook used funny examples and gamified quizzes that most students liked, whereas teacher Smith did not. The term 'subjective perceptions' refers to the possibility of inter-individual heterogeneity, meaning student Max might report higher situational interest than students Emma, Ben, and Anna in the lecture of teacher Cook this morning, despite the fact that the students agreed (on average) that this lecture was more interesting than the lecture by teacher Smith yesterday evening.

We describe a novel strategy for assessing and disentangling objective situation characteristics and subjective perceptions thereof, propose methods for analyzing the resulting data, and illustrate the procedure with an example of a first study using this design to examine situational interest in 155 university students. Situational interest was assessed nine times per weekly lecture with three measurement time points per person and a rotated multi-group schedule. Assessments took place over the course of an entire semester of ten weeks.

One of the advantages of the proposed design is that 'objective' group agreements can be disentangled from subjective deviations from the group's average at each of the nine measurement time points per weekly lecture. Furthermore, the proposed design makes it possible to study the development of both subjective and objective parameters across the time span of one weekly lecture and an entire semester, while the burden for each person is kept relatively low with three beeps per week.

Keywords: subjective self-reports, objective inter-rater agreement, experience sampling method, momentary motivation.

Disentangling objective characteristics of learning situations from subjective perceptions thereof, using an experience sampling method design

Imagine you attend a lecture that you love but that all your classmates seem to hate, dread, or find boring. You just love this lecture of Statistics and Research Methods, because of its exciting implications for epistemology and its answers to the question where knowledge comes from and how much we can(not) trust in what we know. You think this is one of the best, most interesting courses you have ever had, but your fellow students just don't seem to share your enthusiasm for the philosophy of science or mathematical representation of knowledge. While you express your love for this Statistics and Methods course, nearly everyone else would rather study "real Psychology" or sleep in instead of starting the day with the 8:30 am Statistics course. One of your classmates even called you a nerd. While you try to convince everyone that this course is *objectively interesting*, the other students try to convince you that this is an objectively uninteresting lecture, claiming that "if we all agree it's boring, it can't be *objectively interesting*". Your best friend agrees with the others on that, but, trying to put himself in your shoes, also acknowledges that you have *subjective reasons* to find that lecture interesting, while also trying to convey to you that your *subjective interest* just isn't everyone's cup of tea. You discuss to what extent the agreement, or average interest, of the class reflects the *objective* interestingness of that course.

The Dean, in turn, holds the teaching evaluation in hand when announcing the decision to discontinue your favorite course in the future, citing the average lack of interest of the attendants as evidence for the *objective lack of teaching quality*, because all other Psychology courses got higher student ratings in the questions asking about students' enthusiasm. You feel unheard and unseen, after all, aren't you a data point in that statistic the Dean holds in hand, too? Didn't your favorite Statistics teacher just yesterday teach you about the problem that sometimes individual

students or subgroups hide behind the overall trend, so that we need methods to detect and describe these subgroups and deviating individuals?

This article presents a novel approach to disentangle and describe both the overall trend in the agreement of a class on the ratings of a learning situation, and the deviations of individual, subjective, perceptions from that overall trend.

How to assess characteristics of learning situations

Situational self-report assessments of motivation and emotion are more and more frequently used, thanks to new technology that makes it easier and cheaper than ever to ask participants in real-time via mobile devices about their current activities and their subjective perceptions, feelings, motivations, pertaining to these currently ongoing activities. The methods used to gather such data are called Experience Sampling Method (ESM; e.g., Hektner, Schmidt, & Csikszentmihalyi, 2007), ambulatory assessments (e.g., Fahrenberg, 1996), or ecologically momentary assessments (Shiffman, Stone, & Hufford, 2008). In this article, we use the term ESM.

Compared to the ‘classic’ retrospective one-time administered self-report questions for motivation and emotions, ESM assessments have several advantages: A first advantage is that ESM assessments can capture the fluctuating and situation-specific components of motivation and emotions, while common retrospective, one-time administered self-reports do not reveal which aspects of the assessed variables fluctuate or remain stable from one situation to another. It is even possible to disentangle situational determinants (e.g., the exciting learning video used in today’s lecture) from stable personal factors (e.g., this student’s well-developed personal interest in the topic taught today or this students’ general openness to experience), or contextual factors (e.g., the generally monotonous teaching style of this teacher, or the loud noise in that classroom from the construction side next door, which has hampered the students’ attention and motivation

for a year now). To disentangle such situational, personal, and contextual influences, ESM assessments can be combined with multilevel data analysis that decompose the variance on the situational (within) level from the variance due to stable inter-individual differences (between level 1) and the variance between in contexts, such as class or school (between level 2; see e.g., Dietrich et al., 2017; Ketonen et al., 2018).

A second advantage is that situational measures have been discussed to be more valid than the retrospective self-reports, because in-the-moment assessments can reduce memory errors (e.g., Green et al., 2006; Takarangi et al., 2006) and response biases linked to beliefs and stereotypes that are otherwise activated in certain retrospective self-reports (e.g., Bieg et al., 2015; Goetz et al., 2013). While retrospective measures require participants to mentally aggregate their *typical* experience across all the situations they can remember, ESM data enable the researcher to empirically calculate such an aggregated typical experience as the mean score of the many repeated situational assessments for each person.

These advantages of ESM measures notwithstanding, they are still self-reports and therefore share many of the shortcomings related to self-reports with the retrospective measures. One of these shortcomings is the problem that ESM and other self-report measures capture only the subjective perception and rating of an experience, which do not necessarily reflect how other students would perceive the same situation. For example, if a student indicates a current interest of “4 – *very much*” on a four-point scale, the reasons for that choice of this response option remain unclear. Did this student choose this rating because he/she had a personal interest in this topic, while most other students were utterly bored? Or because this was the most captivating topic ever taught, and every student in the class was captivated and would agree? Or did the student just affirm being interested because of a very high individual level of trying to appear socially desirable? In classic ESM studies, it is very difficult to disentangle these different

options, because typically, students are asked about activities at random times, implying that every student has an own individual random survey schedule so that there is usually no way to determine how other students perceived the exact same situation.

To provide a solution for that problem, the present study presents a research design that enables researchers to systematically assess groups of students together, so that inter-individual agreements and subjective deviations from these agreements can be distinguished.

The previous literature provides some examples of theories that distinguish between the subjective and objective components of information provided by self-reports in education (e.g., Göllner et al., 2018; Lüdke et al., 2009). One such example is the research on interest, particularly the person-object theory of interest (Fink, 1991; Krapp, 2002; Krapp & Fink, 1992; Prenzel, Krapp, & Schiefele, 1986), which distinguishes between objective characteristics of a learning situation and the individual's subjective perceptions thereof, as well as distinguishing between fluctuating situational and stable personal determinants of the subjective perceptions. As the name person-object theory suggests, interest is expected to result from two main conditional factors, person characteristics and situation characteristics (Krapp, 1998). According to this theory, interest emerges in the interaction of a person with particular objects (including concrete objects such as texts, and more abstract ideas, events, topics, texts, etc.). Objects are expected to differ in their likelihood of eliciting situational interest in individuals, depending on their verifiable, observable features. For instance, learning materials are more likely to trigger situational interest if their objective features make them surprising, novel, visually stimulating, and intense for the students. Texts are likely to trigger situational interest if they are, for instance, easy to comprehend, cohesive, vivid, if they evoke emotional reactions, and allow for collaborations with others (for overviews, see e.g., Krapp et al., 1992; Krapp, Hidi, and Renniger, 1992).

The (objective) interestingness of a situation is then perceived by individuals who differ in their stable, dispositional personal interests (Krapp, Hidi, and Renniger, 1992) and their perceptions of the situation (a given information about the theory of relativity might be new to most students in a class, except for Max, who has heard about the topic extensively over dinner from his mother, who is a Quantum Physics professor). The individuals then feel more or less interested in the current learning situation, depending on their previous dispositional interest in the currently discussed topic (person characteristic) and the learning situations' objective characteristics. Thus, a fluctuating psychological state of more or less situational interest can be observed, which is either an expression of the currently actualized dispositional interest, or the fluctuating reaction to the objectively interesting situation, or a mixture of both (e.g, Krapp, 1998).

Figure 1. A model of the person-object theory of interest, with the added distinction between objective situation characteristics and subjective perceptions thereof (for the original model, see Krapp, 1998).

We expect that such models of person-object interactions will be fruitful not only for the understanding of interest, but also for the understanding of other motivational constructs, cognitions, and behaviors.

The present research

This article has three main goals: First, we introduce a novel design for ESM studies that enable researchers to disentangle the objective characteristics of a situation (e.g., the situation's interestingness, in terms of the inter-subjective agreement of all students) from each person's subjective perception of that situation (e.g., the subjective interest and deviation from the aforementioned inter-subjective agreement). Second, we propose different analytical strategies to analyze data assessed with this novel design and illustrate some of these proposed analyses using data from a first study that has used this novel assessment design to assess situational motivation in 155 university teacher students. Third, we discuss a number of possible additional strategies of contrasting the situational self-reports of ESM assessments with more objective data, such as behavioral classroom observations or psychophysiological measures of emotion-related data.

This is a theoretical article with the main goal to propose a new assessment design, and to discuss its advantages as well as limitations. Therefore, our research questions refer to theoretical and methodological rationales, while the empirical results presented in this article merely serve as illustration and example for the methodological discussion, rather than being a centerpiece. Thus, the topic examined in the empirical part (students' situational interest in higher education) is

treated as a rather exchangeable example of a construct which to examine the here proposed method could help.

Research questions

RQ1: What concepts of objectivity can be applied to disentangle objective characteristics of situations from participants' subjective perceptions thereof?

RQ2: How do ESM research designs and schedules have to look like in order to capture both the objective situation characteristics and the subjective perceptions thereof?

RQ3: What analyses are needed to disentangle the objective situation characteristics and the subjective perceptions thereof in data collected with a design proposed under RQ2?

The research questions are mostly answered theoretically, but with references to an empirical study that will serve as an illustrating example for the proposed methods. This example study is described in the following.

2. Methods

2.1 Sample and procedure

The participants were 155 German university students, 51% of which were female. The mean age was $M = 21.77$ years ($SD = 2.91$; range: 19 to 46 years). The participants studied in a teacher education program with the aim to become subject teachers for secondary schools. The subject of the lecture was 'Psychological fundamentals of learning'.

Students provided intensive longitudinal data in the form of experience sampling surveys and were followed over one semester in a weekly lecture with 90-minute lessons. In each of ten consecutive weeks, students received notifications and questionnaires at fixed schedules, three times during each lesson, consisting of ten situational motivation items. The participants chose whether to respond online with their own smartphone or on paper-and-pencil questionnaires

(smartphone: 58–71% participants with a mean of 65% across the ten lessons; paper-and-pencil: 29–42% participants with a mean of 35%).

Overall, 155 students provided valid information on situational measures in at least one lesson. During the data cleaning, we removed responses in the following cases: if the response was given more than 15 minutes after the signal; if a person reported being present at the lecture but responded online after the lecture had ended; if a person responded to the three surveys immediately after another; and if a person responded with the same value on all ten items. This resulted in the omission of 251 surveys. A total of 2,221 valid responses could be used in the analyses, which equals 48% of the possible responses (three responses per lesson by ten lessons by 155 participants resulting in 4,650 responses).

The theoretical framework for the data collection originally was Eccles' expectancy-value theory (Eccles et al., 1983), according to which expectancies and values regarding a task are central motivational forces in students' academic behaviors and learning (Eccles et al., 1983; Eccles & Wigfield, 2002). They predict academic choices, persistence, and achievement (e.g., Battle & Wigfield, 2003; Cole et al., 2008; Durik et al., 2006; Liem et al., 2008). The dataset was also used in previous studies (Dietrich et al., 2017 and Dietrich et al., forthcoming). These previous studies examined associations of situational expectancies and task values with effort (Dietrich et al., 2017), and situational expectancy-value profiles (Dietrich et al., forthcoming). None of these previous papers analyzed the cross-classified data structure in this dataset.

2.2 Measures

The ESM assessment captured situational task values and expectancies with eight items (see Dietrich et al., 2017 or <https://osf.io/qjkmz/>). Additionally, situational interest and situational effort were assessed with one item each. The students were instructed to consider the lecture contents of the past couple of minutes and to complete the questionnaire within nine minutes.

They were asked “To what extent do the following statements apply to you in the present moment?” and responded on a 4-point Likert scale ranging from 1 = *does not apply* to 4 = *fully applies*.

In the present article, we constructed a scale, labeled ‘*situational interest*’ from two items measuring situational interest (“I am interested in these contents”) and situational intrinsic value (“I like these contents”). While most ESM studies assess constructs with single items to keep the burden on the participants as low as possible, we opted to assess each construct with multiple items (see Dietrich et al., 2017 or <https://osf.io/qjkmz/>), based on the idea that the shared variance of multiple indicators is a more reliable indicator of an underlying construct than a single item can be. It could be argued that this approach of using scales instead of single items in itself is a contribution to making ESM assessments more objective, as it reduces the risk of confounding a construct of interest with the random and unique influences (unique variance) that a single item captures apart from the construct it is supposed to represent (e.g., a momentary slip in attention causing the respondent to click on a wrong response option, or a idiosyncratic misunderstanding by a given participant of a given item in a given situation). In a cross-classified multilevel model with responses (within level, $n = 2,221$) nested in both individuals (between-individual level, $n = 155$) and time points (between-time point level, $n = 90$), the correlations between the two items of the *situational interest* scale were $r = .62$ at the within level, $r = .92$ at the between-individual level, and $r = .99$ at the between-time point level.

3. Results and discussion

3.1 Which concepts of “objectivity” should be applied to disentangle objective characteristics of situations from participants’ subjective perceptions thereof? (RQ1)

When using the term *objectivity*, we assume that there are true characteristics of an object (in this study, a learning situation) that influence individual’s subjective responses in a somewhat

systematic way that causes at least partial agreements in the subjective responses of multiple individuals. Skipping the important and millennia-long philosophical discussions about whether or not there is a truth and how to define and understand it (for a summary, see e.g., Glanzberg, 2018), we pragmatically define objectivity here as the (approximate) agreement of all observers about the characteristics of an object, with the object here meaning the learning situation. This applied concept of objectivity is based on Popper's claim that "the objectivity of scientific statements lies in the fact that they can be inter-subjectively tested" (1934 [2002], p. 22). While Popper refers to scientific statements rather than laymen's implicit concepts, his idea of objectivity as inter-subjective agreement has been extended: Douglas (2011) has named this applied concept of objectivity the 'concordant objectivity' and defines it as the "simple agreement among multiple observers" (Douglas, 2011, p. 32). This idea of objectivity as the inter-subjective agreement about the truth of an object is reflected in classical test theory, which typically consider assessments to be objective to the degree that all trained assessors come to the same conclusion about an assessed construct in a given individual or population. It is also reflected in the practice of treating a classes' mean score of averaged individual student responses about perceived teaching quality as a proxy for the objective teaching quality in that classroom (see e.g., Göllner, 2018; Lütke et al., 2009). It is important to keep in mind that this is a rather minimalistic concept of objectivity and many more have been discussed for the social sciences, including education (e.g., Eisner, 1992; Fisher, 2000).

How can self-reports ever be objective in the sense of concordant objectivity, given that the construct to be assessed (e.g., an emotion) is typically experienced only by the individual who experiences it, which also is the reason why we ask participants to report us their feelings in self-reports? While it is controversially discussed to what degree it is possible to objectively determine how exactly a person feels without relying on this person's subjective self-report (e.g.,

Barrett, 2018), it is arguably possible and useful to assess the characteristics of a situation that are related to the emotional experiences. For example, since previous research on situational interest suggests that it is largely triggered by objective situation characteristics, such as novel and surprising information being presented, we can agree that multiple individuals agree partially in their situational interest in one learning situation, as long as the information presented to them is equally novel and surprising to each of these individuals.

One possibility of deriving information about objective characteristics of a situation from subjective self-reports is to aggregate multiple reports by different individuals about the same situation. In that sense, the “objective” assessment of, e.g., a situation’s interestingness, would be the agreement of a large enough number of randomly selected individuals about the interest they felt in that situation. In this scenario, we would expect that the group of students tends to report higher situational interest in learning situations presenting students with novel and surprising stimuli, compared to learning situations presenting students with known, unsurprising, and otherwise comparable stimuli. The group average (inter-subjective agreement) of reported interest in a given situation would thus be an indicator of the objective characteristics (“interestingness”) of that situation.

A limitation of the here-applied definition of objectivity is that the group’s mean score in a situation may be sample specific. If we select only the most interested individuals, then their mean interest in a given situation may be high, not because of the situation being novel and surprising, but because of the generally high interest of the group across all situations. Thus, the group mean score in a given situation may reflect the possible interactions between the groups’ person characteristics and situation characteristics, rather than indicating the objective situation characteristics alone.

3.2 How does an ESM assessment have to look like for it to capture both the objective situation characteristics and the subjective perceptions thereof? (RQ2)

With the aforementioned definition of objective assessments of situational characteristics through inter-subjective agreements across individual subjective self-reports, we need momentary assessments from multiple individuals in the same situation to aggregate these multiple self-reports to a situation-specific group mean score.

What exactly the term *same situation* means depends on the research question of a given study. For instance, the objective interestingness of a learning situation can be assessed by asking all the students in the same class in the same instant about their current interest in that moment and then aggregating across these individual responses. If, however, students learn remotely and self-paced with digital learning platforms, then a *situation* in terms of the research question could either be a certain time point (e.g., Tuesdays afternoon, or 24 hours before the final exam), or it could be the individual time point at which each student finishes a given task that is relevant to the research question, or another condition with relevance to the understanding of a digital learning moment. In this article, we use the term *situation* synonymously with a given time point in a given lecture hall in which all students see and hear the same university lecturer talking in the front of the room and are asked at the same time point about their momentary motivation, as described in Dietrich et al. (2017).

In order to assess multiple individuals in the same situation, we need to modify the common design of individually randomly timed survey notifications used in many ESM data collections. For our purpose, we need to assess a large enough group of students at the same time, whereas the common ESM schedules typically assesses each student at their own individual random times in order to capture a true random sample of all the experiences that students make during a relevant unit of time, like a school day (e.g., Hektner et al., 2007). If we deviate from

such truly random and individual schedules in order to examine students' inter-subjective agreements in one given situation, then the so-collected data may not be a representative sample of everyday life activities.

However, there are many research questions that do not require a representative sample of all everyday life activities. For example, research questions referring to specific school subjects, or specific teachers, or specific lectures, require these contexts to be oversampled and particularly targeted to ensure a large enough sample of situational assessments in that chosen context. One challenge in the use of not randomly timed ESM surveys is the risk of systematic context-specific biases in the assessments: The smaller the range of assessed time points or situations, the larger the likelihood of nonrandom influences. For example, in a truly randomly timed ESM study, we would not expect the results to be influenced by the time of the day, or the students' distractedness during the last minutes of a class when everyone already packs their things to jump up at the first ring of the school bell, or other influences that are particular to a certain timing, because these influences are expected to cancel out.

In contrast, if we decide to assess students only in the last five minutes in each class, for instance because of teachers concerned about interruptions and a no-phone policy during lessons, then we cannot rule out that the timing might have biased the responses in a way that a random survey schedule would not have. In order to reduce the risk of contextual biases in the assessments of multiple participants in the same instants, we need to make sure that at least there are no biases concerning the timing of surveys. That means that whatever the time span relevant to the study, no participants should be surveyed only at the beginning or only at the end of that time span. Instead, surveys should be distributed equally across these time spans for all participants.

For that purpose, we have developed an assessment design described below for the study of momentary study motivation in a 90-minute university lecture across an entire semester. The 90-minute lecture is split into nine periods of nine minutes each (not ten minutes, because the participants need at least one minute to answer to the last survey in the lecture and would miss that last notification if it occurred when the end-of-lecture-noise and hectic has already started). To make sure that we have data detailing the motivation across the entire lecture, we assess participants after the first ten minutes, after 19 minutes, after 28 minutes, and so on. We start the first assessment after ten instead of nine minutes, because in the first few minutes, some time tends to get lost on welcoming and waiting for students to calm down. To keep the burden on each individual participant low, each participant is only surveyed three times during the lecture, with a time gap of 27 minutes between each assessment. To assess multiple participants at the same time while still pursuing the aforementioned goals (data across the entire lecture, no participant surveyed more than three times), participants are surveyed in groups, with group A being surveyed after the first 10 minutes, Group B being surveyed 19 minutes into the lecture, Group C being surveyed 28 minutes into the lecture, and then Group A again being surveyed 37 minutes into the lecture, and so on. The same design is then repeated one week later in the same lecture, but with the difference that Group B starts the assessments 10 minutes into the lecture, in order to rotate the survey times across all groups, times, and weeks.

<i>Week 1 (lecture session 1)</i>								
<i>10 min</i>	<i>19 min</i>	<i>28 min</i>	<i>37 min</i>	<i>46 min</i>	<i>55 min</i>	<i>64 min</i>	<i>73 min</i>	<i>82 min</i>
Group A			Group A			Group A		
	Group B			Group B			Group B	
		Group C			Group C			Group C
<i>Week 2 (lecture session 2)</i>								
<i>10 min</i>	<i>19 min</i>	<i>28 min</i>	<i>37 min</i>	<i>46 min</i>	<i>55 min</i>	<i>64 min</i>	<i>73 min</i>	<i>82 min</i>
Group B			Group B			Group B		
	Group C			Group C			Group C	
		Group A			Group A			Group A
<i>Week 3 (lecture session 1)</i>								
<i>10 min</i>	<i>19 min</i>	<i>28 min</i>	<i>37 min</i>	<i>46 min</i>	<i>55 min</i>	<i>64 min</i>	<i>73 min</i>	<i>82 min</i>
Group C			Group C			Group C		
	Group A			Group A			Group A	
		Group B			Group B			Group B

Figure 2. Example signaling schedule in lecture 1, 2, and 3 (to be rotated in following lectures)

3.3 Which analyses are needed to disentangle the objective situation characteristics and the subjective perceptions thereof in data collected with the design proposed above? (RQ3)

3.3.1 Analytical strategy 1: Visualizing the inter-personal agreement (“objective parameter”) and the subjective deviation from that agreement (“subjective parameter”): Jittered violin plots

To start the analyses of the data gathered with the assessment design proposed above, it is recommendable to get an overview of the distribution of the responses at each measurement time point. To explore how much participants agree or individually deviate from the average rating of the interestingness of a learning situation, we suggest examining the inter-individual distribution of interest ratings for every beep in a given lecture with a jittered violin plot. Figure 2 shows an example of such a plot.

Figure 3. Inter-individual distributions of situational interest for each beep across the ten lessons, visualized in a jittered violin plot

The jittered violin plot shows the inter-individual mean score (grey dot), the standard deviation (distance between the grey dot and one end of the grey line), and the inter-individual distribution of interest ratings (black dots) for each measurement time point / ‘beep’ in each lecture. The belly of the violin is proportional to the number of individuals who agreed on a rating, with a thick belly meaning that many participants chose this value in their rating of interest. Since many observations (dots) would have overlapped on the interest values of 2, 3, and 4, we used the option to *jitter* the dots, which “adds a small amount of random variation on the location of each point” (Wickham et al., n.d.; Wickham, 2016) to prevent overlap and display the number of the individual observations for each value.

In the example in Figure 3, the violin plots suggest that there is much agreement among the participants, indicated by the fact that in most violins / moments, the largest group of participants is grouped around the mean score, visualized by the fact that most violin plots have only one instead of multiple round bellies. We can conclude that there seems to be some mechanism that leads a large group of participants to agree on one value, even though everyone answers for himself. We assume that the reason for this agreement is that there are objective characteristics of the learning situation that are perceived similarly by the present students, and that the present students also share a rather similar frame of reference determining how they understand and use the response scale and how they compare their current interest in a given situation to all other possible situations coming to their mind. The agreement thus reflects not only assumed objective situation characteristics, but also characteristics of the measure that participants agree on.

The visual inspection of the violin plots indicates whether the assessed group of students tends to agree, as indicated by violin plots with one clearly distinguished belly (e.g., Figure 3, lesson 1, 10 minutes), or if the responses are randomly distributed across the possible range of

values without any particular group agreement, indicated by a flat plot without any belly (e.g., Figure 3, lesson 3, 46 minutes), or if there are two or more distinct groups each of which agree on their own particular score, indicated by a violin plot with multiple bellies (e.g., Figure 3, lesson 4, 55 minutes). The latter case of a mixed distribution can additionally be examined with statistical tests that tell whether the distribution is unimodal, bi- or multimodal, such as Hartigan's dip test statistic for unimodality versus multimodality (Hartigan & Hartigan, 1985), which can be performed with the R package *dipTest* (Maechler, 2016) or the bootstrapping procedure determining the number of modes described in Efron & Tibshirani (1993), which uses the R package *bootstrap* (Tibshirani & Leisch, 2019). It should be noted that the concept of concordant objectivity applied in this article requires the existence of a unimodal distribution, meaning a high concentration of responses closely around the mean score. If the distribution is bi- or multimodal, then there is no reason to assume that the responses reflect one intersubjective objectivity, and no reason to claim that the inter-individual mean score was an indicator of such concordant objectivity. Whether or not responses reflect intersubjectively objectifiable information likely depends on the construct and needs to be determined with the above-mentioned strategies (number of bellies in violin plots and tests for uni- versus multimodality).

As Figure 3 shows, the distribution and uni- versus multimodality can also differ from moment to moment, not only from construct to construct. Furthermore, Göllner et al. (2018) have also pointed out that the individual's deviation from the group's mean score does not have to be due to individual rater tendencies or biases, but may represent meaningful information about dyadic experiences. Using the example of teaching quality, the authors argue that different students can make different experiences with the same teacher, so that their deviation from the group mean score may reflect such observable differences in different dyadic experiences. This suggests that not only the group average can serve as an indicator of objective situation characteristics, it is

furthermore possible that individual students make experiences that other students don't make, but that other students still would rate the same way if they experienced the same.

3.3.2 Analytical strategy 2: Parameters for the deviation of a subjective rating from the “objective” group rating: Cross-classified multilevel analyses

After getting a visual impression of the degree of inter-rater agreement on the interestingness of a situation, we might want to calculate parameters quantifying the degree of inter-rater agreement and the degree to which each person at each measurement time point deviates from the group average. In particular, we want to get estimates for (1) the individual and time point-specific deviation from (2) the stable person-specific mean over time, and from the (3) the inter-individual group mean which may differ from situation to situation (i.e. from time point to time point). While component three represents the ‘objective’ situation characteristic in terms of the characterization the participants can agree on (the average rating of that situation), component one represents the subjective situation-specific deviation from that objective rating, i.e., the subjective element. We would like both components to be controlled for component two, which represents the stable individual deviation from both the objective situation characteristic and the momentary subjective component due to stable response tendencies of that person (e.g., traits).

Such variance decomposition can be done with a cross-classified multilevel analysis (e.g., Beretvas, 2010). This type of statistical model separates the total variance of the scores Y_{it} (the scores of the different individuals i at the different time points t) in the three aforementioned components:

$$\begin{aligned}
 Y_{it} = & Y1_{i,t} \text{ (component one, within time point and within individual)} \\
 & + Y2_i \text{ (component two, between individuals)} \\
 & + Y3_t \text{ (component three, between time points)}
 \end{aligned}$$

The cross-classified multilevel model has the advantage that it allows disentangling the person- and situation-specific deviation ('subjective state component') from the group average ('objective state component'), while accounting for each person's stable tendency to deviate systematically from other individuals across all measurement time points ('trait component').

Instead of the more common structure of ESM data, with situations nested only in individuals due to the randomness of the time points, the here proposed assessment design results in time points nested in both individuals (Y_{2i}), and the groups A, B, and C with their respective measurement times (Y_{3t}). Time points are crossed with individuals, because each individual appears only once within each measurement time point. To get reliable estimates about the variance components $Y_{1i,t}$, Y_{2i} , and Y_{3t} , sufficiently big samples of individuals and time points are needed (around $n = 50$ on each of these levels; Chung, Kim, Park, & Jean, 2018). The present study design comprises of $n = 155$ individuals and $n = 90$ time points.

We computed the above-described model to separate the total variance [$\text{var}(Y_{it}) = .385$] into the three variance components. The biggest portion of the variance pertained to the subjective deviation from both the situational group average and the stable person-specific trait component. This individual, situation-specific component one showed a variance of $\text{var}(Y_{1i,t}) = .252$, which equals 65% of the total variance. Second, stable inter-individual differences [traits; component two] accounted for 31% of the variance: $\text{var}(Y_{3i}) = .120$, which means that about one third of the variance is due to stable person-specific response tendencies that differ between individuals. Finally, the variance of the 'objective' component three was considerably smaller: $\text{var}(Y_{2t}) = .031$, 8% of the total variance. That means in other words that only a small amount of variance is due to changes in the situation-specific group mean score from one moment to another.

3.4 Summary

This study suggested a novel research design that allows disentangling the subjective characteristics of a situation from participants' individual momentary subjective deviations from those objective situation characteristics. This novel approach allows disentangling the objective interestingness of a situation from a participant's subjective interest in that moment.

The key of this assessment design is the simultaneous assessment of multiple participants in the same situation / time point, which enables researchers to examine to what degree individuals agree on their ratings of a given construct in that given situation, and to what degree individual participants deviate from that group agreement. We proposed several methods to analyze data assessed with this design and to further examine the role of objective versus subjective components, including jittered violin plots displaying the distribution, means and standard deviations of each measure for each measurement time point, and cross-classified time series.

3.5 Practical implications

A groundbreaking advantage of the here proposed assessment design is the fact that it makes feedback to teachers about the *objective* situation characteristics possible. The group agreement indicating the objective interestingness of a situation for example enables teachers to compare their current teaching topics and strategies in terms of how they make their class feel. In common momentary assessments in classes, students are typically asked at random time points, implying that for each assessed situation, there is typically only one answer for one individual student. Imagine you were a teacher wanting to know how your new teaching strategy came across to the students, and the researcher tells you: "See, at this time point, ten minutes into your lecture, you introduced the theory of evolution, and Mary reported high boredom and low interest". Would you, as the teacher, conclude that the new teaching strategy failed to raise the students' interests, or would you rather hypothesize about this one student's idiosyncratic reasons

for not being interested, or remain clueless as to how to interpret this feedback? With the approach of asking multiple students at the same time suggested in this article, it now becomes possible to tell teachers: “See, at this time point, ten minutes into your lecture, you introduced the theory of evolution, and the average interest reported by your students was high, even though a single student, Mary reported high boredom and low interest”. This feedback enables teachers to evaluate the average and the individual perception of their teaching strategies by their students, which we hope will become an important tool for immediate feedback in learning settings. Obviously, collaborations between researchers, and/or software developers and teachers are needed to realize this possibility, unless the researcher and the teacher is the same person (as in the here presented study on motivation in university lectures). The here presented methodological groundwork needed is only the first step in that direction. A next step would require collaborations in which researchers use these methods to identify students’ individual needs as well as momentary classroom levels of motivation and emotions. Systematic collaborations of researchers and teachers are needed to provide teachers with the suitable emotion and motivation measures and assessments, and to provide researchers with the real-time data out of real school classrooms. Technology experts are needed for the further development of feasible feedback systems that show the collected data in comprehensible form and real time to students, teachers, and parents. Science communication and more research are needed to find out which form of feedback about the assessed motivation and emotions would be most helpful to students, teachers, and parents.

3.6 Theoretical implications

The combination of the approaches proposed in this article has much potential for the research on motivational heterogeneity of students. The intensive longitudinal data allow for the intra-individual examination of short-term developments (from one measurement time point in a

given lecture to the next) and intra-individual long-term development of motivation or emotions (from week one to week ten). The jittered violin plots can be used to identify particular students as much as they can be used to detect overall trends, like an increase or decrease in the average inter-individual interest from one moment in the lecture to the next.

While common experience sampling method approaches provided no information about a students' deviation from the simultaneously present peer group, the here proposed approach can be used to identify, within any given learning situation, those students who score substantially below the benchmark of interest typical for the simultaneously present peer group. This information potentially makes assessments of learning-related emotions and motivation at the same time more person-specific and more situation-specific. Instead of classifying students as generally less interested than their peers (which a classic ESM approach can do by examining the person-level mean score), our approach enables researchers or educators to say: "Although Mary has a tendency of being less interested than her peers in Math lessons, you really caught her interest with your most recent novel teaching strategy, which brought Mary's interest even above the level of her peers, as you can see in the last two violin plots (where Mary can be marked as a yellow star among the black dots representing her peers)". Thus, we expect that the approach proposed here will make a contribution to personalized learning and tailored interventions for individual students at the exact times when they are in need of motivational and emotional support. Common experience sampling approaches seem less useful for these purposes, because they leave open whether a given measurement score reflects the individual's subjective interest or the situations' objective interestingness, or, if both, which of those components to what degree.

3.7 Limitations of the rotated survey design proposed in this article

One limitation of the design suggested in this article is the fact that the results inherit the problems linked to self-report data, including the fact that self-reports are always to a certain

degree idiosyncratic, even when they are averaged or when group agreements are disentangled as a separate source of variance. This implies for example that the group mean score, which we described as the indicator of the objective situation characteristics (e.g., the objective interestingness of a situation) can be sample specific. Imagine if we selected only the most interested individuals for some reason, then their group mean score (objective component) in a given situation will be high, not because the situation is objectively highly interesting but because we only asked the highly interested individuals. Therefore, the objective component of the situational assessments is only objective to the degree to which it can be generalized from the observed sample to a larger population, which is a question for replication studies to examine. If all or many participants in a sample are influenced by similar biases, their agreement (the group average in a given situation) will reflect this joint bias rather than an objective situation characteristic. These are limitations to our definition of objectivity that need to be kept in mind.

Another limitation is the possible diversity of different activities that students who are present in one classroom might be engaged in. For example, in a class taught with a personalized learning approach, different students might be working on different tasks with different instructions. In some personalized learning settings, students in one classroom wear hearing protection to concentrate and receive their individual tasks on technological devices (e.g., tablets) contingent on their prior tasks completed, achievements, and goals. In such settings, it seems unreasonable to assume that the agreement of all raters on, e.g., their current interest, would reflect the objective interestingness of the learning moment, since it is likely that different students were thinking about different tasks when answering.

A third limitation is the requirement of large classes for the design proposed in this article. In order to interpret the distribution and degree of agreement of different raters at any given time point, a reasonably large group is needed. The design proposed in this article was developed for

large university lectures, which often involve 200 students or more. In most school classes, it might be less useful to split the class into three groups of responders with different ESM signaling schedules, since many school classes comprise less than 30 students, implying that with the design proposed here, each subgroup at any given time would include no more than ten responses, likely less if school absences, smaller class size, and unwillingness to respond to ESM signals are taken into account. A possible solution in reasonably large classes might be to signal all students at the same times (e.g., after 25, 50, and 75 minutes of a 90-minute lecture). This reduces the number of measurement time points and consequently offers less insight over short-time changes in students' experiences over the course of a lesson, while keeping the burden on each individual student the same (three signals per lesson).

It is furthermore not possible to rule out that nonresponse to ESM signals might be confounded with the constructs being assessed. For example, the most motivated, immersed students might prefer to continue working on their captivating math task and might even miss the ESM signal due to their intense concentration. In some personalized learning classrooms, the headsets that students wear to avoid distractions by their classmates make it difficult to raise their attention to ESM signals, unless these signals come through the same devices their headsets are attached to, which is not always possible. On the other hand, particularly bored and disengaged students might see no point in responding to the ESM surveys. These scenarios of data not missing at random imply that the empirically observed agreement of different students does not necessarily reflect the agreement of all students or the 'objective' situation characteristics, but could itself reflect a biased subsample.

It seems possible that constructs and situation characteristics differ in their potential of being perceived in the same way by different students. It might be easier for students to agree on a question referring to the interestingness of a situation, since situational interest partially

depends on observable situation characteristics, such as novelty or surprising information (Hidi & Renninger, 2006), while other constructs may be more person-specific and difficult to observe, such as questions concerning the students' current feeling of competence or frustration. In part, the here proposed design helps detecting and studying such differences between constructs by providing a quantified degree to which students agreed in their agreements on different constructs. Nevertheless, it is important to bear in mind that a lack of agreement can have many different sources, either rooted in the construct itself being person-specific, or rooted in individual distractions, individual misunderstandings of items, or individualized instructions.

Finally, there is no guarantee that there be only one group agreement on a given question in a given situation. There might be multiple subgroups, each with their own mean score / agreed-upon rating. While this would be easy to detect in the violin plot, it poses a limitation to the idea of using the group mean score as the one and only indicator of objective situation characteristics.

3.8 Future directions to overcoming the general limitations of self-reports

Because of the general limitations of self-reports, it is important to validate self-report data gained with the here proposed research design by linking them to more objective, observable and behavioral data, such as video-recorded observations of the students' behavior or the teacher's behavior, psychophysiological data with relevance to emotions and motivation, such as mobile electrodermal resistance assessments or heart rate variability measures, objective information about the students' demographic background, such as their family's household income, verifiable information about students' performance (ideally standardized test performance), absenteeism, and school dropout.

If only self-report assessments are possible due to organizational or other constraints, then different question formats can help to avoid at least the biases typical to rating scales: For example, emotions could be assessed with both open-ended questions ("Please write down here

how you currently feel”), which can be linked to rating scales after being automatically analyzed with sentiment analyses tools (e.g., Silge & Robinson) or manual coding (e.g., Moeller et al., 2018). Researchers and practitioners around the globe work on methods to gather objective information about participants’ emotions and motivations. For example, there are studies and companies that retrieve information about people’s emotions from their voices (e.g., Krothapalli & Koolagudi, 2013), countless companies and data scientists analyze texts produced by participants for markers of emotions in so-called sentiment analyses (e.g., Altrabsheh, Gaber, & Cocea, 2013), wearable heart rate variability sensors are marketed to researchers and private users with the promise that they will provide objective information about the stress, sleep, recovery, and physical exercise of the wearer (e.g., Firstbeat, 2012). Multiple sensors are integrated to optimize predictions of behavior and emotions, and machine learning algorithms help integrate all these data, reaching never before seen accuracies in predicting emotions and behavior (e.g., Carroll et al., 2013).

On the other hand, a recently emerging debate has questioned whether the subjective information about personal experiences provided by self-reports can be entirely replaced by objective measures, since e.g., Barrett (2018) has suggested that even the presumably *objective* markers of emotions are to some extent idiosyncratic. For these reasons, we might have to keep asking people if we really want to know how an individual feels in a given situation, since the subjective evaluation, a crucial part of the emotional experience, is not always captured in the observable and behavioral measures.

For these reasons, we believe that the research design proposed here will remain a useful tool to examine in the future to what degree a given ESM response in a given situation was idiosyncratic and thus a reflection of person-specific characteristics, or in line with the assessments of other students in the same situation. We hope that the measure of concordant

objectivity proposed here can be compared and integrated with other objective measures of emotions and motivation in learning situations in the future, in order to improve predictions of students' learning and behavior.

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