Within-person analysis in educational psychology: Importance and illustrations. 71–87
BJEP Monograph Series II, 12

The British Psychological Society

Within-person analysis in educational psychology: Importance and illustrations

Kou Murayama
School of Psychology and Clinical Language Sciences, University of Reading & Research Institute, Kochi University of Technology

Thomas Goetz
Department of Empirical Educational Research, University of Konstanz & Thurgau University of Teacher Education

Lars-Erik Malmberg
Department of Education, University of Oxford

Reinhard Pekrun
Department of Psychology, University of Munich & Institute for Positive Psychology and Education, Australian Catholic University

Ayumi Tanaka
Faculty of Psychology, Doshisha University

Andrew J. Martin
School of Education, University of New South Wales, Australia

Abstract

Most of the empirical (especially correlational) research in educational psychology to date has relied on between-person analysis, where constructs are assessed on the person level (i.e. typically only one or a few assessments for each person) and relationships between variables are computed with respect to inter-individual differences. This between-person approach is well-suited to examine individual differences. However, it has often been criticised as it provides little information about intra-individual psychological processes. In contrast, within-person analysis, where people are assessed multiple times and relationships between these multiple assessments are computed within individuals, has attracted attention to address psychological processes within individuals. The current chapter provides some backgrounds, rationales, and illustrative examples of within-person analysis to progress the case for this approach in educational psychology.

Key words: within-person analysis; intra-individual analysis; inter-individual analysis; motivation; emotion; learning.

Correspondence concerning this article should be addressed to Kou Murayama, School of Psychology and Clinical Language Sciences, University of Reading, Harry Pitt Building, Earley Gate, Reading RG6 6AL (email: k.murayama@reading.ac.uk)

If one wants to examine how students' feeling of enjoyment is related to their sense of self-efficacy in a survey, what research design should be used to test this idea? Typically, researchers in educational psychology might assess students' enjoyment and self-efficacy using self-report questions in classrooms (perhaps in one occasion) and conduct a correlation or regression analysis (or more advanced methodologies such as structural equation modeling or multilevel modeling) to examine the relationship between these constructs. Or, some researchers might want to assess enjoyment and self-efficacy at two different time points, in order to examine the predictive relationship between them. Indeed, in *British Journal of Educational Psychology,* there are many papers that adopt such research designs and these tend to be the main ways of examining the relationship between variables of interest in educational psychology.

These designs answer important questions that researchers pose. However, they fail to answer other questions that also have significant educational importance. Because these traditional approaches rely on *between-person analysis* (or inter-individual analysis), they do not adequately contribute to our understanding of the variation that occurs within an individual across time, and neither do they adequately address correlations, predictive relations, or cause-effect relations between variables within individuals. Researchers have thus put forth an alternative option to collect and analyse data, called *within-person analysis* (or intra-individual analysis).

As elaborated later, between-person analysis uses individuals as the unit of analysis, examining relationships between variables based on individual differences. On the other hand, within-person analysis uses multiple stimuli, situations or time-points within individuals as the unit of analysis, highlighting the relationships between constructs/variables within individuals. Importantly, the relationships investigated in the between-person analysis *(between-person covariation)* and the within-person analysis *(within-person covariation)* are statistically independent; unless some unrealistic assumptions were met (called ergodicity), there is no guarantee that these two types of analyses converge (Hamaker, Dolan & Molenaar, 2005). Put it differently, in general, relationships at the within level do not parallel those at the between level of analysis, or in other words, within and between level processes are rarely ergodic (Molenaar, 2004). In fact, both analyses can produce totally opposite relationships.

Figure 1 presents the relationship between reaction time and accuracy of a cognitive task. Each individual is assessed multiple times on their accuracy and response time. For most cognitive tasks, trying to speed up would result in decreased accuracy (so called speed-accuracy trade-off). Therefore, we can reasonably expect that within-person relationships between reaction time and accuracy are positive, and this is represented in Figure 1 – all participants indeed show positive relationships. However, because of large individual differences in their basic performance of the task (i.e. some participants are faster and more accurate than other participants), Figure 1 indicates *negative* relationships between reaction time and accuracy at the between-person level. These large individual differences may reflect participants' general ability to perform the task (some participants have good ability to perform the task and therefore both speed and accuracy are good) or participants' general motivation for the task (some participants are more motivated for the task and therefore both speed and accuracy are good). This means that if we assessed participants' accuracy and reaction time only once (as is commonly done in correlational research in educational psychology), we may reach misleading conclusions about within-person effects (Molenaar & Campbell, 2009). When data are analysed based on this type of between-person covariation, we need to be careful not to misinterpret these findings in terms of within-person psychological processes.

The purpose of this chapter is to provide some background, rationale, and illustrative examples of within-person analysis to progress the case for this approach in educational psychology. The importance of within-person analysis has been repeatedly underscored and discussed in other areas of psychology (Borsboom, Mellenbergh & Van Heerden, 2003; Molenaar & Campbell, 2009; Nesselroade, Gerstorf, Hardy & Ram, 2007), but we feel that this recent trend should receive more attention in educational psychology, because many of the theories in educational psychology, and the research questions derived from these theories, are within-person in nature. Thus, these theories and research questions are best addressed by within-person approaches.

To promote within-person research design and analysis in educational psychology, we held an invited symposium on this topic at a conference (2015, in Liverpool) jointly hosted by the British Psychological Society, Psychology of Education Section, and the British Journal of Educational Psychology. This chapter is based on the presentations in this symposium, starting with a tutorial example (Kou Murayama), followed by three illustrative empirical studies (Lars Malmberg, Thomas Goetz and Reinhard Pekrun, and Ayumi Tanaka) and general discussion and future directions (Andrew Martin). We hope this chapter serves as a stepping stone for future new avenues of within-person research methodology in educational psychology.

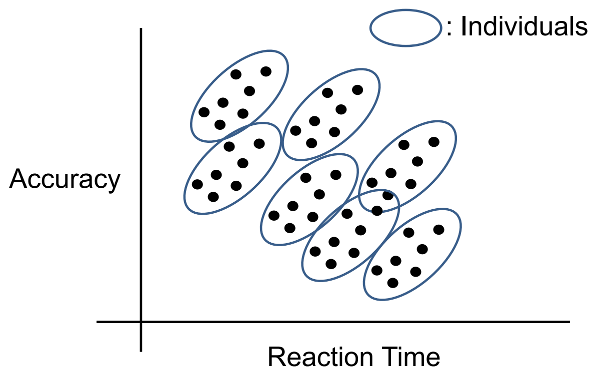

Figure 1. A hypothetical scatter plot for the relation between reaction time and accuracy in a cognitive task. Dots represent data points and individuals are circled (i.e. there are seven individuals in the plot). Within individuals, there is a positive correlation between reaction time and accuracy (people are more accurate when they respond more slowly). However, the correlation is negative at the between-person level, indicating a dissociation of within- and between-person relationships.

A tutorial case study: How different are between- and within-person analyses?

To further understand how between-person and within-person analyses differ from each other, we provide a case study based on Murayama (2003). This study aimed to examine the factors that are related to students' use of learning strategies in history education. The author was especially interested in how students' use of learning strategies is influenced by their perceived effectiveness to get good grades in immediate exams. To address this research question, the author developed a 17-item questionnaire assessing strategies in history learning, and asked secondary and high school students (N=1138) to rate the following aspects on a Likert scale: (1) actual use of the learning strategies (use); (2) perceived effectiveness of the learning strategies to get grades in exams (short-term utility); (3) perceived effectiveness of the learning strategies to achieve long-term consolidation of learning (long-term utility); and (4) perceived mental cost (effort) to use the strategies (cost). This means that each student provided $17 \times 4=68$ responses to the questionnaire.

Following common research practice in educational psychology, the author conducted a factor analysis of the 17 items, and extracted four factors: memorisation (e.g. 'I focus on memorising the facts without considering why'), elaboration (e.g. 'When I learn a new historic event, I try to understand what actually happened'), structure (e.g. 'I try to grasp the overall flow of historic events'), and exploration (e.g. 'I actively read books or magazines about history'). Based on the factor analysis results, the author computed the four subscale scores for each of the four aspects (i.e. use, short-term utility, long-term utility, and cost). To then address the central research question, the author conducted a regression analysis (N=1138) predicting the use of learning strategies from short-term utility, long-term utility, and perceived cost. This was done for each of the four subscales separately, meaning that the author repeated the same regression analysis four times (i.e. for each subscale). Supporting the hypothesis, for all the subscales, short-term utility was the strongest positive predictor of the use of learning strategies, suggesting that concerns about grades in immediate exams may be one of the strong factors of how students learn, over and above the long-term utility or cost of the learning strategies. Based on the results, the author concluded that students prefer to select learning strategies that are effective (in comparison to other learning strategies) to get good grades in immediate exams.

This concluding statement sounds reasonable based on the analysis results, but it actually commits a fundamental interpretative error that highlights the distinction between between-person and within-person approaches. The regression analysis that the author conducted is based on between-person analysis. That is, the analysis treated individuals (i.e. students) as the unit of analysis: if one were to draw a scatter plot, 1138 data points would be observed. In other words, between-person analysis makes use of individual differences to infer relationships between variables. With this between-person analysis, the valid conclusion one can draw from the results is that students perceiving that the strategy (e.g. memorisation strategy) is effective to get grades in immediate exams were more likely to use that strategy (compared with students perceiving the strategy not to be effective). On the other hand, the statement 'students prefer to use learning strategies that are effective to get good grades in immediate exams' (the conclusion the author drew) may sound similar, but it is actually different in that it focuses on the within-person psychological process of strategy choice, rather than individual differences in the use of learning strategies. In fact, when researchers want to make a statement about people's psychological processes, between-person analysis (analysis that makes use of individual differences to compute relationships) provides little information about within-person processes.

Is it possible to conduct a within-person analysis to directly address the research question then? Fortunately, the data collected in Murayama (2003) allow for a within-person analysis that addresses the within-person psychological mechanisms underlying learning strategy use. The trick is to treat items, rather than individuals, as the unit of analysis. In other words, we consider that the variables of 'use of learning strategies', 'short-term utility', 'long-term utility', and 'perceived cost' were assessed with 17 different stimuli (i.e. 17 different learning strategies) for each participant. With this reframing of the data, for each individual, we can conduct a regression analysis predicting the use of learning strategies from short-term utility, long-term utility, and perceived cost using the 17 items as separate data points within persons. This means that we conduct a regression analysis with 17 data points (i.e. N=17) to obtain regression coefficients of short-term utility, long-term utility, and perceived cost (these are the three predictors) for each individual. This process is repeated for all participants (i.e. 1138 times) and we can then average the regression coefficients across participants to get the estimates of the (averaged) within-person relationship between use, short-term utility, long-term utility, and perceived cost of learning strategies[1]. A follow-up

[1] Alternatively, we can conduct a multilevel model or a multilevel structural equation model to estimate the

study, Murayama (2006), indeed conducted an analysis analogous to this approach to the same data. As noted earlier, theoretically, this within-person analysis could produce completely different patterns of results, but in this particular case, our within-person analysis showed similar results with between-person analysis. Importantly, however, because this within-person analysis uses items (i.e. individual learning strategies) as the unit of analysis, the author could now reasonably state 'students prefer to select learning strategies that are effective (in comparison to other learning strategies) to get good grades in immediate exams'.

The data from Murayama (2003) afforded both between-person and within-person analyses (by accident!), and gives a good case of how between-person and within-person analyses are different. However, it is important to note that, in many cases, it is not possible to conduct within-person analysis with data unless researchers carefully consider such a data collection plan in advance. As illustrated earlier, the critical element of within-person analysis is to compute relationships (e.g. correlations) for each individual. This is possible only when the same participant receives repeated measures. Typically, this can be done by assessing the same participants at multiple time points, and the following sections present several different versions of this approach. Alternatively, like the current example (Murayama, 2003), even a cross-sectional survey or experiment can achieve this if we assess participants on multiple features or variables (e.g. 'learning strategy use', 'short-term utility', etc.) using different stimuli (e.g. strategy items; for other examples of this type of within-person analysis, see Castel, Murayama, Friedman, Mcgillivray & Link, 2013; Law, Elliot, & Murayama, 2012; Mcgillivray, Murayama & Castel, in press; Murayama, Elliot & Yamagata, 2011; Przybylski, Weinstein, Murayama, Lynch & Ryan, 2012)[2]. In any case, within-person analysis is not something that we can do in a post-hoc way; it requires careful and deliberate planning before data collection.

Some clarifying notes

We presented a tutorial case study (Murayama, 2003) to provide the basic idea of within-person analysis in educational psychology. There are several notes on within-person analysis that should be made. These notes apply not only to the current study (Murayama, 2003) but also to research utilising within-person analysis in general. First, there are some situations where between-person analysis is more appropriate. For example, we are often interested in predicting individual differences in educational attainment such as achievement test scores (e.g. does IQ predict achievement scores five years later?). In that situation, the main research question is 'what types of individuals will be better off?' Examining psychological processes in learning is not a main concern here. In such cases, conducting between-person research and analysis is the right choice. As such, it is important to think carefully about the research question before planning to conduct within-person analysis.

Second, one may hold the impression that within-person analysis does not address individual differences. In fact, within-person analysis can provide more information about individual differences than between-person analysis does, as long as we collect data from multiple participants. Specifically, as within-person analysis requires the computation of relationships between variables (e.g. correlations)

within-person relationships in a single step (this method will be illustrated in the next sections), but the naïve approach explained here still does a decent job to examine within-person relationship and provides comparable results (Lorch & Myers, 1990; Monin & Oppenheimer, 2005). The following illustrative examples all use multilevel modeling. As the multilevel model adjusts the standard errors for each 'mini' regression model, multilevel modeling is preferable over the two-step analysis explained here, especially when individuals have different numbers of data points.

2 This type of data is often called 'three-mode data' (Tucker & Messick, 1963), where individuals, variables, and occasions or stimuli are crossed (see also Murayama, Sakaki, Yan & Smith, 2014 for a cautionary note on within-person analysis with three-mode data). Note that common cross-sectional surveys do not have this data structure, making it impossible to conduct within-person analysis.

for each individual separately, we can examine the individual differences in within-person relations. Yoshida and Murayama (2013) computed the within-person correlation between students' use of learning strategies and experts' desirability ratings across 715 participants and obtained the averaged correlation of 0.04 (*SD*=0.29). This averaged correlation is very small, indicating little within-person covariation. But as can be seen in Figure 2, which presents the histogram of the within-person correlations across 715 participants, there are actually large individual differences in this within-person correlation --- some showed very strong positive correlations whereas others showed even negative correlations. With such large individual differences, we can even examine what type of individual difference measures (e.g. IQ, personality traits) can explain this between-person variation (in the context of multilevel modeling, this is called cross-level interaction). Note that between-person analysis can typically produce only one correlation coefficient across participants and thus it is impossible to examine such individual differences. On the other hand, within-person analysis produces an average and SD of correlations across participants[3]. Thus within-person analysis can make us more aware of the individual differences in psychological processes.

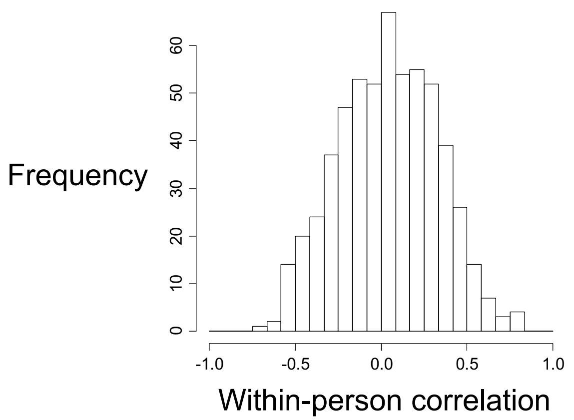

Figure 2. Histogram of the within-person correlations between students' use of learning strategies and experts' desirability ratings across 715 students in Yoshida and Murayama (2013). The averaged within-person correlation is nearly zero (*r*=0.04), but you can observe large individual differences.

Third, there seems to be confusion between within-person approaches and 'person-centred approaches'. In fact, they are different approaches. Typically, person-centred analysis focuses on the mean-structure of the data and aims to classify participants into several different categories (typically using cluster analysis or latent profile/class analysis) based on the individual differences in some psychological variables (e.g. Meece & Holt, 1993). This is indeed an important and interesting approach, but is not equivalent to within-person analysis. In fact, classification is typically made using the information from between-person covariation[4].

3 With between-person data using multiple regression analysis, researchers often test an interaction effect to examine how the relationship between an independent variable (e.g. self-efficacy) and the dependent variable (e.g. academic achievement) is moderated by a personality trait/environmental factor (e.g. trait anxiety, perceived teacher autonomy). However, as this analysis is based on between-person relations, the interpretation is very tricky (i.e. the between-person relationship changes as the function of the individual differences in another trait variable), and we need to be careful not to over-interpret the results.

4 That being said, it is theoretically possible to apply person-centred approach to the individual differences in within-person relations, for example, using multi-level mixture models.

Finally, within-person relationships do not necessarily imply causation. Cause-effect relations of psychological processes should occur at the within-person level, but within-person relationships in observational (i.e. non-experimental) research are correlational in nature, and thus not all within-person relations are causal. If researchers want to make causal inferences to a certain extent, it is important to control for possible confounding variables at the within-person level (for other requirements to infer causality, see Antonakis, Bendahan, Jacquart & Lalive, 2010). Recent studies have proposed some effective ways to make stronger causal inferences with within-person correlational (observational) data, such as within-person cross-lagged modeling (Schuurman, Ferrer, De Boer-Sonnenschein & Hamaker, 2016), and such advanced modeling can be a good design option for future research using within-person approaches.

Other illustrative empirical examples

Within-person relations between task difficulty and effort expenditure: An event-triggered response approach

We now turn to a case in which data were purposefully collected as a within-person design. Malmberg, Walls, Martin, Little and Lim (2013) were interested in intrapersonal learning experiences during one typical week at school[5]. For that purpose, during the week, participants were asked to respond to an electric questionnaire in a handheld device (Personal Digital Assistant, PDA), once for each learning episode such as guitar tutorial, math task, outdoor sport, etc. (i.e. an event-triggered response method). In total, 298 students in years 5 and 6 reported on an average of 15.3 learning episodes each (SD=4.3; Range=2 to 34). All constructs and items were adapted to the situations (Malmberg, Woolgar, & Martin, 2013). For every assessment, students reported on their situation-specific effort expenditure ('In this lesson … how much effort did you put in?'; 1=none at all, 4=a lot), and task difficulty ('how difficult was the task?' on a four-point scale; 1=very easy, 4=very difficult).

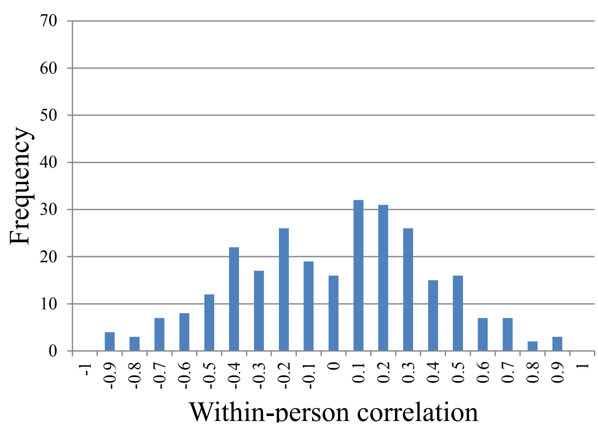

Figure 3. Distribution of within-person correlations between situation-specific task difficulty and effort exertion during one week at primary school (Malmberg et al., 2013).

The main focus of the study was on the within-person relationship between task difficulty and effort expenditure. In order to inspect inter-individual differences in intra-individual associations between the two variables, the authors estimated one correlation coefficient for each participant (as in the example presented in Figure 2). The average raw correlation was 0.00, but there

[5] The models presented in this chapter are simplified from the original study. See Malmberg et al., 2013, for details.

were clear individual differences in the correlations (*SD*=0.39), with a range from -0.90 to 0.90 (Figure 3). Again, this nicely illustrates the richness of the information that within-person analysis provides and the importance of focusing on the individual differences in within-person relations – just considering the average relationship may misrepresent the overall picture. A negative correlation means that the student in question would withdraw effort the more difficult the task, indicative of a 'helpless' pattern. A positive correlation means that the student would put in more effort when the task was more difficult, indicative of a 'mastery approach' (Pintrich, 2000). Given these observations, the authors set up a series of multilevel models to investigate: (1) the proportion of variance explained at the student level using a variance component model; (2) the effect of task difficulty on effort exertion in a fixed effect model; (3) individual differences in the effect of task difficulty on effort exertion in a fixed and random effect model; and (4) whether the individual differences in the random effect of task difficulty on effort exertion can be explained by students' academic performance, as a cross-level interaction (moderation) effect (see Malmberg et al., 2013, for algebraic expression of these models).

Findings from the first model showed that 72 per cent of the total variance in effort was explained by the within-person variation (28 per cent of the total variance was explained by the between-person variation), indicating the importance of focusing on the within-person relationship between the variables. (It should be noted that this within-person variation includes random errors such as measurement errors. Thus, it does not necessarily mean that 72 per cent of the total variance can be explained by meaningful within-person variation.) In the second model, the authors assumed that the relationship between task difficulty and effort expenditure is constant (fixed) across individuals. In other words, in this model, all regression lines were forced to be parallel. Findings from this model showed that task difficulty did not predict effort exertion (B=0.00; *p*=n.s.). This means that the individual regression lines were all flat and parallel as shown to the left in Figure 4. Of course, this is not a reasonable assumption – from Figure 3, it is clear that the within-person relationship between task difficulty and effort expenditure varied considerably across individuals. Thus, the authors relaxed this strong assumption in the third model in which they allowed the regression lines to vary across individuals. As shown to the right in Figure 4, the model showed that the random slope variance was substantial, indicating that the regression lines indeed vary across individuals. Consistent with the interpretations of the correlations, regression lines with a negative slope indicate the helpless pattern and regression lines with a positive slope a mastery approach.

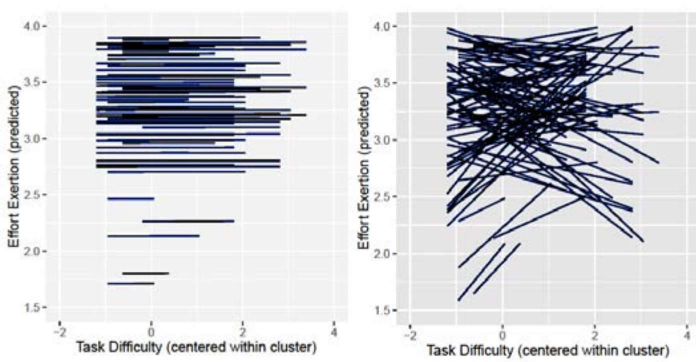

Figure 4. Effort exertion predicted by task difficulty of 100 students. Fixed effects to the left and random effects to the right.

As each line represents an individual, the authors were interested in knowing what could predict the effort-on-difficulty-slopes. When the authors included academic performance as an individual difference measure to explain the effort-on-difficulty slopes, they found that higher performers exerted more effort at difficult tasks as compared with easy tasks, whereas lower performers exerted less effort (i.e. this is called 'cross-level interaction effect' in the context of multilevel modeling). This indicates that academic performance is one potential factor that distinguishes students who exhibit a helpless pattern and those who exhibit a mastery pattern. The authors also found that relatively higher performers tend to exert more effort overall (and relatively lower performers to exert less effort). Overall, the design of the within-person study of school children's learning experiences enabled fine-grained analysis on how task difficulty and effort expenditure are related at the within-person level. As the results indicated, the models lend themselves well to including individual characteristics as predictors at the between-level in the model, integrating both within-person and between-person perspectives.

Within-person predictors of situational interest and boredom: A within-person analysis using longitudinal assessments

Tanaka and Murayama (2014) conducted within-person analyses of interest and boredom in the classroom. Researchers have posited that interest and boredom are first triggered by situational factors (Renniger, 2000). However, aside from a few exceptions (e.g. Moneta & Csikszentmihalyi, 1996; Nett et al., 2011; Turner & Silvia, 2006), much of the research on interest and boredom has focused on variations between individuals. For example, researchers simply assessed students' expectancy and interest cross-sectionally or prospectively and computed relations between these variables. This between-person approach provides information about the relationship between situational factors and interest or boredom, in terms of the relative ranking of individuals at a specific time point (e.g. students who have high expectancy to a situation report higher interest than those who have low expectancy). However, between-person approaches cannot examine whether particular individuals experience interest in response to situational changes (Murayama, Elliot & Yamagata, 2011). Thus, the authors investigated within-person relationships between task-specific perceptions and interest and boredom, using repeated longitudinal measurement.

As for situational antecedents of interest and boredom, the authors focused on three critical task specific perceptions: perceived expectancy, utility, and difficulty. Perceived expectancy reflects beliefs about how well one expects to perform a given activity (Wigfield & Eccles, 2000). Perceived utility is the instrumental usefulness of a task (Eccles et al., 1983). Perceived difficulty is the judgement of the difficulty of the task (Pintrich, 2000). It has been found that expectancy and utility are positively related with interest, while difficulty is negatively related with interest. The authors examined whether these previous findings shown using between-person analyses could be replicated using within-person analyses.

Another important purpose of Tanaka and Murayama (2014) was to investigate the influence of individual differences in achievement goals on within-person relationships. Achievement goals represent competence-relevant aims that individuals strive to accomplish in achievement settings (Muryama, Elliot & Friedman, 2012). Past literature on achievement motivation has indicated that individual achievement goals have a great impact on appraisal processes and emotions in the classroom. Among numerous studies, some have established a direct relationship between achievement goals and either task specific perception or interest and boredom. However, no studies had yet examined how achievement goals can moderate within-person associations of task specific perceptions and interest and boredom.

Participants were 157 undergraduates in an introductory psychology course in Japan. On the semester's first day, the participants completed consent forms and the achievement goals questionnaire. Importantly, from the 2nd to 13th week, the task specific perception and the emotional engagement questionnaire were administered at the end of each lesson. This procedure allowed us to collect up to 12 data points for each participant, allowing the authors to examine the within-person relations between the variables.

The authors used multilevel modeling to analyse the data with each lesson at level 1 and individuals at level 2. In the first model, interest and boredom were predicted by expectancy, utility, and difficulty at the within-person level and slopes were posited to vary across students. In the second model, the authors included person-level predictors (i.e. achievement goals) to account for the between-individual variations in the relationship among task specific perceptions and interest and boredom (i.e. cross-level interaction).

In the first model, the findings showed that expectancy and utility were positive predictors of interest, and negative predictors of boredom at the within-person level. This means that the more the individual perceived they would get a good grade and the course was useful, the more the individual felt interested and the less they felt bored. Also, difficulty was a negative predictor of interest, and a positive predictor of boredom at the within-person level. This indicates that the higher the individual perceived the course to be difficult, the less the individual felt interested and the more they felt bored. This is basically consistent with previous studies (e.g. Pekrun, Goetz, Daniels, Stupnisky & Perry, 2010), but as the current study used a within-person design, the authors could make a stronger case for how situational factors trigger interest and boredom within individuals (Renninger, 2000).

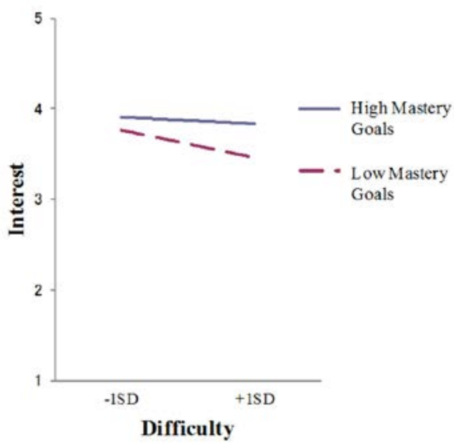

Figure 5. Predicted values of interest as a function of mastery goals at high and low levels of task difficulty

Importantly, the random variance of the slopes of difficulty for interest and the slopes of expectancy and utility for boredom were statistically significant. These results indicate that the slope of difficulty varied significantly across individuals for interest. The authors then estimated the second model where they included achievement goals to account for these individual differences. All results are reported in Tanaka and Murayama (2014), but one finding is highlighted here. Figure 5 shows the result for the relationship between task difficulty and interest. As can be seen, one type of achievement goal, mastery goals (i.e. people's goals or strivings to master the task), was a significant positive predictor of the difficulty slope. The simple slope analyses revealed that difficulty was a positive predictor of interest for the individuals having high mastery goals. This relation was, on the other hand, not significant for the individuals having low mastery goals. The results indicate that difficult learning materials may discourage students and decrease their interest on average, but this is not necessarily the case when students are mastery oriented. In sum, Tanaka and Murayama (2014) showed that situational influence can be captured adequately through within-person analyses. The combination of within- and between- person analyses shed light on the dynamic nature of motivational, cognitive, and emotional interactions.

Within-person relations between achievement goals and discrete achievement emotions: An experience sampling approach

Goetz, Sticca, Pekrun, Murayama & Elliot (2016) investigated the impact of achievement goals on students' achievement emotions. While existing theoretical models on this topic focus on intra-individual functioning, that is, on within-person relationships between goals and emotions (e.g. Linnenbrink & Pintrich, 2002; Pekrun, Elliot & Maier, 2009), the vast majority of empirical studies on this topic have examined between-person relations. However, as noted earlier, between- and within-person relations are statistically independent from each other (Molenaar, 2004). As such, running analyses at the between-person level with the aim of testing assumptions on intra-individual functioning can be misleading.

To overcome this disconnect between theory and empirical research, the present study analysed both between-person and within-person relations between goals from the trichotomous achievement goal framework (mastery, performance-approach, performance-avoidance) and six commonly experienced achievement emotions (enjoyment, pride, anxiety, shame, anger, and boredom; Goetz, Sticca, Pekrun, Murayama & Elliot, 2016). The hypotheses on the relationships between goals and emotions were based on the theoretical framework developed by Pekrun, Elliot and Maier (2006, 2009).

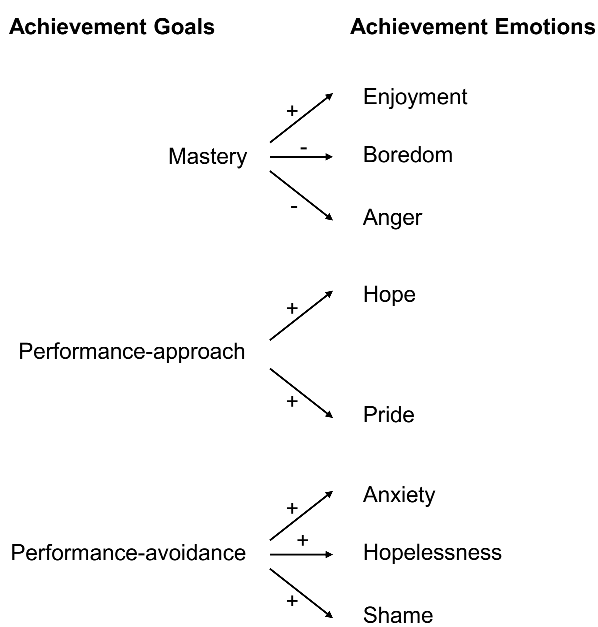

Figure 6. Theoretical propositions on the relations between achievement goals and achievement emotions (adapted from Pekrun et al., 2006, 2009).

Regarding between-person relations, the authors expected to confirm the propositions by Pekrun et al. (2006; see Figure 6 for an overview) and to replicate the findings from previous studies: (1) mastery goals positively predict enjoyment and negatively predict boredom and anger; (2) performance-approach goals (i.e. goals or strivings to perform better than others) positively predict pride; and (3) performance-avoidance goals (i.e. goals or strivings not to perform worse than others) positively predict anxiety and shame. With regard to within-person relations, the authors aimed to investigate whether these theoretical propositions hold for intra-individual functioning as well. This is a critically important issue, given that the Pekrun et al. (2006, 2009) model, as well as other theories on the achievement goal-emotion link (e.g. Linnenbrink & Pintrich, 2002), address the relations between achievement goals and emotions in terms of intra-individual psychological functioning (see Linnenbrink-Garcia & Barger, 2014).

The sample consisted of N=120 Swiss 10th grade students (37 per cent female; mean age=15.61 years, SD=0.59). Participants were randomly selected from 35 classrooms (two to four students from each classroom) from seven upper-track schools (Gymnasium) in the German-speaking parts of Switzerland. To examine within-person relations, state goals (e.g. 'My goal at this moment is to learn as much as possible') and emotions (e.g. 'At this moment I am experiencing enjoyment') were assessed using the experience sampling method (see Goetz, Bieg & Hall, 2016) for a period of 10 school days in a regular classroom setting (altogether 1779 real-time assessments) using handheld devices (iPod Touch 4G; experience-sampling-software: iDialog Pad; Kubiak & Krog, 2012). To examine between-person relations, trait achievement goals (e.g. 'My goal in mathematics is to learn as much as possible') and emotions (e.g. 'In mathematics classes I usually experience enjoyment') were assessed using self-report questionnaires, right after the assessments of state goals and emotions. For both the trait and the state approach, data were assessed with respect to the four academic domains of mathematics, German, English and French.

Preliminary analyses showed that there were some differences between the correlations in the between- versus within-person analyses. For example, at the within-person level, performance- approach and performance-avoidance goals could clearly be separated (r=.48), in contrast to their high correlation at the between-person level (r=.86). Multilevel analyses on the state data (assessments nested within persons) showed that only about 20–33 per cent of the total variance for achievement goals (25.7 per cent – 33.2 per cent) and achievement emotions (20.4 per cent – 33.2 per cent) was explained by the between-person variation. Thus, most of the variance in both constructs originated from situational fluctuations within persons.

As for the main analyses, results of multiple regression analyses and multi-level modeling showed that between-person relations were fully in line with the theoretical hypotheses. Even more, the within-person relations exactly mapped onto the between-person pattern of results: Mastery goals were positive predictors of enjoyment and negative predictors of boredom and anger; performance-approach goals were positive predictors of pride; and performance-avoidance goals were positive predictors of anxiety and shame. Results of the between- and within-person analyses were robust when controlling for gender, age, academic achievement, and the academic domain in which goals and emotions were assessed.

This study was the first investigation examining the link between students' achievement goals and their achievement emotions using a combined between-person and within-person analysis. The findings confirmed that achievement goals and emotions are closely related and support propositions of Pekrun et al.'s (2006, 2009) model. Results indicated that between- versus within-person relations between achievement goals and emotions are likely to be equivalent.

This is an encouraging finding for both theory development and educational practice. As argued by Voelkle et al. (2014), findings on the within-person level are a prerequisite to support theoretical assumptions on within-person functioning and to develop intervention programmes for individuals. For example, although previous findings have shown a positive relation between mastery goals and enjoyment at the between-person level, these findings are not sufficient to justify investing effort in treatment interventions that aim to enhance students' enjoyment by fostering their mastery goals. However, the present study indicates that this relation also holds at the intra-individual level, providing better justifications for such interventions. Clearly, the findings are limited by the correlational study design. To further support conclusions about how to design intervention, future studies should use within-person causal analysis to examine the relations of goals and emotions over time.

Concluding thoughts and next steps

The arguments and examples above have demonstrated the variety of methodologies (i.e. three-mode assessment, event triggered response method, intensive longitudinal assessments, experience sampling method) and range of educational psychology research questions that can be addressed by within-person approaches. Taken together, they show that the value of within-person approaches in educational psychology cannot be emphasised enough. Compared to between-person knowledge and understanding, researchers in educational psychology know less about the within-person (or, intra-individual) ebbs and flows of key phenomena central to their discipline. As a case in point, educational psychologists have collected a great deal of cross-sectional data on students' academic motivation. Although we do collect longitudinal motivation data, these data tend to be limited to two time-points and are often retrospective in nature (asking students how they are typically oriented to their studies over a given period of time). There is hardly any knowledge about real-time motivation variation such as, for example, within a day at school or within a lesson. However, this is precisely students' lived experience - and we rarely capture it. Inevitably this greatly limits what we can know about their motivation - and therefore, what we can do to enhance and then sustain it.

Notwithstanding this neglect of within-person analysis, educational psychology has frequently drawn on and accommodated numerous theories that in one way or another have recognised within-person, intra-individual variability and its importance in students' educational development. Following Vygotsky (1978), for example, there has been recognition of the interaction between individual and environment and recognition that individuals will vary from situation to situation and context to context. Subsequently, major 'modern' theories of child development have recognised the interplay of individual and environment that gives rise to intra-individual variability (Shonkoff & Phillips, 2000). Transactional theories also emphasise the dynamic and idiosyncratic interplay between individual and environment that leads to intra-individual changes over time (Sameroff, 2009). Indeed, 'the transactional model emphasises discontinuities' (Sameroff, 2009, p.17) – a hallmark of intra-individual variance. In similar vein, ecological perspectives emphasise the unique processing of and interaction with the environment by each individual and the within-person chronological processes that play out as a result (Brofenbrenner, 2001). Sociocultural theories posit the origins of psycho-educational factors as social, but the outcome or expression of these psycho-educational factors as unique and individual. Moreover, the same educational environment will evoke different intra- and inter-individual expression (Walker, Pressick-Kilborn, Arnold & Sainsbury, 2004). Going forward, then, educational psychologists have rich theory on which to draw that can guide their within-person, intra-individual research.

Alongside well-established theory, intra-individual research is also greatly aided by technological developments, particularly in mobile technology. These innovations enable convenient and participant-friendly data collection (e.g. via smartphones; personal digital assistants; tablets; iPads; iPods). In addition, online surveys enable easy administration of and responses to questions and items. Thus, utilising technology in any number of research approaches such as diary studies, experience sampling (ecological momentary assessment), contextual activity sampling, and micro-interaction analysis, psycho-educational researchers can capture multiple records or time-reports from many students (Martin, Papworth, Ginns, Malmberg, Collie & Calvo, 2015; Walls & Schafer, 2006). These then allow for intensive longitudinal data analysis (Walls & Schafer, 2006) that provides nuanced insights into students' lived academic experience. In fact, educational psychology researchers are increasingly utilising technology to collect their (typically) cross-sectional data. Without a great deal of adjustment in research design, intra-individual and real-time data can be readily collected by these researchers – opening up new lines of empirical opportunities and substantive and applied contributions.

Researchers in educational psychology also have more statistical software firepower available to them than ever before – and these are proving extremely exciting for analysing within-person data. For example, structured appropriately, real-time data can be analysed using multilevel modeling (Goldstein, 2003; Raudenbush & Bryk, 2002). Again, taking motivation as a case in point, if we collect motivation responses from many students numerous times a day, five-days a week, over the course of a month at school, we have a multilevel design where time is nested within day, day is nested within week, week is nested within month, and month is nested within student. Martin and colleagues (2015) implemented this very design, and using multilevel modeling they were able to answer questions such as: What is the pattern of student motivation over the course of a day, a week, or a month at school? Is there more or less variation in motivation within a day than between days and weeks? Are there particular points in a day, week, or month where educational practice is best directed to enhance student motivation? These questions are qualitatively different to what can be asked using between-student, retrospective, or cross-sectional approaches. According to Gonzalez: 'One freeing aspect of modern statistics is that it is no longer necessary to make simplifying assumptions that all participants within a treatment group are the same or respond to treatment in the same way … this is the major benefit that random-effects [multilevel] models offer - they allow one to model heterogeneity' (2009, p.231). There are analytical and software developments on other statistical fronts that answer important intra-individual research questions, including latent growth modelling, multilevel time series analysis, time series factor analysis, Bayesian dynamic mediation analysis, continuous-time modeling, and transition modeling (Walls & Schafer, 2006). Psycho-educational researchers thus have statistical tools to answer any number of research questions relevant to intra-individual academic development.

Taken together, there are strong theoretical, methodological, and analytical foundations for greater application of within-person, intra-individual research in educational psychology. Because there is substantial reciprocity between the student and his/her educational environment and because each student responds uniquely to this educational environment, there is moment-to-moment variance that researchers in educational psychology can capture. It is important to do so because this intra-individual variability has major implications for students' academic and personal well-being (Shonkoff & Phillips, 2000). As adapted from the Greek philosopher Heraclitus, 'No person ever steps in the same river twice, for it's not the same river, and it's not the same person'. Intra-individual variation has thus been recognised as a core feature of the human condition for centuries or even millenniums. The arguments, findings, and ideas presented in this chapter are a call to action for educational psychologists in the 21st Century.

Author notes

This research was partly supported by the Marie Curie Career Integration Grant (CIG630680; to Kou Murayama), JSPS KAKENHI (Grant Number 15H05401; to Kou Murayama; Grant Numbers 15K04092 and 16H06406 to Ayumi Tanaka), the Research Councils UK (RCUK) and the John Fell Fund (to Lars-Erik Malmberg), the Swiss National Science Foundation (Grant Number 100014_131713/1; to Thomas Goetz), and an LMU Munich Research Chair grant (Grant Number VII.1-H172.10; to Reinhard Pekrun).

References

Antonakis, J., Bendahan, S., Jacquart, P. & Lalive, R. (2010). On making causal claims: A review and recommendations. *The Leadership Quarterly, 21*, 1086–1120.

Borsboom, D., Mellenbergh, G.J. & van Heerden, J. (2003). The theoretical status of latent variables. *Psychological Review, 110*, 203–219. doi: 10.1037/0033-295x.110.2.203

Bronfenbrenner, U. (2001). The bioecological theory of human development. In N.J. Smelser & P.B. Baltes (Eds.), *International encyclopedia of the social and behavioural sciences* (Vol 10, pp.6963–6970). New York: Elsevier.

Castel, A.D., Murayama, K., Friedman, M.C., McGillivray, S. & Link, I. (2013). Selecting valuable information to remember: Age-related differences and similarities in self-regulated learning. *Psychology and Aging, 28*, 232–242. doi: 10.1037/a0030678

Eccles, J.S., Adler, T.F., Futterman, R., Goff, S.B., Kaczala, C.M., Meece, J.L. & Midgley, C. (1983). Expectancies, values, and academic behaviours. In J.T. Spence (Ed.), *Achievement and achievement motivation* (pp.75–146). San Francisco, CA: W. H. Freeman.

Goetz, T., Bieg, M. & Hall, N. C. (2016). Assessing academic emotions via the experience sampling method. In M. Zembylas & P. Schutz (Eds.), *Methodological advances in research on emotion in education* (pp.245–258). New York: Springer.

Goetz, T., Sticca, F., Pekrun. R., Murayama, K. & Elliot, A.J. (2016). Intraindividual relations between achievement goals and discrete achievement emotions: An experience sampling approach. *Learning and Instruction, 41*, 115–125. doi: 10.1016/j.learninstruc.2015.10.007

Goldstein, H. (2003). *Multilevel statistical models* (3rd ed.). London: Hodder Arnold.

Gonzalez, R. (2009). Transactions and statistical modelling: Developmental theory wagging the statistical tail. In A.J. Sameroff (Ed.) *The transactional model of development: How children and contexts shape each other* (pp.223–245). Washington, DC: American Psychological Association.

Hamaker, E.L., Dolan, C.V. & Molenaar, P.C.M. (2005). Statistical modelling of the individual: Rationale and application of multivariate stationary time series analysis. *Multivariate Behavioral Research, 40*, 207–233. doi: 10.1207/s15327906mbr4002_3

Hox, J. (2002). *Multilevel analysis: Techniques and applications*. Mahwah, NJ: Lawrence Erlbaum.

Kubiak, T. & Krog, K. (2012). Computerised sampling of experiences and behaviour. In M.R. Mehl, & T.S. Conner (Eds.) *Handbook of research methods for studying daily life* (pp.124–143). New York: Guilford.

Law, W., Elliot, A.J. & Murayama, K. (2012). Perceived competence moderates the relation between performance-approach and performance-avoidance goals. *Journal of Educational Psychology, 104*, 806–819. doi: 10.1037/a0027179

Linnenbrink, E.A. & Pintrich, P.R. (2002). Achievement goal theory and affect: An asymmetrical bidirectional model. *Educational Psychologist, 37*, 69–78. doi: 10.1207/s15326985ep3702_2

Linnenbrink-Garcia, L. & Barger, M.M. (2014). Achievement goals and emotions. In R. Pekrun & L. Linnenbrink-Garcia (Eds.), *International handbook of emotions in education* (pp.142–161). New York: Routledge.

Lorch, R.F. & Myers, J.L. (1990). Regression analyses of repeated measures data in cognitive research. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 16*, 149–157. doi: 10.1037/0278-7393.16.1.149

Malmberg, L-E., Woolgar, C. & Martin, A. (2013). Quality of measurement of the Learning Experience Questionnaire for Personal Digital Assistants. *International Journal of Quantitative Research in Education, 1*, 275–296. doi: 10.1504/ijqre.2013.057689

Malmberg, L-E., Walls, T., Martin, A.J., Little, T.D. & Lim, W.H.T. (2013). Primary school students' learning experiences of, and self-beliefs about competence, effort, and difficulty: Random effects models. *Learning and Individual Differences, 28*, 54–65. doi: 10.1016/j.lindif.2013.09.007

Martin, A.J., Papworth, B., Ginns, P., Malmberg, L-E., Collie, R. & Calvo, R.A. (2015). Real-time motivation and engagement during a month at school: Every moment of every day for every student matters. *Learning and Individual Differences, 38*, 26–35. doi: 10.1016/j.lindif.2015.01.014

McGillivray, S., Murayama, K. & Castel, A.D. (2015). Thirst for knowledge: The effects of curiosity and interest on memory in younger and older adults. *Psychology and Aging, 30*, 835–841. doi: 10.1037/a0039801

Meece, J.L. & Holt, K. (1993). A pattern analysis of students' achievement goals. *Journal of Educational Psychology, 85*, 582–590. doi: 10.1037/0022-0663.85.4.582

Molenaar, P.C.M. (2004). A manifesto on psychology as idiographic science: Bringing the person back into scientific psychology, this time forever. *Measurement: Interdisciplinary Research and Perspectives, 2,* 201–218.

Molenaar, P.C.M. & Campbell, C.G. (2009). The new person-specific paradigm in psychology. *Current Directions in Psychological Science, 18*, 112–116. doi: 10.1111/j.1467-8721.2009.01619.x

Moneta, G.B. & Csikszentmihalyi, M. (1996). The effect of perceived challenges and skills on the quality of subjective experience. *Journal of Personality, 64,* 275–310. doi: 10.1111/j.1467-6494.1996.tb00512.x

Monin, B. & Oppenheimer, D.M. (2005). Correlated averages vs. averaged correlations: Demonstrating the warm glow heuristic beyond aggregation. *Social Cognition, 23*, 257–278. doi: 10.1037/0022-3514.64.3.431

Murayama, K. (2003). Learning strategy use and short- and long-term perceived utility. *Japanese Journal of Educational Psychology, 51*, 130–140.

Murayama, K. (2006). *Effect of test format on learning strategy use and its underlying psychological processes* (Doctoral dissertation).

Murayama, K., Elliot, A.J. & Yamagata, S. (2011). Separation of performance-approach and performance-avoidance goals: A broader analysis. *Journal of Educational Psychology, 103*, 238–256. doi: 10.1037/a0021948

Murayama, K., et al. (2012). Achievement goals and approach-avoidance motivation. In R.M Ryan (Ed.), *Oxford handbook of human motivation* (pp.191–207). Oxford, UK: Oxford University Press.

Murayama, K., Sakaki, M., Yan, V.X. & Smith, G.M. (2014). Type 1 error inflation in the traditional by-participant analysis to metamemory accuracy: A generalised mixed-effects model perspective. *Journal of Experimental Psychology. Learning, Memory, and Cognition, 40*, 1287–1306. doi: 10.1037/a0036914

Nett, U.E., Goetz, T. & Hall, N.C. (2011). Coping with boredom in school: An experience sampling perspective. *Contemporary Educational Psychology, 36*, 49–56. doi: 10.1016/j.cedpsych.2010.10.003

Nesselroade, J.R., Gerstorf, D., Hardy, S.A. & Ram, N. (2007). Focus article: Idiographic filters for psychological constructs. *Measurement: Interdisciplinary Research and Perspectives, 5*, 217–235. doi: 10.1080/15366360701741807

Pekrun, R., Elliot, A.J. & Maier, M.A. (2006). Achievement goals and discrete achievement emotions: A theoretical model and prospective test. *Journal of Educational Psychology, 98,* 583–597. doi: 10.1037/0022-0663.98.3.583

Pekrun, R., Elliot, A.J. & Maier, M.A. (2009). Achievement goals and achievement emotions: Testing a model of their joint relations with academic performance. *Journal of Educational Psychology, 101*, 115–135. doi: 10.1037/a0013383

Pintrich, P.R. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. Pintrich & M. Zeidner (Eds.), *Handbook of self-regulation* (pp.451–502). San Diego: Academic Press.

Pekrun, R., Goetz, T., Daniels, L.M., Stupnisky, R.H. & Perry, R.P. (2010). Boredom in achievement settings: Control-value antecedents and performance outcomes of a neglected emotion. *Journal of Educational Psychology, 102*, 531–549. doi: 10.1037/a0019243

Przybylski, A.K., Weinstein, N., Murayama, K., Lynch, M.F. & Ryan, R.M. (2012). The ideal self at play: The appeal of video games that let you be all you can be. *Psychological Science, 23*, 69–76. doi: 10.1177/0956797611418676

Raudenbush, S.W. & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (2nd ed.). Thousand Oaks, CA: Sage.

Renninger, K.A. (2000). Individual interest and its implications for understanding intrinsic motivation. In C. Sansone & J. N. Harackiewicz (Eds.), *Intrinsic motivation: Controversies and new directions* (pp.373–404). New York: Academic Press.

Rubin, D.B. (1976). Inference and missing data. *Biometrika, 63*, 581–592. doi: 10.2307/2335739

Sameroff, A.J. (Ed.). (2009). *The transactional model of development: How children and contexts shape each other.* Washington, DC: American Psychological Association.

Schuurman, N.K., Ferrer, E., de Boer-Sonnenschein, M. & Hamaker, E.L. (2016). How to compare cross-lagged associations in a multilevel autoregressive model. *Psychological Methods, 21*, 206–221. doi: 10.1037/met0000062

Shonkoff, J.P. & Phillips, D.A. (Eds.). (2000). *From neurons to neighborhoods: The science of early childhood development*. Washington, DC: National Academy Press.

Tanaka, A. & Murayama, K. (2014). Within-person analyses of situational interest and boredom: Interactions between task-specific perceptions and achievement goals. *Journal of Educational Psychology, 106*, 1122–1134. doi: 10.1037/a0036659

Tucker, L.R. & Messick, S. (1963). An individual difference model for multidimensional scaling. *Psychometrika, 28*, 333–367. doi: 10.1007/BF02289557

Turner, S.A. & Silvia, P.J. (2006). Must things be pleasant? A test of competing appraisal structures. *Emotion, 6*, 670–674. doi: 10.1037/1528-3542.6.2.670

Voelkle, M.C., Brose, A., Schmiedek, F. & Lindenberger, U. (2014). Towards a unified framework for the study of between-person and within-person structures: Building a bridge between two research paradigms. *Multivariate Behavioral Research, 49*, 193–213. doi: 10.1080/00273171.2014.889593

Vygotsky, L.S. (1978). *Mind in society: The development of higher psychological processes*. Cambridge, MA: Harvard University Press.

Walker, R.A. Pressick-Kilborn, K., Arnold, L. & Sainsbury, E.J. (2004). Investigating motivation in context: Developing sociocultural perspectives. *European Psychologist, 9*, 245–256. doi: 10.1027/1016-9040.9.4.245

Walls, T.A. & Schafer, J.L. (Eds.) (2006). Models for intensive longitudinal data. Oxford: Oxford University Press.

Wigfield, A. & Eccles, J. S. (2000). Expectancy-value theory of motivation. *Contemporary Educational Psychology, 25*, 68–81. doi: 10.1006/ceps.1999.1015

Yoshida, T. & Murayama, K. (2013). Why students often fail to use learning strategies that experts find effective? *Japanese Journal of Educational Psychology, 61*, 32–43.