

# Examining the reciprocal influence between undergraduate students' self-regulation and approaches to learning

Jokke Häsä, Johanna Rämö & Zi Yan

To cite this article: Jokke Häsä, Johanna Rämö & Zi Yan (27 Aug 2024): Examining the reciprocal influence between undergraduate students' self-regulation and approaches to learning, Scandinavian Journal of Educational Research, DOI: [10.1080/00313831.2024.2394404](https://doi.org/10.1080/00313831.2024.2394404)

To link to this article: <https://doi.org/10.1080/00313831.2024.2394404>



© 2024 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group



[View supplementary material](#)



Published online: 27 Aug 2024.



[Submit your article to this journal](#)






[View related articles](#)



[View Crossmark data](#)

# Examining the reciprocal influence between undergraduate students' self-regulation and approaches to learning

Jokke Häsä <sup>a</sup>, Johanna Rämö <sup>b</sup> and Zi Yan <sup>c</sup>

<sup>a</sup>Department of Education, Centre for University Teaching and Learning, University of Helsinki, Helsinki, Finland; <sup>b</sup>Department of Physics and Mathematics, University of Eastern Finland, Joensuu, Finland; <sup>c</sup>Department of Curriculum and Instruction, The Education University of Hong Kong, Hong Kong, People's Republic of China

## ABSTRACT

This study explores the relationship between approaches to learning and self-regulation of learning. Approaches to learning characterise students' intentions and strategies regarding learning and studying, divided into deep and surface approaches together with organised studying. Self-regulation of learning is a process of monitoring and directing one's affect and behaviour in learning. It is known that self-regulation correlates with approaches to learning, but the direction of influence has not been demonstrated empirically. Measurements were taken in a first-year mathematics course on 103 Finnish undergraduates. Cross-lagged panel analysis was used to study the direction of time-lagged influence. The results revealed that significant influence existed from self-regulation to deep approach and organised studying, and from lack of regulation and external regulation to surface approach. Based on the results, we conclude that it is important for researchers and practitioners to take self-regulation into consideration when measuring approaches to learning or designing interventions.

## ARTICLE HISTORY

Received 5 June 2023  
Accepted 8 August 2024

## KEYWORDS


Self-regulated learning; approaches to learning; higher education; cross-lagged analysis; mathematics education

## Introduction

This study offers new information about the direction of influence between two psychological frameworks that are widely used in the study of learning in tertiary education. Self-regulated learning (SRL; Zimmerman, 1986; Vermunt, 1996; Pintrich, 2000) describes students' processes of monitoring their learning and adopting meaningful study strategies. Student approaches to learning (SAL; Marton & Säljö, 1976; Entwistle & Ramsden, 1983; Entwistle & McCune, 2004), usually divided into deep and surface approach, focus on the intentions that a student has when coming to a learning situation.

Both self-regulation and approaches to learning are used as predictors of student success and well-being (e.g., Trigwell & Prosser, 1991; Diseth & Martinsen, 2003; Vermunt, 2005; Heikkilä & Lonka, 2006; Haarala-Muhonen et al., 2017; Asikainen et al., 2020). These concepts are often incorporated or blended together under a framework of learning patterns, study strategies, cognitive profiles, or similar (e.g., Vermetten et al., 2001; Heikkilä et al., 2011). There is evidence indicating that efficient self-regulation and deep approach to learning are linked (e.g., Heikkilä & Lonka, 2006; Fryer & Vermunt, 2018), but causal relationships between the two concepts remain inconclusive.

**CONTACT** Jokke Häsä  jokke.hasa@helsinki.fi  Kerokuja 9, Vantaa 01280, Finland

 Supplemental data for this article can be accessed online at <https://doi.org/10.1080/00313831.2024.2394404>.

© 2024 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group  
This is an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. The terms on which this article has been published allow the posting of the Accepted Manuscript in a repository by the author(s) or with their consent.

Moreover, the introduction of a third approach to learning, so-called strategic approach or organised studying (e.g., Entwistle & McCune, 2004), creates a significant overlap between the concepts, as this approach describes students' disposition to be strategic about their learning and time management.

The data used in this study consists of pre- and post-measurements of regulation of learning and student approaches to learning for 103 mostly first-year university students, and it was analysed using a cross-lagged panel analysis (Green, 2016; Selig & Little, 2012). Cross-lagged analysis is a time-delayed path modelling method that is able to suggest causal influence between the study variables. By measuring the strength of influence and comparing it between two directions, we aim to add clarity to the theoretical relationship between self-regulation of learning and approaches to learning by empirically distinguishing between the two related frameworks. Knowing which variables can causally predict others helps to design better interventions as well as analyse their effects.

## Theoretical background

### *Self-regulated learning*

Self-regulated learning (SRL) describes an individual's conscious processes to regulate themselves in order to achieve their chosen learning gains (e.g., Zimmerman, 1986; Pintrich & De Groot, 1990; Zimmerman & Schunk, 2001). Pintrich (2000, p. 453) defines SRL as an "active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features in the environment". SRL is theorised to be an important factor of study success, especially in higher education (e.g., Zimmerman, 1990; Winne, 1995), and this connection has been confirmed in several empirical investigations (e.g., Vermunt, 2005; Heikkilä & Lonka, 2006).

Various models have been developed emphasising different aspects of SRL (Puustinen & Pulkkinen, 2001; Panadero, 2017). Puustinen and Pulkkinen (2001) studied five well-developed models, and they identify three phases that underlie these models: (1) preparatory phase, in which planning and goal-setting take place, (2) performance phase, in which strategies are applied, actions controlled and progress monitored, and (3) appraisal phase, in which feedback is examined and self-reflection applied.

Students lacking self-regulation skills can find support for their regulation of learning in the study environment. From his interviews with university students, Vermunt (1996) recognised patterns of *self-regulation*, *external regulation* and *lack of regulation*. Externally regulated students let themselves be guided by the instructor, and may not engage deeply with the subject or look for resources outside what is provided by the teacher. Students experiencing lack of regulation are willing to follow the instructor's lead, but lack the capacity to do so. For example, they may not understand the instructions, may have difficulties with time management or with recognising what is important in the large quantity of information provided by the teacher. Furthermore, Vermunt (1998) differentiated between *process-* and *content-oriented* self-regulation. Self-regulation of process signifies planning and monitoring of activities as well as posing one's own learning objectives, whereas self-regulation of content is focused on consulting literature and sources outside the course syllabus provided by the teacher.

Self-regulation skills are not fixed in an individual, but they depend on time and situation. Studies have found that self-regulation skills improve with age (Vermunt, 2005) and vary with academic discipline (Vermunt, 2005; Virtanen & Nevgi, 2010). They can also be developed through the learning environment, and there is overwhelming literature to suggest different methods of improvement of self-regulation, such as metacognitive training and modelling (e.g., Pintrich, 1995), self-assessment (e.g., Brown & Harris, 2014) and formative assessment and feedback (e.g., Nicol & Macfarlane-Dick, 2006). Self-regulation may also be developed in collaborative environments through so-called co-regulation, in which students share the regulation of learning with others (e.g., Hadwin et al., 2018). However, there is also a significant amount of regularity and

consistency in an individual's self-regulation strategies, which may be related to personality traits (e.g., Vermetten et al., 2001).

### **Approaches to learning**

There is a long tradition of studying students' approaches to learning in higher education. Marton and Säljö (1976) investigated how university students read an academic text and process the information it contains. They identified two different ways of doing this: surface processing and deep processing. Later the concepts evolved to contain students' intentions related to their studying and learning, in addition to their learning processes. Accordingly, the concepts were renamed *deep approach to learning* and *surface approach to learning* (e.g., Entwistle & Ramsden, 1983; Entwistle et al., 2006). Applying a deep approach to learning means that one has an intention to understand ideas for themselves. Students who apply a surface approach to learning aim to cope minimally with the requirements of a course leading to routine memorisation and unreflective studying (Entwistle & Peterson, 2004).

There is also a third approach called *organised studying* (Entwistle & McCune, 2004; Entwistle & Peterson, 2004), which has previously been called a strategic approach (Entwistle & Ramsden, 1983) or achieving approach (Biggs, 1987). Students who apply this approach organise their studying thoughtfully and manage their time and effort. Organised studying is different from the other approaches to learning as it describes how students organise their learning rather than how they approach their learning. It is considered to be an approach to studying rather than an approach to learning (Biggs, 1987; Entwistle & McCune, 2004).

It should be noted that there is variation *within* approaches to learning. For example, Lindblom-Ylänne et al. (2019) interviewed students who scored high on a surface level scale of an instrument measuring approaches to learning, and identified five different profiles among these students. The students' profiles ranged from full surface approach to deep approach with memorisation.

In several studies, deep approach to learning has been linked to high academic achievement and surface approach to learning to lower academic achievement (e.g., Marton & Säljö, 1976; Trigwell & Prosser, 1991; Minbashian et al., 2004; Diseth & Martinsen, 2003; Diseth, 2007). In particular, the combination of a deep approach to learning and organised studying seems to be positively linked to study success (e.g., Diseth, 2003; Haarala-Muhonen et al., 2017). However, in some studies, no correlation between a deep approach and academic achievement has been found (e.g., Campbell & Cabrera, 2014; Herrmann et al., 2017). Also, in some contexts, such as in particular study programmes, a surface approach can correlate positively with study success (Lizzio et al., 2002).

Even though students have a general tendency to assume a certain approach to learning (Entwistle & Ramsden, 1983), their approaches to learning are not stable. Student-centred learning environments have been found to foster deep approach to learning, (e.g., Baeten et al., 2010; Lahdenperä et al., 2019; Wilson & Fowler, 2005), but there are also studies indicating that they can encourage students towards a surface approach (Baeten et al., 2010). Also, nonoptimal workload, too many or few challenges, and stress can result in applying a surface approach to learning (Cheung et al., 2020; Coertjens et al., 2016).

### **Connections between regulation of learning and approaches to learning**

Previous studies have found connections between the different dimensions of student approaches to learning and regulation of learning. Heikkilä and Lonka (2006) reported a positive correlation between deep approach and self-regulation. They also found a positive correlation between surface approach and both external regulation and lack of regulation. Lonka and Lindblom-Ylänne (1996) formed profiles of medicine and psychology students with regard to study practices, epistemologies and conceptions of learning. One of the profiles combined external regulation with reproduction-oriented learning, and another did the same with self-regulation and meaning-directed learning. In

another person-oriented study, Fryer and Vermunt (2018) found a subgroup of Japanese first-year students exhibiting low deep approach and low self-regulation. This profile was relatively stable during the eight months of the longitudinal study.

Efficient self-regulation may also appear together with different kinds of approaches and strategies. Vermunt (1998) found that self-regulation was connected with many different processing strategies, whereas external regulation was connected only with reproduction-oriented strategies, such as memorising and rehearsing, as well as analysing in detail. Using the same instrument, Vermetten et al. (2001) created a path model to explain the relative consistency of study strategies based on personality traits. They use “deep learning” and “surface learning” as latent variables, with both deep and surface learning loading onto observed self-regulation, but only surface learning loading onto external regulation.

On the contrary, lack of regulation and external regulation seem to be connected only with surface approach and strategies, but there is some variation within this rule. Lindblom-Ylänne et al. (2019) studied students with a high level of surface approach and found features of lack of regulation or external regulation with only some of them. Similarly, Heikkilä et al. (2011) found two maladaptive profiles of university students, with equivalent scores on surface approach, but differing on lack of regulation, critical evaluation and task-irrelevant behaviour.

Several studies have used both self-regulation and approaches to learning together to predict academic achievement (e.g., Beishuizen et al., 1994; Vermunt, 2005; Heikkilä & Lonka, 2006; Phan, 2008; Heikkilä et al., 2011; Ilhan-Beyaztas & Göçer-Sahin, 2018). Some of these studies have used path models to delve further into the predictive relationships between self-regulation and approaches to learning: Ilhan-Beyaztas and Göçer-Sahin (2018) predicted approaches to learning from self-regulation variables, and Phan (2008) predicted self-regulation from learning approaches. These studies found significant connections, but their designs do not allow for conclusions about causation. Other studies, such as that of Lindblom-Ylänne et al. (2019) cited above, have implied causal relationships based on theoretical considerations. However, to our knowledge, no quantitative studies have directly attempted to measure causal or influential relationships between self-regulation and approaches to learning.

### ***The present study***

To respond to the research gap outlined above, this study was designed to explore the reciprocal relationship between students’ self-regulation and their approaches to learning using a 2-wave cross-lagged panel model in the timeframe of one eight-week study module. The study sheds light on the causal relationships between these two concepts, which have remained inconclusive in prior studies. Based on our literature review, we hypothesise that there should be strong links between self-regulation and deep and organised learning approaches, and likewise, between external or lack of regulation and surface learning approach. As studies have indicated that external regulation is almost invariably connected with reproduction-oriented strategies but these strategies can coexist with different regulation profiles, it is reasonable to expect a stronger influence from external regulation or lack of regulation to surface approach than in the other direction. For deep learning approach, it is more difficult to form any hypothesis.

## **Method**

### ***Context and participants***

The study took place in a mathematics course at a research-intensive university in Finland. The topic of the focus course was linear algebra, and the course is one of the first mathematics courses students take. The course lasted for 7 weeks and was worth 5 ECTS credits. The students of the course were either mathematics students or studied mathematics as a minor subject. Common

majors among the latter were computer science, economics, statistics, physics and education. Majority of the students were first-year university students who came from high school. Among the students there were also older students who had work experience, but they formed a minority. There were 375 students who showed some activity during the course (i.e., completed at least one task during the course).

There were 103 students who responded to all study questionnaires and gave their informed consent. They represent 27% of the students in the course. The response rate to each questionnaire is broken down under “Data collection” below. Participants’ ages at the start of the study were between 18 and 60, inclusive, with 56% between 18 and 20, 17% between 21 and 25, 11% between 26 and 30 and 16% older than 30. The gender distribution was: 44 female (43%), 55 male (53%), 1 other (1%). Three students (3%) did not wish to disclose their gender.

### Data collection

Data were collected from three sources. In the focus course, students filled in two electronic questionnaires: one at the beginning of the seven-week course, and one at the end. Both questionnaires were compulsory for passing the course; the first one was open during the first two weeks of the course, the second one opened after the final assessment and was open during one week. In addition, data were obtained from a university-wide electronic survey that all students were required to complete at the beginning of their studies, some weeks prior to the start of the focus course. The university-wide survey and the first course-associated questionnaire were used as pre-course data, and the second course-associated questionnaire as post-course data.

The university-wide survey consists of several research-based scales related to students’ approaches to learning, well-being, reasons to apply to the specific programme, and so on. In this study, we used the student approaches to learning (SAL) Likert-type scale from the survey. This scale is developed by researchers in the focus university based on the Experiences of Teaching and Learning Questionnaire (ETLQ; Entwistle et al., 2003) and validated in the Finnish university context (Parpala et al., 2013). It contains three subscales, corresponding to deep approach (AppDeep), surface approach (AppSurf) and organised studying (AppOrg), with four items to each subscale. The questions in the survey did not pertain to studying in a particular course but rather to studying in general. An example item for each variable (translated from Finnish) is given in Table 1. All SAL scales were measured with Likert points from 1 (strongly disagree) to 5 (strongly agree). Of the students in the focus course, 115 had responded to the university-wide survey (response rate 31%) and gave consent to use their data in this research study.

The first course questionnaire contained Likert-type questions related to students’ self-assessment attitudes and behaviour, and regulation of learning (REG). For this study, we used the regulation of learning scale, which is based on Vermunt’s Inventory of Learning Styles (ILS; Vermunt, 1998), and recently shortened, modified and translated to suit the Finnish university context (Räsänen et al., 2020). The scale contains four subscales, corresponding to self-regulation of process

**Table 1.** Abbreviations and example items for the main study variables.

Measured variable	Abbreviation	Items	Example item (translated)
Deep approach	AppDeep	4	As I study, I will reflect on the ideas and perspectives presented.
Surface approach	AppSurf	4	I have trouble making sense of the things I have to learn.
Organised studying	AppOrg	4	On the whole, I am systematic and organised in my studying.
Self-regulation of process	RegProc	4	To test whether I have mastered the subject matter, I try to think of examples and problems besides the ones given in the study material or by the teacher.
Self-regulation of content	RegCont	3	In addition to the course requirements, I study other literature related to the content of the course.
External regulation	RegExt	4	The instructions and the course objectives given by the teacher are important to me in order to know exactly what to do.
Lack of regulation	RegLack	4	I have noticed that I have trouble processing a large amount of subject matter.

(RegProc, 4 items), self-regulation of content (RegCont, 3 items), external regulation (RegExt, 4 items) and lack of regulation (RegLack, 4 items). Example items are given in Table 1. All REG scales were measured with Likert points from 1 (strongly disagree) to 7 (strongly agree). As in the case of SAL, the questionnaire concerned studying in general as opposed to studying a particular course. There were 344 students (response rate 92%) who responded to the first course questionnaire and gave consent to use their data.

The second course questionnaire contained several sections related to different aspects of learning in the course. The SAL and REG scales were copied from the pre-course questionnaires. There were again 344 students (response rate 92%) who responded to the second course questionnaire and gave consent to use their data. The questionnaires were electronic and did not allow for skipping any items. Only those students who responded to all three questionnaires and gave their consent were included in this study. The final number of participants in this study was  $N = 103$ .

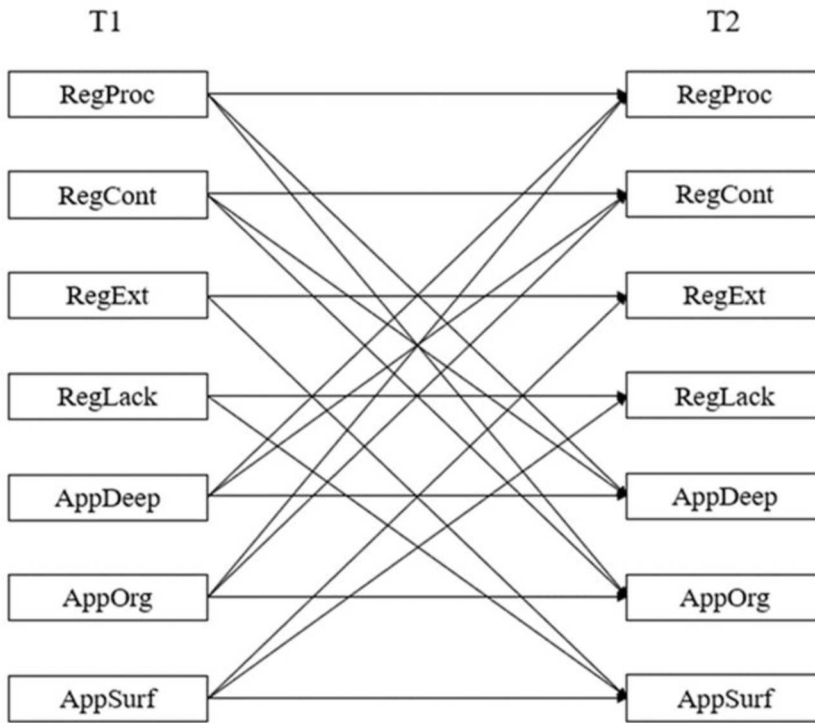
### Data analysis

Before addressing the structural cross-lagged relationships, the Rasch model (Rasch, 1980) was applied (1) to examine the quality of the survey data; (2) to check the measurement invariance for all item estimates; and (3) to calibrate the person measures on all variables. The Rasch model employs a “data fit the model” approach, which requires the empirical data to meet a priori requirements to achieve fundamental measurement (Andrich, 2004; Bond et al., 2020). Rasch analysis helps convert ordinal data collected through Likert-type instruments into continuous interval data which can then be used in subsequent analyses. Additionally, it provides practical benefits such as item-level statistics. Owing to these advantages, Rasch analysis has been increasingly utilised in the evaluation of scale quality (e.g., Brann et al., 2021; van der Lans et al., 2018; Yan, 2020; Yan & Pastore, 2022). As both REG and SAL instruments contain inter-correlated subscales, a multidimensional Rasch model analysis using ConQuest 2.0 (Wu et al., 2007) was applied to each instrument respectively. The Rating Scale Rasch Model (RSM) (Andrich, 1978) was used since all items in the same instrument share the same Likert-type response scale. The Rasch reliability and the item fit statistics were utilised to examine the quality of the data from a Rasch measurement perspective.

It is critical to build an invariant frame of reference for data analysis across different time points (Wright, 1996). The invariance of item estimates across T1 and T2 was checked through the method recommended by Bond et al. (2020, pp. 72–74). Rasch analysis was run separately for T1 and T2 data. The item difficulty estimates (and standard errors) were plotted onto a scatter plot. The 95% confidence band around the diagonal, calculated based on the standard error of each item estimate (Wright & Stone, 1979) was used as quality-control lines to examine whether the item estimates are invariant (within the limits of measurement error). After ensuring all items were invariant, data from T1 and T2 were stacked, i.e., each person appears twice (as rows), but each item appears only once (in columns) (Wright, 2003). Each person’s Rasch-calibrated measures at T1 and T2 were generated. There were no item-level missing data, since the questionnaires were electronic, and respondents had to answer all items in the relevant scales at both T1 and T2.

The Rasch-calibrated person measures were then subject to the cross-lagged panel analysis, as shown in Figure 1, using AMOS version 24. The person measures in logits (Log-Odds Unit), obtained from the Rasch analysis, refer to an individual’s level on the latent trait (in this case, self-regulation and approaches to learning). A high value indicates a high level of the latent trait measured. The cross-lagged panel design is a non-experimental research design to test a causal effect of one variable on another by estimating the directional influence between variables over time (Green, 2016; Selig & Little, 2012). The direction of causality between the two variables is determined by comparing the cross-lagged regression effects.

To address cross-lagged relationships, we tested two nested models: the full model and a restricted model. The full model was a saturated model which allowed all variables at T1 to be regressed on by all variables at T2. In the restricted model, only theoretically supported



**Figure 1.** The conceptual cross-lagged panel model.

relationships across T1 and T2 were specified (see [Figure 1](#)): self-regulation of content (RegProc) and self-regulation of process (RegCont) were connected with deep approach (AppDeep) and organised study (AppOrg); external regulation (RegExt) and lack of regulation (RegLack) were connected with surface approach (AppSurf). After the model comparison, the preferred model was re-run with gender (male vs. female, others omitted because of small sample size) included as a control variable. Model fit was examined using chi-square test of model fit ( $\chi^2$ ),  $\chi^2/df$ , goodness-of-fit index (GFI), comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), and standardised root mean square residual (SRMR) (Awang, 2012; Hu & Bentler, 1999; McDonald & Ho, 2002).

## Results

### *Preliminary analyses*

The multidimensional Rasch analyses on REG at T1 and T2 revealed that infit and outfit MNSQ for all items fall into the acceptable range of 0.5–1.5 (Linacre, 2021), indicating satisfactory item fit to the Rasch model. Furthermore, all items demonstrated sufficient invariance of item difficulty across T1 and T2. However, the multidimensional Rasch analyses on SAL at T1 and T2 identified two problematic items. Item #4 in AppOrg (“I have planned my study time so that I can complete my studies in the intended schedule”) demonstrated marginal misfit to the Rasch model at T1 (infit and outfit MNSQ were 1.54 and 1.49, respectively), and substantial underfit at T2 (infit and outfit MNSQ were 1.68 and 1.62, respectively). Item #3 in AppSurf subscale (“Things I would need to learn feel so complicated that I have trouble understanding them”) had substantially different item difficulties across T1 and T2. These two items were removed from subsequent analyses. The item difficulties and fit statistics for REG and SAL

**Table 2.** Rasch reliabilities and item fit statistics of REG and SAL.

Instrument/subscale	No of items	Rasch reliability	Range of infit MNSQ	Range of outfit MNSQ
RegProc	4	0.73	0.86–1.18	0.88–1.21
RegCont	3	0.80	1.03–1.26	1.04–1.30
RegExt	4	0.70	0.72–0.92	0.74–0.96
RegLack	4	0.70	0.83–1.32	0.86–1.30
AppSurf	3	0.72	0.81–1.25	0.77–1.24
AppDeep	4	0.75	0.75–1.03	0.78–1.05
AppOrg	3	0.72	1.02–1.11	0.99–1.13

items at T1 and T2 are detailed in Table SM1 and Table SM2, respectively, in the Supplementary Materials. The checking for invariance of item estimates across T1 and T2 is illustrated in Figure SM1 and Figure SM2.

Data from T1 and T2 were then stacked and Rasch analyses were applied on REG and SAL, respectively. All subscales had acceptable Rasch reliabilities, ranging from 0.70 to 0.80. All items fit the Rasch model well. Table 2 presents the details of the psychometric properties of the subscales. Table 3 provides descriptive statistics including means, standard deviations, and correlations among variables.

There were some notable correlations between approaches to learning and self-regulation. Deep approach correlated positively with self-regulation of process (Time 1: .54, Time 2: .63), and surface approach correlated positively with lack of regulation at both time points (T1: .57, T2: .71), and with external regulation at Time 2 (.24). Also, organised studying correlated positively with regulation of process (T1: .23, T2: .35).

### Main analyses

The two nested models (the full model vs. the restricted model) were compared with a  $\chi^2$  different test aiming to find a parsimonious model with good data-model fit. The results showed that  $\Delta\chi^2(\Delta df = 24) = 29.815$ ,  $p = .191$ , indicating that the restricted model had a comparable level of model-data fit with that of the full model. Hence, the restricted model (i.e., the theory-driven model) was adopted as a parsimonious model in the subsequent analyses.

Table 4 and Figure 2 present the results of the cross-lagged model between regulation of learning and approaches to learning using the theory-driven model. Overall, the model-data fit was satisfactory:  $\chi^2(24) = 29.815$ ,  $p = .191$ ;  $\chi^2/df = 1.242$ ; GFI = .96; CFI = .99; TLI = .97; RMSEA = .05; SRMR = 0.04. As expected, the autoregressive effects across T1 and T2 for all variables were statistically significant ( $p < .01$ ). The standardized path coefficients for the cross-lagged relationships showed that students' self-regulated learning at T1 predicted their learning approach at T2. In particular, regulation of process predicted both deep approach and organised studying; both external regulation and lack of regulation predicted surface approach. Regulation of content had only a borderline significant predicting effect on deep approach ( $p = .06$ ). In contrast, students' learning approach at T1 did not predict their self-regulated learning at T2. The path coefficients for the cross-lagged paths from learning approaches to regulation of learning were weak and non-significant. The strongest such coefficient was from surface approach to lack of regulation. The results also showed that gender had no significant correlations with any variables at T2 ( $\beta$  ranged from  $-.034$  to  $.087$ ), indicating that the inclusion of gender as a control variable did not confound the cross-lagged model.

## Discussion

### The relationship between self-regulation and approaches to learning

In this study, we investigated undergraduate mathematics students' approaches to learning and regulation of learning. Approaches to learning and regulation of learning were measured at the

**Table 3.** Correlations, means and standard deviations among variables measured at two time instances (*N* = 103).

Variable/time	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. RegProc T1	–													
2. RegCont T1	.54 **	–												
3. RegExt T1	.01	–.14	–											
4. RegLack T1	–.37 **	–.34 **	.20 *	–										
5. RegProc T2	.75 **	.43 **	.14	–.24 *	–									
6. RegCont T2	.46 **	.66 **	–.09	–.26 **	.46 **	–								
7. RegExt T2	–.03	.70 **	.14	.14	.11	–.14	–							
8. RegLack T2	–.23 *	–.28 **	.31 **	.64 **	–.05	–.28 **	.33 **	–						
9. AppSurf T1	–.35 **	–.24 *	.14	.57 **	–.23 *	–.29 **	.08	.46 **	–					
10. AppDeep T1	.54 **	.27 **	.01	–.19	.43 **	.19	–.04	–.17	–.29 **	–				
11. AppOrg T1	.23*	.18	.14	–.20 *	.22 *	.13	.26 **	–.00	–.15	.15	–			
12. AppSurf T2	–.28 **	–.32 **	.32 **	.53 **	–.18	–.29 **	.24 *	.71 **	.60 **	–.24 *	–.05	–		
13. AppDeep T2	.60 **	.46 **	.12	–.24 *	.63 **	.51 **	.13	–.20 *	–.23 *	.54 **	.22 *	–.32 **	–	
14. AppOrg T2	.31 **	.18	.18	–.23 *	.35 **	.27 **	.35 **	–.09	–.27 **	.12	.67 **	–.15	.40 **	–
Mean <sup>a</sup>	0.87	0.31	1.11	–0.55	0.89	0.42	1.10	–0.67	–0.84	1.76	1.05	–0.94	1.95	1.41
SD <sup>a</sup>	0.96	0.99	0.88	1.04	0.89	1.03	1.00	0.92	1.32	1.38	1.29	1.84	1.57	1.61

Note: T1: Time 1; T2: Time 2.

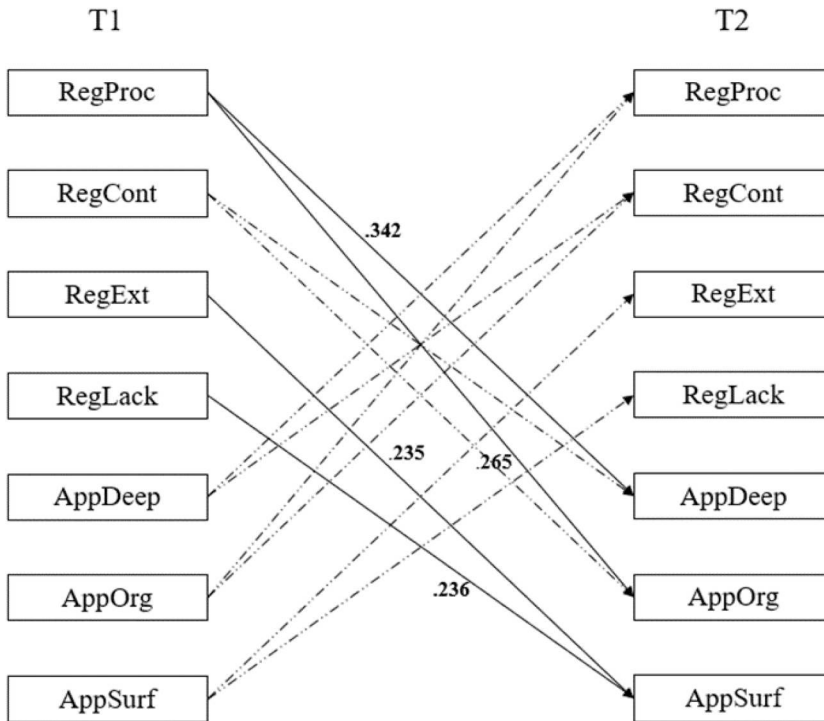
<sup>a</sup>All measures are in Rasch logits.

\**p* < .05. \*\**p* < .01.

**Table 4.** Standardised path coefficients for the cross-lagged model between REG and SAL.

Path	Standardised path coefficient [95% CI]
Autoregressive paths	
RegProc → RegProc T2	.716** [.423, .899]
RegCont T1 → RegCont T2	.571** [.395, .726]
RegExt T1 → RegExt T2	.667** [.524, .774]
RegLack T1 → RegLack T2	.527** [.325, .772]
AppDeep T1 → AppDeep T2	.293** [.114, .470]
AppOrg T1 → AppOrg T2	.601** [.456, .719]
AppSurf T1 → AppSurf T2	.432** [.219, .622]
Cross-lagged paths from REG to SAL	
RegProc T1 → AppDeep T2	.342* [.070, .533]
RegProc T1 → AppOrg T2	.265* [.048, .433]
RegCont T1 → AppDeep T2	.167 [-.004, .354]
RegCont T1 → AppOrg T2	-.045 [-.209, .120]
RegExt T1 → AppSurf T2	.235** [.071, .368]
RegLack T1 → AppSurf T2	.236* [.031, .505]
Cross-lagged paths from SAL to REG	
AppDeep T1 → RegProc T2	.030 [-.132, .240]
AppDeep T1 → RegCont T2	-.072 [-.260, .098]
AppOrg T1 → RegProc T2	.024 [-.116, .186]
AppOrg T1 → RegCont T2	.025 [-.147, .209]
AppSurf T1 → RegExt T2	-.024 [-.204, .158]
AppSurf T1 → RegLack T2	.118 [-.092, .324]

Note: T1: Time 1; T2: Time 2.  
\* $p < .05$ . \*\* $p < .01$ .



**Figure 2.** The cross-lagged relationship between REG and SAL. Note: Significant cross-lagged paths are represented by solid lines, and non-significant cross-lagged paths are represented by dotted lines. For clarity, autoregressive paths are not shown although they were controlled for in the model.

beginning and at the end of a study module, and cross-lagged panel analysis was used to determine time-lagged effects between the two concepts.

It is known from previous studies that students' regulation of learning correlates with their approaches to learning, with deep approach correlating positively with self-regulation and surface approach with external regulation or lack of regulation (e.g., Heikkilä & Lonka, 2006). Our preliminary analysis revealed similar correlations, with positive correlation between deep approach and self-regulation, and also between surface approach and lack of regulation. External regulation had a weaker correlation with surface learning.

The cross-lagged analysis examines reciprocal relationships between the different variables over time. According to our results, self-regulation of process seemed to influence deep approach to learning and organised studying, and external regulation and lack of regulation both seemed to influence surface approach to learning. What is notable, is that cross-lagged influence could not be justified in the opposite direction. In other words, approaches to learning did not have statistically significant time-lagged effects on the self-regulation variables. This means that the two frameworks act distinctly, in spite of their theoretical overlap.

Adopting a surface approach to learning means focusing on memorisation of individual facts instead of building a coherent network of knowledge. Our results suggest that this approach may often be caused by the student's relying on teachers and other external parties for the regulation of their studies, or by an inability to use any means of regulation. These kinds of students were observed by Fryer and Vermunt (2018) to form a very stable subgroup that might benefit from interventions targeting their lack of regulation. However, we also found that surface approach does not necessarily imply poor self-regulation skills, as the time-lagged influence was not observed in this direction. This is in line with the idea that surface approach is a multi-faceted phenomenon (Lindblom-Ylänne et al., 2019; Heikkilä et al., 2011). Also, self-regulation has been found in connection to both deep and surface learning (Vermunt, 1998; Vermetten et al., 2001). One could hypothesise that surface approach may sometimes be adopted as a cost-efficient strategy also by a self-regulating student.

Similarly, we found that deep approach does not necessarily imply strong self-regulation skills. This suggests that some students may be pursuing a deep understanding of their subject, but are not capable of managing their learning effectively. Indeed, such groups of students have been found in other studies, and it seems that these students are often at risk of both academic failure and decline in well-being (Haarala-Muhonen et al., 2017; Asikainen et al., 2020).

On the other hand, our results suggest that good self-regulation skills often lead to a deep approach to learning. One possible explanation is the culture in higher education which emphasises "higher" learning and "deeper" understanding. It may be that the students with good self-regulation abilities realise that choosing a deep approach will pay back in the long run. This feature of self-regulation is known as *academic delay of gratification* (Bembenutty & Karabenick, 2004).

In the context of this study, organised studying referred to concrete means of organising one's work, such as setting timetables. Self-regulation of learning, on the other hand, referred to taking initiative and finding ways to deal with challenges in learning. We found that self-regulation positively influenced organised studying, which suggests that students who are able to deal with challenges related to studying will use timetables and such methods to organise their studies. However, the two concepts are not identical, as organised studying did not influence self-regulation.

### **Limitations of study**

The pre-course data were acquired from two sources: course starting questionnaire and a university-wide survey. When inspecting the data, we noticed that on average, students who answered the university-wide survey had significantly stronger self-regulation than other students in the course. The finding does not undermine our results, but it may hinder their generalisation, as the sample was not representative of students in the course.

The questionnaires used in the study were deemed reliable, as they had been previously validated in higher education context in the same country. Furthermore, the scales were inspected and modified through Rasch analysis before the cross-lagged analysis. However, the number of items for each approach to learning was rather small (3 or 4), and possibly could not capture the full variability of the concept.

Finally, cross-lagged panel analysis requires that the measurements be performed at the same time, but due to using different sources for the pre-course data, there was a delay of some weeks between the pre-data on approaches to learning and on regulation of learning. Based on experience, it is not likely that the measured values of the regulation variables would have changed much in the meantime, but the failure to meet the assumptions means that the results must be taken as tentative and exploratory and should be corroborated in future studies.

### ***Implications for research and practice***

The concepts of approaches to learning and regulation of learning have evolved during the past decades (e.g., Marton & Säljö, 1976; Entwistle & Ramsden, 1983; Entwistle & Peterson, 2004; Lindblom-Ylänne et al., 2019; Puustinen & Pulkkinen, 2001). As a result, definitions in different sources vary and different names can be sometimes used for the same concepts. The close connection between regulation of learning and approaches to learning has led some researchers to use one in place of another, for example, use deep approach as an indicator of self-regulation, use external regulation interchangeably with lack of regulation, or interpret organised studying as a sign of self-regulation. Whereas all of these interpretations are supported by strong correlations, the different concepts are not identical and assumptions about the direction of influence may be misleading. Moreover, there are several different survey instruments designed to measure these constructs, and they may emphasise different aspects. This makes it difficult to relate findings from different studies, and suggests a need for future review studies on these topics.

Our study indicates that self-regulation of learning and student approaches to learning have distinct effects, so they indeed serve different purposes in explaining students' learning behaviour. It seems that self-regulation (or lack thereof) is a more underlying concept that either permits or hinders certain approaches to learning. This may help to explain some findings regarding approaches to learning, such as why some students change their approaches in different learning environments, whereas others do not (Coertjens et al., 2016; Lahdenperä et al., 2019), or why deep approach seems to be beneficial to student success mainly when coupled with organised studying (Haarala-Muhonen et al., 2017; Asikainen et al., 2020). It also seems that self-regulation may be more stable and trait-like than approaches to learning, as both correlations over time and the autoregressive paths of each of deep and surface approach were weaker than those for regulation of learning variables (organised studying lies somewhere in between). More studies should be performed that investigate the combined effect of self-regulation and approaches to learning on student success and well-being.

The results of this study also have implications for teaching practices. Our results suggest that good self-regulation skills lead to higher levels of deep approach to learning and organised studying. On the other hand, deep approach to learning and organised studying are desirable in higher education, not only because they are needed for acquiring expert skills, but also because they are related to study success and well-being. Therefore, in light of our results, it is of utmost importance to develop students' self-regulation. In teaching interventions, it might be more important to focus on fostering self-regulation than deep approach to learning or organised studying.

### **Disclosure statement**

No potential conflict of interest was reported by the author(s).

## Data availability statement

The participants of this study did not give written consent for their data to be shared publicly, so due to the sensitive nature of the research supporting data is not available.

## Ethical statement

The data collection was performed with the informed consent of the participants. According to the ethical principles of research with human participants published by the Finnish National Board on Research Integrity, no ethical review was necessary, since the data collection was done in Finland with participants over 15 years of age, without intervening in the physical integrity of the participants and without exposing participants to strong stimuli exceeding the limits of normal daily life ([https://tenk.fi/sites/default/files/2021-01/Ethical\\_review\\_in\\_human\\_sciences\\_2020.pdf](https://tenk.fi/sites/default/files/2021-01/Ethical_review_in_human_sciences_2020.pdf)).

## ORCID

Jokke Häsä  <http://orcid.org/0000-0001-7490-1205>

Johanna Rämö  <http://orcid.org/0000-0002-9836-1896>

Zi Yan  <http://orcid.org/0000-0001-9305-884X>

## References

- Andrich, D. (1978). A rating formulation for ordered response categories. *Psychometrika*, 43(4), 561–573. <https://doi.org/10.1007/BF02293814>
- Andrich, D. (2004). Controversy and the Rasch model: A characteristic of incompatible paradigms? *Medical Care*, 42(1), 1–16. <https://doi.org/10.1097/01.mlr.0000103528.48582.7c>
- Asikainen, H., Salmela-Aro, K., Parpala, A., & Katajavuori, N. (2020). Learning profiles and their relation to study-related burnout and academic achievement among university students. *Learning and Individual Differences*, 78, 101781. <https://doi.org/10.1016/j.lindif.2019.101781>
- Awang, Z. (2012). *Structural equation modeling using Amos Graphic*. UiTM Press.
- Baeten, M., Kyndt, D., Struyven, K., & Dochy, F. (2010). Using student-centred learning environments to stimulate deep approaches to learning: Factors encouraging or discouraging their effectiveness. *Educational Research Review*, 5(3), 243–260. <https://doi.org/10.1016/j.edurev.2010.06.001>
- Beishuizen, J., Stoutjesdijk, E., & Van Putten, K. (1994). Studying textbooks: Effects of learning styles, study task, and instruction. *Learning and Instruction*, 4(2), 151–174. [https://doi.org/10.1016/0959-4752\(94\)90009-4](https://doi.org/10.1016/0959-4752(94)90009-4)
- Bembenutty, H., & Karabenick, S. A. (2004). Inherent association between academic delay of gratification, future time perspective, and self-regulated learning. *Educational Psychology Review*, 16(1), 35–57. <https://doi.org/10.1023/B:EDPR.0000012344.34008.5c>
- Biggs, J. (1987). *Student approaches to learning and studying*. Australian Council for Educational Research.
- Bond, T. G., Yan, Z., & Heene, M. (2020). *Applying the Rasch model: Fundamental measurement in the human sciences* (4th ed.). Routledge.
- Brann, K. L., Boone, W. J., Splett, J. W., Clemons, C., & Bidwell, S. L. (2021). Development of the school mental health self-efficacy teacher survey using Rasch analysis. *Journal of Psychoeducational Assessment*, 39(2), 197–211. <https://doi.org/10.1177/0734282920947504>
- Brown, G. T., & Harris, L. R. (2014). The future of self-assessment in classroom practice: Reframing self-assessment as a core competency. *Frontline Learning Research*, 2(1), 22–30.
- Campbell, C. M., & Cabrera, A. F. (2014). Making the mark: Are grades and deep learning related? *Research in Higher Education*, 55(5), 494–507. <https://doi.org/10.1007/s11162-013-9323-6>
- Cheung, K., Yip, T. L., Wan, C. L. J., Tsang, H., Zhang, L. W., & Parpala, A. (2020). Differences in study work-load stress and its associated factors between transfer students and freshmen entrants in an Asian higher education context. *PLoS One*, 15(5), e0233022. <https://doi.org/10.1371/journal.pone.0233022>
- Coertjens, L., Vanthournout, G., Lindblom-Ylänne, S., & Postareff, L. (2016). Understanding individual differences in approaches to learning across courses: A mixed method approach. *Learning and Individual Differences*, 51, 69–80. <https://doi.org/10.1016/j.lindif.2016.07.003>
- Diseth, Å. (2003). Personality and approaches to learning as predictors of academic achievement. *European Journal of Personality*, 17(2), 143–155. <https://doi.org/10.1002/per.469>
- Diseth, Å. (2007). Students' evaluation of teaching, approaches to learning, and academic achievement. *Scandinavian Journal of Educational Research*, 51(2), 185–204. <https://doi.org/10.1080/00313830701191654>

- Diseth, Å., & Martinsen, Ø. (2003). Approaches to Learning, Cognitive Style, and Motives as Predictors of Academic Achievement. *Educational Psychology*, 23(2), 195–207. <https://doi.org/10.1080/01443410303225>
- Entwistle, N., & McCune, V. (2004). The conceptual bases of study strategy inventories. *Educational Psychology Review*, 16(4), 325–345. <https://doi.org/10.1007/s10648-004-0003-0>
- Entwistle, N., McCune, V., & Hounsell, D. (2003). Investigating ways of enhancing university teaching-learning environments: Measuring students' approaches to studying and perceptions of teaching. In E. De Corte, L. Verschaffel, N. Entwistle, & J. van Merriënboer (Eds.), *Unravelling basic components and dimensions of powerful learning environments* (pp. 89–107). Elsevier Science.
- Entwistle, N., McCune, V., & Sheja, M. (2006). Student Learning in Context: Understanding the Phenomenon and the Person. In L. Verschaffel, F. Dochy, M. Boekaerts, & S. Vosniadou (Eds.), *Instructional psychology. Past, present, and future trends: Sixteen essays in honour of Eric De Corte* (pp. 131–148). Elsevier.
- Entwistle, N. J., & Peterson, E. R. (2004). Conceptions of learning and knowledge in higher education: Relationships with study behaviour and influences of learning environments. *International Journal of Educational Research*, 41(6), 407–428. <https://doi.org/10.1016/j.ijer.2005.08.009>
- Entwistle, N., & Ramsden, P. (1983). *Understanding student learning*. Croom Helm.
- Fryer, L. K., & Vermunt, J. D. (2018). Regulating approaches to learning: Testing learning strategy convergences across a year at university. *British Journal of Educational Psychology*, 88(1), 21–41. <https://doi.org/10.1111/bjep.12169>
- Green, T. (2016). A methodological review of structural equation modelling in higher education research. *Studies in Higher Education*, 41(12), 2125–2155. <https://doi.org/10.1080/03075079.2015.1021670>
- Haarala-Muhonen, A., Ruohoniemi, M., Parpala, A., Komulainen, E., & Lindblom-Ylänne, S. (2017). How do the different study profiles of first-year students predict their study success, study progress and the completion of degrees? *Higher Education*, 74(6), 949–962. <https://doi.org/10.1007/s10734-016-0087-8>
- Hadwin, A., Järvelä, S., & Miller, M. (2018). Self-regulation, co-regulation, and shared regulation in collaborative learning environments. In D. H. Schunk & J. A. Greene (Eds.), *Educational psychology handbook series. Handbook of self-regulation of learning and performance* (pp. 83–106). Routledge/Taylor & Francis Group.
- Heikkilä, A., & Lonka, K. (2006). Studying in higher education: students' approaches to learning, self-regulation, and cognitive strategies. *Studies in Higher Education*, 31(1), 99–117. <https://doi.org/10.1080/03075070500392433>
- Heikkilä, A., Niemivirta, M., Nieminen, J., & Lonka, K. (2011). Interrelations among university students' approaches to learning, regulation of learning, and cognitive and attributional strategies: a person oriented approach. *Higher Education*, 61(5), 513–529. <https://doi.org/10.1007/s10734-010-9346-2>
- Herrmann, K. J., McCune, V., & Bager-Elsborg, A. (2017). Approaches to learning as predictors of academic achievement: Results from a large scale, multi-level analysis. *Högere utbildning*, 7(1), 29–42. <https://doi.org/10.23865/hu.v7.905>
- Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1–55. <https://doi.org/10.1080/10705519909540118>
- Ilhan-Beyaztas, D., & Göçer-Sahin, S. (2018). Investigation of the predictive power of academic achievement, learning approaches and self-regulatory learning skills on university entrance exam scores using path analysis. *World Journal of Education*, 8(2), 114–126. <https://doi.org/10.5430/wje.v8n2p114>
- Lahdenperä, J., Postareff, L., & Rämö, J. (2019). Supporting quality of learning in university mathematics: A comparison of two instructional designs. *International Journal of Research in Undergraduate Mathematics Education*, 5(1), 75–96. <https://doi.org/10.1007/s40753-018-0080-y>
- Linacre, J. M. (2021). *A user's guide to WINSTEPS/MINISTEP: Rasch-model computer programs*. Winsteps.com.
- Lindblom-Ylänne, S., Parpala, A., & Postareff, L. (2019). What constitutes the surface approach to learning in the light of new empirical evidence? *Studies in Higher Education*, 44(12), 2183–2195. <https://doi.org/10.1080/03075079.2018.1482267>
- Lizzio, A., Wilson, K., & Simons, R. (2002). University students' perceptions of the learning environment and academic outcomes: Implications for theory and practice. *Studies in Higher Education*, 27(1), 27–52. <https://doi.org/10.1080/03075070120099359>
- Lonka, K., & Lindblom-Ylänne, S. (1996). Epistemologies, conceptions of learning, and study practices in medicine and psychology. *Higher Education*, 31(1), 5–24. <https://doi.org/10.1007/BF00129105>
- Marton, F., & Säljö, R. (1976). On qualitative differences in learning: I – Outcome and process. *British Journal of Educational Psychology*, 46(1), 4–11. <https://doi.org/10.1111/j.2044-8279.1976.tb02980.x>
- McDonald, R. P., & Ho, M. R. (2002). Principles and practice in reporting structural equation analyses. *Psychological Methods*, 7(1), 64–82. <https://doi.org/10.1037/1082-989X.7.1.64>
- Minbashian, A., Huon, G. F., & Bird, K. D. (2004). Approaches to studying and academic performance in short-essay exams. *Higher Education*, 47(2), 161–176. <https://doi.org/10.1023/B:HIGH.0000016443.43594.d1>
- Nicol, D., & Macfarlane-Dick, D. (2006). Formative assessment and self-regulated learning: A model and seven principles of good feedback practice. *Studies in Higher Education*, 31(2), 199–216. <https://doi.org/10.1080/03075070600572090>

- Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology*, 8, 422. <https://doi.org/10.3389/fpsyg.2017.00422>
- Parpala, A., Lindblom-Ylänne, S., Komulainen, E., & Entwistle, N. (2013). Assessing students' experiences of teaching-learning environments and approaches to learning: Validation of a questionnaire in different countries and varying contexts. *Learning Environments Research*, 16(2), 201–215. <https://doi.org/10.1007/s10984-013-9128-8>
- Phan, H. P. (2008). Unifying different theories of learning: Theoretical framework and empirical evidence. *Educational Psychology*, 28(3), 325–340. <https://doi.org/10.1080/01443410701591392>
- Pintrich, P. R. (1995). Understanding self-regulated learning. *New Directions for Teaching and Learning*, 1995(63), 3–12. <https://doi.org/10.1002/tl.37219956304>
- Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 451–502). Academic Press.
- Pintrich, P. R., & De Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology*, 82(1), 33. <https://doi.org/10.1037/0022-0663.82.1.33>
- Puustinen, M., & Pulkkinen, L. (2001). Models of self-regulated learning: A review. *Scandinavian Journal of Educational Research*, 45(3), 269–286. <https://doi.org/10.1080/00313830120074206>
- Räsänen, M., Postareff, L., Mattsson, M., & Lindblom-Ylänne, S. (2020). Study-related exhaustion: First-year students' use of self-regulation of learning and peer learning and perceived value of peer support. *Active Learning in Higher Education*, 21(3), 173–188. <https://doi.org/10.1177/1469787418798517>
- Rasch, G. (1980). *Probabilistic models for some intelligence and achievement tests* (Expanded ed.). The University of Chicago Press.
- Selig, J. P., & Little, T. D. (2012). Autoregressive and cross-lagged panel analysis for longitudinal data. In B. Laursen, T. D. Little, & N. A. Card (Eds.), *Handbook of developmental research methods* (pp. 265–278). The Guilford Press.
- Trigwell, K., & Prosser, M. (1991). Relating approaches to study and quality of learning outcomes at the course level. *British Journal of Educational Psychology*, 61(3), 265–275. <https://doi.org/10.1111/j.2044-8279.1991.tb00984.x>
- van der Lans, R. M., van de Grift, W. J. C. M., & van Veen, K. (2018). Developing an instrument for teacher feedback: Using the Rasch model to explore teachers' development of effective teaching strategies and behaviors. *The Journal of Experimental Education*, 86(2), 247–264. <https://doi.org/10.1080/00220973.2016.1268086>
- Vermetten, Y. J., Lodewijks, H. G., & Vermunt, J. D. (2001). The role of personality traits and goal orientations in strategy use. *Contemporary Educational Psychology*, 26(2), 149–170. <https://doi.org/10.1006/ceps.1999.1042>
- Vermunt, J. D. (1996). Metacognitive, cognitive and affective aspects of learning styles and strategies: A phenomenographic analysis. *Higher Education*, 31(1), 25–50. <https://doi.org/10.1007/BF00129106>
- Vermunt, J. D. (1998). The regulation of constructive learning processes. *British Journal of Educational Psychology*, 68(2), 149–171. <https://doi.org/10.1111/j.2044-8279.1998.tb01281.x>
- Vermunt, J. D. (2005). Relations between student learning patterns and personal and contextual factors and academic performance. *Higher Education*, 49(3), 205. <https://doi.org/10.1007/s10734-004-6664-2>
- Virtanen, P., & Nevgi, A. (2010). Disciplinary and gender differences among higher education students in self-regulated learning strategies. *Educational Psychology*, 30(3), 323–347. <https://doi.org/10.1080/01443411003606391>
- Wilson, K., & Fowler, J. (2005). Assessing the impact of learning environments on students' approaches to learning: comparing conventional and action learning designs. *Assessment & Evaluation in Higher Education*, 30(1), 87–101. <https://doi.org/10.1080/0260293042003251770>
- Winne, P. H. (1995). Inherent details in self-regulated learning. *Educational Psychologist*, 30(4), 173–187. [https://doi.org/10.1207/s15326985ep3004\\_2](https://doi.org/10.1207/s15326985ep3004_2)
- Wright, B. D. (1996). Time 1 to Time 2 (pre- test to post- test) comparison and Equating: Racking and Stacking. *Rasch Measurement Transactions*, 10(1), 478.
- Wright, B. D. (2003). Rack and Stack: Time 1 vs. Time 2 or Pre- Test vs. Post- Test. *Rasch Measurement Transactions*, 17(1), 905–906.
- Wright, B., & Stone, M. (1979). *Best test design*. MESA Press.
- Wu, M. L., Adams, R. J., Wilson, M. R., & Haldane, A. A. (2007). *ACER ConQuest*. [Computer Program and Manual]. ACER Press.
- Yan, Z. (2020). Developing a short form of the self-assessment Practices Scale: Psychometric Evidence. *Frontiers in Education*, 4, 153. <https://doi.org/10.3389/feduc.2019.00153>
- Yan, Z., & Pastore, S. (2022). Are teachers literate in formative assessment? The development and validation of the Teacher Formative Assessment Literacy Scale. *Studies in Educational Evaluation*, 74, 101183. <https://doi.org/10.1016/j.stueduc.2022.101183>
- Zimmerman, B. J. (1986). Becoming a self-regulated learner: Which are the key subprocesses? *Contemporary Educational Psychology*, 11(4), 307–313. [https://doi.org/10.1016/0361-476X\(86\)90027-5](https://doi.org/10.1016/0361-476X(86)90027-5)
- Zimmerman, B. J. (1990). Self-regulated learning and academic achievement: An overview. *Educational Psychologist*, 25(1), 3–17. [https://doi.org/10.1207/s15326985ep2501\\_2](https://doi.org/10.1207/s15326985ep2501_2)
- Zimmerman, B. J., & Schunk, D. H. (2001). *Self-regulated learning and academic achievement: Theoretical perspectives*. Routledge.