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Special Issue Article

The relation between cognitive and metacognitive processing: Building bridges between the SRL, MDL, and SAL domains

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Aim. The main aim of this commentary was to connect the insights from the contributions of the special issue on the intersection between depth and the regulation of strategy use. The seven contributions in this special issue stem from three perspectives: self-regulated learning (SRL), model of domain learning (MDL), or the student approaches to learning (SAL).

Procedure. Prior to combining insights from different studies, the definition and operationalization of cognitive and metacognitive processing in the seven contributions is described. Subsequently, the grain size and statistical methods used in these contributions are discussed. This information allows us to – albeit cautiously – combine the results from the different studies regarding the relation between cognitive and metacognitive processing.

Conclusion. Deep processing and self-regulation/monitoring showed a strong correlation, regardless of the theoretical framework or data collection method chosen. The strength of the correlation between surface processing and metacognitive processing differed, however, between the studies. Pathways for future research on students' cognitive and metacognitive processing are suggested, at the methodological level as well as regarding the conceptualization of unregulated learning and surface processing.

Setting up adequate guidance initiatives to help students become more effective learners hinges upon solid theories of learning. Since the 1970s, multiple theories on student learning have been developed and refined (for an overview, see Dinsmore, 2017; Fryer, 2017). Rather than continuing researching separate theories and domains, Dinsmore and Fryer (2018) argue that confronting and combining different perspectives may get us further. Therefore, the current special issue sets out to address the relation between 'cognitive and metacognitive (or self-regulatory) processing' by relying on 'multiple theoretical perspectives crossed with multiple methods' (Dinsmore & Fryer, 2018). It brings together seven contributions, focusing on learning either during higher education or during last years of high school. Three different theoretical perspectives are represented: self-regulated learning (SRL, Deekens *et al.*, 2018; Scheiter *et al.*, 2018; Winne, 2018), model of domain learning (MDL, Dinsmore & Zoellner, 2018; Parkinson &

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Dinsmore, 2018), and student approaches to learning (SAL, Catrysse *et al.*, 2018; Fryer & Vermunt, 2018).

It needs to be pointed out that, in contrast to the MDL, both the SAL and SRL perspectives are families of models (Coffield, Mosley, Hall, & Ecclestone, 2004; Panadero, 2017; Vanthournout, 2011). As such, information on which family members are present in this special issue is warranted. From the two studies from the SAL perspective in this special issue (Catrysse *et al.*, 2018; Fryer & Vermunt, 2018), the study by Catrysse *et al.* (2018) relied on the Vermunt model (Vermunt & Vermetten, 2004). The study by Fryer and Vermunt (2018) used the same model for the metacognitive processing, but relied on students' approaches to map cognitive processing (Trigwell & Ashwin, 2006). The second family, SRL, is represented by three contributions. The study by Deekens *et al.* (2018) did not choose a particular SRL model, but referred to the shared premises between the models. Scheiter *et al.* (2018) made reference to Boekaerts' (1999) three-layered model of self-regulated learning (i.e., the regulation of the self, of the learning process, and of the processing modes). Finally, Winne (2018) relied on the Winne and Hadwin's model of 4 phases of SRL (task definition, goal setting and planning, enacting study tactics and strategies, and metacognitively adapting studying, Winne & Hadwin, 1998).

I had the privilege of reading the seven contributions of this special issue, and in this commentary, I set out to combine the insights from these studies regarding the relation between cognitive and metacognitive processing. Prior to doing so, it seems worthwhile to detail how the different studies have defined and/or operationalized both concepts. Subsequently, I will discuss the grain size and statistical methods used in the seven contributions. Next, the results from the different studies regarding the relation between cognitive and metacognitive processing will be combined. I finalize this commentary by summarizing the topics for future special issues that, as the current one, could constitute a major leap forward in bridging the knowledge bases stemming from SRL, MDL, and SAL.

Cognitive processing in the SRL-, MDL-, and SAL-based studies

When examining how the cognitive aspect of learning was defined in the seven contributions of the current special issue (see Table 1), it can be noted that labels varied from 'cognitive strategies' (SRL and MDL) to 'approaches to learning' and 'processing strategies' (SAL). For the sake of clarity and in line with the Introduction section of this special issue, this dimension of learning will be referred to as cognitive processing.

The distinction between deep and surface cognitive processing was apparent in studies from all three perspectives. Moreover, deep processing is described as desirable. Yet, the reason why deep processing is seen as desirable differs across the frameworks. In the MDL and SRL frameworks, deep processing is the level of processing expected at a proficient level (MDL, Dinsmore & Zoellner, 2018) and it represents higher 'conceptual value of knowledge' (SRL, Winne, 2018). Deep processing thus evidences expertise regarding a specific domain. Put differently, when students are confronted with a new content domain, low levels of deep processing are expected.

The studies from the SAL domain did not explicitly discuss the desirability of deep processing, but generally, at the conceptual level, deep processing is regarded as being beneficial for lifelong learning (Vermunt & Donche, 2017; Vermunt & Vermetten, 2004). Here, deep processing is more viewed as a general way of going about learning that should be strengthened during students' time in (higher) education. In other words, when

Table 1. Overview of the definitions and conceptualization of cognitive and metacognitive processing, the grain size, and research methods

	SRL	MDL	SAL
Cognitive processing	Deekens *et al.*: 'Deep strategies included knowledge elaboration, inferences, prior knowledge activation, summarization, taking notes, reading notes, and coordinating informational sources. Surface level strategies included drawing, memorization, re-reading, and searching'. Scheiter *et al.*: 'regulation of the process model (i.e., choice of cognitive strategies/information processing modes'	Dinsmore & Zoellner: 'cognitive strategies, among which deep- (e.g., arguing, summarizing, elaborating on the results) and surface level strategies (e.g., repeating, restating what is observed)' Parkinson & Dinsmore: 'cognitive strategies that are aimed toward making sense of the problem (i.e., surface-level strategies) such as underlining text and those that are used to integrate or transform a problem (i.e., deep-level strategies) such as interpreting text'	Fryer & Vermunt : 'the processing which student undertake to acquire new knowledge (i.e., approaches to learning)' Catrysse *et al.*: 'Processing strategies refer to the cognitive activities that a student applies whilst processing study material'
Metacognitive processing	Deekens *et al.*: monitoring 'feeling of knowing, judgment of learning, monitor progress toward goals, and monitor use of strategies' Scheiter *et al.*: 'regulation of the learning process (i.e., use of metacognitive skills to direct one's learning)' Winne: 'information at the meta level - metacognitive monitoring and metacognitive control of learning activities'; 'learner's capabilities to enact and adapt tactics for learning academic content'	Dinsmore & Zoellner : metacognitive strategies are 'metacognitive knowledge (i.e., "knowledge or beliefs that guide the course of mental operations at either the person, task or strategy level"), metacognitive experiences (i.e., "cognitive or affective experiences that pertain to a mental operation"), and cognitive goals (i.e., "cognitive or metacognitive goals that direct cognitive or metacognitive activity")' Parkinson & Dinsmore: Metacognitive strategies are strategies 'that are aimed at either monitoring or controlling cognitive strategies, such as evaluative strategies, like an evaluation of one's own comprehension in reading'	Fryer & Vermunt : 'the ways in which student manage or organize their learning behaviour (i.e., regulation of behaviour)' Catrysse *et al.*: 'regulation strategies refer to the activities that students use to steer their processing strategies'

Continued

Table 1. (*Continued*)

	SRL	MDL	SAL
Grain size			
General orientations			Catrysse *et al.*: ILP-SV (deep and surface processing) Fryer & Vermunt : ILS (self-regulation, external, and lack of regulation) and survey of Trigwell and Ashwin (deep and surface approach)
Situational orientation	Scheiter *et al.*: eye-tracking while reading a science text with pictures (text fixation, picture fixation, transitions) Winne: theoretical contribution Deekens *et al.*: think-aloud protocols during science or history learning which includes hypermedia (monitoring, deep, and surface strategies)	Dinsmore & Zoellner: think-aloud protocol during simulation on climate change Parkinson & Dinsmore: think-aloud protocol while reading a text on extraterrestrial life	Catrysse *et al.* : eye-tracking while reading a text on psychology (first reading, re-reading, total reading time)

students are confronted with a new content domain, it is judged beneficial that it is processed in a deep fashion from the start.

Next to this, there was also variation in the conceptualisation of surface processing. In the study by Parkinson and Dinsmore (MDL, 2018), surface-level strategies were described as 'cognitive strategies that are aimed toward making sense of the problem'. When examining how deep- and surface-level strategies were operationalized in the study by Deekens *et al.* (SRL, 2018), this seemed to be in line with this. For example, when students made a drawing to assist in learning or searched for hypermedia environment, this was seen as surface strategies. Moreover, as Dinsmore and Zoellner (2018) stated 'MDL predicts a heavier reliance on more surface-level cognitive processing in acclimation and early competence with a shift toward more deep-level cognitive processing in later competence and proficiency'. Put differently, in the process from a novice to and an expert, the surface-level cognitive processing appears a first and sensible step.

This diverges from how surface processing was seen in studies from the SAL domain. Fryer and Vermunt (2018) mapped students' surface approach, with items such as 'I concentrate on learning just those bits of information I have to know to pass' (Fryer & Vermunt, 2018). Please note that a surface approach is viewed as a combination of a strategy (i.e., what a student does) and a motive (i.e., with what aim). In the study by Catrysse *et al.* (2018), surface processing was operationalized as a strategy (example item 'I learn definitions by heart and as literally as possible', Catrysse *et al.*, 2018). Regardless of the presence or absence of a motive, surface processing hardly seems a first and sensible step in the SAL studies. Especially from the viewpoint of lifelong learning perspective, these surface processing strategies are conceptually judged to be less adequate (Vermunt & Donche, 2017; Vermunt & Vermetten, 2004).

Two remarks need to be made, in my view, regarding surface processing in the SAL domain. First, more detailed views on surface processing have been presented. Meyer and Shanahan (2003), for example, distinguished six forms of memorizing and repetition, with some forms interplaying with deep processing the content (e.g., memorizing before understanding, as a first sensible step perhaps) and other forms not (e.g., memorizing as rehearsal). For future studies, a list of all items for the surface processing scale would be helpful in determining which form of memorizing was predominantly probed.

Second, although it is common to rely on the overarching scale 'surface processing' of the Vermunt model (e.g., Catrysse *et al.*, 2018), this scale consists of two subscales. The memorizing scale maps the degree to which students learn content by heart (see example item above), while the analysing scale captures to what extent students process the learning content from start to finish ('I study each course book chapter point by point and look into each piece separately', Catrysse *et al.*, 2018). This last subscale can be linked to an organized approach to studying as discerned in other SAL models (Coertjens, Vanthournout, Lindblom-Ylänne, & Postareff, 2016; Parpala & Lindblom-Ylänne, 2012) and was found beneficial for academic success (Donche & Van Petegem, 2011).

When comparing the description of these two subscales to how surface processing is defined in the MDL and SRL studies, the analysing scale is clearly more in line with the idea of surface processing being a first and sensible step than the memorizing scale. Hence, for future special issues that set out to relate findings from Vermunt model to findings from studies using the MDL or SRL perspective, it could be worthwhile to use the subscales analysing and memorizing of the Vermunt model, rather than the overarching surface processing scale.

Metacognitive processing in the SRL-, MDL-, and SAL-based studies

For what Dinsmore and Fryer (2018) labelled metacognitive processing, various definitions and operationalizations were used in the articles of this special issue. In the studies using the MDL, the term 'metacognitive strategies' was used, which were defined as strategies 'that are aimed at either monitoring or controlling cognitive strategies' (Parkinson & Dinsmore, 2018). Dinsmore & Zoellner (2018) broke this down into 'metacognitive knowledge', 'metacognitive experiences', and 'goals'. These elements of 'monitoring' and 'control' also appeared in studies from the SRL domain and were defined by Winne (2018) as 'learner's capabilities to enact and adapt tactics for learning academic content'. In the studies from the SAL domain, this element is named 'regulation', being strategies that 'refer to the activities that students use to steer their processing strategies' (Catrysse *et al.*, 2018).

When one compares the operationalizations of these definitions, it appears as if studies from SRL and MDL frameworks focused on what the colleagues from the SAL tradition would label the self-regulation aspect. Fryer and Vermunt (2018) gave the following item example: 'To test my learning progress, I try to answer questions about the subject matter which I make up myself', which could be related to 'setting a cognitive goal' from Flavell's conceptualization of metacognition as described by Dinsmore & Zoellner (2018). Yet, the example item from the external regulation scale 'I study according to the instructions given in the study materials or provided by the teacher' (Fryer & Vermunt, 2018) may also be viewed as 'setting a cognitive goal'. This can be explained by the fact that the items of the self-regulation and external regulation scales of the Vermunt model primarily tap *sources* of regulation students may use when they decide to self-regulate (in the sense that the SRL and MDL studies see it). In other words, when students aim to monitor and control their cognitive strategies, they can seek guidance in internal sources (Vermunt's self-regulation scale) or external sources (Vermunt's external regulation scale). Viewing metacognitive processing in the SRL and MDL frameworks as equivalent to the self-regulation aspect in the Vermunt model thus appears too restrictive.

It becomes even more complex if one tries to relate the lack of regulation scale from the SAL perspective (item example 'when I run into trouble with my studies I don't know when and/or who I should seek help or advice from', Fryer & Vermunt, 2018) to the SRL and MDL frameworks. One may argue that it falls into the category that Dinsmore & Zoellner (2018) described as metacognitive experiences, being 'cognitive or affective experience that pertains to a mental operation'. In their path analysis, these authors used the number of metacognitive strategies, which does not partial out the more positive metacognitive experiences from the more negative ones. This is in line with a frequently espoused criticism of SRL models that it sheds 'little light on students who do not fit the pattern of a self-regulated learner' (Boekaerts & Corno, 2005, p. 202). Yet, exactly information on those who do not fit the pattern may be very informative. Lack of regulation has, for example, been linked to low academic performance and the non-completion of higher education studies (Vanthournout, Gijbels, Coertjens, Donche, & Van Petegem, 2012).

To build bridges between the SRL, MDL, and SAL domain with regard to such unregulated learners, a study in which all three domains share space would be helpful. Interestingly, in my view, this would not even require new data collections. Multiple researchers from the SAL domain could independently code data on metacognitive processing that was already collected in studies on SRL or MDL (Deekens *et al.*, 2018; Dinsmore & Zoellner, 2018; Parkinson & Dinsmore, 2018), while the authors from these studies could flag those statements that are not in line with the pattern of a self-regulated learner. Based on these data, each researcher could, for each student, form a judgement of the metacognitive processing for the given task (e.g., beneficial for learning, partially beneficial, not beneficial, or detrimental). This judgement could subsequently be compared within and across frameworks (Gwet, 2014) and, as also emphasized by Alexander (2018), discussed with the aim of agreeing upon a common conceptualization.

Grain size and preferred research and statistical method the MDL, SRL, and SAL models

Although the initial research in the SAL domain was conducted on level of the task (Marton & Säljö, 1976), later studies on cognitive and metacognitive processing in the SAL domain tended to examine learning at a larger grain size than studies from the SRL or MDL perspectives (Asikainen & Gijbels, 2017; Fryer, 2017; Pintrich, 2004). This is exemplified by the two studies from the SAL domain that examined cognitive and metacognitive processing at the general orientations' level (Catrysse *et al.*, 2018; Fryer & Vermunt, 2018). This level is defined by Lonka, Olkinuora, and Mäkinen (2004), p. 311) as 'the way the student is oriented when entering or later handling studying'.

The studies from the SRL and MDL perspectives looked at the level of the tasks (i.e., situational orientation, Deekens *et al.*, 2018; Dinsmore & Zoellner, 2018; Parkinson & Dinsmore, 2018; Scheiter *et al.*, 2018; Winne, 2018). It is worth noting that, although numerous studies in the SAL domain have examined learning at the course level (Asikainen & Gijbels, 2017; Baeten, Kyndt, Struyven, & Dochy, 2010; Kyndt, Dochy, Struyven, & Cascallar, 2011), this grain size was not present in the seven contributions.

The study by Catrysse *et al.* (2018) stands out given that it combined data at the general level with data at the situational level. Based on data regarding processing strategies at the level of the general orientations (N = 80), four profiles were created regarding students' processing strategies: all low, surface, deep, and all high. Several students from each profile participated in an eye-tracking data collection, while reading an expository text. Overall, the results indicated little significant differences between these four groups of students at the situational level, but the students in the all-high learning profile (N = 4) were found to reread more often than students in the all-low learning profile (N = 6), which was interpreted as indicating deeper processing. As such, the study by Catrysse *et al.* (2018) adds to the small literature base within the SAL domain on data triangulation (e.g., Endedijk & Vermunt, 2013; Schatteman, Carette, Couder, & Eisendrath, 1997). Although the previous studies on data triangulation concluded that results from structured learning reports (Endedijk & Vermunt, 2013) and from interviews (Schatteman *et al.*, 1997) were significantly and meaningfully related to the data from self-report questionnaires, the results as presented by Catrysse *et al.* (2018) do not confirm this. Clearly, more research on data triangulation within the SAL domain is warranted.

In line with different grain sizes, the research and statistical methods varied as well. Studies on cognitive and metacognitive processing at the general level frequently rely on self-report questionnaires (which is an offline measure, Zusho, 2017) administered to a large number of students (e.g., N = 933, Fryer & Vermunt, 2018). This then allows for advanced statistical models, such as confirmatory factor analysis, hierarchical cluster analysis (Catrysse *et al.*, 2018), and latent transition profile analysis (Fryer & Vermunt, 2018).

The studies in this special issue at the level of a specific task relied on online measures (i.e., measures assessing cognitive and metacognitive processing while it is occurring, Zusho, 2017). Studies used either think-aloud protocols (Deekens *et al.*, 2018; Dinsmore & Zoellner, 2018; Parkinson & Dinsmore, 2018) or eye-tracking (Catrysse *et al.*, 2018; Scheiter *et al.*, 2018). Due to these more intensive data-gathering methods, usually sample sizes are smaller compared to studies at the general level, in this special issue ranging from $N = 20$ (Catrysse *et al.*, 2018) to $N = 170$ (Deekens *et al.*, 2018).

As multiple authors in this special issue acknowledged, sample size has an impact on the choice of statistical techniques and the interpretation of results. Dinsmore & Zoellner (2018), for example, indicated that the usual cut-off for fit indices for structural equation models may not hold for small samples. Moreover, it is acknowledged that statistical methods regularly used in studies with large samples may not necessarily be adequate for studies with fewer participants. Rather, statistical methods aiming for similar outcomes but specifically attuned to the smaller sample size are welcomed, for example, the smallest space analysis as an alternative to exploratory factor analysis (Dinsmore & Zoellner, 2018; Maslovaty, Marshall, & Alkin, 2001) or partial least squares path modelling (PLS) as an alternative for structural equation modelling (Willaby, Costa, Burns, MacCann, & Roberts, 2015).

When suitable alternative statistical methods are not readily available, the question of the minimum sample size appears unavoidable. In the current special issue for example, structural equation models were estimated using sample sizes ranging from $N = 40$, over $N = 70$, to $N = 170$ (Deekens *et al.*, 2018; Dinsmore & Zoellner, 2018). Here, it is important to note that, in my experience, small samples are defined differently in methodological literature than in practical research. In fact, common minimum sample sizes in Monte Carlo simulation studies on structural equation models are 200 (B. O. Muthén, du Toit, & Spisic, 1997) and 250 participants (Beauducel & Herzberg, 2006; De Roche, 2009; Nussbeck, Eid, & Lischetzke, 2006). Moreover, it was shown that in the most favourable conditions, a sample size of 180 was needed for a straightforward structural equation model (Wolf, Harrington, Clark, & Miller, 2013).

So, can these numbers be considered a minimal sample size then? There is reluctance in methodological literature to provide such rule of thumb ‘because requisite sample size is closely tied to the specific model and data of a given study’ (Brown, 2006, p. 389), such as non-normality of the data, strength of the paths, and the amount of missing data (Wolf *et al.*, 2013). Instead, it is recommended to use a Monte Carlo simulation to calculate the required N. When data have already been collected, such simulation techniques can be used to determine power (Brown, 2006; Burt & Obradović, 2013; Muthén & Muthén, 2009). Another avenue for complex analysis with small sample sizes is Bayesian estimation (Jackman, 2009; Kruschke, 2015). By including prior information into Bayesian analysis, parameter estimation could be enhanced and power could be increased (van de Schoot, Broere, Perryck, Zondervan-Zwijnenburg, & van Loey, 2015).

Despite the clear relevance, to my knowledge, these methodological advances have not been used in studies on SRL, MDL, or SAL. When embracing the goal of bridging different grain sizes in these domains (i.e., relying on techniques frequently used the general level, at the situational level, with limited N), a special issue with didactical methodological articles appears in order. Such special issue could shed light on the limitations when using regular techniques for small samples and, on the other hand, showcase new statistical advances proven successful for small samples.

Relation between cognitive and metacognitive processing

Keeping the different definitions and operationalizations as well as the grain size and research/statistical methods in mind, I wanted to make a cautious effort in grouping the results of special issue contributions based on the relationships between cognitive and metacognitive processing. Four contributions of this special issue provided findings on five empirical studies (Deekens *et al.*, 2018; Dinsmore & Zoellner, 2018; Fryer & Vermunt, 2018; Parkinson & Dinsmore, 2018). Given that these studies relied on a range of advanced analysis techniques, rendering it difficult to compare the relationships between the concepts researched, I opted to examine the correlations between the cognitive and metacognitive scales. I undertook these examinations first within and then across the five studies. This allowed me to describe similarities and differences between the studies from the three frameworks (SRL, MDL, and SAL) regarding the relation between cognitive and metacognitive processing.

Two empirical studies as reported by Deekens *et al.* (2018) examined the relation between cognitive and metacognitive monitoring from a SRL perspective. Data were gathered using think-aloud protocols during learning from hypermedia. In the first study, 170 American university students learned about the circulatory system in the human body. In the second study, 40 American secondary education students learned about history. Transcripts of these think-aloud protocols were coded with regard to deep and surface strategies and monitoring. In the first study, there was a large correlation between monitoring and deep strategy use (.49), while there was no correlation between monitoring and surface strategy use (.09). Although not reaching the significant cut-off, possibly due to the limited number of students in study 2, the relations appeared similar in study 2 (correlation: monitoring–deep strategy use, .31; monitoring–surface strategy use, -.10).

Relying on the MDL, Dinsmore & Zoellner (2018) engaged 70 American university students from different faculties in an online simulation exercise on the topic of climate change. A think-aloud protocol was used during this exercise. In the transcripts of these verbalizations, the metacognitive and cognitive strategies were coded (deep and surface). Metacognitive strategies showed a large correlation with deep as well as surface strategies (.56 and .49, respectively). Additionally, smallest space analysis revealed that deep and metacognitive processing could be grouped into one cluster.

Using the MDL as well, Parkinson and Dinsmore (2018) engaged 21 American high school students to read one of two texts on extraterrestrial life, while thinking aloud. Students' deep- and surface-level strategies were coded, as well as their evaluative strategies (such as evaluation of the interest in a part of the text, evaluation of the agreement with the arguments provided by the text, and evaluation of how solid the presented argument is). These evaluative strategies were considered an element of metacognitive strategies. The most common pattern found among the 21 students was a combination of both cognitive (deep and surface levels) and metacognitive (evaluative level) strategies, which suggested that cognitive and metacognitive strategies were correlated.

From the SAL perspective, Fryer and Vermunt (2018) had 933 Japanese university students (25.8% female) fill out a survey 4 weeks into the first year in higher education and during the penultimate week of this same first year. Students' deep and surface approaches as well as their regulation strategies were questioned. A large correlation was detected between the deep approach and self-regulated learning (.56) at the wave 1 and at wave 2 (.51), while the deep approach showed also a small correlation with external regulation (.20 and .22, respectively). The surface approach did not correlate significantly with self-regulated learning at either wave, but showed a small correlation with external regulation (.18 and .14 at wave 1 and wave 2, respectively). The surface approach was most strongly correlated with lack of regulation at both waves (.49 and .54, respectively).

In summary, regardless of whether metacognitive processing was operationalized as regulation strategies (Fryer & Vermunt, 2018) or metacognitive strategies (Dinsmore & Zoellner, 2018) or metacognitive monitoring (Deekens *et al.*, 2018), the correlation between self-regulation or monitoring on the one hand and deep processing/deep approach/deep strategy use on the other hand was large (values around .50, Cohen, 1988). Moreover, this relation seemed to hold regardless of whether self-report questionnaires at the general level were relied upon (Fryer & Vermunt, 2018) think-aloud verbalizations stemming from learning tasks including hypermedia (Deekens *et al.*, 2018) or a simulation exercise (Dinsmore & Zoellner, 2018). If this link were to hold strong in an elaborate systematic literature review, it could be considered a common ground linking the MDL, SAL, and SRL perspectives.

In line with the varying definitions and operationalizations of surface processing, as described above, the link between surface processing and metacognitive processing was less clear between the studies. The studies by Fryer and Vermunt (SAL 2018) and by Deekens *et al.* (SAL 2018) found small or absent correlations between surface processing on the one hand and self-regulation and monitoring on the other hand. The studies relying on the MDL theory (Dinsmore & Zoellner, 2018; Parkinson & Dinsmore, 2018) suggested a larger correlation.

The fact that the results differed between the studies relying on the SRL and the MDL perspectives was surprising as these studies used think-aloud protocols and similar operationalizations of surface processing and metacognitive processing were used (see Table 1). One needs to bear in mind here that we were comparing the results from only two studies from the SRL framework (both presented in Deekens *et al.*, 2018) with those from only two studies from the MDL (Dinsmore & Zoellner, 2018; Parkinson & Dinsmore, 2018). It would be worthwhile to see whether this difference emerges in a systematic literature review as well. If so, theoretical contributions are needed on how the two frameworks conceptualize the link between surface processing and metacognitive processing.

Overall, the link between surface processing and metacognitive processing seems like a prime arena for work when setting out to examine similarities and differences between the three different theoretical perspectives. As described above, reanalysing one data set with researchers from different domains could be helpful in making implicit assumptions explicit and, eventually, agree upon a common conceptualization.

Where to go from here?

Throughout this commentary on the special issue 'The intersection between depth and the regulation of strategy use', a number of pathways for future research have been suggested either to construct or to solidify bridges between the SAL, MDL, and SRL domain. At the methodological level, two pathways appear particularly important. First, more studies are welcomed that triangulate data from different methods across and within grain sizes. In the longer run, such studies will hopefully allow researchers to gauge the impact of the research method and of the grain size on the results obtained. Second, the issue of complex analysis with small samples merits proper attention in the coming years.

The boundaries of currently used methods need to be explored (e.g., how to determine power of a given model, taking into account the sample size), and new methodological advances such as Bayesian analysis should be examined.

Next to the pathways at the methodological level, two avenues for research on the relationship between cognitive and metacognitive processing can be formulated. Both concern the 'not ideal learner'. First, the similarities and differences in the conceptualization of surface processing across the three perspectives should be further examined. The six forms of memorizing and repetition as presented by Meyer and Shanahan (2003) may provide a structuring framework for this. Next to this, I recommend that future studies relying on the Vermunt model examine relations at the level of the subscales of surface processing (i.e., the subscale memorizing and the subscale analysing), as the analysing subscale appears more in line with how surface processing is conceptualized in the MDL and SRL perspectives.

Second, the concept of the unregulated learner merits more attention from scholars from MDL, SRL, and SAL perspectives. Ideally, a study in which all three domains share space is set up, possibly reanalysing data collected at the task level using the three perspectives. Such exercise will allow for in-depth discussion and, hopefully, even theory building spanning the three models.

In closing, the current special issue constitutes without doubt a big leap forward in understanding the similarities and differences between the SAL, MDL, and SRL domains regarding the relationship between cognitive and metacognitive processing. It is clear that more research is needed to further clarify the links between the models and, perhaps, formulate an integrated model combining the best of the three worlds. Indeed, 'there is nothing as practical as a good theory' (Lewin, 1943, p. 118), to subsequently conduct well-grounded experimental studies on how student learning can be fostered (e.g., Scheiter *et al.*, 2018) and, from these studies, formulate recommendations for practice.

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