Rérat and Berger
*Empirical Research in Vocational Education and Training* (2026) 18:3
https://doi.org/10.1186/s40461-026-00204-z

Empirical Research in Vocational Education and Training

RESEARCH Open Access

# The role of motivational beliefs and monitoring in learning spatial skills

Olivier Rérat[1*] and Jean-Louis Berger[1]

*Correspondence:
Olivier Rérat
olivier.rerat@unifr.ch
[1]Process, Self-Regulation & Learning Lab, University of Fribourg, Fribourg, Switzerland

**Abstract**
When embarking on vocational training in the STEM field, a considerable proportion of students are required to engage with new and demanding courses. This study aimed to understand the relationship between the self-regulated learning (SRL) process and specific components of STEM fields, with a particular focus on spatial skills and technical drawing. In total, 180 students from the Swiss vocational education and training (VET) sector completed self-report instruments to assess three dimensions: motivational beliefs (self-efficacy and task value), monitoring (confidence judgment and calibration), and spatial skills. The structural equation model indicated that confidence judgments, calibration, and interest directly predicted spatial performance, while the relationship between self-efficacy beliefs and performance was mediated by confidence judgment and calibration. Moreover, the VET program duration was found to be negatively associated with task value. This study highlights the importance of considering the SRL process in the development of spatial skills.

**Keywords** Self-regulated learning, Metacognition, Motivational beliefs, Spatial skills, Technical drawing, STEM

## Introduction

Self-regulated learning (SRL) constitutes a fundamental aspect of academic success. It entails students assuming responsibility for their learning process, establishing goals, monitoring their progress, and implementing necessary adjustments (Usher and Schunk 2018). Students with superior self-regulation abilities tend to achieve significant academic success with less effort and experience higher levels of academic satisfaction (Dent and Koenka 2016; Schunk and Greene 2018). In accordance with the social cognitive theory, SRL theories posit that learning situations are shaped by the students' cognitive variables, motivational beliefs, behaviours, and emotions (Bandura 1997). When students engage in a learning task, a multitude of cognitive and motivational processes are initiated. Zimmerman's (2000) SRL model is a cyclical model that explains that the mobilisation of students' motivational and cognitive processes unfolds in three learning phases: forethought, performance, and reflection. In the forethought phase, which is shaped by motivational beliefs, including self-efficacy and task value, students set goals and develop plans to solve tasks or to study their material based on how they perceive their abilities (Zimmerman 2000). In the performance phase, students engage in metacognitive processes, such as monitoring, and self-regulate their cognition, behaviours, and context to align themselves with the goals defined in the forethought phase. Finally, in the self-reflection phase, students evaluate their performance through self-judgment and self-reaction. This evaluation involves causal attributions of the (presumed) outcome and assessing the effectiveness of their strategies and the achievement of their goals, thus influencing their motivational beliefs and strategies for future learning tasks (Usher and Schunk 2018). This SRL model thus highlights the role of motivational beliefs in influencing the selection of learning activities, the degree of investment needed, and the level of required persistence (Wigfield and Eccles 2000). Metacognitive processes, in a complementary way, facilitate the regulation and adaptation of learning activities for enhanced learning outcomes (Usher and Schunk 2018).

Spatial skills in science, technology, engineering, and mathematics (STEM) education are quite significant (Sorby et al. 2018). According to Wai et al. (2009), spatial skills are a significant predictor of achievement in STEM, which means that it is imperative to investigate whether such abilities can be nurtured or enhanced. Furthermore, the meta-analysis of Uttal et al. (2013) demonstrated that training can enhance spatial skills, thus indicating the importance of understanding how students self-regulate their own learning development. Regarding the relationship between SRL and spatial skills, numerous studies have underscored the predictive value of self-efficacy on spatial skill performance (Power et al. 2016; Safadel et al. 2023; Towle et al. 2005). However, since the role of other SRL components such as task value and metacognition remains relatively understudied, this study aimed to explore the relationships between spatial visualization—defined as the process of "apprehending, encoding, and mentally manipulating three-dimensional forms" (Carroll 1993)—and key components of SRL, namely motivational beliefs, and metacognitive monitoring and calibration.

More broadly, one of the principal objectives of education systems is to prepare young people for the workforce by equipping them with knowledge and skills that align with labour-market demands (Vujanovic and Lewis 2017). As highlighted by the OECD (2016), maintaining this alignment has become increasingly challenging in the context of accelerated technological change. In Switzerland, these challenges are particularly salient given the central role of vocational education and training (VET)[1], which is chosen by around two-thirds of adolescents after lower-secondary education. One domain in which these demands are especially pronounced is the development of spatial visualization skills in mechanical and industrial trades. To operate machinery and manufacture components with precision, future professionals must be able to accurately interpret detailed technical drawings, which place substantial demands on spatial visualization (Sorby et al. 2018). In this context, there is a need for pedagogical approaches that actively support learner engagement with complex technical content in VET (OECD 2021). From a SRL perspective, this implies fostering learners' ability to self-regulate their learning processes when dealing with cognitively demanding tasks (Zimmerman 2000). This context further motivates the examination of the relationships between spatial visualization

[1] The Swiss VET system is organised as a dual system combining workplace-based training with school-based instruction. Practical training in the form of an apprenticeship takes place three to four days per week in a training company and is supplemented by one to two days of school-based instruction at a VET school, where students attend vocationally related technical courses, general education, and physical education.

and self-regulated learning in order to better support vocational education systems in designing instructional approaches that are adapted to the current VET population.

**The role of motivational beliefs in self-regulated learning**

According to Boekaerts (2002), "motivational beliefs are defined as the opinions, judgments and values that students hold about objects, events or subject matter domains." In the SRL process, motivation is pivotal, enabling students to initiate, direct, and maintain their efforts to regulate their learning (Zimmerman 2011). Motivational beliefs are present throughout the learning process, including the forethought phase, the performance phase, and the self-reflection phase, where they are part of the regulation itself. This regulation may entail managing study time, resisting adverse peer pressures, or monitoring one's own progress (Zimmerman 2000).

The expectancy-value theory (EVT; Wigfield and Eccles 2000; recently renamed as the situated expectancy-value theory; Eccles and Wigfield 2020) offers a theoretical framework for understanding motivational beliefs. The EVT posits that students' motivation, engagement, persistence, and performance in learning are directly shaped by their self-efficacy beliefs and the perceived value of a task or subject matter (Wigfield and Eccles 2000).

Self-efficacy refers to an individual's belief in their capacity to learn (Bandura 1997). Self-efficacy beliefs, the literature indicates, are important for SRL (Zimmerman and Schunk 2008). Those with high self-efficacy beliefs are more inclined than others to exert efforts in the face of adversity; moreover, if they possess the necessary competencies, they are more likely to persevere with tasks (Linnenbrink and Pintrich 2003). Task value refers to the factors that influence an individual's motivation to engage in a task. These factors can be classified into four: individual interest, attainment, utility, and cost (Eccles et al. 1983). Individual interest, or intrinsic value, can be defined as the enjoyment derived from undertaking a task. Attainment refers to the importance of performing well in a task, whereas utility refers to the extent to which a task aligns with one's future plans. Finally, costs can be conceptualized as the limitations imposed by engaging in one task on the accessibility of others (Wigfield and Eccles 2000) as well as the anticipated effort needed to complete a task (Eccles et al. 1983). Cost can be divided into four subdimensions: task effort cost, outside effort cost, loss of valued alternatives, and emotional cost (Flake et al. 2015).

A substantial body of research has demonstrated that expectancy, often gauged using self-efficacy, is a reliable predictor of performance (Pajares 1996; Schunk et al. 2013; Zimmerman 1995). Although the model proposed by Eccles and Wigfield (2020) suggests that task value is also a direct predictor of performance, several studies have indicated that it is a more effective predictor of choice, effort, and persistence in achievement-related activities (Eccles et al. 1984; Marsh et al. 2005; Nagengast et al. 2011).

The intricate interrelationships between the expectancy and value dimensions call for a deeper understanding of the underlying processes driving these connections. For example, Trautwein et al. (2012) sought to better understand the interaction between self-efficacy (expectancy) and task value in a large-scale study involving 2508 German high school students (mean age 19.6 years). They tested several regression models predicting academic performance: one including only main effects of expectancy and value, and another including an interaction term (expectancy x value). They found that when the students' values were entered in the model after expectancies, the values were no longer a significant predictor of performance. However, the interaction term "expectancies x values" was a significant predictor in the interaction model, with the values amplifying the positive effect of expectancies (Trautwein et al. 2012). Wigfield et al. (2016) support this finding: If one does not value a task, then expecting to do well on it may not be a sufficient reason to engage in it. The converse is also true: Low success expectations limit the value one attributes to a task.

#### The role of metacognition in self-regulated learning

Flavell (1979) laid the foundation for the concept of metacognition, defining it as cognition about cognition. It comprises two components: metacognitive knowledge and metacognitive skills (Veenman 2013). Metacognitive knowledge represents knowledge about cognition and includes three subtypes: declarative knowledge (i.e., knowledge about self and about strategies), procedural knowledge (i.e., knowledge about how to use strategies), and conditional knowledge (i.e., knowledge about when and why to use strategies) (Flavell 1979; Schraw and Dennison 1994). Metacognitive skills relate to the performance of the skills required to monitor and control (i.e., regulate) one's own learning behaviours. These strategies include orientation, goal setting, planning, monitoring, evaluation, and recapitulation (Veenman 2013). All these components are an integral part of the SRL model proposed by Zimmerman (2000). Combining 11 studies, involving participants of different ages and belonging to subject areas, Veenman (2008) explored whether metacognitive skills are part of intelligence. The results revealed that metacognitive skills accounted for about 18% of the variance in the learning outcomes above and beyond intellectual ability.

Monitoring is a core concept of the SRL model. While learning, students must continuously monitor their understanding, progress, and strategy use to adjust their learning process accordingly. Metacognitive monitoring gives rise to explicit metacognitive judgments, such as confidence judgments, which reflect an individual's subjective assessment of the correctness of their responses (Nelson and Narens 1990). For assessing metacognitive competence in monitoring, calibration is a suitable methodology. It is defined as the degree of correspondence between an individual's confidence judgments and their actual performance on a particular task (Hacker et al. 2008). Importantly, confidence judgments should be distinguished from calibration. Whereas confidence judgments reflect subjective beliefs about the correctness of one's answers, calibration refers to the degree of correspondence between theses judgments and actual task performance (Stankov et al. 2012).

As per Hacker and Bol (2019), monitoring is particularly important in the performance phase, as it allows students to assess their learning progress. Moreover, calibration is positively related to student achievement, with better calibrated students attaining higher achievement (Bol et al. 2012; Hacker and Bol 2019), as they self-regulate their learning by accurately assessing their knowledge (Chen and Rossi 2013).

#### Relationship between monitoring activities, motivational beliefs, and performance

According to the Zimmerman (2000) model, self-efficacy beliefs can directly influence performance phase processes such as self-monitoring (Zimmerman and Moylan 2009). To better understand the relationship between self-efficacy and monitoring, Huang et al. (2022) conducted a study of 1063 university students in health science education and found that metacognitive monitoring frequency moderated the relationship between self-efficacy and performance, such that the influence of self-efficacy on performance decreased as monitoring increased. Linnenbrink and Pintrich (2003) stated that "students who were confident in their abilities were much more likely to try to understand and think deeply about their schoolwork. They were also more metacognitively active, i.e. more likely to plan, monitor, and regulate themselves while working on their schoolwork" (p. 130). Although these findings point to strong associations between self-efficacy and metacognitive judgments, such relations do not imply conceptual equivalence. While self-efficacy beliefs correspond to judgments of the ability to perform certain types of activities (Bandura 1997), confidence judgments concern the subjective probability that a response is correct (Koriat 2012). In other words, self-efficacy beliefs operate at the level of a specific activity (e.g. solving mathematical problems or understanding written texts), whereas confidence judgments are related to a particular response.

## Aims and research questions

The present study aimed to analyze the relationships between metacognitive processes, such as confidence judgments and their calibration, and motivational beliefs, such as self-efficacy and task value, and their link to spatial skills performance. To test the relationship between motivational beliefs, monitoring, calibration, and spatial skill performance, structural equation modelling (SEM) was conducted. The model construction (Fig. 1) was guided by two questions. The first question was the following: Which variables predict performance in a spatial ability test? Specifically, do motivational beliefs (self-efficacy and task value) and metacognition (confidence judgment and calibration) directly predict performance?

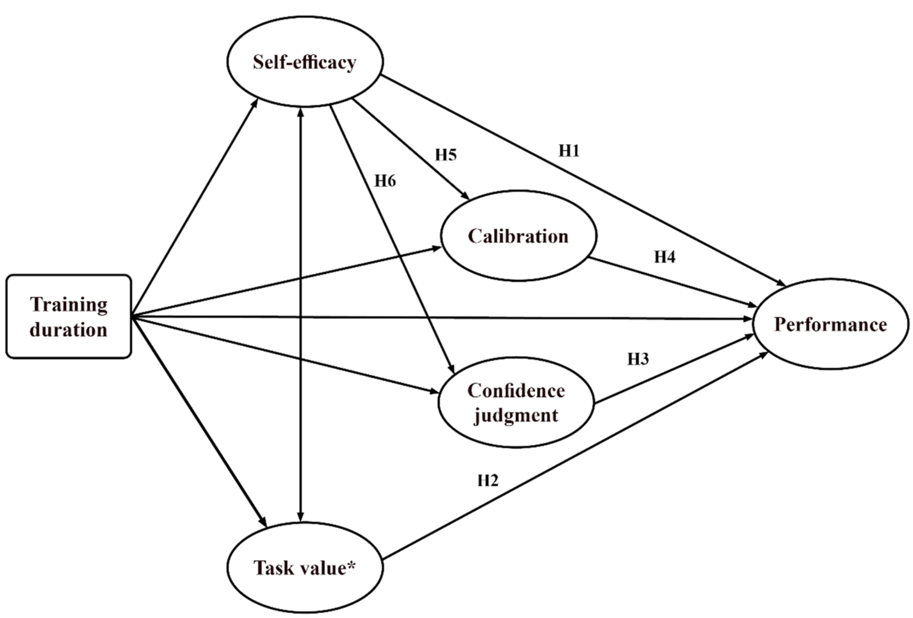


**Fig. 1** The Hypothesised Path Model Depicting the Mediation Effect of Calibration and Confidence Judgment on the Relationship Between Motivational Beliefs and Spatial Ability Performance. *For ease of reading, the four dimensions of task value (interest, utility, attainment, and cost) are combined in Fig. 1; the analyses of each of the dimensions, however, were conducted separately

We hypothesised that self-efficacy (H1; Pajares 1996; Schunk et al. 2013; Zimmerman 1995), task value (H2; Eccles and Wigfield 2020), confidence judgment (H3; Dent and Koenka 2016; Veenman 2008), and calibration (H4; Bol et al. 2012; Chen and Rossi 2013; Hacker and Bol 2019) will be positively related to performance.

The second question was as follows: Does metacognition mediate the relationship between motivational beliefs and performance? Specifically, do motivational beliefs (self-efficacy and task value) indirectly predict performance via metacognition (confidence judgment and calibration)?

We hypothesised that self-efficacy would indirectly predict performance via confidence judgment (H5; Zimmerman 2000; Zimmerman and Moylan 2009) and calibration (H6; Huang et al. 2022; Zimmerman 2000; Zimmerman and Moylan 2009). Such indirect effects were not expected for task value.

The model illustrated in Fig. 1 shows our hypotheses. It incorporates training duration (see the Method section) as an exogenous variable. Given the lack of research and theoretical basis to formulate hypotheses regarding the role of training duration, we tested whether training duration (1, 2, 3, or 4 years) was related to each of the model's variables. However, we assumed training duration as a proxy indicator[2] of academic skills—the longer the duration, the better the academic skills.

## Method

### Participants and procedure

In total, 180 students—160 men and 20 women—from a Swiss vocational education and training (VET) school voluntarily participated. Data were collected during the school-based component of the programme, in which participants attended occupation-related courses, including technical drawing. The instruments were administered during regular class time toward the end of the academic year. 53.9% of participants were first-year students, 31.7% were second-year students, and 14.4% were third-year students. Participants were enrolled in vocational programmes of varying duration, including one-year ($N = 13$), two-year ($N = 16$), three-year ($N = 65$), and four-year ($N = 86$) programmes, reflecting structural differences across vocational pathways. The mean age was 18 years and 7 months (SD = 4 months); 13 students followed a one-year curriculum, 16 a two-year curriculum, 65 a three-year curriculum, and 86 a four-year curriculum. Courses of longer duration typically involve more extensive curricular content and greater exposure to technical subjects such as technical drawing. The students were informed about the voluntary nature of participation and the measures that would be taken to protect their anonymity. Given the high proportion of male participants (89%), a gender comparison was not conducted.

### Measures

The participants completed an online self-report survey with the following structure: 30 items assessing spatial ability (DAT and PSVT) with a confidence rating after each response (metacognition), and 16 items assessing motivational beliefs (self-efficacy, interest, attainment, utility, and cost).

[2] Access to training of different durations depends on the learners' prior academic performance.

**Spatial ability** We used two spatial tests to assess spatial ability: the Differential Aptitude Test: Space Relations (DAT: SR; Bennett et al. 1973) and the Purdue Spatial Visualization Test: Rotations (PSVT: Guay 1977; Maeda et al. 2013). The DAT5: SR, developed by Bennett et al. (1973) to assess an individual's ability to move from a 2D to a 3D world, contains 30 items with four response options. Bennett et al. (1956) found evidence of reliability with a split-half coefficient of 0.90 for girls and 0.93 for boys. The PSVT: R, developed by Guay (1977) and revised by Maeda et al. (2013), measures an individual's ability to visualize rotated solids. The test involved 30 items with five response options. In total, 15 items per test were included to measure spatial ability. Maeda et al. (2013) found evidence of adequate internal consistency for the PSVT, with a Cronbach's alpha exceeding 0.80. In the context of this study, a convergent validity of 0.70 was found between the DAT and PSVT.

**Task value** Four dimensions of task value, as defined by Eccles et al. (1983), were assessed using the items translated in French and adapted from Berger and Karabenick (2011): interest (e.g., "I like technical drawing"), attainment (e.g., "It is important for me to be someone who is good at technical drawing"), utility (e.g., "I believe that technical drawing is useful for my professional future"), and from Beymer et al. (2022): cost (e.g., "Technical drawing forces me to give up too many activities that are important to me"). All the items were rated on a Likert scale from 0 to 100.

**Self-efficacy** To measure technical drawing self-efficacy, seven items developed by the authors (e.g., "I feel I can draw properly") were answered by the participants on a Likert scale from 0 to 100. The item development was based on the expertise of technical drawing teachers and followed the guide for constructing self-efficacy scales (Bandura 2006). Table 2 shows the seven items.

**Confidence judgment and calibration** After each spatial ability item, the participants were asked to rate their confidence judgment ("How sure are you of your answer?") on a Likert scale from 0 to 100. Confidence scores were calculated as the average ratings across items. To assess metacognitive monitoring accuracy, confidence judgments were then compared with actual performance using a calibration index (Schraw 2009). For each item, the calibration accuracy was calculated by taking the absolute value of the difference between the confidence judgment and the performance score (Bol et al. 2012). Item-level calibration accuracy scores were then averaged across items to obtain a single calibration accuracy for each participant. Higher values indicate greater calibration accuracy, reflecting a closer correspondence between confidence judgments and performance.

### Data analysis

Confirmatory factor analysis (CFA) and SEM were conducted with R language version 4.3.3 (R Core Team 2021) through RStudio version 2023.12.1 (RStudio Team 2020) using tidyverse (Wickham et al. 2019) and Lavaan (Rosseel 2012). CFA (Kline 2023) was used to determine whether self-efficacy, interest, attainment, utility, cost, calibration, and spatial ability could be represented as separate factors by the sets of observed items. To reduce the number of indicators per latent variable, item parcels consisting of the mean scores of three items were created (Little et al. 2002). Accordingly, all the latent variables were constructed based on either three items or three item parcels. For performance, five PSVT items and five DAT items were randomly assigned to each of the three item parcels. The same was done for the calibration items. Table 2 displays the full item distribution. SEM was then conducted to test our hypotheses.

We used the chi-square test ($\chi^2$), the comparative fit index (CFI), the Tucker–Lewis index (TLI), the standardised root mean square residual (SRMR), and the root mean square error of approximation (RMSEA) as indicators of model fit. To obtain a well-adjusted model, goodness of fit indices must meet certain criteria: a non-significant $\chi^2$, a CFI and TLI greater than 0.95, an RMSEA less than 0.06, and an SRMR lower than 0.08 (Kline 2023).

Following recommendations for power analysis in structural equation modeling, statistical power was evaluated using a Root Mean Square Error of Approximation (RMSEA)–based framework (MacCallum et al. 1996). Power was assessed for a test of close model fit, with the null hypothesis defined as RMSEA ≤ 0.05 and the alternative hypothesis as RMSEA ≥ 0.08, using an alpha level of 0.05. Given the sample size ($N = 180$) and the model's degrees of freedom (df = 130), this design would be expected to be sensitive to a substantively meaningful degree of model misspecification.

## Results

### Descriptive statistics

Table 1 presents the descriptive statistics of the various motivational, calibration, and performance variables. Given the deviation from normality observed for the calibration variable (CAL), CFA and SEM were conducted using the maximum likelihood estimator with robust standard errors (MLR) (Kim 2013; Kline 2023).

### Confirmatory factor analysis

The initial CFA yielded an acceptable fit: $\chi^2$ (201) = 305.03, $p = < 0.001$, RMSEA = 0.05, CFI = 0.95, TLI = 0.94, SRMR = 0.07. Examining the results, we found a covariance of 0.80 between the attainment and utility scales. We thus decided to combine the six items into a new factor called attainment/utility value. The CFA did not allow us to identify a cost dimension. Except for one item (0.70), all the other loadings were below 0.5. We therefore removed cost from the subsequent analysis. The second CFA revealed an acceptable

**Table 1** Descriptive statistics of motivational, calibration, and performance variables

| Variable | M | SD | Skewness | Kurtosis |
|---|---|---|---|---|
| INT (1) | 0.59 | 0.27 | -0.51 | -0.52 |
| ATT (1) | 0.62 | 0.21 | -0.35 | -0.08 |
| UTI (1) | 0.69 | 0.21 | -0.77 | 0.58 |
| COS (1) | 0.39 | 0.19 | 0.01 | -0.26 |
| SEF (1) | 0.69 | 0.19 | -0.48 | -0.26 |
| COJ (1) | 0.74 | 0.18 | -0.60 | -0.39 |
| CAL (1) | 0.22 | 0.12 | 0.78 | 3.05 |
| PER (30) | 20.10 | 6.15 | -0.32 | -0.75 |

INT = interest (0–1); ATT = attainment (0–1); UTI = utility (0–1); COS = cost (0–1); SEF = self-efficacy (0–1); COJ = confidence judgment (0–1); CAL = calibration (0–1); PER = performance (0–1). Except for the performance score, all other scores were divided by 100 fit, with a significant chi-square: YB$\chi^2$ (197) = 306.19, $p$ < .001, robust RMSEA = 0.06, robust CFI = 0.96, robust TLI = 0.95, SRMR = 0.06.

Cronbach's alpha coefficients for each latent construct are reported in Table 2 and ranged from 0.81 to 0.96, indicating good to excellent internal consistency.

### Structural equation modelling

Figure 2 shows the hypothesized causal structure, the standardized coefficients, and the fit indices obtained.

Except for the chi-squared test, all the indices revealed the tested model's good fit with the data: $\chi^2$ (130) = 177.13, $p$ < .01, RMSEA = 0.05, CFI = 0.98, TLI = 0.98, SRMR = 0.05. The model explained 84% of the variance in the students' performance.

### Direct relationships with performance

The first research question aimed to explore the possible relationships between self-efficacy (H1), task value (H2), confidence judgment (H3), calibration (H4), and spatial ability performance. Contrary to our expectations, the two motivational beliefs (self-efficacy

**Table 2** Factors and parameters of the final measurement model

| Latent construct and items or groups of items | Factor loading[a] |
|---|---|
| **Interest (α = 0.92)** | |
| 1. INTA: I like technical drawing. | 0.95 |
| 2. INTB: I enjoy doing technical drawing. | 0.89 |
| 3. INTC: I find technical drawing fascinating. | 0.84 |
| **Attainment/utility (α = 0.81)** | |
| 1. ATTUTIA: It is important for me to be someone who is good at technical drawing.<br>I believe that technical drawing is useful in the future. | 0.86 |
| 2. ATTUTIB: I believe that technical drawing is useful for my professional future.<br>It is important for me to be able to represent objects in space. | 0.80 |
| 3. ATTUTIC: I believe that being good at technical drawing will be useful for my future training or studies.<br>For me, failing technical drawing would be serious. | 0.74 |
| **Self-efficacy (α = 0.88)** | |
| 1. SEFA: I believe I am able to draw properly.<br>I believe I am able to draw a piece in the three basic views (front, top, and left). | 0.90 |
| 2. SEFB: I believe I am able to draw accurately.<br>I believe I am able to draw a cavalier view (3D). | 0.88 |
| 3. SEFC: I believe I am able to find my own way of visualizing the different parts of a piece.<br>I believe I am able to recognize the different types of features shown on a map.<br>I believe I am able to draw an isometric view (3D). | 0.80 |
| **Confidence judgment (α = 0.96)** | |
| 1. COJA: Randomisation of 5 PSVT and 5 DAT-SR confidence judgments items | 0.96 |
| 2. COJB: Randomisation of 5 PSVT and 5 DAT-SR confidence judgments items | 0.91 |
| 3. COJC: Randomisation of 5 PSVT and 5 DAT-SR confidence judgment items | 0.95 |
| **Calibration (α = 0.86)** | |
| 1. CALA: Randomisation of 5 PSVT and 5 DAT-SR calibration items | 0.89 |
| 2. CALB: Randomisation of 5 PSVT and 5 DAT-SR calibration items | 0.88 |
| 3. CALC: Randomisation of 5 PSVT and 5 DAT-SR calibration items | 0.81 |
| **Performance (α = 0.87)** | |
| 1. PERA: Randomisation of 5 PSVT and 5 DAT-SR items | 0.86 |
| 2. PERB: Randomisation of 5 PSVT and 5 DAT-SR items | 0.85 |
| 3. PERC: Randomisation of 5 PSVT and 5 DAT-SR items | 0.83 |

[a]Standardized factor loadings from confirmatory analysis

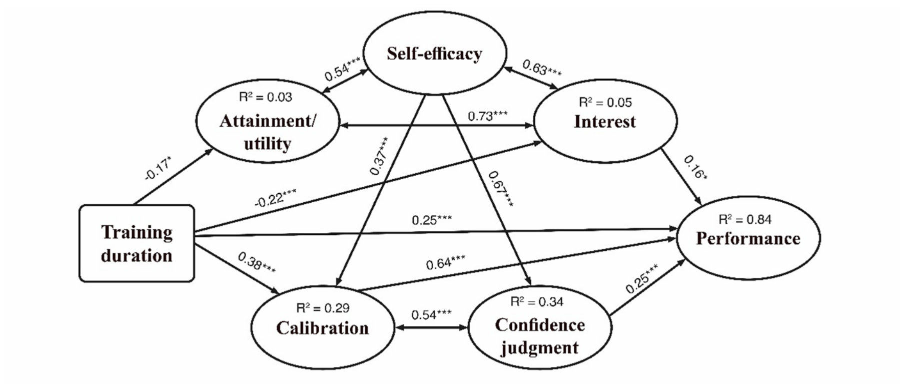


**Fig. 2** Structural Equation Model with Significant Path Correlation Coefficients. *$p < .05$, **$p < .01$, ***$p < .001$

**Table 3** Indirect effects of calibration and confidence judgment on the relationship between self-efficacy and performance

| Independent variable | Mediator | Dependent variable | Indirect effect | Total effect | *p*-value |
|---|---|---|---|---|---|
| Self-efficacy | Calibration | Performance | 0.24 | 0.38 | < 0.001 |
| Self-efficacy | Judgment of confidence | Performance | 0.14 | 0.38 | < 0.01 |

and attainment/utility) were found to have no direct effect on performance. However, calibration ($\beta = 0.64$, $p < .001$), confidence judgment ($\beta = 0.25$, $p < .001$), and interest ($\beta = 0.16$, $p < .05$) were significant predictors of performance.

### Indirect effect of self-efficacy on performance

Although the results indicate that self-efficacy beliefs are not directly related to performance in spatial skills, indirect effects (H5 and H6) were tested to ascertain whether metacognitive variables mediate the relationship between self-efficacy and performance. Self-efficacy showed a significant relationship with confidence judgment (H5) and calibration (H6). Table 3 presents the indirect and total effects of these variables.

### Effect of training duration

The analysis of the effect of apprenticeship duration revealed four key findings. First, training duration was positively associated with performance ($\beta = 0.25$, $p = < 0.001$). Second, training duration was a significant predictor of calibration ($\beta = 0.38$, $p < .001$) but not of confidence judgment ($\beta = 0.12$, $p = .09$). Third, training duration was negatively associated with task value, both for interest ($\beta$ = -0.22, $p < .001$) and attainment/utility ($\beta$ = -0.17, $p < .05$). Fourth, training duration is unrelated to self-efficacy beliefs. Ultimately, calibration mediates the relationship between training duration and performance (indirect effect: $\beta = 0.24$, $p < .001$).

## Discussion

In this study, we examined the associations between specific components of self-regulated learning—in particular, motivational beliefs and metacognition—and spatial skills. We focused on a population of apprentices in the context of a Swiss VET school who specifically enrolled in technical drawing courses that place heavy demands on spatial skills. In this section, we examine the direct effects of self-regulation on performance and explore the relationship between self-efficacy and performance, that is mediated by confidence judgments and performance calibration. Because the study adopted a cross-sectional design, causal inferences cannot be drawn. The analyses tested a theoretically plausible model and showed that the observed relationships were supported by the data, without implying causality.

**Statisticals effects on spatial performance**

Primarily, we aimed to determine the extent to which SRL plays a role in spatial skills. Regarding metacognition, the two variables under examination—calibration ($\beta = 0.64$, $p < .001$) and confidence judgments ($\beta = 0.25$, $p < .001$)—were significant predictors of performance, suggesting that higher levels of metacognitive abilities were associated with better performance on the spatial test. This finding, which aligns with the existing literature (Bol et al. 2012; Chen and Rossi 2013; Dent and Koenka 2016; Hacker and Bol 2019; Veenman 2008) and our hypotheses, is significant for several reasons, particularly regarding calibration. First, when compared to other studies that explored the relationship between calibration and academic achievement, the effects we observed were of a comparable magnitude (Bol et al. 2012; Hacker and Bol 2019). Second, and building on the previous point, the robustness of our findings is reinforced by the fact that they pertain to a relatively underresearched domain of skills. Indeed, the majority of studies that emphasised the role of metacognition in academic success focused on disciplines such as mathematics, reading, and writing (Graham et al. 2018; Mevarech et al. 2018; Stillman and Mevarech 2010; Thiede and de Bruin 2018). Our study highlights that metacognition—more specifically, calibration—also plays a significant role in the domain of spatial skills, thereby extending the scope of previous research. Finally, this result is of particular interest, as it relies on an objective measure of metacognition: performance calibration. In contrast to more subjective indicators, this measure enables a more precise assessment of metacognitive processes, with reduced susceptibility to biases such as social desirability or limitations linked to self-report (Winne 2010).

Regarding motivational beliefs, the SEM results indicate that only interest ($\beta = 0.16$, $p < .05$) was directly related to spatial performance. Neither attainment/utility nor self-efficacy beliefs were directly predictive of performance. Although the theoretical model of Eccles and Wigfield (2020) predicts a direct effect of interest on performance, the question regarding the interactions between self-efficacy and other task value components in explaining this result remains open, particularly from a developmental perspective. Indeed, Eccles and Wigfield (2020) conjecture that interest can be, over time, elaborated and internalised, notably through the concepts of attainment and utility value (Eccles and Wigfield 2020).

Finally, our results suggest that training duration explains spatial performance—this finding is not surprising, as training duration implies the development of more sophisticated academic skills. The correlation between training duration and spatial skills could also be interpreted as reflecting a shared latent variable. In such a case, training duration might not be the cause of higher spatial skills performance but rather an indicator of such skills.

#### Self-regulated processes

Our hypotheses regarding the relationship between self-efficacy and performance, based on the literature in various academic domains such as mathematics, reading and writing (Pajares 1996; Schunk et al. 2013; Zimmerman 1995) and spatial skills (Power et al. 2016; Safadel et al. 2023; Towle et al. 2005), were not supported by our findings. Interestingly, our findings indicate an indirect association between self-efficacy and performance via confidence judgments ($\beta = 0.14$, $p < .01$) and calibration ($\beta = 0.24$, $p < .001$). These results underscore the intricate interplay between self-efficacy beliefs, metacognition, and performance (in this case, spatial performance). While we found an indirect effect of self-efficacy beliefs on performance via metacognition (both confidence judgment and calibration), suggesting a mediating role for the latter, other studies, such as those of Huang et al. (2022), revealed a moderating effect. According to this moderation model, metacognition modulates the strength of the relationship between self-efficacy beliefs and performance. This apparent divergence between the two studies highlights the dynamic and contextual nature of the relationship between these variables, which can vary according to the statistical methods used (e.g., regression, moderation models, or SEM). Nevertheless, further factors must be considered. As mentioned by Schunk and Greene (2018), "learners use self-regulation processes, monitor their levels of understanding and learning, and adapt processes as necessary in an ongoing manner to promote learning or accommodate to changing conditions" (p. 5). This perspective invites us to consider the relationship between self-regulation and performance in a dynamic and cyclical way. Since our study did not capture the reciprocal relationships within self-regulation processes, adopting microanalytic methods could provide a more comprehensive understanding of the nature of these relationships. This type of methodology would be particularly useful for understanding how the different phases of the self-regulation process influence each other.

Additionally, large correlations between self-efficacy and the two task value variables (interest: $r = .63$, $p < .001$; and attainment/utility: $r = .58$, $p < .001$) were observed. The significance of self-efficacy in relation to other motivational beliefs and metacognitive variables underscores its pivotal role in the SRL process, particularly in the development of spatial skills (Power et al. 2016; Safadel et al. 2023; Towle et al. 2005).

Our results revealed a negative relationship between training duration and the two task values (interest and attainment/value). One possible explanation is that the students enrolled in longer courses have already developed spatial skills. Moreover, this result once again highlights the complex relationships between the different components of motivational beliefs.

### Limitations and recommendations for future research

One study limitation is that we did not consider perceived cost in analysing the task value components. To assess this dimension, we used the short scale developed by Beymer et al. (2022). In fact, the four items proposed by these authors assessed the different dimensions of costs (task effort cost, outside effort cost, loss of valued alternatives, and emotional cost). Our factor analyses were thus unable to identify a single cost factor. Another explanation is that the French translations modified the items' meaning and thus the scale validity.

Another limitation concerns the population studied. The curriculum for industrial vocational training includes technical drawing, which likely fosters spatial visualization skills. It is thus likely that the students who participated had already developed, to some extent, these abilities during their training, thereby suggesting that our results could differ if applied to a different population.

Future studies may adopt a longitudinal research design to test how motivational beliefs, metacognition, and performance interact over time. Indeed, the cross-sectional design adopted in the present study did not allow testing or confirming causality between the variables considered, but rather it tested potential association based on theoretical models. This would offer a more stringent test of the relationships conjectured in this study and could help researchers discover more complex associations.

## Conclusion

In this study, we illustrated the relationship between SRL processes and spatial skill performance. The SEM model explained 84% of the variability in performance. Our study deepens the understanding of SRL processes, both globally and in the context of spatial skills. Regarding the practical implications for the classroom, our findings highlight the importance of considering SRL processes when working with students. Specifically, since metacognition and self-efficacy were identified as crucial elements of the learning process, teaching practices should particularly emphasize these components by, for example, developing personalised and progressive learning paths and training students to enhance their metacognitive abilities. Moreover, incorporating SRL strategies that specifically target metacognition and self-efficacy beliefs can benefit student performance and improve their learning outcomes, especially in VET contexts involving cognitively demanding tasks.

**Abbreviations**

| | |
|---|---|
| ATT | Attainment |
| CFA | Confirmatory factor analysis |
| CFI | Comparative fix index |
| CAL | Calibration |
| COJ | Confidence judgment |
| COS | Cost |
| DAT:SR | Differential aptitude test: spatial relations |
| EVT | Expectancy–value theory |
| INT | Interest |
| MLR | Maximum likelihood estimator |
| PER | Performance |
| PSVT:R | Purdue spatial visualization test: rotations |
| RMSEA | Root mean square error of approximation |
| SEF | Self–efficacy |
| SEM | Structural equation modelling |
| SRL | Self–regulated learning |
| SRMR | Standardized root mean square residual |
| STEM | Science, technology, engineering, and mathematics |
| TLI | Tucker–Lewis index |
| UTI | Utility |
| VET | Swiss vocational education and training |
| YB | Yuan–Bentler |
| $\chi^2$ | Chi square |

**Author contributions**

O.R. and J-L.B. jointly designed the study and collaborated on the data analysis. O.R. collected the data and wrote the manuscript. J-L.B. revised, improved, and contributed to the final version of the text. All authors reviewed and approved the final manuscript.

**Funding**

This research received no external funding.

**Data availability**

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

## Declarations

**Competing interests**

The authors declare no competing interests.

**Ethics Approval**

This study did not require formal approval from an independent ethics committee, as it was conducted within the framework of institutional guidelines. All students enrolled at CEFF, a Swiss vocational education and training (VET) school, signed an informed consent agreement at the beginning of their training, which explicitly allows their anonymised data to be used for research purposes. Participation in this study was voluntary, and all data were collected and analysed anonymously.

Received: 7 August 2025 / Accepted: 3 February 2026

Published online: 12 March 2026

**References**

Bandura A (1997) Self-efficacy: the exercise of control (pp. ix, 604). W H Freeman/Times Books/ Henry Holt & Co

Bandura A (2006) Guide for constructing self-efficacy scales. In: Pajares F, Urdan TC (eds) Self-efficacy beliefs of adolescents. Information Age Publishing, pp 307–337

Bennett GK, Seashore HG, Wesman AG (1956) The differential aptitude tests: an overview. Personnel Guidance J 35(2):81–91. https://doi.org/10.1002/j.2164-4918.1956.tb01710.x

Bennett GK, Seashore HG, Wesman AG (1973) Differential aptitude test: forms S and T. The Psychological Corporation

Berger J-L, Karabenick SA (2011) Motivation and students' use of learning strategies: evidence of unidirectional effects in mathematics classrooms. Learn Instruction 21(3):416–428. https://doi.org/10.1016/j.learninstruc.2010.06.002

Beymer PN, Ferland M, Flake JK (2022) Validity evidence for a short scale of college students' perceptions of cost. Curr Psychol 41(11):7937–7956. https://doi.org/10.1007/s12144-020-01218-w

Boekaerts M (2002) Motivation to learn. International Academy of Education/International Bureau of Education (Education practices Series – 10)

Bol L, Hacker DJ, Walck CC, Nunnery JA (2012) The effects of individual or group guidelines on the calibration accuracy and achievement of high school biology students. Contemp Educ Psychol 37(4):280–287. https://doi.org/10.1016/j.cedpsych.2012.02.004

Carroll JB (1993) Human cognitive abilities: A survey of factor-analytic studies. Cambridge University Press, Cambridge Core. https://doi.org/10.1017/CBO9780511571312

Chen PP, Rossi PD (2013) Utilizing calibration accuracy information with adolescents to improve academic learning and performance. In: Bembenutty H, Cleary TJ, Kitsantas A (eds) Applications of self-regulated learning across diverse disciplines: A tribute to Barry J. Zimmerman. IAP Information Age Publishing, pp 263–297

Dent AL, Koenka AC (2016) The relation between self-regulated learning and academic achievement across childhood and adolescence: A meta-analysis. Educational Psychol Rev 28(3):425–474. https://doi.org/10.1007/s10648-015-9320-8

Eccles JS, Adler TF, Futterman R, Goff SB, Kaczala CM, Meece JL, Midgley C (1983) Expectancies, values, and academic behaviors. In: Spence JT (ed) Achievement and achievement motives: psychological and sociological approaches. Freeman, pp 75–146

Eccles JS, Adler T, Meece JL (1984) Sex differences in achievement: A test of alternate theories. J Personal Soc Psychol 46(1):26–43. https://doi.org/10.1037/0022-3514.46.1.26

Eccles JS, Wigfield A (2020) From expectancy-value theory to situated expectancy-value theory: A developmental, social cognitive, and Sociocultural perspective on motivation. Contemp Educ Psychol 61:101859. https://doi.org/10.1016/j.cedpsych.2020.101859

Flake JK, Barron KE, Hulleman C, McCoach BD, Welsh ME (2015) Measuring cost: the forgotten component of expectancy-value theory. Contemp Educ Psychol 41:232–244. https://doi.org/10.1016/j.cedpsych.2015.03.002

Flavell JH (1979) Metacognition and cognitive monitoring: A new area of cognitive–developmental inquiry. Am Psychol 34(10):906–911. https://doi.org/10.1037/0003-066X.34.10.906

Graham S, Harris KR, MacArthur C, Santangelo T (2018) Self-regulation and writing. Handbook of self-regulation of learning and performance, 2nd edn. Routledge/Taylor & Francis Group, pp 138–152. https://doi.org/10.4324/9781315697048-9

Guay, R. (1977). Purdue spatial visualization test: Visualization of rotations. Purdue Research Foundation

Hacker DJ, Bol L (2019) Calibration and self-regulated learning: Making the connections. In J. Dunlosky & K. A. Rawson (Eds), *The Cambridge handbook of cognition and education* (pp. 647–677). Cambridge University Press. https://doi.org/10.1017/9781108235631.026

Hacker DJ, Bol L, Keener MC (2008) Metacognition in education: A focus on calibration. In: Dunlosky J, Bjork RA (eds) Handbook of metamemory and memory. Psychology, pp 429–455

Huang X, Bernacki ML, Kim D, Hong W (2022) Examining the role of self-efficacy and online metacognitive monitoring behaviors in undergraduate life science education. Learn Instruction 80:101577. https://doi.org/10.1016/j.learninstruc.2021.101577

Kim H-Y (2013) Statistical notes for clinical researchers: assessing normal distribution (2) using skewness and kurtosis. Restor Dent Endod 38(1):52–54. https://doi.org/10.5395/rde.2013.38.1.52

Kline RB (2023) Principles and practice of structural equation modeling. Guilford

Koriat A (2012) The self-consistency model of subjective confidence. Psychol Rev 119(1):80–113. https://doi.org/10.1037/a0025648

Linnenbrink EA, Pintrich PR (2003) The role of self-efficacy beliefs in student engagement and learning in the classroom. Read Writ Quarterly: Overcoming Learn Difficulties 19(2):119–137. https://doi.org/10.1080/10573560308223
Little TD, Cunningham WA, Shahar G, Widaman KF (2002) To parcel or not to parcel: Exploring the question. Weigh merits Struct Equation Model 9(2):151–173. https://psycnet.apa.org/doi/10.1207/S15328007SEM0902_1
MacCallum RC, Browne MW, Sugawara HM (1996) Power analysis and determination of sample size for covariance structure modeling. Psychol Methods 1(2):130–149. https://doi.org/10.1037/1082-989X.1.2.130
Maeda Y, Yoon SY, Kin-Kang G, Imbrie PK (2013) Psychometric properties of the revised PSVT:R for measuring first year engineering students' Spatial ability. Int J Eng Educ 29(3):763–776
Marsh HW, Trautwein U, Lüdtke O, Köller O, Baumert J (2005) Academic self-concept, interest, grades, and standardized test scores: reciprocal effects models of causal ordering. Child Dev 76(2):397–416. https://doi.org/10.1111/j.1467-8624.2005.00853.x
Mevarech ZR, Verschaffel L, De Corte E (2018) Metacognitive pedagogies in mathematics classrooms: from kindergarten to college and beyond. In: Schunk DH, Greene JA (eds) Handbook of self-regulation of learning and performance, 2nd edn. Routledge/Taylor & Francis Group, pp 109–123. https://doi.org/10.4324/9781315697048-7
Nagengast B, Marsh HW, Scalas LF, Xu MK, Hau K-T, Trautwein U (2011) Who took the 'x' out of expectancy-value theory? A psychological mystery, a substantive-methodological synergy, and a cross-national generalization. Psychol Sci 22(8):1058–1066. https://doi.org/10.1177/0956797611415540
Nelson TO, Narens L (1990) Metamemory: A theoretical framework and new findings. Psychol Learn Motivation 26:125–173. https://doi.org/10.1016/S0079-7421(08)60053-5
OECD (2016) Skills matter: further results from the survey of adult skills. OECD Publishing. https://doi.org/10.1787/9789264258051-en
OECD (2021) Teachers and leaders in vocational education and training. OECD Publishing. https://doi.org/10.1787/59d4fbb1-en
Pajares F (1996) Self-efficacy beliefs in academic settings. Rev Educ Res 66(4):543–578. https://doi.org/10.2307/1170653
Power J, Buckley J, Seery N (2016), January 25 Visualizing success: Investigating the relationship between ability and self-efficacy in the domain of visual processing. In ASEE Engineering Design Graphics Division 70th Mid-Year Conference, Florida, USA. ASEE. https://sites.asee.org/edgd/wp-content/uploads/sites/22/2017/12/Visualizing-Success-Investigating-the-Relationshipbetween-Ability-and-Self-Efficacy-in-the-Domain-of-VisualProcessing.pdf
R Core Team (2021) R: A language and environment for statistical computing. [Computer software]. R Foundation fo Statistical Computing, Vienna, Austria. URL. https://www.R-project.org/
Rosseel Y (2012) Lavaan: an R package for structural equation modeling. J Stat Softw 48(2):1–36. https://doi.org/10.18637/jss.v048.i02
RStudio Team (2020) RStudio: Integrated Development for R. RStudio [Computer software]. http://www.rstudio.com
Safadel P, White D, Kia A (2023) Spatial self-efficacy and Spatial ability: an analysis of their relationship. New Rev Hypermedia Multimedia 29(2):114–150. https://doi.org/10.1080/13614568.2023.2248057
Schraw G (2009) Measuring metacognitive judgments. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), Handbook of metacognition in education. Routledge/Taylor & Francis Group, pp 415–429
Schraw G, Dennison RS (1994) Assessing metacognitive awareness. Contemp Educ Psychol 19(4):460–475. https://doi.org/10.1006/ceps.1994.1033
Schunk DH, Greene JA (2018) Historical, contemporary, and future perspectives on self-regulated learning and performance. In: Schunk DH, Greene JA (eds) Handbook of self-regulation of learning and performance, 2nd edn. Routledge/Taylor & Francis Group, pp 1–15. https://doi.org/10.4324/9781315697048-1
Schunk DH, Meece J, Pintrich P (2013) Motivation in education: Theory, Research, and applications. Pearson Deutschland. https://elibrary.pearson.de/book/99.150005/9781292055251
Sorby S, Veurink N, Streiner S (2018) Does Spatial skills instruction improve STEM outcomes? The answer is 'yes'. Learn Individual Differences 67:209–222. https://doi.org/10.1016/j.lindif.2018.09.001
Stankov L, Lee J, Luo W, Hogan DJ (2012) Confidence: A better predictor of academic achievement than self-efficacy, self-concept and anxiety? Learn Individual Differences 22(6):747–758. https://doi.org/10.1016/j.lindif.2012.05.013
Stillman G, Mevarech Z (2010) Metacognition research in mathematics education: from hot topic to mature field. ZDM Mathematics Education 42(2):145–148. https://doi.org/10.1007/s11858-010-0245-x
Thiede KW, de Bruin ABH (2018) Self-regulated learning in reading. In: Schunk DH, Greene JA (eds) Handbook of self-regulation of learning and performance, 2nd edn. Routledge/Taylor & Francis Group, pp 124–137. https://doi.org/10.4324/9781315697048-8
Towle E, Mann J, Kinsey B, O'Brien EJ, Bauer CF, Champoux R (2005) Assessing the self efficacy and Spatial ability of engineering students from multiple disciplines. Proc Front Educ 35th Annual Conf S2C–15–S2C–20. https://doi.org/10.1109/FIE.2005.1612216
Trautwein U, Marsh HW, Nagengast B, Lüdtke O, Nagy G, Jonkmann K (2012) Probing for the multiplicative term in modern expectancy-value theory: A latent interaction modeling study. J Educ Psychol 104(3):763–777. https://doi.org/10.1037/a0027470
Usher EL, Schunk DH (2018) Social cognitive theoretical perspective of self-regulation. In: Schunk DH, Greene JA (eds) Handbook of self-regulation of learning and performance. Routledge/Taylor & Francis Group, pp 19–35. https://doi.org/10.4324/9781315697048-2
Uttal DH, Meadow NG, Tipton E, Hand LL, Alden AR, Warren C, Newcombe NS (2013) The malleability of Spatial skills: A meta-analysis of training studies. Psychol Bull 139(2):352–402. https://doi.org/10.1037/a0028446
Veenman MVJ (2008) Giftedness: predicting the speed of expertise acquisition by intellectual ability and metacognitive skillfulness of novices. In: Shaughnessy MF, Veenman MVJ, Klein Kennedy C (eds) Meta-cognition: A recent review of research, theory, and perspectives. Nova Science, pp 207–220
Veenman MVJ (2013) Training metacognitive skills in students with availability and production deficiencies. In: Bembenutty H, Cleary TJ, Kitsantas A (eds) Applications of self-regulated learning across diverse disciplines: A tribute to Barry J. Zimmerman. IAP Information Age Publishing, pp 299–324
Vujanovic P, Lewis C (2017) Ensuring a dynamic skills-training and life-long learning system in Switzerland. OECD Publishing. https://doi.org/10.1787/438423d9-en

Wai J, Lubinski D, Benbow CP (2009) Spatial ability for STEM domains: aligning over 50 years of cumulative psychological knowledge solidifies its importance. J Educ Psychol 101(4):817–835. https://doi.org/10.1037/a0016127

Wickham H, Averick M, Bryan J, Chang W, McGowan L, François R, Grolemund G, Hayes A, Henry L, Hester J, Kuhn M, Pedersen T, Miller E, Bache S, Müller K, Ooms J, Robinson D, Seidel D, Spinu V, Yutani H (2019) Welcome to the tidyverse. J Open Source Softw 4(43):1686. https://doi.org/10.21105/joss.01686

Wigfield A, Eccles JS (2000) Expectancy–Value theory of achievement motivation. Contemp Educ Psychol 25(1):68–81. https://doi.org/10.1006/ceps.1999.1015

Wigfield A, Tonks SM, Klauda SL (2016) Expectancy-value theory. Routledge Handbooks Online. https://doi.org/10.4324/9781315773384.ch4

Winne PH (2010) Improving measurements of self-regulated learning. Educational Psychol 45(4):267–276. https://doi.org/10.1080/00461520.2010.517150

Zimmerman BJ (1995) Self-efficacy and educational development. In: Bandura A (ed) Self-efficacy in changing societies. Cambridge University Press, pp 202–231. https://doi.org/10.1017/CBO9780511527692.009

Zimmerman BJ (2000) Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds), Handbook of self-regulation (pp. 13–39). Academic Press. https://doi.org/10.1016/B978-012109890-2/50031-7

Zimmerman BJ (2011) Motivational sources and outcomes of self-regulated learning and performance. In: Zimmerman BJ, Schunk DH (eds) Handbook of self-regulation of learning and performance. Routledge/Taylor & Francis Group, pp 49–64

Zimmerman BJ, Moylan AR (2009) Self-regulation: where metacognition and motivation intersect. In: Hacker DJ, Dunlosky J, Graesser AC (eds) Handbook of metacognition in education. Routledge/Taylor & Francis Group, pp 299–315

Zimmerman BJ, Schunk DH (2008) Motivation: an essential dimension of self-regulated learning. In: Schunk DH, Zimmerman BJ (eds) Motivation and self-regulated learning: Theory, research, and applications. Lawrence Erlbaum Associates, pp 1–30

## Publisher's note