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Topic- and learning-related predictors of deep-level learning strategies

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Abstract:	The aim of this study was to examine which topic- and learning-related knowledge and motivational beliefs predict the use of specific deep-level learning strategies during an independent learning task. Participants included 335 Estonian fourth- and sixth-grade students who were asked to read about light processes and seasonal changes. The study was completed electronically. Topic-related knowledge was assessed via an open question about seasonal changes, and learning-related knowledge was assessed via scenario-based tasks. Expectancies, interest, and utility values related to learning astronomy and using deep-level learning strategies were assessed via questions based on the Situated Expectancy-Value Theory. Deep-level learning strategies (using drawings in addition to reading and self-testing) were assessed while completing the reading task. Among topic-related variables, prior knowledge and utility value — but not interest or expectancy in learning astronomy — were related to using deep-level learning strategies. Among learning-related variables, interest and utility value of effective learning — but not metacognitive knowledge of learning strategies or expectancy in using deep-level learning strategies — were related to using deep-level learning strategies. This study confirms that it is not enough to examine students' knowledge and skills in using learning strategies with general or hypothetical questions; instead, it is of crucial importance to study students in real learning situations.
Response to Reviewers:	Revision for EUPE-D-23-00377R1 "Topic- and learning-related predictors of deep-level learning strategies" Dear Dr. Valerie Tartas, Thank you for kind answer. We have corrected the parts referred to by the reviewer. We really thank for the reviewer for thorough explanations. We have leart a lot. Below you find our responses. We are looking forward to hearing from you soon.

Kind reards,
The authors

Reviewer #1:
Thank you very much for the opportunity to review the revised manuscript. I enjoyed re-reading the paper and the author's replies to my comments.
Only some minor issues should be corrected before the manuscript can be accepted for publication.
Lines 325-326: As you have a saturated model, it is obvious that the $\chi 2=0$ and df=0. I suggest deleting the items as all those tests and fit indices do not apply to a regression model, although Mplus prints those numbers out. However, this printout is largely misleading because a $\chi 2$distribution with 0 degrees of freedom is not defined.
Answer: Deleted.
Measure section, starting at line: You may want to start with the independent variable. Given that these are the predictors for the dependent variable, it would be more natural to start with the predictors. Just a hint, not a requirement.
Answer: Yes, it is better. We changed the order.
Method section, lines 296-302: I personally believe that while changing the use of drawings to a continuous variable was correct, I think changing the self-test-variable to be continuous in the analysis was not a good choice, or perhaps the bay was thrown out with the bathwater.
I want to make the authors aware that categorical does not necessarily mean nominal. There are also ordered categorical variables. Here, there are categories as in the case of nominal variables, but the categories have a natural ordering that they can be arranged in ascending or descending order. Given the variable's description (score) in lines 234-248, it's obvious that the variable is continuous (or metric). Self-testing with less than half of the questions answered correctly (score 2) can be considered as a deeper learning activity than reading (score 1), but at the same time, they are from a different category, but the categories have an order in their "learning deepness". Similarly, self-testing with more than half of the questions answered correctly (score 3) has gained a greater "learning deepness" than score 2. Note, score 2 and 3 are not from a different category (as for score 1 and 2), but the score adds some level of "deepness," but the amount of this "deepness" is unclear and therefore lacks the metric element which is required for continuous variables (equidistance between the scales levels). Please note that this is different for the variable use of drawing: Using 2 drawings instead of 1 drawing is the same difference as between using 3 drawings instead of 2 drawings (because the use of drawing is a count variable and has a natural zero point).
There are basically two options: Firstly, changing the variable back to categorical option in Mplus. The great thing in Mplus is that it can handle two types of independent variables at the same time.
However, I can understand when the authors do not want to change the manuscript again. Especially, because it is common in (educational) psychology to treat such variables as continuous and ignoring their real nature. I have to confess I do it myself. However, in this case, I recommend that the author add some considerations about this issue in the limitations section to show the reflected reader that they know this potential shortcoming. Perhaps there is citation that justifies the consideration of this variables as continuous, it would augment your argument.
Answer: Yes, we fully agree with the explanation and changed self-testing to categorical variable. We explained in Analysis Strategy section: “Due to the lack of metric element between its categories (equidistance between the scale levels), the self-testing variable was specified to be categorical.” We changed the results in Table and text.

Sincerely,
Authors

Topic- and learning-related predictors of deep-level learning strategies

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Declarations

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kind.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Author contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Eve Kikas Gintautas Silinskas, and Eliis Härma. The first draft of the manuscript was written by Eve Kikas and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Eve Kikas

Current themes of research

Children's development and learning in kindergarten and school. The role of individual characteristics and contextual factors (e.g., teaching practices, parental support) in students' learning. Assessing and supporting learning strategies and motivation.

Most relevant publications in the field of Psychology of Education

Kikas, E., Silinskas, G., Mädamürk, K., Soodla, P. (2021). Effects of Prior Knowledge on Comprehending Text About Learning Strategies. Frontiers in Education, 6. https://doi.org/10.3389/feduc.2021.766589.

Kikas, E., Mädamürk, K., Hennok, L., Sigus, H., Talpsep, T., Luptova, O., & Kivi, V. (2021). Evaluating the efficacy of a teacher-guided comprehension-oriented learning strategy intervention among students in Grade 4. *European Journal of Psychology of Education*. https://doi.org/10.1007/s10212-021-00538-0

Soodla, P., Tammik, V., & Kikas, E. (2021). Is part-time special education beneficial for children at risk for reading difficulties? An example from Estonia. *Dyslexia, 27*, 126-150. https://doi.org/ 10.1002/dys.1643

Kikas, E., Mädamürk, K., & Palu, A. (2020). What role do comprehension-oriented learning strategies have in solving math calculation and word problems at the end of middle school? *British Journal of Educational Psychology. 90, 105–123.* https://doi.org/10.1111/bjep.12308

Kikas, E., Peets, K., and Hodges, E. (2014). Collective student characteristics alter the effects of teaching practices on academic outcomes. *Journal of Applied Developmental Psychology, 35,* 273–283.

Kikas, E. (2004). Teachers' conceptions and misconceptions concerning three natural phenomena. *Journal of Research in Science Teaching, 41,* 432–448.

Gintatuas Silinskas

Current themes of research

The role of parents and teachers in children's outcomes (learning, motivation, and adjustment). Longitudinal modeling. Development and learning in kindergarten and school. Transition from kindergarten to school.

Most relevant publications in the field of Psychology of Education

Silinskas, G., Ahonen, A. K., & Wilska, T. (2023). School and family environments promote adolescents' financial confidence: Indirect paths to financial literacy skills in Finnish PISA 2018. *Journal of Consumer Affairs, 57(1), 593-618. https://doi.org/10.1111/joca.12513*

*T*unkkari, M., Aunola, K., Hirvonen, R., Silinskas, G., & Kiuru, N. (2022). A person-oriented approach to maternal homework involvement during the transition to lower secondary school. *Learning and Individual Differences*, *97,* Article 102164. https://doi.org/10.1016/j.lindif.2022.102164

Silinskas, G., Torppa, M., Lerkkanen, M.-K., & Nurmi, J.-E. (2020). The home literacy model in a highly transparent orthography. *School Effectiveness and School Improvement*, *31*(1), 80-101. https://doi.org/10.1080/09243453.2019.1642213

Silinskas, G., Pakarinen, E., Lerkkanen, M.-K., Poikkeus, A.-M., & Nurmi, J.-E. (2017). Classroom interaction and literacy activities in kindergarten: Longitudinal links to grade 1 readers at risk and not at risk of reading difficulties. *Contemporary Educational Psychology*, *51*, 321-335. https://doi.org/10.1016/j.cedpsych.2017.09.002

Silinskas, G., Pakarinen, E., Niemi, P., Lerkkanen, M.-K., Poikkeus, A.-M., & Nurmi, J.-E. (2016). The effectiveness of increased support in reading and its relationship to teachers' affect and children's motivation. *Learning and Individual Differences*, *45*, 53-64. https://doi.org/10.1016/j.lindif.2015.11.025

Eliis Härma

Current themes of research

Surface and deep learning, learning strategies, learning-related motivational beliefs.

Most relevant publications in the field of Psychology of Education

Granström, M., Härma, E. & Kikas, E. (2022). Teachers' Knowledge of Learning Strategies. *Scandinavian Journal of Educational Research*, DOI: 10.1080/00313831.2022.2074536

Abstract

The aim of this study was to examine which topic- and learning-related knowledge and motivational beliefs predict the use of specific deep-level learning strategies during an independent learning task. Participants included 335 Estonian fourth- and sixth-grade students who were asked to read about light processes and seasonal changes. The study took place on computers. Topic-related knowledge was assessed via an open question about seasonal changes,

and learning-related knowledge was assessed via scenario-based tasks. Expectancies, interest, and utility values related to learning astronomy and using deep-level learning strategies were assessed via questions based on the Situated Expectancy-Value Theory. Deep-level learning strategies (using drawings in addition to reading and self-testing) were assessed while completing the reading task. Among topic-related variables, prior knowledge and utility value — but not interest or expectancy in learning astronomy — were related to using deep-level learning strategies. Among learning-related variables, interest and utility value of effective learning — but not metacognitive knowledge of learning strategies or expectancy in using deep-level learning strategies — were related to using deep-level learning strategies. This study confirms that it is not enough to examine students' knowledge and skills in using learning strategies with general or hypothetical questions; instead, it is of crucial importance to study students in real learning situations.

Topic- and learning-related predictors of deep-level learning strategies

Abstract

The aim of this study was to examine which topic- and learning-related knowledge and motivational beliefs predict the use of specific deep-level learning strategies during an independent learning task. Participants included 335 Estonian fourth- and sixth-grade students who were asked to read about light processes and seasonal changes. The study was completed electronically. Topic-related knowledge was assessed via an open question about seasonal changes, and learning-related knowledge was assessed via scenario-based tasks. Expectancies, interest, and utility values related to learning astronomy and using deep-level learning strategies were assessed via questions based on the Situated Expectancy-Value Theory. Deep-level learning strategies (using drawings in addition to reading and self-testing) were assessed while completing the reading task. Among topic-related variables, prior knowledge and utility value — but not interest or expectancy in learning astronomy — were related to using deep-level learning strategies. Among learning-related variables, interest and utility value of effective learning — but not metacognitive knowledge of learning strategies or expectancy in using deep-level learning strategies — were related to using deep-level learning strategies. This study confirms that it is not enough to examine students' knowledge and skills in using learning strategies with general or hypothetical questions; instead, it is of crucial importance to study students in real learning situations.

Keywords: deep and surface learning, learning strategies, expectancies, interest value, utility value

Topic- and learning-related predictors of deep-level learning strategies

Introduction

The importance of self-regulation and the need to support the development of self-regulated learners beginning in elementary school, is widely acknowledged (Schunk & Greene, 2018). A critical dimension of self-regulated learning is the knowledge and application of learning strategies (LS), i.e., activities carried out during learning that directly affect the process and outcomes of learning (Dinsmore & Hattan, 2020; VanMeter & Campbell, 2020). It is well known that deep-level LS (e.g., self-testing) — compared with surface-level LS (e.g., rereading) — tend to support comprehension of new material such that learned knowledge can be later recalled and flexibly used for solving novel tasks (Dinsmore & Hattan, 2020). However, empirical studies have indicated that students tend to use easily applicable surface-level LS (Dirkx et al., 2019). To support students in applying deep-level strategies, it is important to know which factors enhance students' choice of LS in specific learning situations.

As confirmed by various studies (e.g., Finn, 2020; Rosenzweig et al., 2019; Taboada et al., 2008; Vu et al., 2021), knowledge and motivation are important in choosing and using specific LS. In addition, a distinction can be made between topic-related and learning-related indicators (cf. Karabenick et al., 2021). Topic-related indicators include prior topic knowledge and motivation to study the topic, while learning-related indicators include general metacognitive knowledge of LS, a tendency to apply these strategies, and motivation to use effective learning strategies.

While earlier studies have confirmed the importance of specific knowledge and motivational factors, there has been a lack of studies examining the effect of concordant topic-and learning-related knowledge and motivation on using deep-level LS. Our study attempts to fill this gap. The aim of our study was to examine which topic- and learning-related knowledge and motivational beliefs predict the use of specific deep-level LS when learning from written material. Participants were elementary school students (fourth and sixth graders) in Estonia who had to learn about light processes and seasonal changes. We examined the use of two specific deep-level LS: 1) making use of drawings in addition to simple reading, and 2) self-testing instead of re-reading. We studied motivational beliefs based on the situated expectancy-value theory SEVT (Wigfield & Eccles, 2020).

Learning strategies: Using drawings and self-testing

As mental or cognitive processes that a student carries out during learning, LS are related to what is learned, memorized, and understood (Alexander et al., 2018; Van Meter & Campbell, 2020). With deep-level LS, a student perceives new information, differentiates between more and less important information, and actively tries to integrate new knowledge with existing knowledge, resulting in the construction of new knowledge that is not simply a restatement of new material. In contrast, with surface-level LS, a student perceives new information and tends to mechanically repeat or memorize it, but does not attempt to integrate this new information with existing knowledge (Alexander et al., 2018; Chi & Wylie, 2014; Dinsmore & Alexander, 2012). While deep learning involves the creation of memory content that can be recalled and flexibly applied long after learning takes place, surface learning leads to the memorization of isolated facts that are not easily recalled and cannot be used flexibly later on (Carpenter et al., 2020; Dinsmore & Hattan, 2020). It should be noted that deep-level LS are not always superior to surface-level LS (Alexander et al., 2018; Dinsmore & Alexander, 2012). There is no single or group of most-effective LS, as the usefulness of each strategy depends on the student’s current knowledge and abilities as well as the specific learning task and context (Dinsmore & Alexander, 2012). Learning outcomes also depend on the quality of students' LS application (Leopold & Leutner, 2015). Since deep-level LS require more effort and time than surface-level LS, deep-level LS also presuppose higher motivation (e.g., Finn, 2020).

One way to enhance deep learning is by making use of visuals (e.g., drawings) in addition to reading a text. Visuals are widely used in science education (Galano et al., 2018; Wang & Tseng, 2019), including in learning basic astronomy phenomena (Galano et al., 2018). Although many studies have shown the advantages of using and generating drawings over simple reading, other studies have indicated challenges and misunderstandings (e.g., Guo, McTigue, et al., 2020; Guo, Zhang, et al., 2020; for astronomy, see Authors, 1998a, 1998b). Learning efficacy depends on the quality of learning materials as well as the learner's prior knowledge (Mayer, 2021). For instance, written material is easier to comprehend when visuals appear nearby the relevant portion of the text (e.g., Mayer, 2017). For learners with low knowledge, visuals presented in scientific texts may add new comprehension challenges and lead to cognitive overload (McTigue & Flowers, 2011).

Another way to enhance understanding is to test what has been learned by answering questions (referred to as testing-effect, retrieval, practice testing; Adesope et al., 2017; Agarwal et al., 2021; Kubik et al., 2021). The testing effect refers that tests provide not only opportunities to assess what has been learnt also good learning opportunities (Kubik et al., 2021). When testing learned material, learners activate previous knowledge, thereby restructuring existing knowledge such that new information is integrated with prior knowledge. Retrieval has been found to consolidate learned material, improve recall, and support meaningful learning at all ages (e.g., Karpicke et al., 2009; Smith et al., 2013). Studies have referred to great variability in the effectiveness of feedback, depending on the level it is provided, how it is formulated etc. (Kubik et al., 2021; Wisniewski et al., 2020). However, retrieval has been shown to be effective even without feedback (Adesope et al., 2017). Retrieval has also been found to be more effective than rereading, during which a learner reads a text or its parts repeatedly (Karpicke et al., 2009).

Topic-related prior knowledge, motivational beliefs, and their relationship with deep-level learning

In scholastic settings, students frequently learn via prepared written texts, and comprehension requires using prior knowledge to interpret textual information and construct meaning from the text (Wiley & Guerrero, 2018). Many studies, including those focusing on learning scientific concepts, have shown that prior knowledge influences text comprehension (Kendeou & van den Broek, 2007; Linnenbrink-Garcia et al., 2012). With well-structured prior knowledge and without misconceptions that contradict new knowledge, it is relatively easy to find appropriate information from the text and integrate it with existing knowledge. In contrast, misconceptions and fragmental knowledge inhibit reading comprehension and meaning construction (Kendeou & van den Broek, 2007). Strong, well-structured, topic-related knowledge may refer to students' habit of using deep-level LS in prior learning (for the relationship between deep-level learning and understanding, see Hattie & Donoghue, 2016; Dinsmore & Hattan, 2020; for the importance of habit, see Fiorella, 2020). Strong knowledge, consequently, may support further use of deep-level LS.

Researchers have analyzed the effects of LS on learning and the relationship between LS and learned knowledge (e.g., Diseth, 2011), but relatively few studies have examined the effects of prior knowledge on LS. Zakariya et al. (2021) showed that, among university students, prior math knowledge decreased the likelihood of using surface LS but had no significant effect on using deep LS. The authors used self-report questionnaires that tapped surface and deep LS separately, but the authors did not ask about specific use of LS. Such effects have not been studied in elementary school or in relation to actual use of LS.

In addition to prior knowledge, motivational beliefs play an important role in learning. According to the SEVT, student's expectancies and values as motivational beliefs guide their subjective interpretations of learning situations and tasks that, in turn, can trigger and/or enhance the learning process (Wigfield & Eccles, 2020). Expectancy (closely related to self-efficacy and academic self-concept; Bandura, 1993; Schroeders & Jansen, 2020) is defined as a student's belief about how well he/she will do on future tasks in a specific field. As self-efficacy refers to a person's confidence that they can succeed in a future specific task, expectancy refers to their perception of the relationship between their actions and outcomes (Bandura, 1993; Eccles & Wigfield, 2020). As to the values, in this study, we focused on examining intrinsic and utility value. Intrinsic value can be defined as the enjoyment a learner gains from doing a given task (Eccles & Wigfield, 2020) and is similar to intrinsic motivation and interest (Renninger & Hidi, 2011; Ryan & Deci, 2020). Utility value can be defined as the perceived relevance or usefulness of a task or subject area with regard to a student's current or future plans.

Learners' expectancies and values to learn specific subjects have been found to be strong direct predictors of different learning outcomes (e.g., test scores, academic engagement) starting from elementary school and lasting through higher education (Wigfield & Eccles, 2020). Studies in scientific areas where conceptual change is needed have also referred to the importance of interest and self-efficacy in learning (Andre & Windschitl, 2003; Linnenbrink-Garcia et al., 2012). Motivational beliefs may support learning and outcomes via two routes: quantity and quality of learning (Vu et al., 2021). Learning quantity can be measured via persistence, frequency and intensity of study, and so on. Learning quality refers to using adaptive, deep-level, LS. Since deep-level LS are effortful and time consuming, students who value certain tasks or domains are more likely to employ these strategies. Previous research, primarily studying middle-schoolers and older students, has shown that students with higher expectancies (academic self-efficacy; Bandura, 1993; Diseth, 2011; Linnenbrink & Pintrich, 2003; Trigwell et al., 2013) and subject-related task values (for overview, see Vu et al., 2021) tend to value and use deep-level LS and have better learning outcomes. In elementary school, Chatzistamatiou et al. (2013) showed positive relationships between students' math self-efficacy, the value they attribute to math, their enjoyment of learning math, and their reported self-regulatory strategies. In general, students' expectancies tend to better predict achievement than task values, but task values tend to better predict course-taking intentions and choices (Perez et al., 2014; Rosenzweig et al., 2019).

Although the importance of motivational beliefs (expectancies and values) on using LS has been extensively shown in previous research, only a few studies have been carried out at the elementary school level. Moreover, previous research has not considered the concurrent effects of topic-related knowledge and motivational beliefs on the use of specific LS; thus, we aimed to examine these effects among elementary school students.

Learning-related knowledge, motivational beliefs, and their relationship with deep-level learning

As learning strategies vary in usefulness depending on students' knowledge, abilities, and the current learning task (Dinsmore & Alexander, 2012), there is no single most-effective LS. Instead, it is valuable for students to know the advantages and disadvantages of different LS

(Bjork et al., 2013). The need for such metacognitive knowledge of LS has been confirmed by intervention studies. Namely, one of the key components enhancing the learning and later use of LS is explicit teaching and discussions about LS (Dignath et al., 2008; Dignath & Büttner, 2008; Feeney, 2021). Specifically, when learning complex topics and striving for conceptual understanding, deep-level LS tend to be more effective than surface-level LS (cf. Alexander et al., 2018).

In addition to differences in topic-specific expectancies and values, students differ in how confident they are and how much they value different LS. Applying deep-level LS assumes increased attention, working memory capacity, reasoning skills, persistence, and motivation (Schleepen & Jonkman, 2012; Seufert, 2020). Karabenick et al. (2021) referred to two types of motivation: 1) outcome motivation (i.e., expectancies and values related to learning specific topics); and 2) strategy motivation (i.e., expectancies and values related to the learning process). Strategy motivation includes beliefs about how easy, difficult, or useful a strategy is, and these expectancies and values guide engagement in the learning process and the selection of specific strategies. Karabenick et al. (2021) emphasized that students decide to use a given strategy when they see its value and efficacy. So far, strategy motivation has been rarely recognized and assessed (for an exception in composing drawings during math learning, see Schukajlow et al., 2022). Thus, we aimed to examine the effects of metacognitive knowledge of LS, together with motivation to use LS, on actual use of deep-level LS.

The present study and hypotheses

The main aim of our study was to examine the role of both topic- and learning-related factors in choosing and applying two deep-level LS — making use of drawings, and self-testing — while learning about a scientific topic (light processes and seasonal changes). Students were asked to read and comprehend a prepared text. In addition to reading, students were allowed to make use of drawings. After reading the text once, students were given the possibility to review the text by either reading it again or answering prepared questions (i.e., self-testing). Using drawings and self-testing are referred to here as deep-level LS. Our theoretical model and hypotheses are shown in Figure 1. Our research questions and hypotheses are as follows.

First, what topic-related factors are related to choosing and using deep-level LS? We expected (H1) that students with strong prior astronomy-related knowledge would use deep-level LS. Strong knowledge may indicate that a student has good learning skills and habitually uses deep-level LS (cf. Fiorella, 2020). With good knowledge, a student can also better detect lack of information in text and search for missing details in drawings (Linnenbrink-Garcia et al., 2012). We also expected (H2) that higher values and expectancy would guide students to use deep-level LS. Specifically, we expected a higher effect of values compared to expectancy (Perez et al., 2014; Rosenzweig et al., 2019).

Second, what learning-related factors are associated with choosing and using deep-level LS? We expected that students who had metacognitive knowledge of deep-level LS (H3) and those who self-reported using deep-level LS in daily learning (H4) would use deep-level LS in this study's specific learning situation. Strong metacognitive knowledge of LS is important in self-regulated learning (Bjork et al., 2013), and self-reported use of deep-level LS during independent test preparation may refer to a habitual way of learning (cf. Fiorella, 2020). One pathway in which motivational beliefs may support learning and outcomes is through the use of high-quality learning behaviors (i.e., deep-level LS; Vu et al., 2021), thus we expected (H5) that students with higher expectancy and values would use deep-level LS. Similar to topic-related motivational beliefs, we expected a higher effect of values compared to expectancy (Perez et al., 2014; Rosenzweig et al., 2019).

Method

Participants and procedure

Participants included 335 Estonian fourth- and sixth-grade students (50.2% boys) from six mainstream schools in different regions of Estonia.

Schools were first invited to participate in a study conducted by a university research group. School participation was voluntary. Students and their parents were informed of the content of the test. Student participation was voluntary. Written consent from at least one parent or guardian was required to participate in the study. Students were allowed to discontinue the study at any time.

Students were tested at the beginning of the school year. Students took the tests in computer labs during regular school days and were supervised by teachers. The test assessed students' learning-related indicators, including metacognitive knowledge of LS, use of LS, motivational beliefs, text comprehension, topic-related knowledge, and reasoning skills. The test took approximately 45 minutes to complete.

Measures

Independent variables

Topic-related indicators

Astronomy-related knowledge was assessed with one open question before reading the text: "Write briefly why in Estonia it is colder in the winter than in the summer." The answers were coded in four broad categories: 1) incorrect or missing answers, 2) descriptive answers, 4) answers with misconceptions or partly incorrect explanations, 4) scientific explanations (see

Appendix A). One-third of the answers were coded by two researchers (the first author of the paper and one doctoral student in psychology); the rest of the answers were coded by the first author of the paper. Inter-rater reliability was very high, Cohen κ = 0.95 (SE = 0.027; 95% CI: 0.893–0.998).

Expectancy-values to learn astronomy was assessed via a questionnaire based on the expectancy-value theory (Eccles & Wigfield, 2020). Students had to think about how well each description characterized them and mark their answers using a 5-point scale (1—*do not agree at all*; 5—*completely agree*). One item assessed *expectancy of learning astronomy* (“Learning about the sun and the planets is easy for me”); one item assessed *interest in learning astronomy* (“I am interested in knowledge related to the sun and the planets”); and one item assessed the *utility value of learning astronomy* (“Knowledge related to the sun and planets is useful in my out-of-school life and in future”).

Learning-related indicators

Metacognitive knowledge of deep-level LS. Participants were given the following instructions: “You are given descriptions of different learning tasks in which two students use different learning procedures or strategies. Evaluate how effective each strategy is for understanding, later recalling, and applying the learned material.” The scenarios and strategies are given in Appendix B. They based on previous empirical studies indicating that deep-level LS were related to better outcomes than surface-level LS (e.g. Carpenter et al., 2020; Dunlosky et al., 2013; Roediger & Karpicke, 2006). The scenarios and strategies were modified from earlier studies (Authors, 2022; McCabe, 2011; Surma et al., 2022) to be suitable for elementary school students. Students had to evaluate the effectiveness of each strategy on a 5-point Likert-type scale (1—*the strategy is* *ineffective*; 5—*the strategy is very effective*). *Metacognitive knowledge of deep-level LS* was assessed as a mean score of six deep-level LS evaluations. Cronbach's α was 0.70.

Self-reported use of deep-level LS. After evaluating the effectiveness of each strategy, students were asked to mark which strategy they would use in the described learning situation (the strategy of Student A, or the strategy of Student B). In this study, we use answers to Scenario 1 (choosing between rereading and self-testing) and Scenario 5 (choosing between rereading and reading and looking at drawings; see Appendix B). We formed scores *Self-reported use of self-testing* and *Self-reported use of drawings*. For both, a score of 1 means that the student marked the deep-level strategy (using self-testing and drawings) rather than the surface-level strategy (reading).

Expectancy-values to use deep-level LS was assessed via a questionnaire based on the expectancy-value theory (Eccles & Wigfield, 2020). Students had to think about how well each description characterized themselves and mark their answers using a 5-point scale (1—*do not agree at all*; 5—*completely agree*). One item assessed *expectancy of using deep-level learning strategies* ("I am able to use effective learning strategies"); one item assessed *interest in effective learning* ("I am interested in knowing how to learn more effectively"); and one item assessed the *utility value of effective learning* ("Knowledge of how to learn effectively is useful in my extracurricular life and in my future").

Dependent variables

Using deep-level LS (drawings and self-testing)

Students had to read and comprehend a prepared text about the scientific phenomenon of light and why the seasons change (see Appendix C). Before reading, students were told that they would be asked questions about the text one week later (the results of testing one week later are not used in this paper) and in order to better understand the text, they can also look at the drawings about the text. The text was composed of three sections, and in each section was supplemented with a drawing/schema, supporting section comprehension. After each section of the text, students were asked the question: “Do you want to look at the drawing?” If a student answered “Yes”, a related drawing appeared below the text. If a students answered “No”, the drawing did not appear and a student had the option to move on to the next section. Students had the opportunity to look at up to three drawings, which formed a *Using drawings* score (0–3).

After reading the text once, students were told that, in order to better understand and remember the topic, they needed to choose a single strategy to review the material. One strategy was rereading, which was presented as follows: “Read the text again and look at the drawings.” Another strategy was self-testing (retrieval), which was presented as follows: “You will be asked revision questions about the text. Answer them! You don’t have to write the answers, just answer them in your head. You will also get the correct answers.” Students were first shown a question about the text and then asked the question: "Do you want to see the correct answer to this question?" If the student answered "Yes", the correct answer was displayed below the question. If the student answered "No", the answer was not displayed. Based on a student’s choice, a *Using self-testing* score (1–3) was formed. A score of 1 meant that the student selected rereading. A score of 2 meant that the student selected self-testing, but checked the correct answers for less than half of the questions (i.e., 0–3 questions). A score of 3 meant that the student selected self-testing and checked the correct answers for more than half of the questions (i.e., 4 or more questions).

Analysis Strategy

All analyses were carried out using Mplus version 8.8 (Muthén & Muthén, 1998–2017). The model parameters were estimated using maximum likelihood estimation with robust standard errors (MLR), thus not requiring variables to follow normal distribution. A multivariate multiple regression model was constructed to answer our research questions. Our two dependent variables — using drawings and using self-testing — were predicted by all independent variables. Due to the lack of metric element between its categories (equidistance between the scale levels), the self-testing variable was specified to be categorical. All independent variables were allowed to correlate with each other, and the error terms of both dependent variables were specified to correlate.

We did not have missing data except for one case in the variable "using self-testing" (the overall multivariate data coverage was 99.7–100%). Mplus was set to use the full information maximum likelihood option (FIML) which accounted for all 350 cases when estimating the final model. As children were nested within six schools, we used School ID as a cluster for the COMPLEX function of Mplus. The COMPLEX option of Mplus estimates parameters while taking nestedness into account (i.e., children belonging to certain schools).

Results

Descriptives

Descriptions of all study variables are presented in Table 1, and correlations among all study variables are presented in Table 2. According to Cohen's (1988, 1992) interpretation of effect sizes (the effect size for r values around 0.1, medium for r values around 0.3, and large for r values larger than 0.5), using drawings and using self-testing were moderately related (r = .208, p < .05). Astronomy related knowledge did not correlate with values and expectancy of learning astronomy, but weakly related to deep-level strategy use (.143–.167). We found medium positive relations among values and expectancy of learning astronomy (.252–.456) and their weak-to-nonsignificant relations with deep-level LSs. Metacognitive knowledge of deep-level learning strategies positively related to deep-level strategy use (.235–.241; medium effect). Self-reported use of drawings and self-testing differentially correlated with actual using of drawings and self-testing (from nonsignificant to medium effect). We also found medium-to-large effects among values and expectancy of using deep-level LS (.434–.502), which consistently related to using drawings (weak-to-medium effect), but not using self-testing.

Hypotheses Testing

To answer our research questions, the multivariate multiple regression model was constructed, and the saturated model was obtained. The results showed that residuals of the dependent variables — using drawings and using self-testing — were not associated (r = .155, p = .212). As presented in Table 2, the model explained 14.8% of the variance of the using drawings and 18.6% of the variance of using self-testing.

To answer our first research question concerning the relations between topic-related factors and children's deep-learning strategy use, the results showed that astronomy-related knowledge positively predicted using drawings and using self-testing. Thus, Hypothesis 1 (H1) was supported. In partial support to our Hypothesis 2 (H2), we found that utility value of learning astronomy was positively related to using self-testing. However, expectancy of learning astronomy was negatively related to using drawings and using self-testing. All other connections between values, expectancy and strategy use were not significant.

To answer our second research question concerning learning-related factors and children's deep-learning strategy use, we found that metacognitive knowledge of deep-level LS was not related to deep-level strategy use (Hypothesis H3 rejected). In support to the Hypothesis

4 (H4), we found that self-reported use of drawings was positively related to both using drawings and using self-testing, whereas self-reported using of self-testing was positively related to actual using of self-testing (but not using drawings). Finally, we found some partial support for our Hypothesis 5 (H5), indicating that interest in effective learning and utility value of effective learning were positively related to using drawings. Other relations between values, expectancies and strategy use were not significant.

Discussion

The aim of this study was to examine which topic- and learning-related knowledge and motivational beliefs predict the use of specific deep-level LS during an independent learning situation. Elementary school students were provided a written text about light processes and seasonal changes, then asked to study these topics by either only reading the text (surface-level LS) or by additionally looking at drawings and answering prepared questions (deep-level LS). It is complex topic that can be more easily understood by using visuals (Galano et al., 2018; Mills et al., 2016) and answering questions (Agarwal et al., 2021). Among topic-related variables, we found that prior knowledge and utility value — but not interest in learning astronomy — were related to using deep-level LS. Among learning-related variables, we found that interest and utility value of effective learning — but not metacognitive knowledge of LS and expectancy in using deep-level LS — were related to using deep-level LS.

Astronomy-related knowledge and motivation as predictors of using drawings and self-testing during learning

We hypothesized (H1) that better topic-related knowledge would relate to better use of deep-level LS. Our results showed that better knowledge of seasonal changes was related to both making use of drawings and answering questions rather than simply reading and rereading. The topic of light processes and seasonal changes is a difficult scientific topic for elementary school students because daily experiences contradict scientific explanations, thereby bolstering misconceptions. Namely, young students who tend to use everyday, unscientific concepts (cf. Authors, 2003; Vygotsky, 1997) are guided by visible changes (e.g., snow during the winter months) and assume these visible changes can help explain temperature changes. In addition, it is well known from daily life that it is warmer close to a heat source (e.g., fireplace), which naturally leads many children to assume that the sun is closer to the earth in summer and further in winter. This misconception, sometimes called distance theory, is a widespread inaccurate explanation of seasonal changes both in schoolchildren and adults (Authors, 1998a, 2003, 2004; Lelliott & Rollnick, 2009; Trumper, 2006).

All participants in the current study had learned about light processes and seasonal changes at school before taking part in this study, but according to our findings, students' level of knowledge varied widely. While 39% of students gave scientifically correct answers, 30% of students either referred to visible changes (e.g., there is snow in the winter) or gave general factual information without referring to any reasons behind the change (e.g., Estonia is in the northern hemisphere). Additionally, 15% of answers included misconceptions, and several of these referred to the distance between the earth and the sun. When learning complex topics in which learners may have misconceptions, understanding is supported by conceptual, constructive, deep-level LS (Alexander et al., 2018; Brod, 2020; Chi & Wylie, 2014; Dinsmore & Hattan, 2020; Van Meter & Campbell, 2020).

In addition, it is possible that better topic-related knowledge indicates that students have been engaged in deep-level learning before and, thus, may tend to habitually use deep-level LS in specific learning situations. Correlations between astronomy knowledge, metacognitive knowledge of deep-level LS, and self-reported use of self-testing also refer to this possibility. However, as these correlations were low, the use of deep-level LS may not have been conscious or purposeful. Estonian science lessons and textbooks often rely on models and drawings. Textbooks also provide study questions at the end of each unit, and students are directed to refer to these questions when studying at home. This means that all participants had been exposed to drawings and questions at least to some extent previously. However, observational studies have shown that, although teachers use different cognitive strategies when teaching, they rarely explicitly talk about their value for supporting learning (e.g., Authors, 2023; Dignath & Büttner, 2018; van Loon et al., 2021). Many students need direct instruction to become aware of the advantages of some LS over others (Zepeda et al.,2015). The need for explicit teaching of LS in supporting students' metacognitive knowledge has been found in intervention studies (Dignath et al., 2008; Dignath & Büttner, 2008; Feeney, 2021). It is possible that many students are not explicitly aware of the advantages of using drawings and asking questions while learning and, thus, may not start to use them on their own. Instead, students are more likely to view these strategies only as tasks given by the teacher rather than strategies that support learning. Moreover, better prior knowledge may be related to higher reasoning skills (Salmi & Thuneberg, 2018; Stender et al., 2018), spatial ability (Wang & Tseng, 2019), and effortful, persistent learning behavior (e.g., Authors, 2018), all of which support using more complex, deep-level LS.

Our second hypothesis (H2) about the role of topic-related motivational beliefs was only partially confirmed. Empirical studies in older students have confirmed the positive role of subject-related task values and expectancies in deep learning and learning outcomes (e.g., Linnenbrink-Garcia et al., 2012; Vu et al., 2021). However, in our study, only utility value — a student's perceived relevance or usefulness of learning scientific concepts in their current or future plans — predicted the use of self-testing. We may speculate that, although students participated in the study voluntarily, the potential for future evaluation was still at the back of their minds, thus the students used self-testing as a way of preparing themselves for a future assignment.

Higher interest was not related to using deep-level LS. We hypothesized that higher interest would be related to more curiosity, which in turn may lead students to look at drawings and check their answers (for a discussion about the relationship between interest and curiosity, see Alexander & Grossnickle, 2016). The lack of such activities may be related to the way interest was assessed in this study. We asked about individual interest (see Renninger & Hidi, 2011) regarding solar and planetary knowledge, but the actual study topic was about light movements and temperature fluctuations throughout the seasons — not about planets. Student age should also be taken into account when explaining this finding. Namely, younger students interpret interest as enjoyment, which is typically accompanied by a positive mood, while older students interpret interest as being accompanied by increased attention, challenge seeking, and persistence in learning (Renninger & Hidi, 2011). Thus, emotion-based statements of interest may not affect real learning activities like choosing between more- or less-complex LS. Earlier studies investigating conceptual change in scientific domains have referred to the need to use person-oriented methods to describe subgroups of students with different motivational characteristics, including interest (Linnenbrink-Garcia et al., 2012; Sinatra & Mason, 2013; Weinstein et al., 2011).

Since earlier studies investigating conceptual change in scientific domains have emphasized the importance of self-efficacy (Linnenbrink-Garcia et al., 2012), we expected that expectancy in learning about the sun and planets would be positively related to choosing deep-level LS. However, expectancy had negative effect on choosing and using deep-level LS. We may argue that students who are self-confident and who think that learning about astronomical phenomena is easy for them, may use easily applicable surface strategies reading and re-reading. However, we should be cautious of this interpretation as direct bivariate correlations between expectancy of learning astronomy and using deep-level LS were insignificant. Earlier studies carried out in the expectancy-value paradigm that used self-report questionnaires indicated relations between expectancy, valuing, and use of LS in older students (Bandura, 1993; Diseth, 2011; Linnenbrink & Pintrich, 2003; Trigwell et al., 2013). Thus, expectancy may play a more minor role at younger age. Future studies are needed to explore the role of expectancies in learning in younger children. Studies have also shown that, compared to task values, students' expectancies more strongly predict achievement and academic performance (Perez et al., 2014; Rosenzweig et al., 2019). However, this was not examined in the current study.

Learning-related knowledge and motivational beliefs as predictors of using drawings and self-testing during learning

Surprisingly and contrary to our hypothesis (H3), metacognitive knowledge of deep-level LS as assessed via perceived effectiveness of deep-level LS was not related to choosing or using deep-level LS. According to bivariate correlations, metacognitive knowledge of LS was interrelated with self-reported use of deep-level LS (drawings and answering questions) when preparing for a comprehensive test for all motivational beliefs and topic-related knowledge. Thus, when taken together with other variables, the effect of metacognitive knowledge of LS on the use of deep-level LS was not visible. In contrast, as expected (H4), self-reported use of specific deep-level LS predicted the use of the same LS during learning. Moreover, self-reported use of drawings predicted answering questions but not rereading. A higher tendency to use deep-level LS may be a result of raising metacognitive knowledge of LS (Dignath et al., 2008; Dignath & Büttner, 2008; Feeney, 2021). Using deep-level LS tends to be more effective than surface-level LS, especially when learning complex topics and striving for conceptual understanding (cf. Alexander et al., 2018).

Applying deep-level LS assumes higher attention, persistence, and motivation than when using surface-level LS (Karabenick et al., 2021; Schleepen & Jonkman, 2012; Seufert, 2020). Our hypothesis (H5) concerning the effects of learning-related motivational beliefs on using deep-level LS was partially confirmed. While topic-related utility value had an effect on answering questions, students who showed higher utility value in effective learning made more use of drawings in addition to simply reading. Moreover, looking at drawings during reading was also related to higher interest in effective learning. Thus, both examined values had an effect on choosing and using drawings during learning, but not on reviewing learned knowledge by way of answering questions. Visuals are widely used in science classes (Galano et al., 2018; Mills et al., 2016), and even if teachers have not explicitly discussed how and why visuals support learning (cf. Dignath & Büttner, 2018; van Loon et al., 2021), students may have experienced it themselves via metacognitive experiences (cf. Efklides, 2014). In this regard, visuals support students but may cause students to encounter new comprehension challenges, especially in students with low knowledge and reading skills (McTigue & Flowers, 2011). These different experiences may impact a student's motivation to use drawings. So regardless of their experience, students are likely to use a given strategy when they see its value and efficacy (Karabenick et al., 2021). However, low motivation to use drawings may be related to the fact that drawings are considered too time-consuming and confusing (i.e., visuals are not explained, students are not taught how to use them, and some visuals can be difficult to understand).

Similar to topic-related expectancy, learning-related expectancy did not predict the use of deep-level LS. We should also emphasize that these LS were not difficult to use. Students did not have to create summaries or draw by themselves, which is a more difficult strategy but can also be more effective. We also do not know how students applied these strategies (cf. Leopold & Leutner, 2015). We monitored how many times students looked at drawings and how many times they checked their answers in response to researcher-raised questions, but we do not know how well they understood the drawings or if their own answers were correct or not.

Limitations, conclusion, and future directions

Some limitations of the study should be mentioned. First, this was a cross-sectional study that used correlations. Therefore, we cannot make causal inferences. As effects among variables may be reciprocal, further longitudinal studies are needed. Second, we used only one specific learning task: learning about a challenging scientific topic in which students are known to have various misconceptions. To generalize our findings, different tasks could be used. Third, the learning situation itself was unusual (i.e. independently studying about the complex topic on a computer). Although students knew that their knowledge would be tested after some time, they also knew that they would not be graded or given immediate feedback. Thus, students may not have tried as hard as they might in a real lesson or testing scenario. Fourth, motivational beliefs were assessed using only one item which could tap only a few facets of the constructs. We based this item on the expectancy-value model's motivational beliefs, but there are other motivational variables (e.g., achievement goals) that may play a role in using deep-level LS. Future studies should describe motivational constructs in more detail, and other measures should be used. Fifth, although we described specific learning situations and clearly distinguishable learning strategies, elementary school students may be in difficulties when using evaluation-scales and reporting which learning strategies they tend to use. Future studies should use other methods like interviewing or observations. Sixth, *Using drawings* was assessed via student looking at the drawing. However, we cannot be sure that each student deeply engaged in learning the information from the drawing (i.e., used it as a deep-level strategy). Also, we did not assessed how students comprehended drawing. Last, our dependent variables were treated as continues due to the ordinal alignment of their answer options. However, cautions should be acknowledged due to their small ranges consisting of only a few categories.

In summary, our study confirmed that it is not enough to examine students' knowledge and skills in using LS with general and hypothetical questions, but that it is of crucial importance to study students in real learning situations. We showed that both topic- and learning-related variables play a role in what LS students use in a specific learning situation. Moreover, topic- and learning-related knowledge and motivational beliefs may differently affect students' choice and application of LS. From a practical point of view, our study confirmed that students need to be taught both subject knowledge and explicit knowledge about LS and how to apply them. In addition to supporting topic-related motivation, teachers should support students' motivation to use deep-level LS by discussing and demonstrating the value of deep-level LS in specific learning situations. While prior studies have shown the effectiveness of interventions tapping topic-related utility value (Nagengast et al., 2017; Rosenzweig et al., 2020), our findings refer to the need to raise interest in and utility value of deep learning.

Further studies are needed to examine the learning process and outcomes; e.g., how students interpret drawings and answer questions as well as how students comprehend text and understand given topics. Moreover, as studies have shown that subgroups of students vary considerably in motivational beliefs and their impact on learning (e.g., Linnenbrink-Garcia et al., 2012), person-oriented analyses should be carried out to detect practical effects that might go unnoticed using variable-oriented methods.

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Table 1

Descriptive Statistics of All Study Variables

	N	*M*	*SD*	*Min*	*Max*	*Skewness*	*Kurtosis*
Astronomy-related knowledge	335	1.75	1.14	0	3	-.18	-1.45
Interest in learning astronomy	335	3.59	1.13	1	5	-.57	-.44
Utility value of learning astronomy	335	3.32	1.17	1	5	-.20	-.80
Expectancy of learning astronomy	335	3.44	.96	1	5	-.37	-.02
Metacognitive knowledge of deep-level learning strategies	335	4.06	.64	1	5	-.86	1.19
Self-reported use of drawings	335	.64	.48	0	1	-.58	-1.67
Self-reported use of self-testing	335	.48	.50	0	1	.07	-2.01
Interest in effective learning	335	3.70	.93	1	5	-.34	-.33
Utility value of effective learning	335	4.10	.97	1	5	-.89	.04
Expectancy of using deep-level LS	335	3.51	.94	1	5	-.41	-.12
Using drawings	335	2.13	1.08	0	3	-.80	-.84
Using self-testing	334	2.07	.90	1	3	-.14	-1.76

Table 2

Pearson Correlations of All Study Variables

		1	2	3	4	5	6	7	8	9	10	11
1	Astronomy-related knowledge											
2	Interest in learning astronomy	.035										
3	Utility value of learning astronomy	.014	.456**									
4	Expectancy of learning astronomy	-.023	.401**	.252**								
5	Metacognitive knowledge of deep-level learning strategies	.150**	.265**	.289**	.211**							
6	Self-reported use of drawings	.062	-.021	.083	.068	.336**						
7	Self-reported use of self-testing	.111*	-.028	-.055	.071	.260**	.292**					
8	Interest in effective learning	.034	.260**	.281**	.210**	.358**	.041	-.056				
9	Utility value of effective learning	.045	.122*	.255**	.144**	.370**	.008	-.015	.502**			
10	Expectancy of using deep-level LS	.102	.227**	.308**	.275**	.257**	.007	-.033	.434**	.450**		
11	Using drawings	.143**	.117*	.137*	-.004	.241**	.183**	.021	.250**	.257**	.139*	
12	Using self-testing	.167**	.052	.135*	-.002	.235**	.240**	.249**	.105	.053	.055	.208**

Note. * $p < .05$, ** $p < .01$

Table 3

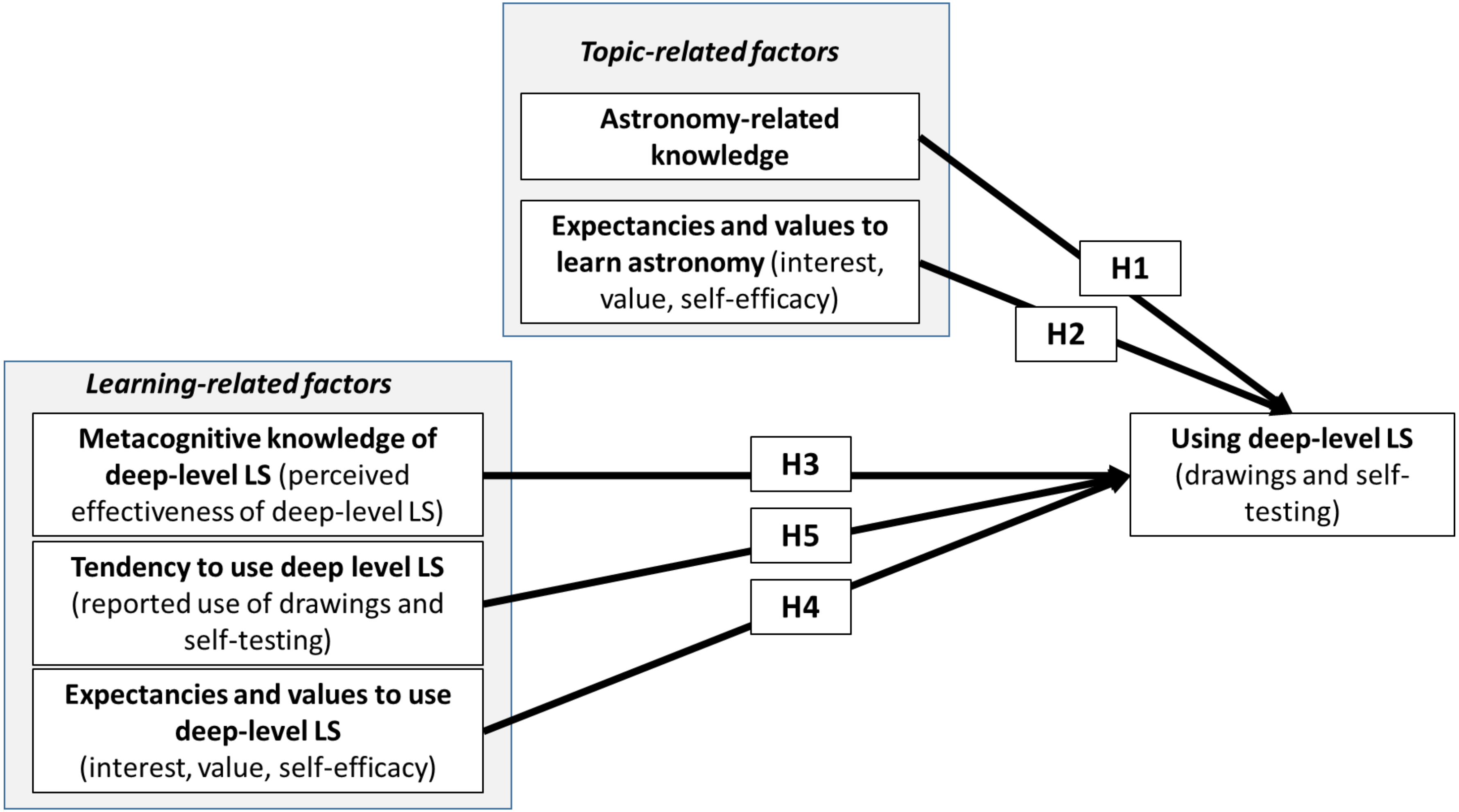
Multivariate Multiple Regression Predicting Using Drawings and Using Self-Testing

Variable	Using drawings (R^2 = .148)			Using self-testing (R^2 = .186)		
	β	*SE*	*p*	β	*SE*	*p*
Astronomy-related knowledge	.111	.047	**.017**	.139	.064	**.030**
Interest in learning astronomy	.084	.078	.281	-.003	.089	.971
Utility value of learning astronomy	.014	.019	.460	.136	.042	**.001**
Expectancy of learning astronomy	-.109	.055	**.048**	-.092	.033	**.005**
Metacognitive knowledge of deep-level learning strategies	.070	.057	.216	.098	.078	.213
Self-reported use of drawings	.165	.069	**.017**	.160	.060	**.008**
Self-reported use of self-testing	-.038	.023	.091	.214	.079	**.007**
Interest in effective learning	.133	.043	**.002**	.095	.134	.480
Utility value of effective learning	.168	.054	**.002**	-.045	.107	.673
Expectancy of using deep-level LS	-.019	.099	.844	-.005	.072	.950

Note. In **bold**—significant predictors at the $p < .05$ level

Figure 1

Theoretical Model



Note. LS = learning strategy.

Appendix A. Coding answers for astronomy-related prior knowledge

The answers for the question **“Write briefly why in Estonia it is colder in winter than in summer”** were coded in four broad categories.

Category 1: no answer, repetition of the information in the question, unrelated to the question answer.

Category 2: answers basing on visible observations (e.g., there is snow in the winter; the sun is lower in the sky during winter; there are clouds in the sky in the winter) or providing broad everyday information that does not properly explain the phenomenon (e.g., Estonia is in the Northern Hemisphere; we have northern climate; climate is different in the summer than during wintertime).

Category 3: explanations related to the movements of the Sun and the Earth, but including incorrect information. The majority of these included some form of distance theory that connected the changes in temperature to the distance between the Sun and Estonia (e.g., the Sun is closer to the Earth in the summer; the Sun is closer to Estonia in the summer; the axis of the Earth is tilted and, therefore, the Sun is closer to Estonia in the summer). Some answers were correct, but too general and missed some important information (e.g., the Earth revolves around the Sun and rotates around its axis; the axis is tilted, and the Earth is tilted).

Category 4: scientifically correct explanations that contained both critical parts of the explanation: 1) the Earth revolves around the Sun, and 2) the Earth's axis is tilted with respect to its orbital plane and/or the light’s inclination angle changes in relation to the surface of the Earth.

Appendix B. Scenarios and the described learning strategies for assessing metacognitive knowledge of deep-level learning strategies

Scenario	Choice of answers	Learning strategies
1. Students need to familiarize themselves with a new topic before a Science lesson. They have to read a chapter from the textbook as homework. Their knowledge of the subject is not very good. They use different strategies to learn the new topic.	Student A reads the textbook twice. Student B tests their knowledge by closing the textbook and answering study questions without looking at the text.	Rereading versus self-testing
2. Students need to prepare for a Maths lesson. Students solve the same number of problems in preparation for the test but use different strategies.	Student A solves example problems given by a teacher several times. Student B solves example problems given by a teacher and also several other problems.	Solving example problems versus solving example and novel problems

3. Students have to read three pages of text on how viruses spread. In the next lesson, students must be prepared to talk about this topic to classmates and the teacher. Both students study for the same length of time but use different strategies.	Student A reads through the text and then tries to make sense of what they have read. They think about what they already know about the topic and try to relate the new information to what is already available. Student B reads the text and marks important parts of the text.	Underlining important parts of the text versus integrating new knowledge with prior knowledge
4. Students need to prepare for a major test in History class. They choose to do a summative piece of work covering the topics studied in this subject. They use different strategies.	Student A systematizes what they have learned according to links and themes. They try to find common features and themes and categorize them in the summarized material. Student B starts summarizing the material from the beginning. They arrange the different topics in the order in which they have learned them.	Creating a linear summary according to the text versus systematizing the material before creating a summary

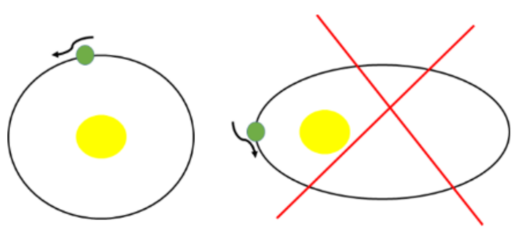
5. Students have to read and understand a scientific text about how rainbows are formed. Both students study for the same length of time but use different strategies.	Student A thoroughly reads the text twice. Student B reads the text, then looks at the pictures and drawings that clarify the text.	Rereading versus reading and making use of drawings
6. Students need to prepare for a Science lesson. They read a chapter in the textbook about plants and have to learn all the parts of a plant. Both students study for the same length of time but use different strategies.	Student A reads the text once, makes a drawing, and writes the parts of the plant on the drawing. Student B thoroughly reads the text twice.	Rereading versus composing drawings

Appendix C. Test

The introductory text reads as follows: “This text explains how heat sources heat different surfaces and how the seasons change. You can also look at the drawings to get a better understanding. Learn it! Next week you will have to answer questions about the text”. The text consisted of three parts that were accompanied with drawings. Each part was presented in one slide. If a student decided to look at the drawing, the text and the drawing were presented together.

I Mart got a torch for his birthday present. He tested how far the torch would point and tested whether reading a book with it was better. He discovered that the torch was a heat source - it warmed up Mart's arm. The arm was warmer when the torch was closer and colder when Mart moved the torch further away. He thought it was probably the same as with the oven - warmer near the oven and colder away from it. He further discovered that the torch heats up more when the torch is pointed directly at his arm and less when the torch is tilted.

II He told his father about his discovery. Father explained why the arm heated differently. Namely, if you point the torch directly at your arm, all the light and heat will go there. If you point the torch at an angle, part of the light will bypass your arm and only a part of the light will reach it. Father also made a drawing. He said that the same explanation is used to explain how the seasons change in Estonia. Mart knew that the Earth revolved around the Sun and that the Sun gave light and heat. Just like a torch. But he had thought that Estonia is further from the Sun during winter time and closer in the summer.



III Father explained: the distance of the Earth from the Sun hardly changes, but during winter time the Sun's rays strike the ground at a shallower angle and the ground does not receive as much heat as in the summer. The Earth orbits around the Sun and rotates on its axis. The Earth's imaginary axis of rotation is tilted with respect to the orbit. So the different hemispheres of the Earth receive different amounts of sunlight. Estonia is located in the Northern Hemisphere. When the Northern Hemisphere is tilted towards the Sun, it is summer in Estonia. When the Southern Hemisphere faces the Sun, it is summer there and winter in Estonia. If the Earth's rotation axis were vertical (perpendicular to the orbital plane), the seasons would not alternate. The movement of light and heat fascinated Mart and he wanted to learn more about it. Mart's father advised him to study more physics.