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Why most definitions of modeling competence in science education fall short: Analyzing the relevance of volition for modeling

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Abstract

Definitions of modeling competence in science education do not yet include noncognitive factors. However, noncognitive factors are central to competence and might thus substantially improve our understanding of modeling competence. In this article, we analyze volition during preservice science teachers' engagement with a black-box modeling task and its relation to established aspects of modeling competence: metamodeling knowledge, modeling process, and modeling product. A cluster analysis of the occurrence of volition categories resulted in three clusters of volitional behavior. The clusters describe three different volition types: one action-oriented type applying a self-regulative strategy and two state-oriented types applying self-controlling strategies. Correlation analyses between clusters, volition categories and modeling process variables indicate benefits of the self-regulative strategy.

KEYWORDS

modeling competence, scientific inquiry, self-regulation, teacher education, volition

1 | INTRODUCTION

Developing and using models is described as a core practice in science education (Next Generation Science Standards [NGSS], 2013), and many countries address modeling competence in science education curricula (Australian Curriculum, Assessment and Reporting Authority [ACARA], 2015; British Columbia Ministry of Education [BCMOE], 2019; Kultusministerkonferenz [KMK], 2020; Victorian Curriculum and Assessment Authority [VCAA], 2016). However, the central role of modeling might be overlooked in the science classroom as teachers and preservice teachers lack the necessary competencies to use modeling in scientific reasoning and inquiry in class (Justi & Gilbert, 2002; Krell & Krüger, 2016; Torres & Vasconcelos, 2015). To make use of the full potential of modeling in the science classroom, modeling competence must take center stage in teachers' professional development (Günther et al., 2019; Justi & van Driel, 2006; Nielsen & Nielsen, 2021). Following definitions of the term competence (e.g., Weinert, 2001), one can define modeling competence as “the ability to gain insightful knowledge with models, to be able to judge models with regard to their purpose, and to reflect on the process of gaining knowledge through models and modeling” (Upmeier zu Belzen et al., 2019, p.12). However, despite a wide consensus regarding the importance of motivation, volition, and affect for any competence (Weinert, 2001), research in science education has mainly focused on the cognitive aspects of modeling competence (Chiu & Lin, 2019). As modeling can be frustrating (Thomas & Hart, 2010) because of its nonlinear approach (Morrision & Morgan, 1990) and high cognitive demands (Hogan & Thomas, 2001), the modeler's volition will be critical for engaging in a modeling process. Thus, considering volition might be crucial in efforts toward a comprehensive understanding of modeling competence. This study analyzes the role of volition in preservice science teachers' modeling performance, aiming to identify the relevance of volition for preservice science teachers' modeling competence.

2 | THEORETICAL BACKGROUND

The following introduces central concepts of this study: modeling, competence, modeling competence, and volition. We argue that contemporary concepts of modeling competence in science education solely focus on cognitive aspects and, therefore, fail to encompass key dispositions for modeling performance.

2.1 | Modeling

Modeling is a powerful epistemic tool for investigating, representing, explaining, and predicting phenomena (Giere, 1997; Passmore et al., 2014). This tool targets the phenomena in a cyclic process of developing and using models (Giere, 1997) to reduce the inherent complexity (Godfrey-Smith, 2006; Knuuttila, 2011). Consequently, scientific models can be defined as epistemic tools for sense-making (Knuuttila, 2011). Modeling is described as a core scientific method (Passmore et al., 2014), framing other scientific methods, for example, using an experiment to validate a model (Giere, 1999; Lehrer & Schauble, 2015). From this perspective, modeling becomes the paradigm of “model-based science” (Godfrey-Smith, 2006) itself (Kuhn, 1970).

In practice, a scientific question or problem guides the process of modeling (Knuuttila, 2011). Knuuttila (2011) describes modeling as externalizing thinking using means of representation for construction and manipulation of the target. These properties allow using the model to predict or formulate a hypothesis. Comparing the model-based prediction to the data collected in the “real world” (Giere, 1997) allows evaluating whether the model fits or needs revision (Giere, 1997). The scientist iterates this cyclic process until the fit is satisfactory. However, as all models are approximations in some way, a perfect fit will never exist between model and reality (Levins, 1966; Odenbaugh, 2005).

2.2 | Competence

According to Weinert's (2001) pioneering definition, competencies are cognitive skills and abilities and the associated motivation, volition, social skills, and willingness to solve specific problems in variable but related situations. Without challenging the relevance of its original complexity, this definition has often been reduced to its cognitive aspects to allow for defining specific competence models and enable a more pragmatic assessment (e.g., Klieme et al., 2007). Rychen and Salganik (2003) highlight the importance of the mobilization of psychosocial prerequisites to meet complex demands in a particular context. They thus connect back to Weinert's definition in its complexity. Blömeke et al. (2015) describe competence as a continuum: the competent person translates cognitive and affect-motivational dispositions into situation-specific skills, that lead to the observable performance.

Despite the reduction of competence to its cognitive aspects for pragmatic reasons in empirical studies (e.g., Baumert & Kunter, 2013; Kauertz et al., 2012; Waddington et al., 2007), the relevance of both cognitive and noncognitive aspects for any competence remains uncontested and even central to the theoretical discussion. In conclusion, we define competence as a complex set of cognitive and noncognitive dispositions needed to solve tasks in specific contexts. Following this definition, cognitive dispositions are not sufficient for successful performance. Neither are assessments of cognitive dispositions sufficient to assess a person's competencies.

2.3 | Modeling competence in science education

Modeling competence is defined as the skills needed to initiate an epistemic process while constructing models, to draw evidence from models, to judge models based on their purpose, and to reflect the modeling process (Upmeier zu Belzen et al., 2019). Most conceptions divide modeling competence in the metamodeling knowledge and modeling process (Nicolaou & Constantinou, 2014; Nielsen & Nielsen, 2021).

Metamodeling knowledge is "a type of nature of science understanding," which includes knowledge about "how models are used, why they are used, and what their strengths and limitations are, in order to appreciate how science works and the dynamic nature of knowledge that science produces" (Schwarz, Reiser, et al., 2009). The modeling process defines the actual modeling activity or practices aiming at developing a specific modeling product (e.g., Schwarz, Reiser, et al., 2009). Under this conception, metamodeling knowledge should guide the modeling process (Krüger et al., 2018; Nielsen & Nielsen, 2021; Schwarz, Reiser, et al., 2009), of which the modeling product indicates the quality (Karnaou et al., 2018; Schwarz, Reiser, et al., 2009). Hence, metamodeling knowledge, process, and product constitute the three core dimensions of modeling competence in science education (see Table 1 for a summary of prominent frameworks).

Göhner, Bielik, and Krell (2022) developed scales to measure the quality of a modeling process in terms of its complexity and homogeneity, that is, independent of the modeling product. The variety of modeling activities indicate the complexity of the modeling process and the pattern of transitions between the activities the homogeneity. This approach allows to assess the two dimensions of modeling process and modeling product separately. In line with theoretical frameworks (Table 1), we can thus empirically separate knowledge, process, and product as core modeling competence dimensions.

Studies indicate teachers' and preservice science teachers' limited modeling competence: The metamodeling knowledge of many teachers is reduced to understanding models as representations (Justi & Gilbert, 2002; Krell & Krüger, 2016). Such limited understanding hinders a model-based engagement in scientific reasoning and inquiry in the classroom (Khan, 2011; Schwarz & Gwekwerere, 2007). Thus, it seems apparent that preservice science teachers' modeling practice lacks complexity and skill (Dauer et al., 2021; Göhner & Krell, 2022) and their modeling products leave room for improvement (Ammoneit et al., 2023; Göhner et al., 2022; Mulder et al., 2011). A comprehensive understanding of modeling competence can help systematically improve teachers' modeling competence (Chiu & Lin, 2019). However, based on the concepts of competence, the various concepts of modeling competence in science education remain too narrow and focus on cognitive dispositions and observable processes or products (Table 1). Thus, considering the noncognitive factors might contribute to a better understanding of modeling competence in science education.

TABLE 1 Summary of prominent frameworks for modeling competence in science education along the three dimensions of knowledge, practice, and product.

	Knowledge	Practice	Product
Schwarz, Reiser, et al. (2009)	Models change to capture improved understanding built on new findings Models are generative tools for predicting and explaining	Constructing models Using models to explain and predict Evaluating modelsRevising models	
Nicolaou and Constantinou (2014)	Metamodeling knowledge (purpose of models, use of models) metacognitive knowledge of the modeling process	Create use compare revise validate	
Chiu and Lin (2019)	Models and modeling knowledge (ontology, epistemology, methodology) metacognitive knowledge of models and modeling (planning, monitoring, executing, evaluating)	Development elaboration application reconstruction	Internal representations external representations
Nielsen and Nielsen (2021)	Nature and purpose of models value and utilization of models in science, society, and education	Using models for: (a) describing, explaining, and communication (b) prediction designing models evaluating models revising models comparing models selecting models	
Göhner et al. (2022)	Nature of models multiple models purpose of models testing models changing models	Modeling activities: exploration, development, prediction	Quality of modeling product

2.4 | Volition

A clarification of the targeted noncognitive aspects becomes necessary to allow consideration of noncognitive aspects in modeling competence. We find the following noncognitive aspects within the definitions of competence: motivation, volition, social skills (Weinert, 2001), noncognitive psychosocial prerequisites (Rychen & Salganik, 2003), and affect-motivation (Blömeke et al., 2015). We focus this study on individual preservice science teachers' modeling and thus do not consider social skills (Weinert, 2001) or psychosocial prerequisites (Rychen & Salganik, 2003). The affect-motivation (Blömeke et al., 2015) can be differentiated into motivation and volition (Weinert, 2001). Motivation describes how needs, goals, and motives contribute to initiating action (Baumann et al., 2018). Volition describes how people, once committed to a course can convert their intentions and goals into action (Baumann et al., 2018). Concerning modeling, the motivational aspect might be connected to the diffidence some students encounter while modeling for the first time (Han & Gutierez, 2021). However, many novices engage actively in modeling (e.g., Ammoneit et al., 2023; Gray et al., 2022). Nonetheless, students (Pierson et al., 2017) and preservice teachers (Göhner et al., 2022; Göhner & Krell, 2022) generally do not reach high levels of modeling competence. The lacking proficiency is so far explained with lacking possibility to gain modeling experience (Böschl et al., 2023; Wade-Jaimes et al., 2018). However, new inquiry methods, inquiry-based learning, and modeling are often experienced as challenging (Cheng & Lin, 2015; Crawford & Cullin, 2004; Schwarz, 2009), highlighting that an opportunity for engaging in modeling practice is not enough, but that successful modeling also requires sufficient affect-motivational skills. Considering volitional factors in learning and research settings can lead to a more comprehensive understanding of modeling competence and sophisticated instruction. While both aspects of affect-motivation appear relevant to modeling competence, all participants volunteered to take part in this study, so their motivation will be biased. Therefore, this study will focus on volition.

Kuhl describes volition as a system (e.g., Kuhl, 2001; Kuhl & Fuhrmann, 1998) (see Figure 1). In this system, the interplay of goal orientation and self-assertion is central, involving both conscious and subconscious processes. Goal orientation is focused on the external world; the goal arises from the orientation in the world surrounding the individual (Kuhl & Fuhrmann, 1998). In the context of modeling, the goal could be to construct a model that will be rewarded with recognition or a good grade needed to pursuit greater goals. Self-assertion is the agent for the individual. It is recognizing emotional needs and the individual's identity (Kuhl & Fuhrmann, 1998). In the context of modeling, this could be the epistemological interest in developing models, or fun in tinkering, but also the identification as a modern scientist and the recognition of needs outside the goal that need satisfaction. Obtaining self-assertion enhances easy access to subconscious resources (Baumann et al., 2018; Kuhl, 2001). Contrary, giving up self-assertion enhances introjection. The individual becomes alienated from the goal, denying access to subconscious resources. This hinders an enduring and creative work process (Kuhl, 2001).

Self-regulation is the volitional process that is enhanced by self-assertion (Kuhl, 2001). The self-regulated individual feels self-efficient and is self-determined; these attributes enable decisiveness and result in automatic goal-orientation. Self-regulated individuals meet challenges with emotional management, including self-motivation and self-soothing (Fröhlich & Kuhl, 2003). Self-inhibition counteracts self-regulation (Kuhl, 2001): The individual alienates from the goal, resulting in brooding, perceptual rigidity, and compulsive preservation (Fröhlich & Kuhl, 2003).

Low self-assertion, lack of self-regulation, or unexpected challenges require self-control to maintain goal orientation, prioritizing outer goals over emotions (Kazén & Kuhl, 2022; Kuhl, 2001). The self-controlled individual exercises self-discipline, controlling impulses while pursuing the goal actively. Self-control encompasses the ability to plan and manage failure. Emotions are directed to anxious motivation imaging negative consequences of failure (Fröhlich & Kuhl, 2003). This introjection can lead to volitional inhibition if reaching the goal remains difficult even with exercising self-control (Baumeister et al., 1998). Volitional inhibition counteracts self-control. The individual has a reduced self-efficacy and acts only on foreign determination. A lack of energy, low concentration, and listlessness hinder a self-determined process (Fröhlich & Kuhl, 2003). The individual gives up self-control, because it feels unfit for reaching the goal it is not identifying with (Kuhl, 2001). It works superficial and resistant.

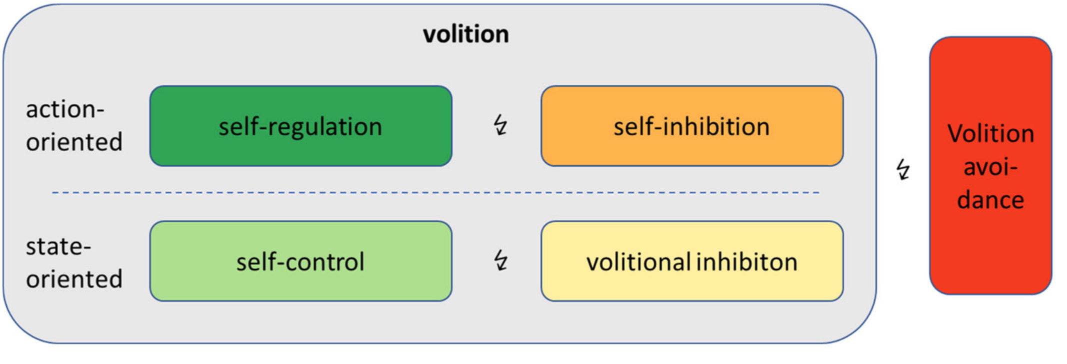

FIGURE 1 Model of volition after theory by Kuhl (2001). The action-oriented type includes self-regulating own behavior, while the state-oriented type is self-controlling. Self-inhibition counteracts self-regulation and volitional inhibition counteracts self-control. Volition avoidance counteracts volition altogether.

Volitional inhibition can result in volition avoidance, which describes the general avoidance of self-managing processes (Kuhl, 2001; Kuhl & Fuhrmann, 1998). Volition avoidance is characterized by effort avoidance, resignation, and defiance (Fröhlich & Kuhl, 2003). Perceived difficulties and requirements are deliberately not met (Kuhl, 2001). The individual does not want to reach the goal.

Empirical studies found two volitional orientations: action-orientation and state-orientation (Kazén & Kuhl, 2022; Koole et al., 2012). An action-oriented person's dominant strategy involves self-regulation. A state-oriented person's dominant strategy is self-control. Under nondemanding conditions, both types perform equally well (Jostmann & Gieselmann, 2014), but in complex tasks, the action-oriented type outperforms the state-oriented type (Jostmann & Gieselmann, 2014; Kazén & Kuhl, 2022). Modeling poses high cognitive demands (Hogan & Thomas, 2001). Thus, we expect these volitional strategies to explain individuals' modeling performance and expect volition to constitute an important part of modeling competence.

2.5 | Goal and research questions

This study aims to investigate the relevance of volition (including categories of self-regulation, self-inhibition, self-control, volitional inhibition, and volition avoidance) in preservice science teachers' modeling competence. Specifically, we address the following research questions (RQ):

RQ1: *How does volition occur in preservice science teachers' modeling processes?*

RQ2: *How does volition relate to metamodeling knowledge, modeling process, and modeling product?*

Based on prior studies, we expect to find distinct patterns of the volition categories, indicating an action-oriented and a state-oriented type (Kazén & Kuhl, 2022; Koole et al., 2012). As modeling is challenging, we expect the action-oriented type to engage in a more complex modeling process (Jostmann & Gieselmann, 2014; Kazén & Kuhl, 2022), resulting in a higher-quality modeling product (Göhner et al., 2022). Generally, self-regulation should positively relate to the complexity and homogeneity of preservice science teachers' modeling processes, and a higher quality product, as highly developed self-regulation generally allows for better academic performance in science (Schraw et al., 2006; Schunk, 1996; Zheng et al., 2020). Because self-regulation enhances a comprehensive engagement with a complex task (Baumeister et al., 2007), we also expect it to incubate the use of metamodeling knowledge.

3 | METHODS

The data for this study partly comes from existing published studies (Göhner et al., 2022; Göhner & Krell, 2022; Nordheimer, 2019). We analyze the data secondarily in this study to investigate the relevance of volition in preservice science teachers' modeling competence.

3.1 | Sample

The sample consisted of preservice science teachers enrolled in the teacher education program (bachelor or master) in one of two participating German universities. Preservice science teachers in Germany usually study two subjects in a six-semester bachelor's program, followed by a four-semester master's program. The grounding studies used a theoretical sampling strategy, heterogeneous sampling (Patton, 1990) to increase the likelihood of observing various modeling processes. Established pen-and-paper instruments measured the screening variables scientific reasoning (Krüger et al., 2020) and general cognitive abilities (Liepmann et al., 2007). Fifty-seven preservice science teachers with extreme scores (one-half standard deviation higher or lower than the mean scores of the respective norm sample) in both assessments qualified to participate in the study. Thirty-six preservice science teachers participated, aged between 17 and 39, with an average age of 24. All of them studied biology; twenty-three participants in the bachelor's program, and 13 in the master's program. Eight preservice science teachers studied another scientific subject (e.g., chemistry or physics).

Participation in the study was not mandatory for any university courses or obligatory parts of the curriculum; participation was voluntary and each participant gave informed consent. Researchers and participants had no formal relationships with one another.

3.2 | Context—Think aloud during black box modeling task

The grounding study applied a water black box modeling task. The black box approach is established in science education research to study processes of scientific thinking and modeling (Krell & Hergert, 2019). It presents an artificial object without direct access to the inner structure to the participants. Filling the black box with water (input) and measuring the outputs of water are the only means to explore the water black box. This setting allows to test hypotheses about the object easily, allowing the participants to focus on modeling the inner structure without technical challenges (see Krell, Walzer, Hergert, et al., 2019, for a detailed description of the black box). Asking the participants to concurrently think aloud (Leighton & Gierl, 2007) gave additional insights into the participants' reasoning and volition processes. The participants developed their model by drawing on a chalkboard without time constraints. They received several vessels, measuring cylinders, and a water reservoir to solve this task (for more detail on the setting, see Göhner et al., 2022).

The black box approach does not constitute a modeling environment situated authentically within a research field. This is beneficial for studying the connection between the modeling process and volition; the black box approach confronts all participants with a challenging modeling task independent of their prior knowledge that might bias volitional processes making the task easier for knowledgeable participants.

3.3 | Data collection and analysis

The behavior and verbalizations of the participants engaging in the black box modeling task were videotaped. The length of the participants' modeling processes varied between 8 min to almost 2 h (mean length: 1 h 9 min). The verbalizations were transcribed verbatim, including selected behavioral aspects (e.g., making an input or observing an output). Göhner et al. (2022) analyzed these transcripts qualitatively in MAXQDA to identify single modeling activities and expressions of metamodeling knowledge. Nordheimer (2019) analyzed the same transcripts for volition. In these grounding works, all qualitative data analyses followed the methodological frame of qualitative content analysis. Category systems guided the analysis; different persons coded the transcripts, finding consensus coding after discussion, and calculating Cohen's Kappa (κ) as a measure of intrarater- and interrater-agreement (Schreier, 2012). We combine and reanalyze the data to address our research questions. The following provides an overview of the included variables and conducted procedures.

3.3.1 | Volition

The assessment of volition is guided by Fröhlich and Kuhl's volition survey (2003) consisting of the five main concepts and subcategories in the conception of volition: Self-regulation, self-inhibitions, self-control, volitional inhibition, and volition avoidance (see Supporting Information: Appendix 1 for subcategories). Nordheimer (2019) developed a corresponding coding framework by adapting the survey to the material. She reduced the subcategories to the occurrence in the participants' statements, combined nondiscriminate ones, and selected anchor examples. Two research then assigned the participants' statements during the black box modeling task to the subcategories, consisting of a few connected sentences, with a satisfying intercoder reliability (Nordheimer, 2019). One of the the subcategories, self-soothing, was only coded for three statements all belonging to the same participant. We included this subcategory in self-motivation, as it was not discriminate. Both subcategories belong to self-regulation. Table 2 displays all included subcategories, including a definition and example.

We used the proportion of statements in each (sub-) category of the total number of volitional statements to reduce the influence of sequence length and tendency to express volition to address RQ1 (indicators for self-regulation in preservice science teachers' modeling processes).

3.3.2 | Cluster analysis

The k-means and PAM algorithm facilitated by the statistic software R (R Core Team, 2020) clustered the proportion of each volition main category to identify types of volition in modeling activity. The Hopkins Statistic of 0.933 indicated a pattern in the data structure suitable for cluster analysis (Hopkins & Skellam, 1954). The functions *pamk* and *kmeansruns* from the R-Package *fpc* (Hennig, 2020) determined the appropriate number of clusters both estimate the number of clusters by optimum average silhouette width and Calinski–Harabasz index (Calinski & Harabasz, 1974).

3.3.3 | Metamodeling knowledge, modeling process, and model score

We reanalyzed data from Göhner et al. (2022) to address RQ2. They assessed the participants' metamodeling knowledge based on the framework by Upmeier zu Belzen et al. (2019). Statements related to the five aspects nature of models, multiple models, purpose of models, testing models, and changing models of metamodeling knowledge, verbalized by the participants throughout their modeling process, were identified and coded accordingly (for detail, see Göhner et al., 2022).

The modeling process was analyzed by Göhner et al. (2022), who coded the modeling activities the participants engaged in. The participants conducted between 6 and 18 (mean: 12) different modeling activities in their modeling processes. Göhner et al. (2022) assigned the activities to the categories of exploration, development, and prediction (see Supporting Information: Appendix 2 for subcategories). The variables exploration, development, and prediction give the proportion of the respective category in the number of total activities. The category pattern allows calculating the modeling process' complexity and homogeneity (Göhner & Krell, 2022). Complexity determined using the graph metric known as "communities," which involves counting all subgraphs within each state transition graph (Porter et al., 2009). The basic communities score was normalized by subtracting the communities score of each participant from the maximum communities score achieved in this study. Thus, the complexity is higher the more different activities are included in the modeling process. The centrality of every state transition graph was determined to estimate homogeneity. The centrality score was reciprocally transformed, as centrality describes the dependence of a graph on a single knot (Newman, 2018). The homogeneity is high if the transition between the modeling activities distribute equally (for details, see Göhner and Krell, 2022). We include the following variables in our analysis: number of activities, complexity, homogeneity, exploration, development, and prediction.

The quality of the modeling product resulting from the modeling process was scored on a range from 0 to 3 (for detail, see Göhner et al., 2022). We included the model score to measure the outcome of the process. For overview, see Table 3.

TABLE 2 Framework for assessing volition.

Category	Subcategory	Definition	Example
Self-regulation	Decisiveness	The participants dare to make critical decisions.	"Am I going to delete the rest now? I don't know. But I think I'll delete the rest now. That just confuses me anyway." (wipes the blackboard) (Angelina)
	Self-motivation	The participants show positive emotions to keep going.	"[…] well I put in 400 and 600 came out. […] So, this time more came out than I put in. Um. That's kind of humorous." (James)
	Self-determination	The participants formulate own goals and interests instead of focusing on external demands only.	"Since we are into models, it would also be interesting for me to think about what that might be a model for. […] Um, but maybe there is one correspondence in nature which I can't think of right now." (James)
	Self-efficiency	Participants show believe that their own skills are sufficient to solve the task.	"That's how I think the whole thing should look roughly […] so I don't know what else I should do to get the whole thing [the mechanism of the BB] more precisely." (Raphael)
Self-inhibition	Brooding	Participants are blocked by thought spiraling with negative emotions.	"Sorry, I don't really know what I'm thinking right now. I have the feeling I am blocked right now." (Angelina) "Ok, I have to think about it, it's really confusing. Everything here annoys me. It's really annoying." (Frida)
	Compulsive preservation	Participants show difficulties to switch between tasks	T: "Are you remembering to think out loud?" […] P: "Yeah, okay. I forget that because I can't, so some things are just difficult to think out loud." (Frida)
Self-control	Anxious motivation	Participants associate negative feelings or consequences with failure.	"What if I get no result at all?" (Lauren) "I hope this is actually not a student experiment for the 5th grade or something and I'm gritting my teeth." (Angelina)
	Goal-oriented attention	Participants concentrate on processing the task.	"Okay, focus. 400 milliliters. If I put in 400 milliliters and there's 400 in the black box […]" (Cynthia)
	Impulse control	Participants actively suppress distractions that do not belong to the task but impulsively gain their attention.	"It's probably not so good that I spilled things like that, but ok." (Lauren) "Then 400 run out again. […] There are still mosquitoes. It bit, that gives a mosquito bite. There are about 800 in it. 400 don't run out 600." (Iris)
	Failure management	Participants resume the task productively after miss.	"Or did I make a mistake writing it down? I'll make another table, go through it again completely and write it down again in a clearer way, not with the arrows." (Iris)

(Continues)

TABLE 2 (Continued)

Category	Subcategory	Definition	Example
	Ability to plan	Participants structure the task.	"I'm trying to be at least somewhat systematic [...]. So that means I make a table. Enter the volume in the column, how much I put in, and then ultimately see the effect of how much water comes out, and then note both each time. In order to be able to deduce what this model could be like." (Carlo)
	Pursuit of goal	Participants direct their activities toward the immediate aim of the task (drawing the inside of the box).	"Maybe I shouldn't dwell on the theory, but think about what it looks like in there [in the BB]." (Iris)
Volitional inhibition	Foreign determination	Participants only work upon foreign activation.	T: "Ok, can you imagine how it could work?" P: "Well, I can only guess that there would definitely have to be several vessels [...]." (Carlo)
	Low self-efficiency	Participants doubt their skills will suffice to solve the task.	"[...] I'm not an engineer or a technician either [...] I just lack a bit of background knowledge or a few ideas [...] because I don't usually deal with that either." (James)
	Low concentration	Participants are being distracted.	P: "Shit, I spilled something. I need." T: "Don't you want to clean it up afterwards?" P: "Yes." (Frida)
	Listlessness	Participants show a lack in energy to proceed.	"Ok, I'm kind of tired of it." (Frida) "I'm done." (Angelina)
Volition avoidance	Effort avoidance	Participants actively avoid effort.	"I would finish it with that, because otherwise I would really ruin myself. T: So, this is your final model? P: This is my final model actually." (Boris)
	Resignation	Participants are not willing to resume after a miss.	"Oh, that's enough for me now. I can't figure it out, I don't see a pattern in there." (Carlo) "I think the point will soon be reached where I say I can't think of anything else. It bothers me because I can spend hours on such puzzles." (Iris)
	Defiance	Participants reject meeting basic requirements of the task (try to draw the inside of the box).	T: You don't want to draw anything? P: "No." T: "Ok." P: "I'm not that enthusiastic about drawing." (Carlo)

3.3.4 | Relationships between the modeling performance and volition

We calculated Spearman's rank correlations to analyze the relationship between all z-standardized variables of the modeling performance (metamodeling knowledge, exploration, development, prediction, complexity, homogeneity, and the model score) and for each category and the subcategories of self-regulative behavior. Furthermore, we applied the nonparametric Mann–Whitney U test due to the relatively small sample size to identify possible group differences. We address RQ 2 using these analyses.

TABLE 3 Summary of variables and scales describing metamodeling knowledge, modeling process, and modeling product.

	Data	Scale	Framework
Metamodeling knowledge	Transcripts	Average of scores in: nature of models, multiple models, purpose of models, testing models, changing models on a scale with Levels 0–3	Upmeier zu Belzen et al. (2019)
Modeling activities	Transcripts	Exploration, development, predi ction	Krell, Walzer, Hergert, et al. (2019)
Complexity	Modeling activities	Inverted communities, scale from 0 to 14	Göhner and Krell (2022)
Homogeneity	Modeling activities	Reciprocal centrality of graphs, scale from 0 to 2.5	Göhner and Krell (2022)
Model score	Modeling products	Scale with Levels 0–3	Göhner et al. (2022)

3.3.5 | Analysis of sample cases

We provide three sample cases for in-depth insights into the potential nature and direction of the relationships between preservice science teachers' modeling process and self-regulative behavior. Code lines illustrate the modeling processes of the selected cases showing the sequential order of the individual modeling activities and their self-regulative behavior. We chose three distinct cases to illustrate the range of volitional processes and highlight challenges for the design of modeling settings for research or learning.

4 | FINDINGS

4.1 | Volition in preservice science teachers' modeling processes (RQ1)

4.1.1 | Overview of volition categories

The number of volitional statements the participants made ranged between 6 and 54; the median was 22. The volition categories differed in their proportions (see Figure 2); self-regulation, self-control, and self-inhibition with higher scores and variances than self-inhibition and volition avoidance. Self-control had the highest median (0.32), indicating that about one-third of all volitional statements have a self-controlling nature. We clustered the results to gain more insight in interindividual differences.

4.1.2 | Volition patterns in preservice science teachers' modeling processes

Overall, the cluster analysis produces stable results: both algorithms give near identical clusters, similar in size and fit (see Figure 3). The average silhouette width is 0.37 and, thus, acceptable. No person was mismatched

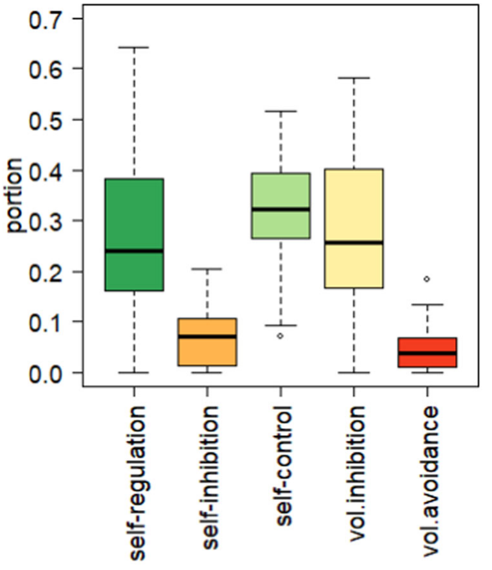

FIGURE 2 Proportion of volitional categories in participants' statements.

(silhouette < 0). From here, we refer to the numbering of the k-means algorithm (see Figure 3). Cluster 1 is the smallest (n = 10). Its average silhouette width is 0.45. Cluster 2 is the biggest (n = 15). Its average silhouette width is 0.3. Cluster 3 includes 11 participants. Its average silhouette width is 0.38.

Looking at each cluster in detail, different volition patterns become visible (see Figure 4). A Mann–Whitney U test also indicates a significant difference in self-regulation, self-control, and volitional inhibition between clusters (see Supporting Information: Appendix 3 for all values). Participants in Cluster 1 show the highest proportion in volitional inhibition ($f = 1$, both cases), in which all clusters differ significantly (p values < 0.01, $f = 0.88$, cluster 2~3). Participants in Cluster 2 show a significantly higher proportion of self-control than people from clusters 2 and 3 (p values < 0.01, $f = 1$ in both cases). Participants in Cluster 3 occupy significantly more often with self-regulation than individuals in Clusters 1 and 2 (p values < 0.01, $f = 1$, both cases). No significant differences exist between the clusters regarding self-inhibition and volition avoidance.

4.2 | Relation between volition and the competence dimensions metamodeling knowledge, modeling process, and modeling product (RQ 2)

4.2.1 | Overview of metamodeling knowledge, modeling process, and model score

First, we provide an overview of the assessed metamodeling knowledge, modeling process, and the model score (see Figure 5). The median of the articulated metamodeling knowledge was at level 2 on a scale ranging from 0 to 3. Regarding the activities, exploration dominated 2/3 of the modeling process, development had a median of 0.2, and prediction 0. The median for complexity was 5 on a scale ranging from 0 to 13. The homogeneity was evenly spread with a median of 1.5 and a third quantile from 0.75 to 2.5. The median of the model score was 1, with only few participants reaching the highest level (3).

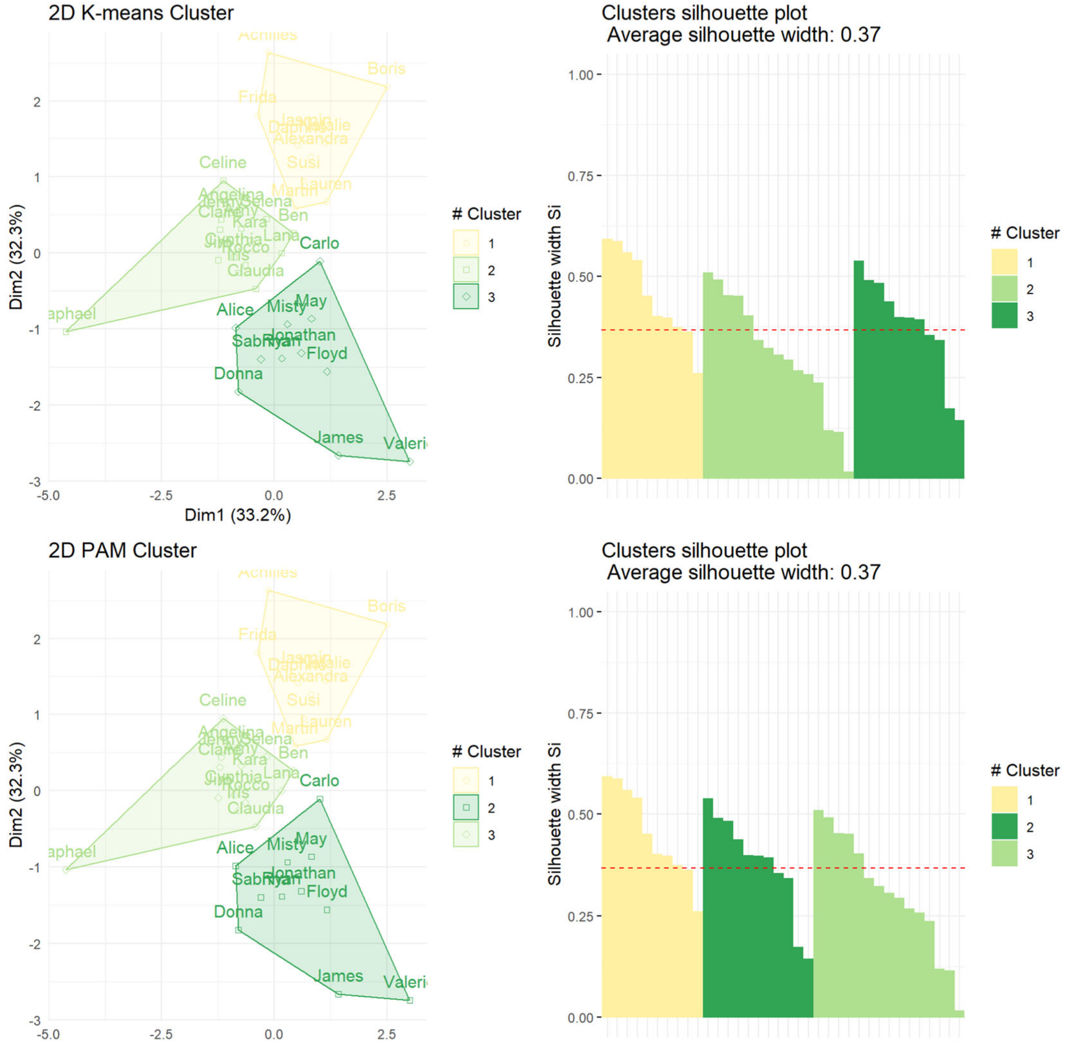

FIGURE 3 Visualization of clustering and silhouette with for (1) kmeans and (2) PAM algorithms of participants' volitional statements.

4.2.2 | Relation between volition categories and metamodeling knowledge, modeling process, and model score

The correlation analysis of the individual categories (see Figure 6) revealed significant relations between volition categories and modeling performance variables (see Figure 6). For example, self-regulation is positively related to model development. Thus, participants with a high proportion in self-regulative statements engage in a higher proportion of developing activities or vice versa, compared with participants with a preference for other dimensions in their volitional pattern. There was no significant relation between the volition categories and metamodeling knowledge or the model score. We will now report on all significant correlations found in the subcategories.

The self-regulation subcategory self-efficiency is related to homogeneity (0.34, p value < 0.1), exploration (−0.57, p value < 0.01), and development (0.58, p value < 0.01). The self-control subcategory failure management is

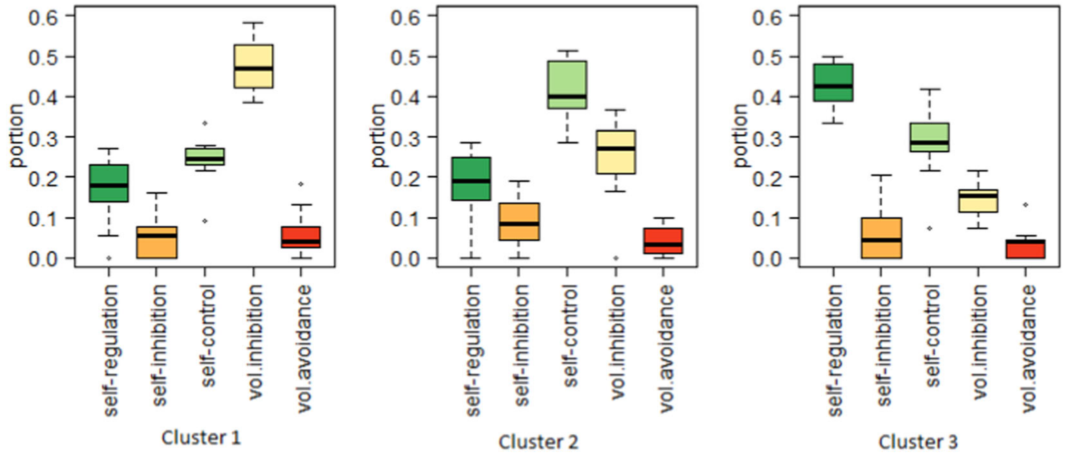

FIGURE 4 Boxplots of volition dimension for each cluster.

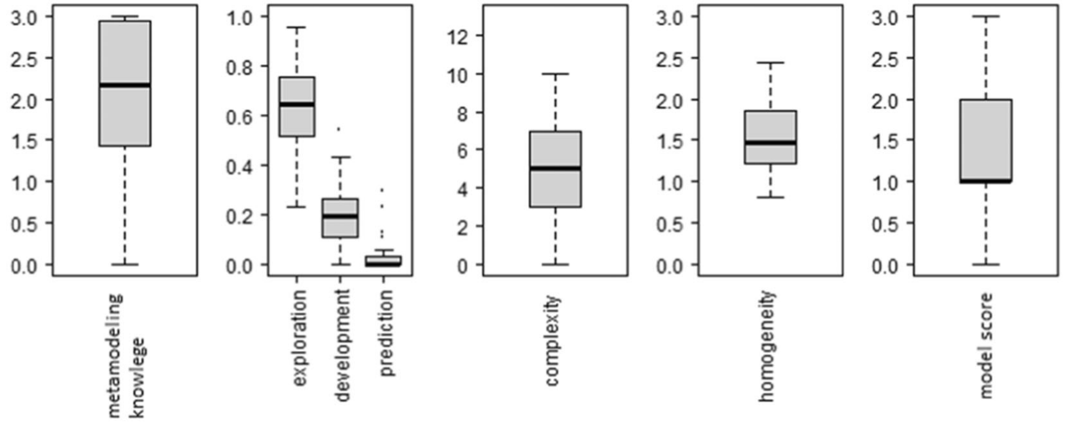

FIGURE 5 Boxplots of variables for metamodeling knowledge, modeling process, and modeling product.

related to development (0.34, p value < 0.1) and pursuit of goal negatively to homogeneity (−0.47, p value < 0.05). Volitional inhibition is not related to metamodeling knowledge, the modeling process, or model score. However, the subcategory foreign determined is negatively related to metamodeling knowledge (−0.34, p value < 0.1) and complexity (−0.46, p value < 0.05), and the subcategory listlessness is positively related to metamodeling knowledge (0.36, p value < 0.1). The volition avoidance subcategory resignation is positively related to exploration (0.45, p value < 0.05) and negatively to prediction (−0.37, p value < 0.1).

4.2.3 | Relation between clusters and metamodeling knowledge, modeling process, and model score

Regarding the process variables (see Supporting Information: Appendix 4 for all values), Cluster 2 has significantly higher proportions in exploration (p value < 0.05, $f = 0.74$) and lower proportions in development than Cluster 3 (p value < 0.05, $f = 0.78$). Cluster 1 had fewer total activities than Cluster 2 (p value < 0.1, $f = 0.70$) and a lower

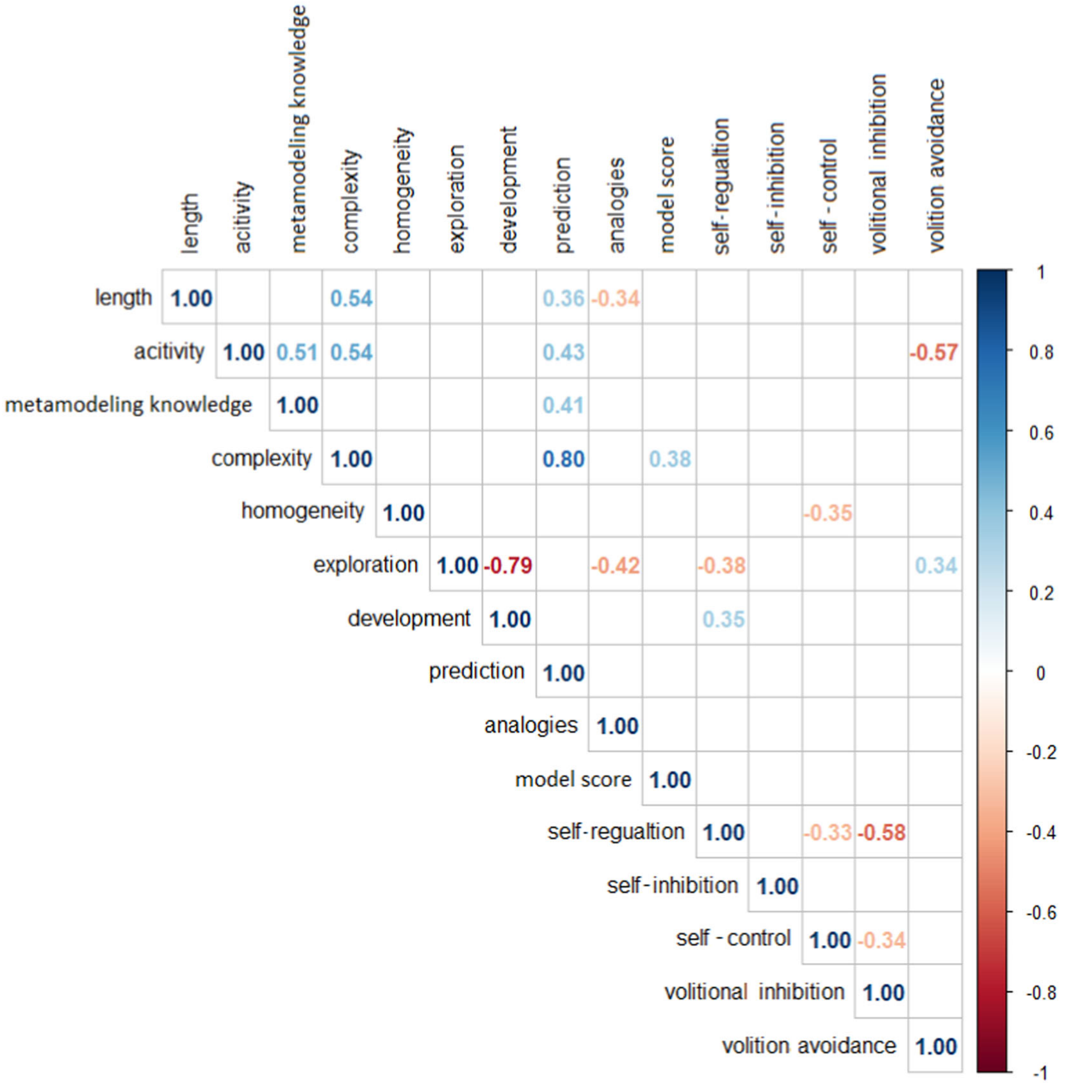

FIGURE 6 Correlation plot for metamodeling knowledge, modeling process, and modeling product variables and volition categories, p value < 0.1.

metamodeling knowledge (p value < 0.05, f = 0.77). However, Cluster 1 has a significantly higher homogeneity than Cluster 2 (p value < 0.01, f = 0.83). No other significant differences exist between the three clusters, they do not differ significantly in prediction, complexity, and the model score.

4.2.4 | Sample cases

This section will present three cases in more detail as illustrative examples. The examples each belong to a different cluster. However, the chosen examples (see Table 4) do not represent the cluster but shall illustrate different volition strategies during the model process.

Boris' pattern is very distinct (see Figure 7). He elaborates rather quickly from exploration to prediction and quits after only 25 min. A strong volitional inhibition characterizes his volition pattern; he expresses a feeling of foreign determination throughout the modeling process. The first occurrence of volition avoidance at minute 15 is very early compared with the other cases. He expresses effort avoidance at this instance and shortly before he ends his process. Initially, he feels self-efficient; he is self-motivating once and feels decisive before quitting. He self-controls himself once; while engaging in a predictive activity, he controls an impulse.

In summary, Boris modeling process is concise with a quick elaboration accompanied by strong volitional inhibition. His final model was scored on level 1 (see Table 4).

Rocco's pattern was a rather common pattern (see Figure 8). Rocco starts exploring the model under self-control, focusing on pursuing the goal and controlling impulses. He also shows self-regulating behavior, specifically decisiveness, self-motivation, and self-efficacy. During a development phase, he shows listlessness at a possible setback. Notably, he made no volition statement during the developing activities. After 35 min he goes back to exploring the model. After one impulse control, he starts brooding, expresses listlessness again, and resigns.

In summary, Rocco's modeling process is shaped by two distinct parts: the first part is dominated by self-control and self-regulation, and the second part by inhibition and avoidance. Rocco does not engage in predictive activities in his process, lasting 46 min and resulting in a modeling product scored at level 2 (Table 4).

Floyd's modeling activities are similar to Rocco's in the first 45 min (see Figure 9). His process starts with exploring the black box with self-control; first, he focuses on the goal and then manages failure. He is self-regulating himself, being decisive. After a phase of developing his model, he resumes the exploration and is also struggling with volitional inhibition, especially expressing a feeling of low self-efficiency. Nevertheless, in contrast to Rocco, he does not resign after about

TABLE 4 Case scores in the variables measuring metamodeling knowledge, modeling process, and modeling product.

Case	Meta-modeling knowledge	Exploration	Development	Prediction	Complexity	Homogeneity	Model score
Boris	2	0.23	0.23	0.23	5	1.85	1
Rocco	3	0.74	0.18	0	3	2.17	2
Floyd	2	0.54	0.28	0	5	1.96	3

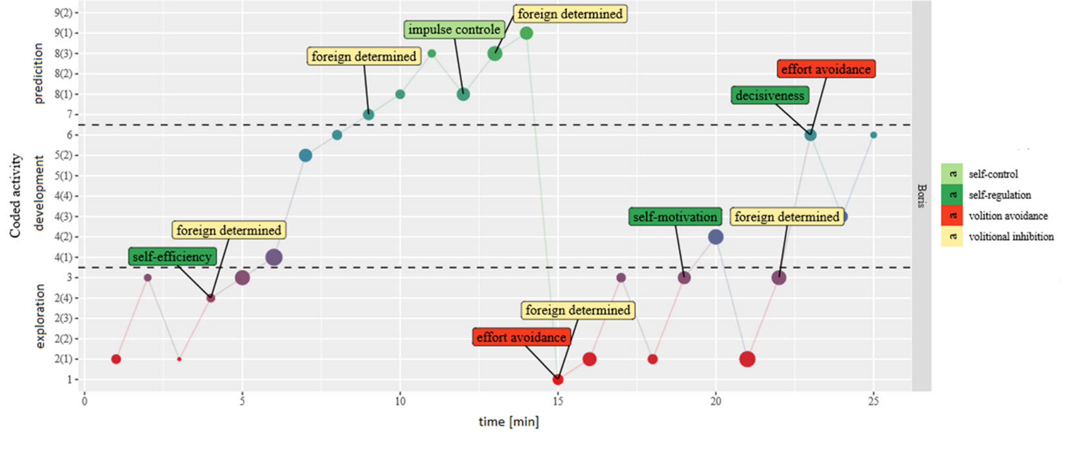

FIGURE 7 Boris' process for details on *y*-axis see appendices. The size of each data point corresponds to the time spent on each activity. The color scale of the data points from red over blue to green indicates the activity category.

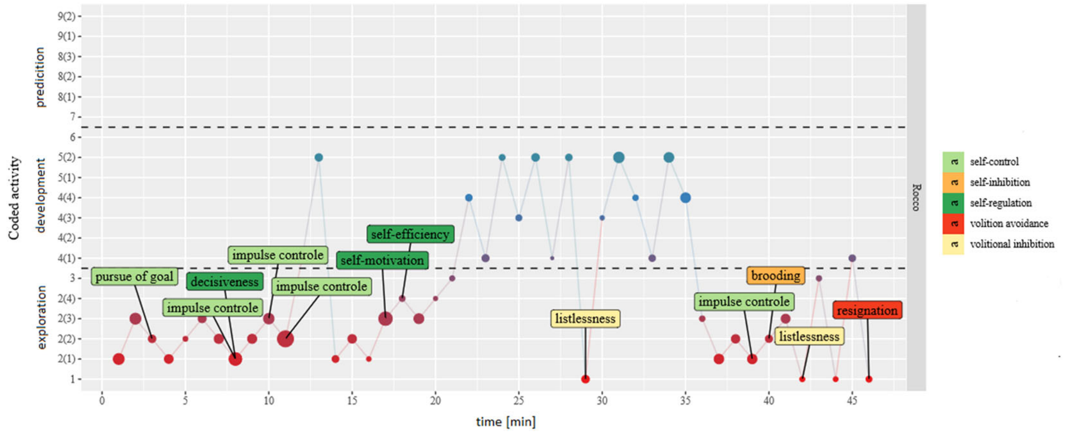

FIGURE 8 Rocco's process for details on *y*-axis see appendices. The size of each data point corresponds to the time spent on each activity. The color scale of the data points from red over blue to green indicates the activity category.

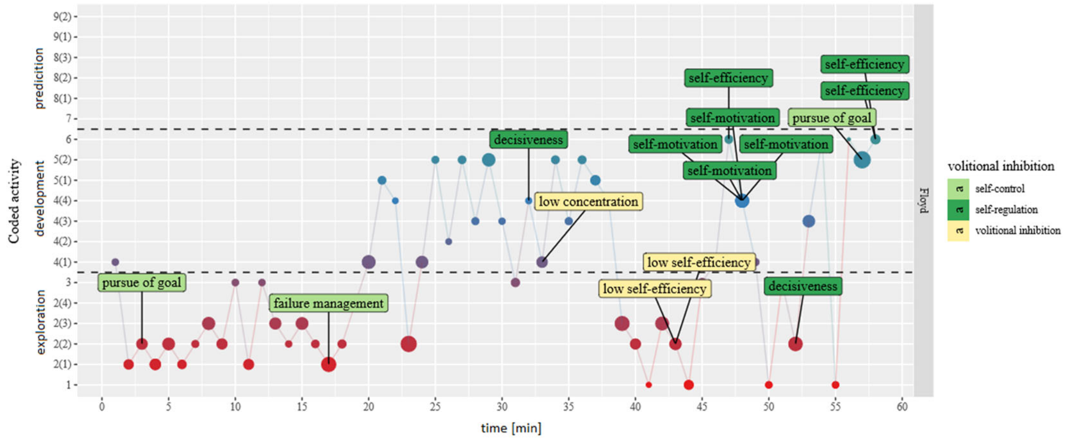

FIGURE 9 Floyd's process for details on *y*-axis see appendices. The size of each data point corresponds to the time spent on each activity. The color scale of the data points from red over blue to green indicates the activity category.

45 min but continues his process, going back to developing the model. His volition is now dominated by self-regulation, mainly self-motivation and self-efficiency. He resumes pursuing his goal before finishing his process.

In summary, Floyd begins the task with self-control. He reacts with volitional inhibition after the first set-backs and then switches to the action-oriented mode, self-regulating his actions. Floyd is one of the few high-performing students with a model score of 3 (Table 4). Notably, though, he is not involved in predictive activities.

5 | DISCUSSION

We will start with the discussion on the occurrence and patterns of the volition categories self-regulation, self-inhibition, self-control, volitional inhibition, and volition avoidance (RQ1). Then, the relation between volition and metamodeling knowledge, modeling process, and modeling product will be discussed (RQ2). We will elaborate on the different variables used to indicate the modeling process.

5.1 | Volition in preservice science teachers' modeling processes (RQ 1)

During the modeling task, preservice science teachers mainly expressed processes of self-regulation, self-control, and volitional inhibition. Statements on self-inhibition and volition avoidance have smaller proportions. Many participants might have regulated self-inhibition with self-control since self-control can be used to substitute for self-regulation when self-assertion cannot be upheld (Baumeister et al., 1998). The study design explains the small proportion of volition avoidance. As participants were free to quit the modeling task at any time, one can assume participation ended when volition avoidance occurred, such as in the cases of Boris and Rocco. This interpretation is supported by the negative correlation between volition avoidance and the number of activities.

We expected to find distinct volition patterns that differ between an action- and state-oriented type (Kazén et al., 2008). As expected, the data structure was clustered. Two algorithms identically reproduced three clusters with no person mismatched. The clusters can be interpreted as one action-oriented and two state-oriented types. The state-oriented types differed in the proportion of self-control and volitional inhibition. An interpretation of this difference is that participants in Cluster 1, due to the high demands of the task, could not uphold the self-controlling strategy resulting in volitional inhibition. Cluster 2 participants were either not as challenged by the task or could, despite the challenge, maintain self-control (Baumeister et al., 1998). Individual resources could explain the difference and the amount of self-control the participant had to exert before participating in the modeling task (Baumeister et al., 1998).

5.2 | Volition in relation to modeling process, metamodeling knowledge, and modeling product (RQ2)

5.2.1 | Volition in relation to modeling activities of exploration, development, prediction

The action-oriented type is expected to involve more complex activities than the state-oriented (Baumeister et al., 2007; Kazén et al., 2008). Consequently, self-regulation was expected positively related to complex activities. The modeling process' complexity is increased by developing and predictive activities and decreased by a dominance of explorative activities (Göhner et al., 2022). Thus, the action-oriented type was expected to have higher values in development and prediction, and the action-oriented type higher values in exploration. Self-regulation was expected to relate positively to development and prediction. As volition is of general importance to engage in complex tasks (Kuhl, 2001), we expected volition avoidance to relate positively to explorative activities.

Our results show the expected significant difference between Clusters 2 and 3 in exploration and development but none in prediction. We also find that self-regulation is positively related to model development activities in the modeling process and negatively to exploration. Volition avoidance was positively related to explorative activities, as expected.

Self-efficiency is a subcategory of self-regulation. It is of extraordinary importance in self-regulated learning because it allows one to meet challenges productively (Bandura, 1999; Schraw et al., 2006; Zimmerman, 1989). In this study, self-efficiency shows a higher correlation with development and a stronger negative correlation with exploration than overall self-regulation. Thus, self-efficiency might be a crucial component in elaborate modeling activity.

In summary, the volition pattern is likely to influence the modeling activity. Self-regulative behavior and the active-oriented type relate to higher engagement in developing a model instead of just exploring the existing one. We did not find the expected relation to predictive activity, probably due to the small number of participants engaging in predictive activities ($n = 14$).

5.2.2 | Volition in relation to complexity and homogeneity

The results of the modeling activities indicate that self-regulation might positively relate to the complexity of the modeling process. However, the relation did not show in the study. As complexity is calculated from the variety of activities (Göhner et al., 2022), the lack of significant relation between volition variables and predictive activities is a likely reason.

Also, no positive relation between self-regulation on homogeneity was found. Only the subcategory self-efficiency was significantly positively related to homogeneity. Further, self-control is negatively related to the homogeneity of the modeling process. Self-efficiency allows actively and often switching between activities. Self-control, on the other hand, hinders such switching, as it hinders action and, therefore, leads to a higher persistence in one activity (Goschke & Kuhl, 1993). Since homogeneity seems to not have a significant impact on the modeling product, its relevance to modeling competence requires further investigation.

5.2.3 | Volition in relation to the modeling product

Highly developed self-regulation generally allows for better academic performance in science (Schraw et al., 2006; Schunk, 1996; Zheng et al., 2020). It was thus expected to relate positively to the model score. But the modeling process's complexity remains the only significant impact on the model score, and as self-regulation is unrelated to complexity, it is unrelated to the model score. There was also neither a relation between any volition category nor between a cluster and the model score.

5.2.4 | Volition in relation to the metamodeling knowledge

Metamodeling knowledge is described as a prerequisite for advanced modeling performance, guiding activity under metacognition (Krüger et al., 2018; Nielsen & Nielsen, 2021; Schwarz, Reiser, et al., 2009). Thus, we assumed that metamodeling knowledge positively relates to self-regulation because it describes an encompassing engagement with the task while easily accessing personal resources (Baumeister et al., 2007; Kuhl, 2001). The only relation to metamodeling knowledge found was between subcategories of volitional inhibition: a negative relationship between foreign determination and the positive relation to listlessness.

The negative relation of foreign determination seems to support our understanding; people who are foreign determined during their modeling process do not access metamodeling knowledge. The positive relation to listlessness is challenging to interpret. Participants may feel listless when reflecting on what is needed to solve the task. Possibly, their listlessness lets them escape from the actual activity and start reflecting on general modeling knowledge. In this sense, metacognition might be related to a lack of positive emotion and, in fact, be negatively related to self-regulation (Goschke & Kuhl, 1993). A phenomenon called "lost in thought" (Kazén et al., 2008). Either way, no strong evidence exists for the relation between the activation of metamodeling knowledge and volition style. Yet, metamodeling knowledge relates positively to prediction.

6 | LIMITATIONS

This study has some limitations. First, the sample size is modest and only consists of preservice science teachers, potentially limiting our findings' generalizability to this specific group. We did not test general preference in volition, for example, in a pen-and-paper test to compare the volition expressed during the modeling process. Neither did we ask the participants how volitional tied they were at the time of the participation, for example, if they had to complete a task requiring much self-control right before participation or were emotionally worn out for any reason. Regarding assessing the modeling processes, the black box as a modeling task may have limited the participants in their engagement, as it is a rather abstract and complex task (Leden et al., 2020). Also, regarding noncognitive aspects, connecting the modeling task to an authentic research scenario over a longer period of time might be crucial (Vasconcelos & Kim, 2020). In this context, other noncognitive factors of competence still require testing regarding their relevance for modeling performance and volition. As motivation is a prerequisite for volitional processes (Baumann et al., 2018), the motivation for modeling task will probably influence the volition pattern during modeling activity. Motivation may also have direct relevance for the modeling process not mediated by volition.

6.1 | Conclusion and outlook

Our results show that volition is a relevant but not a crucial factor in modeling competence. Three different volition types during the modeling process of preservice teachers could be distinguished, one action-oriented and two state-oriented types. The three types differ between the volition categories and some modeling process variables. The state-oriented types specifically differ between the proportion of self-control versus volitional inhibition. We find a positive, yet weaker than expected, relation between self-regulation and the modeling process. There was no impact of self-regulation on the model score. We reject the hypothesis that self-regulation will enhance the use of metamodeling knowledge due to the lack of evidence.

Self-regulation regulates learning processes in general (Schraw et al., 2006; Zimmerman, 1989), while metamodeling knowledge should help regulate modeling processes (Chiu & Lin, 2019; Schwarz, Reiser, et al., 2009). Although self-regulation does not enhance metamodeling knowledge, it could still constitute a complementary or consecutive part of this dimension of modeling competence. Self-regulation and the action-oriented type positively relate to development and metamodeling knowledge to prediction. Modeling is a complex task with high cognitive demands (Hogan & Thomas, 2001). Possibly, self-regulation is needed to start involvement in the modeling process and metamodeling knowledge to reach a high level. More research on this observation is needed, as the sample is too small to prove this relationship.

An experimental approach introducing training in self-regulated learning to enhance modeling competence may possibly help investigating the relationship between self-regulation and metamodeling knowledge. Although inquiry-based learning in general (Jacobs, 2022; Sabourin et al., 2013; Schraw et al., 2006) and modeling in specific (Panaoura et al., 2009; Schunk, 1981) have been discussed and assessed in their benefit for self-regulated learning, the reverse relation is yet to be investigated.

High level modeling processes have so far been difficult to study empirically, because they seldomly occur (Pierson et al., 2017). Although the first evidence for connection between volitional processes and the modeling process is weaker than expected, the creative element in modeling and its cycling nature in which an ongoing evaluation and revision is necessary (Upmeier zu Belzen et al., 2019) call for self-regulated processes. Actively supporting self-regulative strategies might benefit endeavors to strengthen high level modeling processes and thus enable further research and improve modeling processes in classrooms.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

ETHICS STATEMENT

In accordance with local legislation and institutional requirements, our study did not require the approval of an ethics committee because the research did not pose any threats or risks to the participants, and it was not associated with high physical or emotional stress. Nevertheless, it is understood, that we strictly followed all ethical guidelines as well as the Declaration of Helsinki. Before taking part in our study, all participants were informed about its objectives, absolute voluntariness of participation, possibility of dropping out of participation at any time, guaranteed protection of data privacy, no-risk character of study participation, and contact information in case of any questions or problems.

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