Qualitative Representations for Systems Thinking in Secondary Education

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Abstract

Systems thinking is a complex skill for learners in secondary education. We argue that qualitative representations can be valuable tools to actively engage in learning this skill. However, the effectiveness of these tools is currently hampered by complexity and the lack of instructional embedding. In this contribution, we present our developments on scaffolds for learning, instructional formats, and automated support in order to unleash the potential of qualitative representations for secondary education.

1 Introduction

Qualitative Reasoning has a long held promise of being useful for education [Bredeweg and Forbus, 2003; Bredeweg and Forbus, 2016]. In fact, initial publications focused on explicating commonsense and tacit knowledge essential for intelligent tutoring systems, which were then thought to be missing in such systems [Brown *et al.*, 1984; Hollan *et al.*, 1984; Kleer and Brown 1984]. Meanwhile, various qualitative representations and accompanying algorithms have been developed and are well understood. Yet, the actual deployment in education is still a challenge.

We are working on bridging the gap between the potential of Qualitative Reasoning and its actual use in education. Our approach is interdisciplinary and focuses on the interplay between Artificial Intelligence and Educational Sciences. Solutions are partly technical but they also involve proper positioning and the development of an effective didactic approach.

Specifically, we focus on learners (K7-12) acquiring systems thinking skills. Systems thinking is difficult to learn [Jensen and Brehmer, 2003; Cronin et al., 2009]. Learners may easily ignore relevant factors, apply causal relationships incorrectly, fail to see feedback mechanisms and their impact, and not recognize cause-effect patterns across systems (so called transfer) [Perkins and Salomon, 1992; Hajian, 2019].

We argue that Qualitative Reasoning has laid the foundation for automated systems *thinkers*. Consequently, interactive qualitative representations have the potential of becoming relevant educational tools for learning systems thinking in secondary education. In this contribution, we discuss our research and achievements in this respect.

1.1 Related Work

The Vanderbilt group has a long standing work on teachable agents using qualitative representations, albeit with numerical underpinning [Biswas *et al.*, 2016]. Middle school learners construct diagrams to learn about biological facts. The pedagogical approach embraces the 'learning by teaching' paradigm and part of the research focused on the effectiveness of this approach. The subject matter is typically represented as a single state system in which quantities cause each other to increase or decrease.

VMODEL [Forbus *et al.*, 2004] was presented as an education tool for learners to created single state representations using simplified Qualitative Process Theory (QPT) vocabulary [Forbus, 1984]. VMODEL generates an explanation of the system behavior based on the learner-created representation. Learners are expected to correct their expression if they think the explanation is incorrect.

CyclePad [Forbus *et al.*, 1999] uses qualitative representations to generate explanations to complement numerical analysis and simulation. It supports engineering students in understanding the quality of their design.

A Graphical User Interface (GUI) was designed and implemented to improve the usability of qualitative reasoning software for both learners and experts [Bouwer and Bredeweg, 2010]. This approach was further developed for Garp3 [Bredeweg *et al.*, 2009] and DynaLearn [Bredeweg *et al.*, 2013]. The latter established multiple scaffolds to support learners in working with qualitative representations, such as the notion of learning spaces [Bredeweg et al., 2010] and ontology-based explanation [Beek and Bredeweg, 2012]. Various evaluation studies were performed, e.g. on knowledge structure development by learners in higher education [Zitek et al., 2013], on supporting problem-based learning [Lozano et al., 2015], and on acquiring scientific concepts to improve language skills and inferential reasoning by deaf students [Salles et al., 2011].

1.2 Next steps

In the work presented here, we focus on the challenges formulated in the Denker project (https://denker.nu/): learning system thinking and content knowledge by constructing qualitative representations. In this project, we collaborate with teachers in secondary education and adhere to three principles to realize the potential of Qualitative Reasoning for education. Firstly, *embedding in ongoing education*. Complementing or substituting regular educational activities enlarges the chances of teachers being able and willing to try out a new approach. Secondly, *easy to use software*. The software should be without further challenges regarding the execution in the classroom and preferably reduce the workload of the teacher. Thirdly, *creating added value beyond current school practice*. Working with the software should deliver added value that is needed and wanted and otherwise not easily obtained.

Below we describe how these principles resonate in the status and recent developments of the DynaLearn software (https://www.dynalearn.nl) and the actual deployment of this approach in education.

2 Explicit Representation

Artificial Intelligence (AI) typically focusses on creating machines that can perform smart reasoning, often inspired by and mimicking human abilities [Russell and Norvig, 2020]. Although educational machines should be equipped with such capabilities, at least to a certain extent, the goal for Artificial Intelligence in Education (AIED) is different. For AIED the goal is to create *smart people* and the AI is used as a tool to enable that. There are at least two reasons why qualitative representations form an interesting set of intelligent tools that fit the AIED goal.

Firstly, as with any representation, when used by people they strongly steer the development of knowledge and insights [Davis et al., 1993; Bod, 2019]. As such, having learners construct representations is a valuable pedagogical instrument for implementing active learning [Quillin and Thomas, 2015].

Secondly, the Qualitative Reasoning community particularly focused on explicating the implicit knowledge considered essential for reasoning about the behavior of (physical) systems. This resulted in an explicit vocabulary underpinning automated reasoning. In fact, the community developed an explicit ontology [Liem 2013] for (automated) *systems thinking*. Modern educators emphasize the importance and challenge of supporting learners (K7-12) in acquiring systems thinking skills [National Research Council, 2012; Curriculum.nu, 2021]. Qualitative representations can be deployed for this purpose. Their suitability is even more profound because of the accompanying automated reasoners, which makes them outstanding candidates for intelligent interactive tools for learning systems thinking.

2.1 DynaLearn – Representation and Reasoning

DynaLearn is an interactive tool that allows learners to create and simulate qualitative representations. It provides a web-based graphical user interface to Garp3 [Bredeweg *et al.*, 2009], facilitating online usage of the latter. The following ingredients are available via this interface to create representations. *Entities* can be used for representing physical objects and/or abstract concepts that make up the system. *Configurations* can be used for represent structural relationships between entities. *Quantities* can be used for representing changeable and measurable features of entities. Quantities have *Direction of change* (∂) (decreasing, steady, and increasing) and a *Quantity space* (a set of alternating point and interval values that the quantity can take on). *Causal dependencies* can be used for representing directed relationships between quantities. *Correspondences* can be used for representing co-occurring values and co-occurring directions of change. *In/equalities* can be used for representing order information among values and among directions of change. Finally, there is the option to represent *conditional statements*: IF *A* THEN *B*, where *A* and *B* can refer to the above mentioned ingredients.

When simulating, *Initial values* are defined for quantities, typically (but not exclusively) at the start of *Causal paths* (sequences of causal dependencies). This can be a direction of change, an initial value or an *Exogenous* behavior. Additionally, in/equalities can be specified. The simulation produces a *State-graph*, which consist of one or more *States* (unique qualitative behavior of the system) and possibly *Transitions* (continuous passage) between pairs of states. The changes of system behavior throughout the state-graph can be inspected using the *value-history* and the *inequality-history*.

3 Modelling Levels as Learning Scaffolds

An effective tool for learning systems thinking would be a great added value in secondary education. How to accomplish that? Firstly, it is important to acknowledge that systems thinking is a complex skill. It requires an approach in which the skill is gradually build up. Secondly, to be welcomed by teachers, it is important to blend in with ongoing education. From that perspective it is interesting to realize that the subject matter currently taught in secondary education is also complex and learned stepwise across multiple years as specified by the school curricula.

Addressing these requirements, we have chosen to organize the qualitative representations into a set of distinct levels with increasing complexity [Bredeweg et al., 2010]. From a knowledge representation angle this introduces the following challenges on how to define these levels:

- Levels should be logically consistent and self-contained such that they allow for automated reasoning at each level.
- Levels should be upwards compatible, so that running representations at a higher level delivers the same output as obtained at the lower level.
- Levels should reflect proper stages of systems thinking that can be learned incrementally and that align with the subject matter as specified in the school curricula across the different years.

Our current approach takes as a starting point earlier work in which we defined six levels [Bredeweg et al., 2010]. In that approach level one referred to traditional concept maps [Novak and Gowin, 1984]. We now start at level two, because the focus is entirely on systems thinking. Below the main features of each level are summarized.

Level 2 allows for simple cause-effect representations to support reasoning about how changes propagate through a system (Figure 1). Learners represent the *entities* and *configurations*, the associated *quantities*, the *causal dependencies* (+ & –) between these quantities, and the *initial change* for the quantities at the beginning of the causal paths. When simulating, the initial changes are propagated through the representation determining the possible states of behavior. This typically results in single state or multiple states in the case of ambiguity.

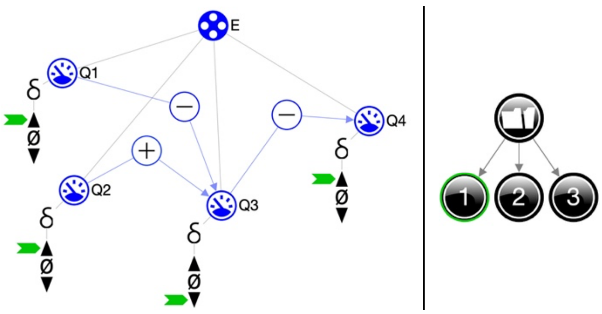

Figure 1. LHS shows a general level 2 representation consisting of one entity (E) with 4 quantities (Q1-Q4) and 3 causal dependencies. RHS shows 3 possible states, Q4 increases (state 1, shown), remains steady (state 2, not shown) or decreases (state 3, not shown). This is due to ambiguity, because Q1 and Q2 increase and have competing impact on Q3.

Note that, the underlying engine (Garp3) always performs a complete simulation taking *all* ingredients (as discussed in Section 2) into account. Three mechanisms ensure that learners only interact with the ingredients belonging to the level they are working with:

- *Filtering.* Only a subset of the available ingredients is actually shown at each level (e.g., influences and quantity spaces are not shown at level 2).
- *Completion.* Missing but for the engine required ingredients are automatically added (e.g., at level 2 all quantities are given a default quantity space with a single interval value).
- *Translation.* Some ingredients are renamed before being shown to the user (e.g., at level 2 the causal dependencies P+ and P- are translated into + and –).

At level 3, *quantity spaces* are included (for selected quantities as deemed necessary by the educators), which allows for representing the idea that a system can move through different states (e.g., a solid substance becoming liquid) characterized by a 'state-variable' (e.g., temperature) (Figure 2). Additionally, the ingredients *agent* (special kind of entity) and *exogenous quantity behavior* (continuously decreasing, increasing, random, etc.) are available. With this, learners can learn to distinguish the 'system' from the 'external factors' affecting it. Finally, *correspondence* (C) can be used to specify co-occurring values (e.g., IF Population Size = 0 THEN Natality = 0). When simulating, a *state-graph* appears (sequence of states and transitions) and the *value history* (overview of quantity values for a sequence of states) can be used to inspect the simulation results.

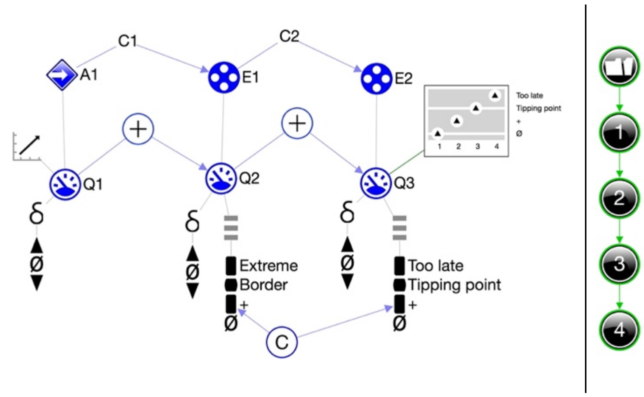

Figure 2. LHS shows a general level 3 representation. In addition to level 2, it includes *quantity spaces* (e.g., {0, +, Border, Extreme}), *exogenously* defined quantities (Q1 is always increasing), a *correspondence* (between values + in the two quantity spaces), and *value history* (for Q3). There is no ambiguity, hence the simulation on the RHS has a *state-graph* consisting of 4 states, each referring to one of the 4 values in the quantity spaces (0, 0), (+, +), etc.

Level 4 introduces *influence* (I+/I-) and *proportionality* (P+/P-) [Forbus, 2018]. Learners can focus on the distinction between processes (I) (initial causes) and the propagation (P) of these through the system. Positive and negative *feedback loops* are now available and *in/equality* ($< \leq = \geq >$) to represent the relative impact of competing processes. The inequality history can be used to inspect how in/equality between quantities changes during the evolution of the behavior.

Level 5 allows for representing *conditional statements*. They can be used to specify that certain ingredients become active only when conditions regarding values and/or inequalities hold (e.g., IF A>B THEN C I+ D). However, we doubt whether this level will be needed in secondary education.

Finally, simulation preferences can be set within each level. This allows to further refine notions regarding systems thinking. For instance, the idea of making assumptions, and whether the engine will use 2^{nd} and 3^{rd} order reasoning for inferring the system dynamics.

The modelling levels described above are fully implemented and available for teaching and learning systems thinking skills.

4 Instructional Formats

The modelling levels are an important scaffold for teaching and learning systems thinking. At each level, activities can be defined to work on specific subject matter (conform the school curriculum) as well as on the related overarching systems thinking skills. Of course, it makes sense to start at the lowest level and gradually work towards the higher, more complex levels. Notice, that the subject matter may come from any topic involving the notion of a system and that it is not a priori limited to a particular domain or system. Wellsuited areas in secondary education include: biology, geography, economics, physics, and more.

Having defined the levels and their interdependencies still leaves the question of how to start working with learners at a specific level. We have developed various formats to address this issue. They are described next.

Workbook. Most of our work with learners includes a written document that stepwise explains and instructs the learner on the issues relevant for the task. Typically, these workbooks address (*i*) the subject matter, intertwined with (*ii*) the involved systems thinking, and (*iii*) some details regarding the GUI of the software.

Instruction clip. A short video (approx. 5 mins) that shows the kind of modelling and simulation steps as required by the learners to create their own representation, but using a different example. The clip is shared as an independent asset but also regularly referred to in the workbook in order to highlight specific systems thinking aspects.

Example model. A representation of a small system that learners can relate to and start experimenting with before they start the 'real' assignment (Figure 3). Learners can open this representation from a repository, save it as their own and perform basic steps, such as setting or changing initial values and inspecting the simulation outcome.

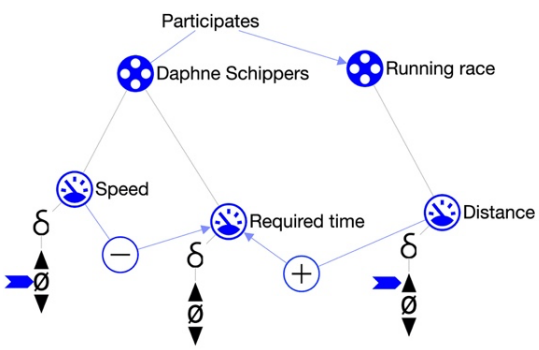

Figure 3. Simple representation of a small system involving a famous person. In this case, *Daphne Schippers* (well-known Dutch athlete) *Participates* in a *Running race*. The *Required time* (to complete the race) increases when the *Distance* (of the race) increases, and decreases when the *Speed* (of Daphne) increases.

Content flip. While maintaining the overall structure transform the representation of a specific system (that was just discussed) into the representation of a (completely) different system. See for instance Figure 4 which is a content flip of the details shown in Figure 3. Performing a content flip life during an event often has a (positive) mind-boggling impact on learners and even teachers.

Template. To further steer the work of the learners a template can be used. A template is basically a subset of the complete representation, and is given to learners at the start of the lesson. A bigger representation can be addressed in a shorter time by using a template. However, care must be taken to ensure that learners still create a significant part of the representation themselves. After all, the learning takes place especially during the construction of one's own representation.

Diagnosis. Instead of having learners create a representation, learners can be given a pre-developed *faulty* representation. The assignment then focusses on finding the culprit(s), correct these, and work towards obtaining a particular behavior with the representation (when simulating it).

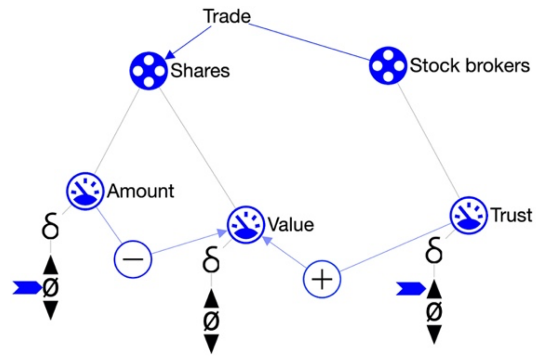

Figure 4. Content flip of the representation in Figure 3. In this case, *Stock brokers Trade Shares*. The *Value* (of shares) increases when *Trust* (of brokers) increases, and decreases when the *Amount* (of shares) increases.

5 Automated support

The above described instructional formats suffice for formulating assignments that learners can work on independently and successfully complete. However, learners may make mistakes and potentially learn incorrect details or get stuck in executing the assignment. Hence the teacher has to be alert, monitor and assess the progress of the learners, and intervene where deemed necessary. Although doable in regular classes, it does make the teaching laborious. To alleviate this burden, and to also stimulate learners' self-reliance, we have developed three types of domain independent automated support.

5.1 Norm-based Cueing and Help

In our situation, teachers select their own topics for their learners to work on which makes that lessons vary in content depending on the teacher's preference. This hampers the use of advanced learner modelling techniques to generate support from, because the available data is sparse and distributed across miscellaneous topics. To address this issue, we investigate how support generated from a norm-representation can be deployed effectively, and whether this can be done without taking any learner specific information into account.

Our current implementation compares a learner-created representation with the norm (created by the teacher). After each manipulation executed by the learner in the canvas a new mapping is made using a Monte-Carlo-based heuristic approach. The engine runs for at most 5 seconds and then returns the best mapping. Next, for each discrepancy the support provides two options for feedback. **Cueing**: a small red circle is placed around each deviating ingredient (Q2 in Figure 5) and a red question mark appears on the right-hand side in the canvas. **Help**: when clicking on the question mark, a message-box appears showing a sentence for each deviation (in Figure 5: Quantity: Q2: wrong name?). Note that when working on a specific representation, learners get confronted with subject specific information. For instance, whether they assign the correct quantities to each of the entities.

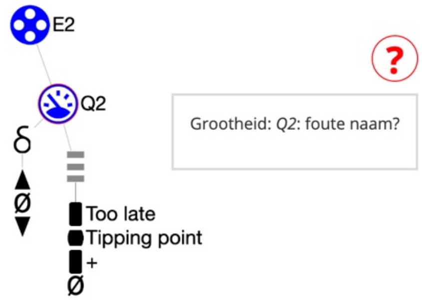

Figure 5. Cueing and Help. While creating the representation shown in Figure 3 quantity 'Q3' is wrongly named. *Cueing* highlights the erroneous ingredient (here: Q2). *Help* suggests an error (here: Quantity: Q2: wrong name? (translated from Dutch)).

5.2 Progress Bar

Next to being informed about errors, it may also be helpful for learners to get information on the degree to which they have accomplished the goal representation. This will support them in knowing what still needs to be done and when the goal is reached, and may also be relevant to stimulate meta-cognitive reflection.

Our current approach implements the idea of a progress bar (Figure 6). For each ingredient *type* present in the target representation the bar shows (*i*) how many instances of that ingredient need to be created, (*ii*) how many at each moment have been created, (*iii*) how many of those created are incorrect, and (*iv*) when all the details for that ingredient are addressed. Research is needed to find out whether this support is helpful and sufficient, without giving away too much.

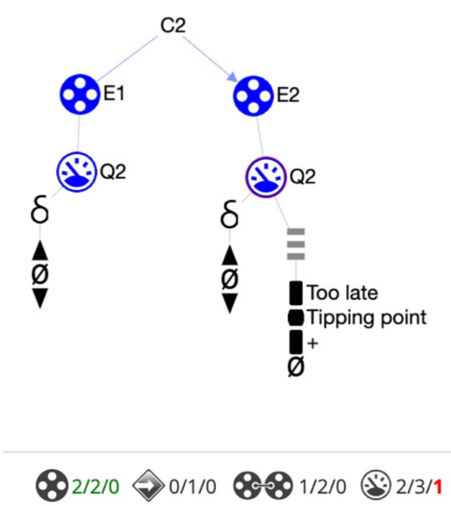

Figure 6. Progress bar (partly shown). The status is shown for each ingredient type at the bottom of the canvas. For instance, "Quantities 2/3/1" tells the learner that 2 quantities have been created, 3 need to be created in total and that 1 is currently incorrect (shown in red). When all ingredients have been created correctly the numbers become green, as for entities here.

5.3 Feedback-loops (at Level 2 and 3)

At level 2 and 3 causality is represented using directional dependencies of type – and +. When simulating, these dependencies are mapped onto proportionalities (Section 3). Feedback-loops of proportionalities are by definition impossible [Forbus, 1984]. To specify feedback-loops, the notions of (initial) cause (I-/I+) and propagation (P-/P+) need to be distinguished, but at level 2 and 3 the ingredient for representing influences is not yet available (Section 3).

The GUI at level 2 or 3 does not a priori prevent feedback-loops from being created. When created, one of following two outcomes occurs. In the case of a *negative* feedback-loop the engine returns 'no simulation' as output, because such a loop is inconsistent according to the qualitative calculus underpinning proportionalities. Alternatively, a *positive* feedback-loop is without such a serious impact on the simulation output, because the result is consistent. Still, the loop has no real impact on how the simulation results are calculated

Consequently, when creating assignments for level 2 and 3 it is important to circumvent the need for feedback-loops. Although this can be done successfully [Kragten *et al*., 2021; Spitz *et al*., 2021a] we cannot always prevent learners from creating feedback-loops. They may even create them by mistake. How to cope with that? We have opted for a clarifying solution that (*i*) identifies and highlights loops in the representation and that (*ii*) explains the consequences to the learner. This works as follows. If one or more loops are present, a blue exclamation mark appears as part of the simulation results (Figure 7). Selecting the exclamation mark opens a message-box with unique identifiers for each loop. Clicking on an identifier (number 1 in Figure 7) results in two additional details being shown: it highlights the loop by coloring the involved dependencies red, and it provides a short text explaining of the kind of loop found and its consequences for the simulation (one of following two):

- Positive feedback: change is reinforced.
- Negative feedback: change is reduced (simulation often not possible at this level).

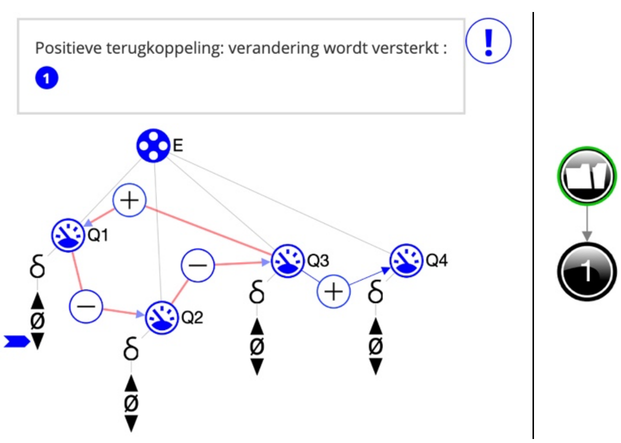

Figure 7. Feedback-loops. At level 2 and 3 sequences of causal dependencies that form a loop are highlighted. A text message characterizes and explains the type of feedback (in this case *positive*).

We have also considered preventing the creation of feedback-loops at level 2 and 3 completely. However, that option provides a much less insightful setting for explaining the characteristics of this construct. One important reason being that prohibition results in the loop not being shown as an external representation to reflect upon.

6 Coping with COVID-19

The COVID-19 pandemic puts extra pressure on the work presented in this paper. Fortunately, the *collaboration* feature, available in the DynaLearn software, turns out to be helpful in coping with the crisis. Users can share representations with other users to jointly work on them (by sharing a software created 9-digit code, e.g. 123-456-789). We use the collaboration option to work online with the teachers, typically with 3 to 6 people per session. Notice that, teachers in secondary education are not used to working online, at least not in the Netherlands. However, after a hesitating start the online collaboration turns out to be an effective way of working. We believe that the shared external representation is an important factor for this because it provides a strong focus and steering to the substantive discussion.

We use a specialized version of the same feature to have teachers support learners during online classes. In this case, the representation stays with the learners (they do not need to share the 9-digit code). Instead, we enable teachers to real-time inspect the learner-created representation and provide feedback (as if the teacher walks around in the classroom helping learners where necessary). This makes it possible to have effective online classes during the pandemic.

We did not yet use the collaboration feature for learners to engage in a collaborative learning activity with peers. Obviously, this is an option for future research.

8 Conclusion and Discussion

Qualitative representations can be valuable tools for learners to actively develop their systems thinking skills. In this contribution we present various features that enable the effectiveness of qualitative representations for this purpose, including modelling levels to scaffold learning, various instructional formats, and different kinds of automated support. This conglomerate of features allows learners to engage in active learning fostering systems thinking as well as learning domain specific subject matter. Moreover, learners can do this independently to a large extent.

Ongoing research focusses on establishing and improving the value of the presented approach: (*i*) do the modeling levels sufficiently match the characteristics of subject matter in the intended grades, (*ii*) what is the best use and order of the various instructional formats, and (*iii*) is the automated support effective and do learners have additional needs [Spitz et al., 2021b].

Future research plans to focus on learning analytics and provide teachers with a dashboard to monitor the learning activities and further improve coaching the learners.

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