Commentary

# Why not have the best of both worlds? How to use direct instruction principles in inquiry-based instructional design

Ton de Jong [a,*] , Martha Georgiou [b] , Hasan Ozgur Kapici [c] , Martin Schwichow [d] ,
Talitha Christine Visser [e]

[a] *Department of Instructional Technology, University of Twente, the Netherlands*
[b] *Department of Biology, National and Kapodistrian University of Athens, Greece*
[c] *Department of Mathematics and Science Education, Bogazici University, Istanbul, Turkey*
[d] *Department of Physics and Physics Education, University of Education Freiburg, Germany*
[e] *ELAN Department of Teacher Development, University of Twente, the Netherlands*

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ABSTRACT

This paper explores how principles drawn from direct instruction can inform the design of inquiry-based instruction, moving beyond traditional debates that pit one method against the other. Inquiry-based instruction encourages students to infer and construct knowledge through activities such as hypothesis generation, experimentation, data analysis, and drawing conclusions, while direct instruction involves explicit guidance, modeling, and structured practice, so as to minimize errors. Both methods have unique strengths: inquiry-based instruction fosters conceptual understanding and higher-order thinking, while direct instruction ensures mastery of foundational skills such as problem solving. Recent work has tried combinations of these approaches, using designs where inquiry cycles are supported by just-in-time direct instruction or alternating methods to try to optimize learning; this paper presents another approach and attempts to apply direct instruction principles within guided inquiry learning. Examples from disciplines such as mathematics, biology, chemistry, and physics as presented within the Go-Lab ecosystem illustrate how blending these methods can support students' active engagement while ensuring robust knowledge development.

There is often discussion in the literature about what type of instruction should be preferred over another. An example of this type of discussion concerns inquiry-based versus direct instruction. Recent work, however, has suggested moving away from the traditional "horse race" and instead placing the student at the center, by seeking ways to combine the strengths of both methods (de Jong et al., 2023; Martella & Schneider, 2024). When researchers search for such combinations, these two different types of instruction, inquiry-based and direct instruction, are often used in succession, with one form of instruction preceding the other (Barzilai & Blau, 2014; Brant et al., 1991; Kollöffel & de Jong, 2013; Martin & Evans, 2019; Newman & DeCaro, 2019; Wecker et al., 2013). In more complex designs, both forms of instruction are continually alternated, which can be efficient if the knowledge that is being developed is appropriately analyzed (Loibl et al., 2024, in press). A slightly different approach is to develop instructional systems in which an inquiry-based approach is supported by just-in-time direct instruction (see e.g., Lazonder et al., 2010; Matuk et al., 2015). A final way to

combine both methods could be to see how design principles of direct instruction can be used in designing inquiry-based instruction. The last is the focus of the current paper.

## 1. Inquiry learning and direct instruction

As usually happens with complex concepts that are used in practice, there are many definitions of both inquiry-based and direct instruction, as well as many different ways of implementing these two methods. For inquiry-based instruction, Rönnebeck et al. (2016) analyzed 96 empirical studies and identified the following as characteristic inquiry activities for students: identifying research questions; searching for information; formulating hypotheses and generating predictions; planning, designing, and carrying out investigations; analyzing, interpreting, and evaluating data; developing explanations; constructing models; engaging in argumentation and reasoning; and communicating. These activities, or phases of activities, are similar to what we can find in

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inquiry models, such as those from Pedaste et al. (2015), Bell et al. (2010), and the National Research Council (2012). In each phase of an inquiry cycle, the initiative can be given more to the student or to the teacher/instructional system, creating situations that are more student-led (e.g., when students start by generating the research question themselves) or more system- or teacher-initiated, as when the system/teacher provides students with a beginning research question (see Bonnstetter, 1998; Magkouta et al., 2024). Across all definitions, however, the crucial aspect of inquiry-based instruction is that not all information to be learned is given to the students; they must infer, induce, or draw conclusions about information from the data or other sources that they generate (de Jong et al., 2024; Lombardi et al., 2021).

In contrast, in direct instruction (see Engelmann (1980) the initiative is always with the teacher (or method), and all information to be learned is presented explicitly to the student. This does not mean that direct instruction does not stimulate student activity. In fact, Spencer (2021, p. 822) listed as one of the key principles of direct instruction: "Prioritize learner responding and minimize teacher talk." However, in direct instruction, it is essential that before students practice a skill (often problem solving) themselves, this competence is modeled by the teacher, and errors should be avoided during the learning process. In direct instruction, student errors are prevented by moving only gradually from teacher-demonstrated (problem solving) skills, through guided practice, to independent practice (Rosenshine, 2008). Errors are also avoided by breaking larger skills into subskills that are practiced until they are mastered before being assembled into larger skills (Magliaro et al., 2005) and by connecting the tasks to be performed with students' prerequisite knowledge (Stockard et al., 2018).

In the following section, we apply certain principles of direct instruction to (guided) inquiry learning. One complicating factor in doing so is that direct and inquiry-based instruction often have a different focus. Direct instruction is often geared towards acquiring specific (basic) competences (e.g., solving physics problems), whereas the focus of inquiry-based instruction is often the acquisition of deep conceptual knowledge as well as higher-order thinking skills (like inquiry skills or self-regulation skills). In this article we focus on domain knowledge as the target learning outcome and, we will see that, in this context, many

principles of direct instruction are fully compatible with inquiry-based instruction. We will illustrate these considerations with examples from a number of disciplines (mathematics, biology, chemistry, and physics) created in the Go-Lab ecosystem (de Jong et al., 2021).

## 2. The Go-Lab ecosystem

The Go-Lab ecosystem is an online system for designing, developing, and delivering what are known as Inquiry Learning Spaces (ILSs) for science domains (de Jong et al., 2014; de Jong et al., 2021). The center of an ILS is an online laboratory, such as the physics-related laboratories from the PhET collection (Wieman et al., 2008). In an ILS, these online labs are included in an inquiry cycle in which students go through different phases, and are combined with other multimedia material (text, videos) and Go-Lab apps. The Go-Lab apps can be dedicated to the inquiry process (e.g., apps to create hypotheses or to design experiments), be of a more general character (e.g., a concept mapping tool), or have a learning analytics character (e.g., an app showing a student's timeline through an ILS in comparison to the timelines of other students). Teachers can adapt the phases students follow, include labs and multimedia material, and include apps that can be configured and (partially) pre-filled with content. Fig. 1 shows an example of a Go-Lab ILS as a student might see it.

In Go-Lab, an inquiry cycle guides the students through the inquiry process. The default inquiry cycle in Go-Lab follows a number of phases that were extracted based on an analysis of a large set of inquiry cycles (see Pedaste et al., 2015). It consists of the following phases: Orientation (students acquire a basis for the inquiry process), Conceptualization (students think about the underlying theory and set up research questions and/or create hypotheses), Investigation (students conduct experiments with digital laboratories to gather data), Conclusion (students draw conclusions about their theoretical considerations on the basis of the data gathered), and Discussion (students reflect on their inquiry process and share their considerations and conclusions with others). These phases are depicted on the left side of the interface, as shown in Fig. 1. In this paper, we will use this default Go-Lab inquiry cycle to frame principles of direct instruction within an inquiry approach and
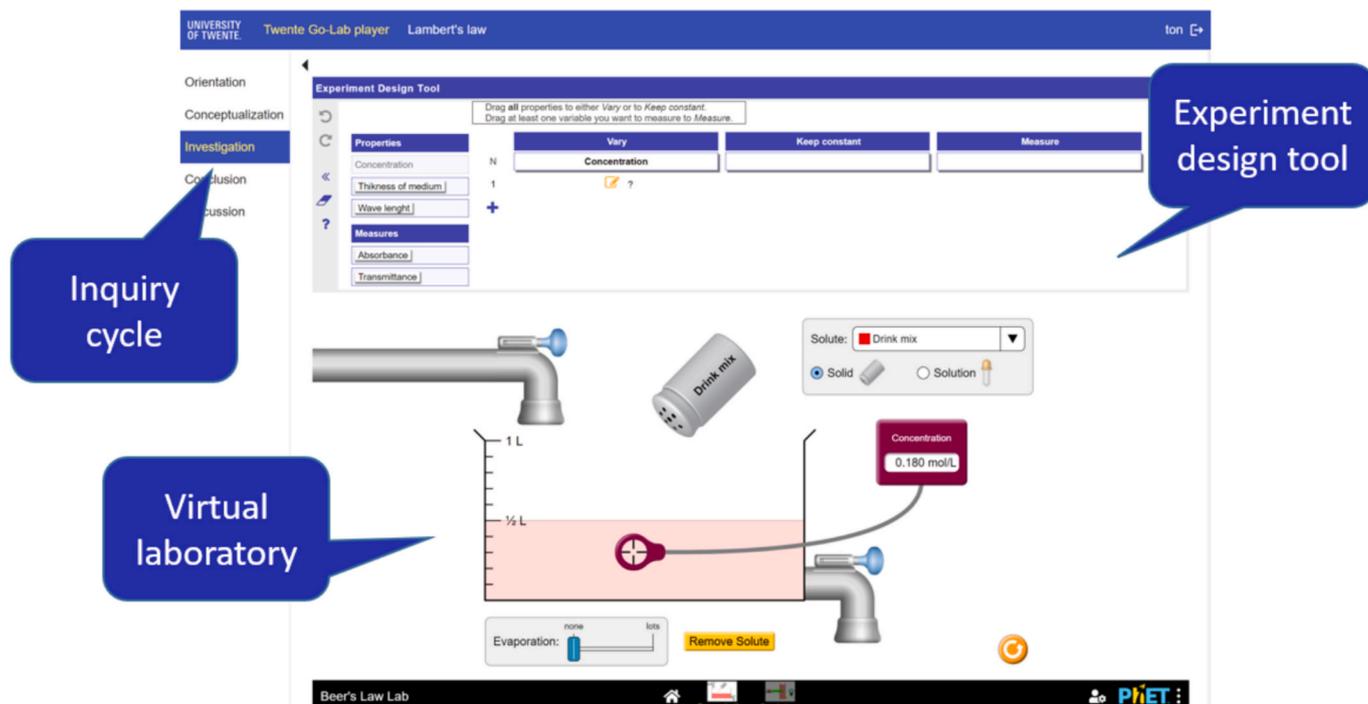


**Fig. 1.** Interface of a Go-Lab Inquiry Learning Space (ILS), with a lab and experiment design tool included.

will illustrate this with examples from Go-Lab ILSs. However, every designer/teacher can use his/her own inquiry cycle to guide the students, as we will also see in the examples that follow.

## 3. Principles of direct instruction applied to inquiry-based instruction

In the current section (and subsections), we will explore how a set of principles of direct instruction can be applied to inquiry-based instruction. This does not include one of the main principles of direct instruction, namely, that every piece of knowledge and every skill is presented or modeled by the teacher (or the book or any instructional medium), because that principle is not compatible with inquiry-based instruction, the central tenet of which is that students create essential aspects of knowledge themselves. In our exploration, we will focus on domain knowledge as a learning outcome, because that is a shared goal of direct instruction and inquiry-based instruction, and not on learning scientific methods, which may be an additional goal of inquiry-based instruction.

Since there are many different operationalizations of direct instruction, we have created a synthesis of principles based on a set of key papers on direct instruction, including Gersten et al. (1987), Kim and Axelrod (2005), Kirschner and Hendrick (2020), and Rosenshine (2008). These principles of direct instruction are presented in the following subsections, together with ideas on how to apply these principles in inquiry-based instruction, and illustrated with a Go-Lab-based example.

### 3.1. Present objectives (learning goals)

One starting point in direct instruction is to make students aware of the learning objectives of a lesson or a course, so that they know exactly what type of performance is expected after the lesson or course is completed (Huitt et al., 2009). In fully student-controlled inquiry-based instruction, students can set up their own research questions and thus their learning objectives for learning domain content. Of course, some guidance for expressing learning objectives would be very helpful, but in this approach no learning objectives are given to the student at the start. In addition, in this type of inquiry-based instruction, initial learning

goals can evolve during the learning process, under the student's control. However, in many cases, making students aware of what should be known at the end can also be done in inquiry-based instruction, even in similar terms as in direct instruction. Informing students about what concepts they should be able to comprehend at the end does not interfere with an inquiry-based approach in which the route towards these learning goals is still open. For example, Hardy et al. (2006) designed an inquiry learning environment to foster elementary students' understanding of why objects float or sink. The guiding question was "Why does a ship of iron float?", and the environment showed students at the beginning of the inquiry activities what they were supposed to learn. In addition, students were further guided through the environment by subordinate learning goals in the form of research questions that built on each other towards an integrated understanding of the floating and sinking phenomenon. The most obvious phase in the Go-Lab inquiry cycle in which to present objectives (e.g., in the form of guiding research questions) to students is the *orientation phase*. This phase is at the start of an ILS and can be used to orient students to the specific learning goals of the ILS. Fig. 2 shows an example of how learning goals can be given to students at the start of an ILS. In this example from mathematics, the designer has renamed the orientation phase as "What do we want to find out?"

### 3.2. Relate to prior or prerequisite knowledge

In direct instruction, the activation of prior knowledge (what the student already knows about the topic to be learned) and prerequisite knowledge (the specific knowledge that is necessary for understanding the new knowledge) is seen as a critical condition for successful learning (see for example, Hattan et al., 2024). Therefore, prior and prerequisite knowledge need to be activated before new knowledge is learned, for example, in the orientation phase of an ILS (see e.g., Magliaro et al., 2005). Or, as Kim and Axelrod (2005, p. 114) put it: "New knowledge is built upon the review, application, and mastery of older knowledge." This starting point holds for inquiry-based instruction as much as it does for direct instruction. Despite the fact that the influence of prior knowledge on learning can be diverse (Simonsmeier et al., 2022), new

**Fig. 2.** Explaining the learning goals of an ILS to students during the orientation phase.

knowledge always builds on what students already know and needs to be integrated with existing knowledge (see e.g., Huynh & Yang, 2024; van Dulmen et al., 2023). Therefore, activation of prerequisite and prior knowledge is a general requirement for well-designed (inquiry-based or direct) instruction, and adapting the inquiry strategy to the level of prior knowledge is important. For inquiry learning, this principle was illustrated in a study by Perez et al. (2017), who compared students with low prior knowledge who learned much in a simulation on electrical circuits to students with low prior knowledge who did not gain much new knowledge. These authors found that the high-gain students chose to work on circuits that were less complex, thus staying within their own zone of proximal development. This demonstrates that in inquiry learning, students need to activate what they know and what they do not know to initiate an inquiry process that is appropriate for their level of prior knowledge. In guided and/or collaborative inquiry-based instruction, the role of prior knowledge may go even further. For example, van Riesen et al. (2018) found that students in an inquiry context needed enough prior knowledge to be able to profit from the guidance that was offered in that learning environment, while Gijlers and de Jong (2005) found that students' dialogue in collaborative inquiry learning was influenced by students' (differences in) prior knowledge.

There are many ways in which prerequisite or prior knowledge can be activated (for a number of examples, see Hattan et al., 2024). Techniques to elicit prior (prerequisite) knowledge that have been mentioned for direct instruction include studying contrasting cases (Schwartz &

Bransford, 1998), quizzes, and assessment tools (Magliaro et al., 2005). Similar techniques can be used in inquiry-based instruction. In Go-Lab, quizzes can be created with the Quiz tool.

Fig. 3 shows an orientation phase from an ILS about solving linear equations, with a diagnostic quiz that is designed to measure and activate students' prerequisite knowledge necessary for solving linear equations in one variable. This phase aims to elicit learners' existing cognitive structures so that subsequent phases can be built meaningfully upon them. The quiz focuses on foundational concepts such as arithmetic operations, the order of operations, the concept of equality, and basic one-step equation solving, all of which are critical precursors to successful equation manipulation. Each item is designed either to surface with a core concept or to reveal a potential misconception. The results inform both students and teachers about learning needs, and they also prime students cognitively for the upcoming tasks in the conceptualization phase.

As another example, teaching about photosynthesis requires that learners have knowledge about cells, and, more specifically, about plant cells (Bransford et al., 1999). Moreover, understanding that chloroplasts are present in the green parts of the plant—and not in other plant tissues or animal cells—is prerequisite knowledge for comprehending photosynthesis (Ross et al., 2006). Additionally, the concept of energy, particularly the conversion of solar energy into chemical energy, plays a critical role in grasping this biological process (Bransford et al., 1999). A specific way to activate students' prior knowledge is to ask them to



**Fig. 3.** Assessing and activating the student's prerequisite knowledge with a quiz.

create a concept map. In a concept map (which can be partially pre-structured), students can show their prior or prerequisite knowledge by linking concepts through directed relations. An advantage of concept maps is that they can be automatically analyzed (see for example, Kroeze et al., 2021), which opens up ways to further structure the ILS on the basis of students' prior knowledge. Fig. 4 gives an example of a semi-structured concept map related to the biology topic of photosynthesis. The tool also offers several concepts (e.g., sunlight, water) and links (e.g., uses, contains, produces) for students.

### 3.3. Wonderment

Getting students' attention at the start of the learning process is often mentioned as part of a direct instruction strategy (Magliaro et al., 2005). And indeed, an important condition for learning and for making students willing to learn is to increase their attention and interest by using techniques that evoke wonderment. Wonderment goes together with curiosity and emotional excitement (Gilbert & Byers, 2017). In recent work, Kang and Kim (2024) showed that students' temporary curiosity state (wonderment) in STEM fields is a more important and direct influence on learning than longer term characteristics such as science curiosity and interest. It is, therefore, vital to stimulate students' wonderment right at the start of the learning process, again in the orientation phase. There are several ways to arouse students' wonderment at the start of an ILS. One is to present students with a phenomenon that seems illogical or counterintuitive and to ask them for an explanation of this phenomenon (Schraw & Lehman, 2001). The idea is that students will then become aware that they do not have a good explanation and will be motivated to seek one. Fig. 5 shows an example of such a surprising phenomenon for the physics topic of light refraction.

Wonderment can also come in the form of a question. Sensory perception is known to cause difficulties for the accurate scientific interpretation of natural phenomena (Driver et al., 1994), as when students think that plants, among other things, feed on the soil (Wandersee & Schussler, 2001) that they see them rooted in, which forms a consistent explanatory framework. Hence, the question "How do the water lilies we see on the surface of river water grow?" can "rock the boat."

Another way to raise (and keep) students' interest is to embed the content in a story or game-like situation in which students must use domain-related information to meet a challenge (see for example, Hamari et al., 2016). Creating this kind of "suspense" helps to raise students' interest (Schraw & Lehman, 2001). An example of this from chemistry is given in Fig. 6. In the ILS presented in this figure, students are confronted with a mysterious situation in a fictional case: Chemical substances have gone missing from the school laboratory, and only a broken bottle remains as evidence. Although several students claim they had permission to take certain chemicals, their accounts conflict. Acting as trainee chemists, students must investigate the clues and use their chemical knowledge to determine which substance was spilled, stimulating curiosity and engagement through a narrative challenge. While solving the case, they learn which bonds are broken during evaporation, how molecular mass relates to the boiling points of nonpolar substances, why isomers have different boiling points, and how hydrogen bonding influences boiling behavior.

Yet another way to motivate students is to let them see in an investigation how predictions based on misconceptions prove to be wrong. This may make students wonder and may be a motivation to find out why these predictions are wrong. An example can be found in a recent publication by van der Linden et al. (2024). In using an educational game on the physics topic of Newtonian mechanics, they started by letting the students explore different, preset situations that potentially were counterintuitive for them, for example, when they see an acceleration after applying a force that exceeds friction, instead of a deceleration. Similar techniques can be used in Go-Lab, potentially using the digital laboratory that is also used in the investigation phase, but with preset values that will show students results that are expected to go against their prior knowledge.

### 3.4. Structuring the learning sequence

A central design principle in direct instruction is that the knowledge or (problem solving) competence that needs to be known or mastered at the end is divided into smaller, manageable elements that are offered and practiced separately. Students therefore learn by taking small steps, avoiding making errors and acquiring full mastery of what is addressed in each intermediate step (Gersten et al., 1987). Dividing the overall task into smaller tasks is sometimes called "thin-sliced tasks" (To, 2024). In this context, Rosenshine (2008) recommended initially reducing the difficulty of the task for the students. A way to reduce task complexity without pre-structuring students' learning path is to tell them to focus their inquiries on the role of a single variable at a time. Kuhn and Dean
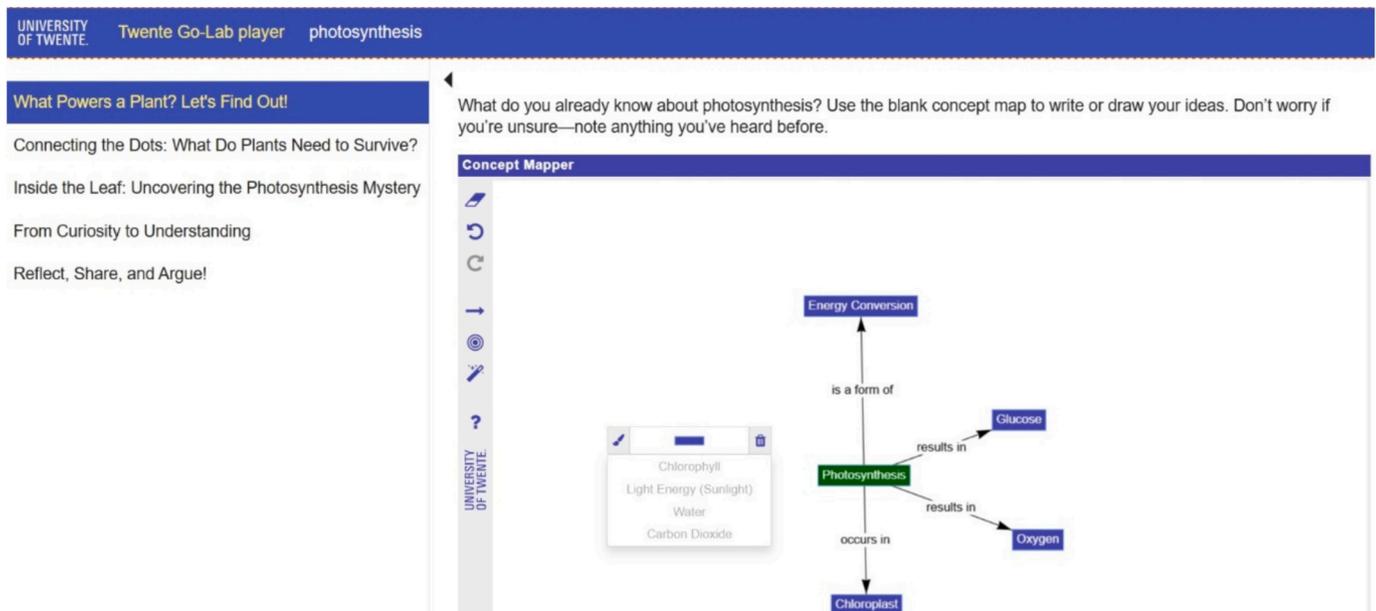


**Fig. 4.** Example of a Go-Lab concept map in the making.

**Fig. 5.** Example of a surprising phenomenon.

(2005) used such general prompts in digital learning environments on variables impacting earthquake risk. They found that students who received such prompts (suggestions as they were called by the authors) conducted more controlled comparisons and were more successful in finding the correct variables. Such general prompts are easy to implement in an ILS because they do not require any knowledge about specific students or the content of the ILS.

However, careful sequencing of knowledge or tasks based on an in-depth content or task analysis (Slocum & Rolf, 2021) can also be used to manage the sequenced knowledge building of students. The work by Schramm et al. (2018) provides an example of this in inquiry learning. These authors created a learning sequence for the domain of carbon-transforming processes, with the learning progression taking place over four different key ideas and levels of reasoning about them. In this way, students were taken over all the different topics and gradually moved to more difficult levels of reasoning. This approach is related to the work on "science learning progressions" (see e.g., Duncan & Rivet, 2013; Jin et al., 2024), which also advocated the careful and structured sequencing and assessing of content over time, often organized around what are called "big ideas." Although science learning progressions focus on the sequencing of content over the span of a curriculum, this idea can also be applied to a single lesson or Go-Lab ILS.

As an example, Fig. 7 shows an ILS on photosynthesis in which a sequence of experiments has been pre-structured for the student. This is reflected in the phases of this ILS, shown to the left. In the "Experiment with a green plant" phase, students can simply experiment with what will happen with $O_2$ and $CO_2$ levels over time. They can insert and remove a plant (sun or shade plant or fungus) in a closed space where light is entering. In the phase called "Intensity and color of light," they can start changing the light intensity and frequency and see how this affects photosynthesis. After that, they can manipulate the temperature and see the effect of this on photosynthesis. Finally, they can include a living organism in the space and see how this interacts with the plant with regard to the resulting $O_2$ and $CO_2$ levels. In this way, the student is gradually taken through the content and can focus on specific variables one by one. For a similar example, see Fermani and Georgiou (2023).

A specific way to sequence content is to gradually increase the complexity of the lab (or labs) that the students are working with in an ILS. In this way, students will not face the model's full complexity at once; they only move to the next level when they understand the previous one. An example can be found in an ILS on the physics topic of Newton's laws that demonstrates a model progression approach used in three steps of the investigation.

Fig. 8 presents the first step (Force in Action: What If Nothing Acts?) of this ILS. In the first model progression step, students are provided with a partial hypothesis that they have to complete to start investigating the motion of an object under zero net force using the Graphing Motion Lab. This first step is expected to help learners build an initial understanding of uniform motion consistent with Newton's First Law. In the digital lab, students can collect data from the simulation of a boat moving at near-constant speed, which they can later use to construct position–time graphs. They will simply observe the boat with two different paddle strengths, "Achillean" and "Herculean."

In the next step (More Force, More Speed?), another digital lab is presented in which students can change the force and mass of an object and observe the effect of changes in these two variables on the motion of the object. This step aims to help students understand the proportional relationship between force and mass as described by Newton's Second Law ($F = m*a$). The task is intentionally designed to be more complex than the first one. Students now consider two variables and observe how they interact to affect the acceleration.

In the third step (Tug-of-War: When Forces Compete), the complexity increases by including multiple opposing forces and friction. In this "tug-of-war" simulation, students examine net force outcomes under various balanced and unbalanced conditions. Students are required to calculate net force, determine the resulting motion (e.g., acceleration, stopping, or constant speed), and record these findings in a table. This final step helps students build a more realistic conceptual understanding of

**Fig. 6.** Presenting students with a challenge to raise interest and motivation.

everyday physical interactions. Fig. 9 illustrates a component of the third step in the model progression.

Together, these different steps and investigations move from simple to complex representations, which is close to what authors such as Swaak et al. (1998) and Mulder et al. (2011) called "model progression." This approach supports students in gradually deepening their conceptual understanding of Newtonian mechanics.

In inquiry-based instruction, introducing a learning sequence can also ensure that students cover all important aspects of a domain during their inquiry. If exploring a domain is just left to the students, they may miss information. For example, they may not set the temperature variable to below zero in a model that includes water. Coverage of important aspects can be accomplished by giving the students sequences of assignments that let them explore (combinations of) specific variables or specific values of (combinations of) variables. In Go-Lab, these assignments can be given as textual (or multimodal) instructions, and they can be offered based on students' behavior in the ILS or digital lab.

### 3.5. Guided practice

Guided practice in direct instruction is the principle that students receive (immediate) feedback on their performance until mastery is reached (Gersten et al., 1987). If this concerns a competence (as is often the case in direct instruction where problem solving performance is mostly aimed at) and students are not able to exercise the competence on their own, the feedback can consist of the teacher (or software)

modeling the competence (again). If it concerns knowledge (which is often the focus of inquiry-based instruction), the feedback cannot be just telling students the correct knowledge, since the idea of inquiry is that students find that knowledge themselves. An alternative form of support, therefore, is to give students an assignment to perform a specific experiment geared towards the student's specific incomplete knowledge or misconception. For example, to address students' preconception that the mass of objects is causing their floating and sinking, a student can test this idea by comparing the floating and sinking behavior of bodies with the same mass but different volumes to discover that the mass in relation to the volume is what causes this behavior (Hardy et al., 2006).

A challenge here for both direct and inquiry-based instruction is to constantly measure students' level of performance. If a teacher is managing a whole class, such ongoing individual assessment is (almost) impossible. The use of software (such as Go-Lab) helps by conducting individual assessments automatically or by providing teachers with a dashboard showing their students' evolving knowledge.

There are several ways to gather information on the progress of students' knowledge in Go-Lab. First, students can be provided with intermediate quizzes. Second, several apps also give a window on what students know. These include making a concept map (see also Fig. 4) or, for example, the "Observation Tool", which is a simple open-ended textbox that students are asked to fill in after they have done a (series of) experiment(s). Go-Lab has a few more open-ended text field apps, such as the (Shared) Wiki and the Conclusion Tool, in which students can be asked to express their knowledge. Other apps that can be used to

**Fig. 7.** Example of an ILS showing how to structure content following a specific sequence.

measure students' knowledge are the "Fill in the Gap" app, where students have to complete sentences, and the "Name the Frame" app, in which labels need to be dragged to certain parts of a figure. Student input in these last two apps can be assessed in a very straightforward way, but in principle it can also be assessed automatically in the more open-ended apps such as the Concept Mapper and the text-based Observation Tool (see for example, Gao et al., 2024; Kroeze et al., 2021).

Modeling of the inquiry process is guidance that is specific to inquiry-based instruction. An example here can be found in the Conceptualization phase, in which students have to create hypotheses. Teachers/designers can include the Hypothesis Scratchpad and provide students with conditionals (if, then), relations (is larger than, increases), and variables (depending on the domain). All these terms are configurable by the teacher. However, the teachers/designers can also present full or partially filled-in hypotheses to the students, and in this way model the hypothesis generation process (see, for example, Kuang et al., 2020). The ILS presented in Fig. 8 gave an example of such a partial hypothesis. A similar approach can be used when students plan their experiments with the Experiment Design Tool. Here the teacher/designer can present students with fully or partially specified experiments.

### 3.6. Review and reflection

In direct instruction, it is often recommended that learning task completion be followed by a review. This means that once students have completed (a subsection of) the learning task, they must rethink what

they have done and learned (Gersten et al., 1987); possibly an expert model will again be presented summarizing what was covered (and supposedly) learned (Rosenshine, 2008). Indeed, there are indications that reflection helps to improve inquiry learning processes and outcomes (Mäeots et al., 2016), and it can take different forms (Runnel et al., 2013).

In Go-Lab, students can use the Conclusion Tool to draw final conclusions by confronting their initial hypotheses with data and/or observations they have collected in previous phases. In this tool, students can select one of their previously made hypotheses and select data they collected or observations they made after experimenting that they think are relevant for this hypothesis, and they can write their conclusions about the hypothesis next to it. In this way, students need to think explicitly about their initial ideas and how these possibly may have changed. Another possible summative reflection exercise is to have students create a final concept map and display it in the Aggregated Concept Map. The Aggregated Concept Map shows an individual student's concept map in relation to the concept maps of other students in their group. In this way, students can reflect on what they have learned differently (in terms of concepts added or relations drawn) than others in their peer group. Of course, this group concept map can be replaced by an expert concept map as well.

## 4. Individual differences

Introducing principles of direct instruction in inquiry-based

Fig. 8. First step in a model progression ILS on Newton's laws.

instruction may be beneficial to all students, but some may benefit more from this than others. A recent meta-analysis, for example, made it very clear that students with lower prior domain knowledge profit from instructional assistance, whereas students with higher prior domain knowledge flourish under low-assistance conditions (Tetzlaff et al., 2025). Empirical findings have also shown that direct instruction is particularly effective for less privileged or underachieving students (Lorch et al., 2010). In general, inquiry-based instruction better suits students who are higher in the spectrum of knowledge and abilities. We may, therefore, assume that introducing principles from direct instruction into inquiry-based learning environments may be more helpful for lower achievers than for higher achievers.

Inquiry-based learning is an approach that offers opportunities to cater to individual differences due to its more open character, as it allows for different learning routes and pacing of the learning. Some principles from direct instruction, such as setting learning goals, may reduce the flexibility that inquiry-based instruction offers. Other direct instruction principles, however, may extend the potential of inquiry-based instruction. For example, continual assessment of student progress and tuning the guidance to the results of this assessment enables

provision of dedicated support in students' inquiry process (Schlatter et al., 2020). In this way, guidance of students may be adapted to their ability levels (van Dijk et al., 2016). Assessing students' prior and prerequisite knowledge may also help to adapt the learning environment to students' knowledge differences (Liu et al., 2008; Roll et al., 2014; van Riesen et al., 2022). Using Learning Analytics techniques to show individual learning paths gears reflection towards students' personal learning trajectories, which may differ between students.

In inquiry learning, students must set their own goals, ask questions, monitor their progress, make decisions on how to proceed throughout the process, and challenge their own learning outcomes in reflection. These learning activities are obviously the most difficult for students with low self-confidence, high anxiety, and low self-efficacy. Hong et al. (2017) showed that students with high self-confidence gained the most knowledge in an inquiry-based learning environment. England et al. (2019) concluded that, for a biology course, class anxiety negatively impacted students' performance. Vitasari et al. (2010) found that anxiety level and poor academic performance were (modestly) correlated; in addition, active learning could raise students' anxiety level (Cooper et al., 2018). Ketelhut (2007) found that the initial level of self-efficacy

**Fig. 9.** The third and final step in an ILS using model progression for Newton's laws.

for students learning in a simulation-based inquiry environment positively influenced their inquiry process, but also that self-efficacy had improved after inquiry learning. Applying principles from direct instruction to inquiry-based learning introduces structure and monitoring facilities, which may be most beneficial for students with low self-confidence, high anxiety, and low self-efficacy. Wang et al. (2021), for example, showed that providing students with metacognitive support during inquiry learning, including support to monitor progress, helped to improve students' level of confidence.

In addition, metacognitive skills are essential for effective learning because they enable students to monitor and regulate their cognitive processes, thereby improving their comprehension and problem-solving abilities (Flavell, 1979). In a recent paper, Chen & Chen, 2025 (in press) discussed the potential of learning analytics to improve inquiry learning. Go-Lab also includes a set of Learning Analytics Tools. These tools present students with an overview of their behavior in the ILS, often in comparison to (an average of) the (anonymized) behavior of their class. These behaviors include students' activities in the different Go-Lab apps, the time spent in the different phases of an ILS, or the transition between phases over time. These overviews can be coupled with a reflection component in which students are guided in their reflection by specific teacher-defined questions (see Fig. 10 for an example). These structured supports, such as goal-setting, progress monitoring, and guided reflection, not only help students with low self-efficacy, but also promote the development of metacognitive skills, which are essential for effective and autonomous inquiry learning.

## 5. Discussion

The argument that is often used for preferring direct instruction over inquiry-based instruction is that this approach fits with cognitive load theory, so that students do not overtax their cognitive resources when following direct instruction (Sweller et al., 2024). Direct instruction lowers cognitive load and thereby is effective teaching, but it comes with the risks of teaching the wrong knowledge to learners, for example, by not addressing individual students' misconceptions. Inquiry learning instead offers room for individualized learning goals and pathways, but requires prerequisite knowledge and skills, so that it comes with the risk that students will not learn much if they lack these prerequisites and are not properly supported. Combining both approaches in an individualized way, by alternating them or by just-in-time direct instruction, thus offers the opportunity to overcome the limitations of both approaches (de Jong et al., 2024). In addition, as was the core of this paper, combining inquiry learning with principles of direct instruction that do not concern directly explaining the content can help to improve inquiry-based instruction, especially for students with low prior or prerequisite knowledge and students who have low self-confidence, high anxiety, and/or low self-efficacy. We therefore claim that a purposeful choice of principles from direct instruction can make inquiry learning accessible and productive for more students. The principles of direct instruction that we discussed aim to avoid cognitive overload for the students. Examples from learning arrangements in different disciplines created with the Go-Lab ecosystem were used to illustrate the application of these
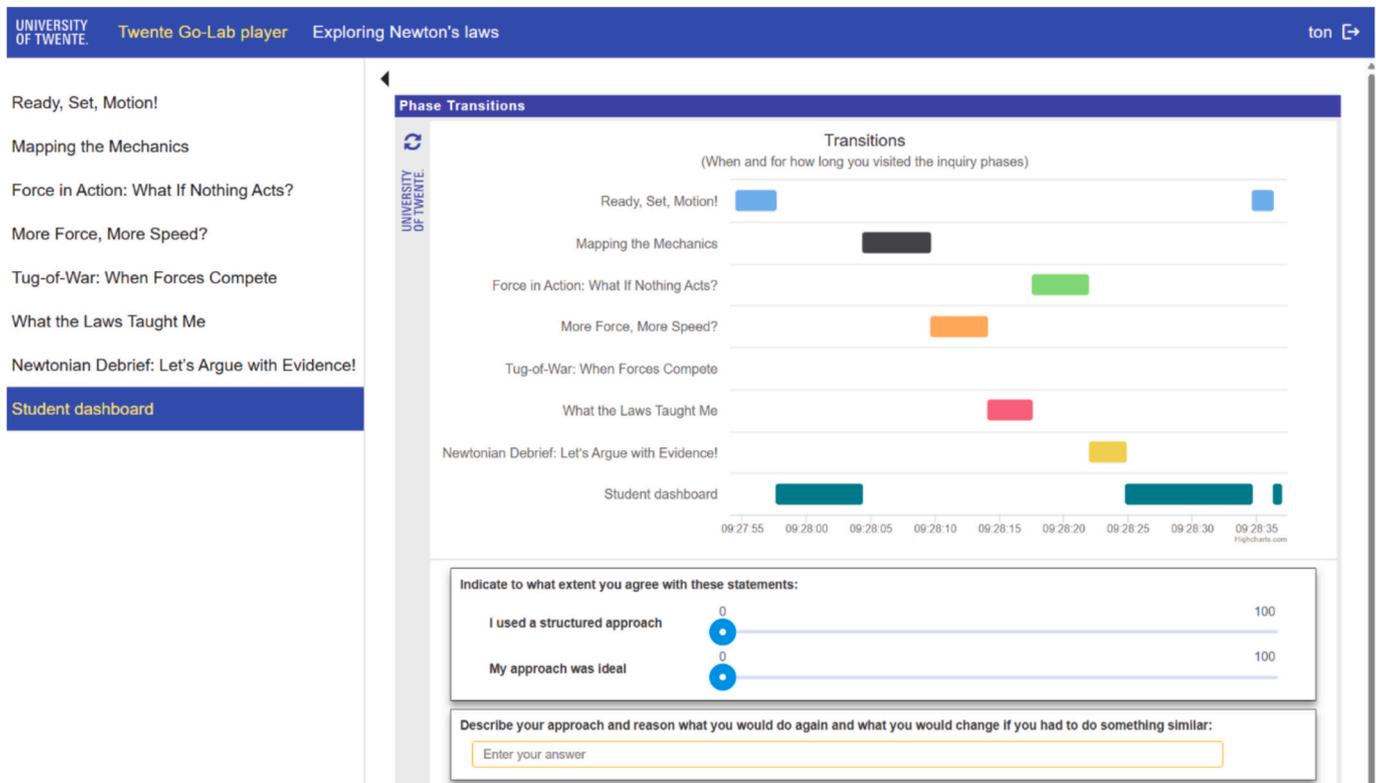
**Fig. 10.** Example of a Learning Analytics tool in Go-Lab with reflection questions.

principles in inquiry-based learning.

These principles for design covered several phases of the Go-Lab inquiry cycle. They should be implemented for the specific topic of an ILS before giving the ILS to students. This can be a time-consuming process, but it can be facilitated by the use of AI-based systems. A recent paper by Moundridou et al. (2024), for example, illustrated how GenAI tools can be used to make content for the different Go-Lab phases. Another aspect in which AI can play a role is assessment of the student's developing skill (competence) or knowledge to adapt the ILS to individual differences. Having these assessments is the necessary first step for providing students with immediate and personalized feedback in both direct and inquiry-based instruction. Digital learning arrangements such as Go-Lab ILSs are very rich sources of information that can feed AI systems for these diagnostic and feedback tasks. Information resources from ILSs include: a) information about students' navigation through the ILS; b) students' activities (variable manipulations, data configurations) in online laboratories; c) students' inputs in Go-Lab apps, including students' hypotheses, experiment designs, concept maps, conclusions, and observations; and d) students' chats when the ILS is collaborative. All of these types of information can be used to make a solid assessment of students' current knowledge state, which can then be used to suggest activities to the students (Gao et al., in press; Kubsch et al., 2024). Currently, there is much focus on the analysis of students' text inputs, for example, when giving explanations of phenomena (see e.g., Hee-Sun et al., 2024), but as the above lists exemplify, environments such as Go-Lab contain much richer information about students' conceptual states. This is comparable with a system such as Inq-ITS, in which a diverse set of students' activities and products (e.g., their manipulations of a digital lab and analysis of gathered data) are used to steer guidance using AI techniques (Gobert et al., 2024). Moreover, this feedback is not restricted to skills and knowledge; if students act collaboratively, it can also be applied to their communicative performance (de Araujo et al., 2023, 2024, 2025). Feedback or feed-forward that is based on cognitive measures can be enhanced when these measures are complemented with

data from physiological measures, such as eye tracking or captures of facial expressions (Sharma & Giannakos, 2024).

In conclusion, principles of direct instruction can be used for the design of inquiry-based learning environments in order to align inquiry with cognitive load theory. Modern, AI-based technology can help to create digital learning environments in which these designs can be realized, so that instructional design can take advantage of the best of both worlds, inquiry-based and direct instruction.

**Declaration of competing interest**

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The labs displayed in the figures come from different sources. The labs in Figs. 1 and 9 are from the PhET collection, while the lab in Fig. 8 was designed by Frank McCulley. The ILS shown in Fig. 2 was made by Sharanya Lal, Ydalia Linares Perez, and Ruyi Zhao.

## Declaration of usage of AI

For creating the abstract of this article the authors used Co-Pilot. After using this tool, the author(s) reviewed and edited the abstract as needed and take full responsibility for the published abstract. The image in Figure 6 was created with the help of ChatGPT.

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