Organisation for Economic Co-operation and Development

PISA 2025 LEARNING IN THE DIGITAL WORLD FRAMEWORK (SECOND DRAFT)

October 2023

OECD member countries and Associates decided to postpone the PISA 2021 assessment to 2022 to reflect post-Covid difficulties. This in turn postponed the PISA 2024 assessment to 2025.

Tables

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PISA 2025 Learning in the Digital World - FAQ

What is the purpose of the PISA 2025 LDW assessment?	1) To understand whether students can solve problems using computational tools and practices in digital learning environments (LDW cognitive test); 2) To provide comparable evidence on the use of digital technologies at school (PISA questionnaires) and how these technologies are associated to learning outcomes in traditional (PISA core domains) and computer-intensive learning areas (LDW test).
What does the LDW assessment measure?	The construct involves both computational problem solving (i.e. the ability to build step-by-step solutions that can be executed by a computer) and self-regulated learning (i.e. the ability to effectively manage one own's learning process). The assessment will provide comparable metrics on what types of problems students are able to solve using digital tools, and how well they use learning resources (e.g. tutorials, worked examples, intelligent feedback) and engage their motivation to make progress through the tasks.
What does the LDW assessment NOT measure?	Although an important aspect of learning in the digital world, the PISA 2025 test will **not** measure students' ability to search for and evaluate online information.

What are the key features of the LDW assessment?	• In each unit, students learn to use a new computational tool either for instructing a digital agent, creating a computer model of a complex system, or collecting and analysing data with simulations.
	• 30-minute units broken down into four distinct phases (Show, Learn, Apply and Reflect). The "Show" phase measures what students already know. The "Learn" phase includes a tutorial and a progression of 3 tasks where students practice specific concepts and operations. Students apply what they practice in a more complex task in the "Apply" phase. The units also include some self-reflection questions.
	• Students have access to **examples, automated feedback and annotated solutions** to help them learn.
	• Partial credit scoring will reward students for productive work towards a solution, even if they do not solve the task. The open-ended tasks are designed to have a **"low floor, high ceiling"** to accommodate learners with varying levels of proficiency.
	• Multidimensional reporting:
	    ○ PISA scale on students' ability to solve computational problems
	    ○ Learner profiles, describing how students across countries engage in self-regulated learning while working through complex problems

How will the LDW test be administered?	The computer-based LDW test uses automated scoring (no human scoring required). The complexity and timing of the unit phases have been adjusted based on data collected during two rounds of cognitive laboratories and pilot studies in diverse countries (Australia, Bulgaria, Chile, Colombia, Germany, Norway, Spain, United States).

PISA 2025 Learning in the Digital World Assessment Framework (Second Draft)

1. Introduction: The importance of learning in the digital world

1.1. How is learning changing in an increasingly digital world?

1. Learning is an active and participatory process. It can take many shapes and forms but deeper learning – applying concepts, relating relevant ideas and extending them to other areas – depends on learners taking an active role in developing their emergent knowledge and understanding. Over the past decade, some disciplines – particularly science, technology, engineering and mathematics (STEM) subjects – have shifted from "learning about" towards "doing", in turn promoting more active inquiry- and problem-based contexts of learning and practice (OECD, 2019[1]).

2. Digital learning technologies are fundamentally transforming how people learn: they deliver significant autonomy to learners, shape the way that people interact with information and learning resources, and deeply influence how we make sense of our reality. They also combine human inquiry with computing power, enabling (among other things) new and more powerful forms of independent learning and problem solving. Computational tools allow learners to build tangible representations of their emergent understanding and ideas, like computer programs or models, that can be used to iteratively develop solutions to problems. These tools radically expand the ways in which individuals can explore and experiment with their ideas and understanding, in turn providing opportunities for more active and authentic learning experiences.

3. Harnessing the power of computational technology has proven exceptionally productive for advancing knowledge and solving complex problems in several fields – from the sciences (e.g. DNA sequencing and editing) to the humanities (e.g. dating ancient objects) and from the professional sphere (e.g. analysing large datasets) to the everyday personal (e.g. planning a journey). In the education community, computational tools and applications like Scratch, NetLogo and Code.org have established global learning communities. Millions of secondary (and primary) education students and practitioners engage with these tools to actively explore and visualise complex concepts and to build, create and share personalised objects of their learning.

4. Learning and problem solving will increasingly involve technology in both formal and informal contexts. Developing skills for learning and problem solving with technology is therefore a major premise for young people's successful participation in all spheres of life, including their educational, social, cultural, civic and future professional lives. Research has also shown that being able to productively use digital tools to solve problems can promote other areas of personal and social development, including learner agency, coping with failure to achieve success, and a mind-set of creativity, curiosity, openness, and persistence (Clapp et al., 2017[2]).

5. Despite its potential for student-centred learning experiences, instruction on how to use digital technology often focuses on narrow aspects of computer literacy. Students can encounter significant challenges related to how they manage their own learning processes when engaging in inquiry- or discovery-based learning with technology. Being a good self-regulated learner is therefore particularly important in open and interactive digital environments that invite students to construct their own understanding.

1.2. Why assess learning in the digital world in PISA?

6. The PISA 2025 assessment will provide internationally comparable insights on how well students can engage in an autonomous learning process using computational tools to solve problems and build their knowledge and understanding. Students will solve problems in open, scaffolded and interactive learning environments with computational tools and learning resources. The assessment is grounded in a social constructivist approach that emphasises the active and iterative process of learning by interacting with external tools and resources. In each 30-minute unit, students will progress through increasingly complex tasks to demonstrate how effectively they can combine what they already know and can do with the learning opportunities afforded to them by technology.

7. The focus on autonomous learning skills of this new assessment aligns closely with the goals of 21st century education, as defined in the OECD Learning Framework 2030 (OECD, 2019[3]). The assessment will produce multi-dimensional measures of performance that can better reflect than one single score point on a scale what students can achieve in real-life situations where opportunities to learn with technology are available.

8. Many countries have also made large investments in digital education in recent years, accelerated by the global COVID-19 pandemic that forced school closures and mass shifts to online learning affecting millions of students around the world. Yet the global education community lacks evidence on whether these investments have been productive for learning and whether education systems sufficiently prepare students to be able to learn autonomously with technology. Research and data underline that technology itself does not guarantee effective and deeper learning outcomes – indeed, a striking finding from PISA data is that students who report using computers very frequently at school perform worse in most learning outcomes than other students, even after accounting for students' socio-economic background. This finding points towards large asymmetries in the quality of digital education – both between and within countries – and that we need better data and research on how technology is used in the classroom by students and teachers.

9. The PISA 2025 assessment will provide direct measures of the skills students need for learning with technology, combined with more comprehensive contextual information on the digital learning activities that students engage with both inside and outside the classroom. It provides a unique opportunity to measure and compare the effectiveness of different national approaches on digital education and student learning outcomes, addressing the lack of internationally comparable evidence on this important topic. High quality data collection instruments and analysis can guide policy makers in the transition to digitally empowered education and help teachers to better integrate technology in the classroom.

2. Theoretical perspectives on learning in the digital world

2.1. A grounding in social constructivist theory

10. Constructivist learning theories centre on the idea that learners actively construct and reconstruct their knowledge base (Bodner, 1986[4]; Collins, Brown and Newman, 1989[5]). Constructivism evolved from the works of Jean Piaget (1971[6]; 1976[7]) who considered knowledge to be the product of personal experience, where new information is incorporated into one's pre-existing knowledge and mental schemas, instead of the product of information that is received, encoded, memorised, retrieved and applied (Ackermann, 2001[8]). This fundamental idea is reflected in modern approaches to teaching and

instructional design (e.g. student-centred pedagogy, inquiry-based learning, "learning-by-doing", etc.) that do not view learners as empty vessels into which "ready-made" knowledge can be poured but instead stress both the active role of learners in building their own representations and meanings and the importance of their prior knowledge and experiences. Instruction is thus a directed process of supporting learners to construct their own knowledge rather than the transmission of knowledge by a teacher to be consumed by learners.

11. Social constructivists extended these ideas to emphasise the importance of social context and interaction in learning. Social constructivism views learning as a situated process that is intimately tied to the socio-cultural context of an individual's experiences. Knowledge is not constructed individually in a vacuum but rather "co-constructed" through socially negotiated interactions with other people or objects. Any learning experience is therefore mediated by the tool(s) and method(s) of communication involved in such interactions. According to (Vygotsky, 1978[9]), the "zone of proximal development" represents the gap between what an individual knows and can do independently and what they are able to learn from others – especially those that are more knowledgeable.

12. Constructionism shares these views of learning but emphasises the importance of building external knowledge constructions (Papert, 1986[10]). This is underlined by the belief that learning happens best when learners create tangible artefacts that represent their emergent knowledge and understanding, and that learners are most likely to become intellectually engaged when working on a personally meaningful project. During the process of building an artefact, a learner puts ideas, concepts and skills into action, and these further develop as the learner interacts with and iterates upon their artefact. Learners might also face unexpected problems throughout the building process for which they need to engage in complex (and perhaps multidisciplinary) problem solving.

13. In sum, these different constructivist perspectives on learning all emphasise:

- the active role of learners in constructing their own knowledge and understanding;
- the importance of critical thinking and problem solving in active learning;
- the importance of authentic learning experiences;
- the social negotiation of knowledge, and;
- the shifting role of teachers towards learning facilitators rather than disseminators of information (Kaffash et al., 2010[11]).

2.2. The digital world as a productive context for social constructivist learning

14. Digital learning environments provide particularly productive contexts for constructivist learning – but not all digitally-mediated experiences provide the same opportunities. In its broadest sense, information and communications technology (ICT) refers to the diverse forms of technology that are used to create, store, manage, communicate, share or exchange information. These include hardware (computers, tablets, etc.), the Internet, software applications, online platforms, intelligent tutoring systems, and other digital (or digitised) resources. The OECD PISA ICT framework (OECD, 2019[12]) defines three major types of ICT resources for teaching and learning:

1. Digital content (i.e. online courses, digital books and multimedia resources);
2. Communication and tracking tools (i.e. those that facilitate communication among schools, parents and students);

3. Virtual learning environments and intelligent tutoring systems (i.e. those aimed at helping students practice particular skills).

15. Other frameworks differentiate how ICT tools and resources are used in education for learning. Four typologies, summarised in Table 1, frequently emerge from the literature: 1) learning about technology; 2) learning with technology; 3) learning from technology, and; 4) learning through technology. Each typology describes an inherently different learning experience in which ICT plays more or less of a fundamental role in shaping students' learning opportunities and processes.

Table 1. Summary of different types of ICT use for learning in education

Typology of ICT use	Description
Learning about ICT	Using ICT in a disciplinary way to acquire operational ICT skills
Learning from ICT	Using ICT as a source of information and provider of digital (or digitised) content in multimedia formats (e.g. online courses, graphics, digital textbooks, etc.)
Learning with ICT	Using ICT in an interdisciplinary and functional way, generally as a communication medium (e.g. presentation device), to enhance existing curricula and pedagogical approaches.
Learning through ICT	Using ICT to transform how and what is learned, generally by providing experiential learning opportunities (e.g. virtual learning environments, intelligent tutoring systems) and/or by providing tools to create tangible products, reflect on ideas and collaborate with others.

Source: (Salomon and Perkins, 2005[13]; OECD, 2019[12]; Lloyd, 2005[14])

16. ICT-mediated learning experiences can therefore be viewed along a continuum, from less to more transformative (Mioduser et al., 2003[15]; Puentedura, 2011[16]). On one end, technology only substitutes or functionally enhances otherwise unchanged teaching and learning experiences, often to make it easier, faster or more convenient to teach in traditional ways (i.e. to deliver knowledge via the transmission model of teaching) (Maddux, Johnson and Willis, 2001[17]). In contrast, "transformative" uses of technology – learning through technology – enable new and better ways of teaching and learning that would otherwise not be possible. These uses best represent the kinds of active and participatory learning experiences emphasised by social constructivism by providing learners with interactive, knowledge-building tools and resources to support their cognitive and metacognitive processes. They can help learners to process and shape their ideas, providing scaffolding and feedback to assist learners through their learning process and illustrating concepts in a similar way to a "more knowledgeable" other (Mhlongo, Dlamini and Khoza, 2017[18]). Technology can thus enhance student-centred inquiry processes, problem solving and decision-making, enabling students to make mistakes, iterate, take responsibility for their learning outcomes, and develop into independent and self-regulated learners (Tubin, 2006[19]).

17. Technology particularly empowers learners when it allows them to manipulate and build computational artefacts. Digital environments with modelling and simulation tools allow learners to process, generate and visualise data on a scale and timeline that would otherwise be unimaginable, making complex concepts more accessible, as well as design computational solutions to problems. By providing tools that help learners process and generate information as well as build tangible representations of their emergent knowledge and ideas, "computers provide an especially wide range of excellent contexts for constructionist learning" (Papert and Harel, 1991[20]).

2.3. Learning, problem solving and computational thinking

18. Building computational solutions or artefacts in digital environments requires learners to instruct a computer to do something. This goes beyond their capacity to simply write and execute a program: learners must understand the reasoning behind the instructions they give to the computer and use relevant concepts and strategies purposefully and meaningfully. In other words, they must engage in computational thinking – an approach to problem solving that draws upon practices that are fundamental to computer science and that promotes a deep understanding of the entire problem-solving process (Wing, 2006[21]). Translating ideas into a tangible computational form enables learners to develop a deeper understanding of their own conceptual models and thought processes, and these tangible representations also enable educators to interpret where students are in their learning process and what knowledge they mobilised to get there (Valente and Blikstein, 2019[22]).

19. In education systems, science and mathematics curricula increasingly integrate computational thinking as a key competency, and building computational artefacts readily lends itself to learning and applying concepts and practices drawn from the wider STEM disciplines (Valente and Blikstein, 2019[22]; Zhang and Biswas, 2019[23]; Brennan and Resnick, 2012[24]; Sengupta et al., 2013[25]; Basu and Biswas, 2016[26]; Basu, Biswas and Kinnebrew, 2017[27]). In general, these disciplines share a core set of evidence-based reasoning and problem-solving practices, often discussed under the umbrella of scientific inquiry (Pedaste et al., 2015[28]), and for which computational tools provide new and more powerful opportunities. For example, computational models can simulate complex phenomena and support the experimentation of ideas that would be neither practical nor feasible to replicate in the real world (Weintrop et al., 2016[29]). Using computational tools for scientific inquiry aligns with contemporary approaches to STEM education that actively engage students with scientific ideas and practices in real-world contexts (Krajcik, 2015[30]).

20. Several educational researchers have developed digital learning environments and computational tools to foster students' computational thinking as well as their understanding of STEM concepts and practices. These include concept mapping environments (e.g. Betty's Brain, (Biswas, Segedy and Bunchongchit, 2015[31]), simulation environments (e.g. PhET Interactive Simulations, (Wieman, Adams and Perkins, 2008[32]); GoLabs, (de Jong, Sotiriou and Gillet, 2014[33]), interactive games (e.g. Crystal Island, (Rowe et al., 2009[34]); Mecagenius, (Galaup et al., 2015[35])), agent-based modelling environments (e.g. NetLogo, (Wilensky, 1999[36]); CTSiM, (Sengupta et al., 2013[25]; Basu et al., 2012[37])), and graphical programming environments (e.g. LOGO, (Papert, 1980[38]); Scratch, (Maloney et al., 2010[39])). In these types of environments, students learn and solve problems by creating computational models or other artefacts (Hutchins et al., 2020[40]).

21. These constructivist learning activities with technology also require students to engage in a process of self-regulated learning. Self-regulated learning refers to the monitoring and control of one's metacognitive, cognitive, behavioural, motivational, and affective processes while learning (Panadero, 2017[41]). In open digital environments with potentially large amounts of unstructured information, opportunities for exploration and distraction, students need to purposefully direct their actions, monitor their knowledge gaps, iteratively build and debug their models or computational artefacts, and identify and correct their misunderstanding and errors by seeking and interpreting feedback from the environment (Järvelä and Hadwin, 2015[42]). Metacognition is particularly relevant to student-centred learning, yet research has demonstrated that students frequently lack

the metacognitive understanding necessary to engage in optimal inquiry learning (Dedić, 2014[43]; Keselman and Kuhn, 2002[44]; Kuhn et al., 2000[45]).

3. The PISA definition of learning in the world

22. In its 2025 cycle, PISA defines learning in the digital world as *"the capacity to engage in an iterative and self-regulated process of knowledge building and problem solving using computational tools and practices"*.

23. The definition recognises learning in a digital world as a self-regulated process that requires learners to be active participants in their learning. It recognises knowledge building and problem solving as particular forms of constructivist learning. In this definition, problem solving does not refer to the reproduction of existing knowledge to an unfamiliar problem situation (as for example in the PISA 2012 definition of problem solving) but rather to the process of using external resources to develop one's own knowledge and reach a particular goal. In this assessment, students are expected to progress to their zone of proximal development using scaffolds and other opportunities to learn from external resources. In other words, during iterative problem solving, students are expected to self-regulate their learning by activating cognitive, metacognitive and affective processes.

24. Using computational tools and practices clarifies that learners engage in knowledge building and problem solving by constructing computational artefacts, like models or algorithms, that can be executed by a computer. Doing so thus requires computational problem solving. These artefacts can be used to represent (i.e. model) a system and make predictions on how this system will evolve, or to control automated agents to solve real-life problems. For the sake of clarity, information-search activities using computational tools (e.g. Internet search engines) are not included in this narrower definition of learning in the digital world as these also draw upon other skills (e.g. information-seeking and critical evaluation skills) beyond computational problem solving.

4. The PISA assessment and measurement approach

25. The PISA 2025 learning in the digital world assessment has two main instruments:

- A cognitive test that measures the extent to which students can engage the cognitive, metacognitive and affective processes required for learning in the digital world;
- PISA questionnaire modules that will collect information about students' use of digital tools for learning – both inside and outside of the classroom – as well as their attitudes towards ICT and their learning strategies. Modules in the teacher and school leader questionnaires will supplement this information with data about students' school environments, such as the school's pedagogical culture, teachers' beliefs, and availability of supporting technology.

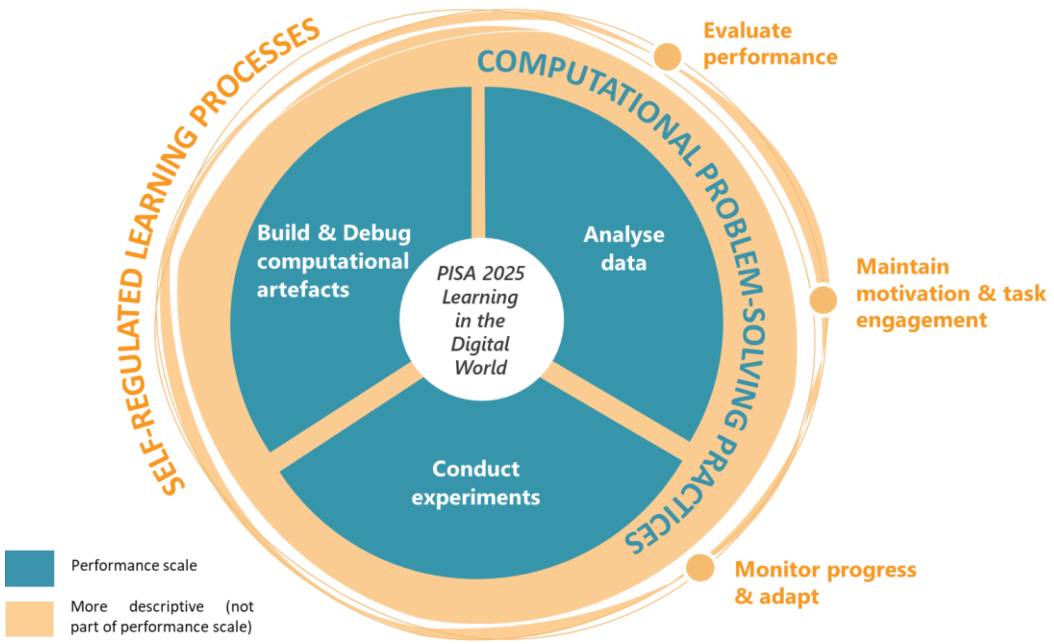
26. Evidence-Centred Design (ECD) (Mislevy, Steinberg and Almond, 2003) provides a conceptual framework for developing innovative and coherent assessments that are built on evidence-based arguments, connecting what students do, write or create on a computer platform with multidimensional competences. Section 2 and 3 of this framework describes the domain analysis and rationale underpinning the PISA 2025 definition of learning in the digital world. In this section, we present the measurement approach in PISA. This includes

a presentation of the competency model, the task model(s), and the evidence and accumulation model.

4.1. Competency model (Student model)

27. The competency model operationalises the construct, as defined in Section 3, for the purposes of measurement. The competency model contains two main components, each of which are further broken down into several sub-components: (1) computational problem-solving practices; and (2) self-regulated learning processes (Figure). In addition to the two main components of the competency model, both prior knowledge and attitudes may influence student performance on the assessment.

Figure 1. Competency model for the PISA 2025 learning in the digital world assessment



4.1.1. Computational problem-solving practices

28. Several frameworks address the synergies between computational thinking and inquiry-based learning, identifying a set of interrelated practices that support learning and problem solving using computational tools (Weintrop et al., 2016[29]; Zhang and Biswas, 2019[23]). We refer to these as computational problem-solving practices. For measurement purposes in PISA, computational problem-solving practices are divided into the following three sub-components.

Conduct experiments

29. Being able to determine the relationships between variables or agents within a system through systematic experimentation is an important computational problem-solving practice. It is underpinned by knowledge about certain concepts, such as dependent and

independent variables, and strategies for collecting data for analysis, such as the control of variables.

30. Conduct experiments refers to students' ability to:

- use computational models, simulations and other tools to generate data;
- identify relevant hypotheses and conduct controlled experiments;

Analyse data

31. Being able to analyse data to understand how systems work is another important foundation for building computational models. It is underpinned by knowledge of mathematical and graphical representations of the relationships between variables, knowledge of different types of data, and the ability to select and use appropriate tools and methods to clean, manage, explore and analyse data.

Analyse data refers to students' ability to:

- use data to make conclusions about how different elements of a system are related;
- use data to make predictions about how a system will change over time.

Build and debug computational artefacts

32. Being able to translate ideas into instructions that can be executed by computers is fundamental to computational problem solving. This involves reframing problems so that they can be rendered suitable for computation through reflective practices, such as decomposition and abstraction, that simplify the problem by eliminating less relevant elements and enable the incremental development of modular solutions whose components can be tested independently (Weintrop et al., 2016[29]). Building and debugging computational artefacts is also underpinned by knowledge of fundamental computational operations such as iteration, looping and conditional branching, and of the outcomes of varying the sequence in which these operations are executed (i.e. control flow).

33. Build and debug computational artefacts refers to students' ability to:

- identify sub-goals and address the constituent parts of a problem independently;
- identify and address repeated patterns through the same computational procedure;
- implement a generalisable sequence of solution steps by using control flow structures, such as repetitions and conditional statements;
- create an abstract representation of a system that can be executed by a computer;
- adapt and/or debug algorithms and computational models.

4.1.2. Self-regulated learning processes

34. Self-regulated learning processes include metacognitive, cognitive and affective processes. For measurement purposes, self-regulated learning processes are broken into three sub-components.

Monitor progress and adapt

35. This facet refers to the processes through which individuals shape and control their learning. It has both cognitive and metacognitive components. The cognitive component includes cognitive actions or strategies for making progress towards one's learning goals, whereas the metacognitive component refers to a critical awareness of one's understanding of the task demands and monitoring of one's thinking and learning processes. Metacognition enables individuals to identify their knowledge gaps and in turn effectively enact and adapt cognitive strategies based on their emergent understanding.

36. Monitor progress and adapt refers to students' ability to:

- monitor their understanding and identify knowledge gaps;
- systematically test and debug their computational artefacts;
- act on feedback from the learning environment;
- engage in appropriate help-seeking behaviours when needed (e.g. when stuck or after repeated, negative feedback).

Evaluate performance

37. A self-regulated learning cycle also includes a reflective phase, during which learners evaluate their successes or failures to inform their future performance on similar tasks.

38. Evaluate performance refers to students' ability to:

- evaluate their progress towards achieving their learning goal;
- evaluate the quality of their computational artefact with respect to the task requirements.

Maintain motivation and task engagement

39. Motivation influences learners' desire to engage in nearly all learning activities (Pintrich and De Groot, 1990[46]; Bandura, 2001[47]), and research has found a positive relationship between motivation and deeper learning (Järvelä, Järvenoja and Muukkonen, 2021[48]; Saab, van Joolingen and van Hout-Wolters, 2009[49]). Affect (i.e. emotions, feelings and attitudes) also closely interacts with learners' motivation and engagement with learning tasks (Efklides, 2011[50]). The motivational and affective components of self-regulated learning describe the processes through which individuals manage their motivation and emotional states while learning, such as persisting in the face of difficulty (Järvenoja et al., 2018[51]; Fredricks, Blumenfeld and Paris, 2004[52]; Kim et al., 2015[53]).

40. Maintain motivation and task engagement refers to students' ability to:

- avoid prolonged periods of inactivity or unproductive actions;
- make efforts to adapt and improve their computational artefact after receiving negative feedback and using all available time;
- engage with the task despite experiencing negative affective states (e.g. frustration, boredom).

4.2. Other factors influencing student performance in the test

4.2.1. Prior knowledge

41. Students' prior knowledge of a given topic, as well as their knowledge of and basic familiarity with digital tools, may influence their performance on the PISA 2025 learning in the digital world assessment. In any inquiry-based learning task, a student's prior knowledge and understanding of the topic might inform their initial ideas about the characteristics and relationships between relevant variables, in turn helping them to conduct better experiments, or about the procedures that govern the behaviour of a computational artefact. Insufficient prior knowledge may therefore lead learners to misinterpret data, engage in unsystematic or flawed experimentation behaviour, or lead to confusion about task requirements (de Jong, 2006[54]; Glaser et al., 1992[55]; Schauble et al., 1991[56]; van Riesen et al., 2018[57]; Quintana et al., 2004[58]). However, prior knowledge can also hinder inquiry-based learning because pre-existing, faulty ideas are likely to lead students to ignore anomalous data (Chinn and Brewer, 1993[59]) or adversely influence the types of experiments they conduct (Klahr, Fay and Dunbar, 1993[60]).

42. Using computational tools for inquiry-based learning also presupposes some functional knowledge about ICTs (e.g. how to navigate an interface, click on affordances, etc.) without which individuals will not be able to fully exploit the features of digital tools and learning environments. However, greater digital literacy does not necessarily translate into better learning outcomes using digital tools. For example, Wecker et al. (2007[61]) found that students who were more familiar with computers acquired significantly less knowledge in a digital science inquiry environment because they tended to exhibit more shallow information processing strategies (e.g. browsing).

43. Prior knowledge about the topics and practices covered in each unit will be measured through a short battery of during the first part of the unit (see Section 4.3.2). Information about students' functional knowledge of ICT will be measured by analysing how students interact with the different affordances of the digital learning environment and whether they can execute the instructions in the tutorial.

4.2.2. Attitudes and beliefs

44. Several attitudes interact with motivation and task engagement, including task interest, self-efficacy, the extent to which a task or outcome are valued, and the cost or effort involved in committing to the task (Flake et al., 2015[62]; Eccles et al., 1983[63]). In particular, mastery orientation and ICT self-efficacy are likely to influence students' ability to engage in learning in the digital world. These attitudes and beliefs (among others) will be measured through scales that are adapted from existing literature and included in the student questionnaire.

Mastery orientation

45. Mastery orientation refers to the goal of learning and mastering a task according to self-set standards (Hsieh, 2011[64]). Learners with a mastery orientation focus on developing new knowledge and skills and improving them towards the level of mastery. The contrast to mastery orientation is performance orientation, where learners' primary concern is competently performing a task to receive favourable judgments from others.

46. Mastery-orientated learners therefore find intrinsic satisfaction in completing a task and are less influenced by external performance indicators, such as grades. They also tend to engage in activities that will increase their knowledge, pay more attention and process information at a higher level, and ask for help (Hsieh, 2011[64]). They also tend to view negative feedback as valuable information for improvement and treat failures as a learning experience, rather than as a sign of insufficient ability (Dweck and Leggett, 1988[65]).

ICT self-efficacy

47. A person's confidence in their ability to carry out specific tasks (i.e. self-efficacy) is strongly associated with their performance (Bandura, 1993[66]). This may particularly be the case in computer-based learning digital environments (Moos and Azevedo, 2009[67]). For example, students who feel confident using ICT may engage more readily with ICT-mediated learning experiences and persevere through difficulties they might encounter while using technology. Research has also shown that ICT self-efficacy is associated with better learning outcomes (Fraillon et al., 2014[68]; Thompson, Meriac and Cope, 2002[69]).

4.3. Task model

48. A task model in ECD describes the design of the task activities in a test, including the objectives, prompts, desired student output(s) and interface features of the tasks. Constraining these task "variables" can elicit the observables needed to make claims about students' ability in the test construct (Mislevy et al., 1999[70]). A major challenge to developing the task models within the constraints of the PISA assessment design, especially for the learning in the digital world assessment, is the limited amount of testing time available per student. Students will complete one hour's worth of test material for the learning in the digital world assessment, meaning the test must focus on the types of learning that students can reasonably achieve within the given testing time. For this reason, "learning goals" in each unit are framed as intermediate steps towards developing a computational model of a system or building a computational artefact to solve a problem.

49. Detailed task models define exactly what students are supposed to do in each task (e.g. seek information by consulting a report, conduct experiments using a control of variable strategy, use experiment results to define relationship between variables, etc.) and what opportunities they have to learn (e.g. scaffolding, worked examples). The tasks are also structured into different unit phases, according to their difficulty and level of scaffolding, in order to provide multiple opportunities to learn and to apply what they have previously learnt to their learning goal. This organisation of the test unit into a sequential learning progression aims to replicate authentic learning experiences in digital learning environments.

4.3.1. Digital learning environments

50. While the specific tools provided to students vary across units, the digital learning environment of each unit share structural and stylistic similarities. These include:

- A computational tool (or tools) and a workspace in which students can build an executable computational representation (e.g. a model, an algorithm);
- Affordances that enable students to engage in a self-directed learning process (e.g. feedback mechanisms, annotated examples for similar problems, annotated solutions);

- Well-defined records of 'events' (i.e. event data models) generated by students' interactions within the environment (e.g. total time spent on a task, number and characteristics of tests executed, use of resources, edits/additions to a computational artefact, etc.). These event data are defined as part of the task and unit design to collect all the relevant information as specified in the evidence rules.

Types of computational tools

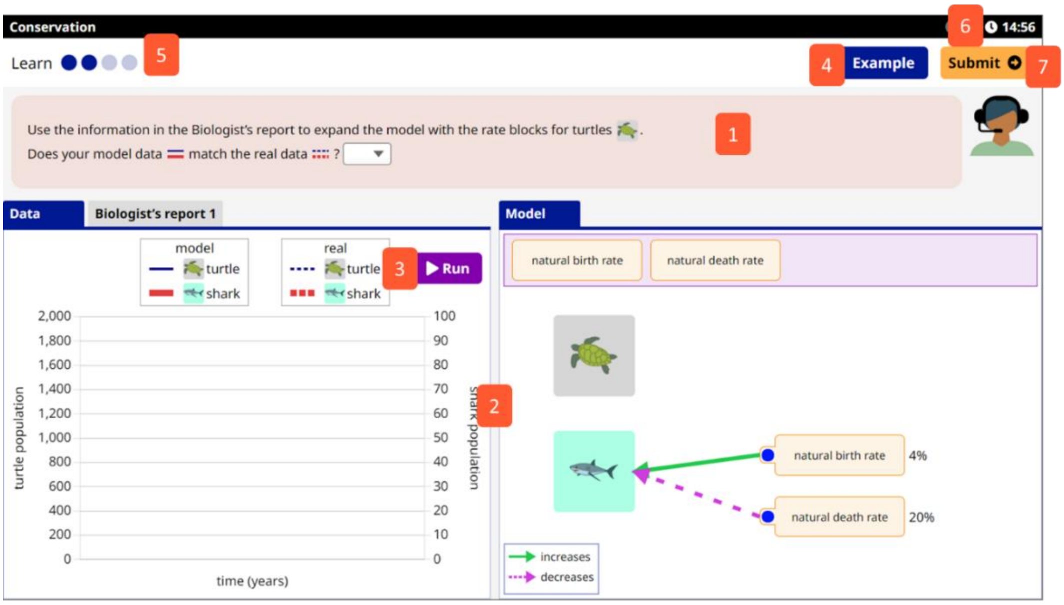
51. The computational tools that students will use in the test include block-based programming tools, (executable) concept map builders, flowcharts and simulations. These can be used to represent and manipulate the relationships between variables in a system, generate data to validate hypotheses or make predictions, or control multiple agents within a simulation. In short, each tool enables students to build an executable computational artefact that serves to advance their understanding of a phenomenon (e.g. how variables in a system are interrelated and how the system functions) or to solve a complex problem.

52. These tools have been designed to be accessible and intuitive for students to use. For example, block-based programming environments allow individuals without any prior knowledge of complex programming languages to build algorithms. Command blocks within a pre-determined library can be dragged-and-dropped into the workspace, where they can be attached to other blocks to create an algorithm. Flowcharts are another simple tool with pre-defined commands that can be used to model the behaviour of agents or control a simulation. Agent-based models help students understand how complex systems work by observing the behaviours of the system that emerge from the agents' interactions (Sengupta & Wilensky, 2011).

Affordances

53. The general task affordances serve two key design objectives for this assessment: (1) to support students – especially those with lower levels of initial preparedness – to make progress on the test; and (2) to produce evidence of how students engage in self-regulated learning processes while building knowledge and problem solving.

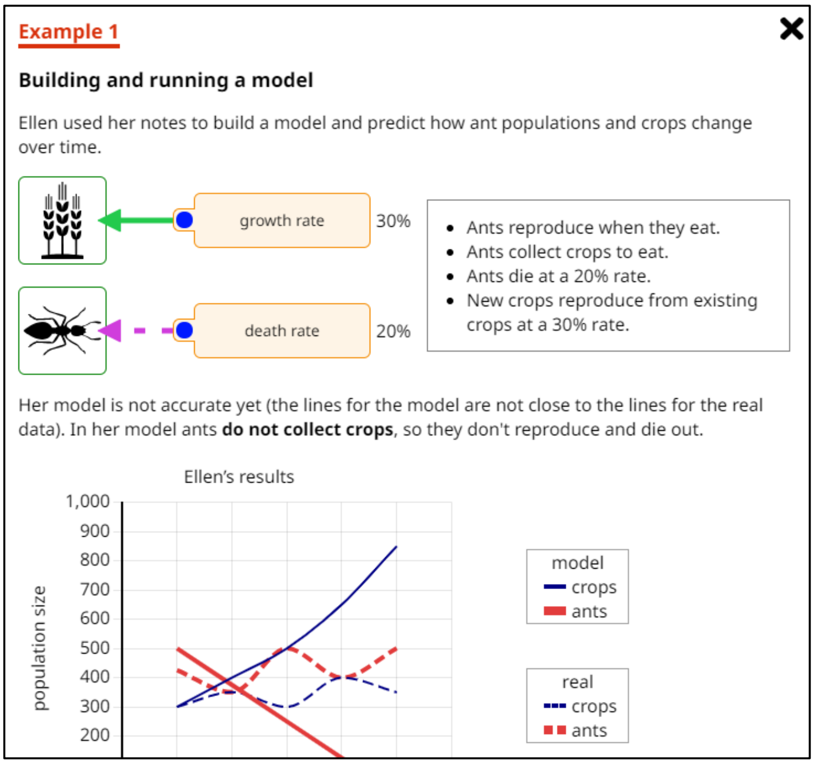
Figure 2. Key elements and affordances of the task interface, illustrated by the Conservation unit



54. The key elements and affordances of the open interactive tasks within each learning environment are enumerated in Figure 2. They include:

1. Task instructions and question space: This space contains task instructions. The task goal may be represented visually, for example displaying the desired final state of the environment. In some tasks, students may need to respond to questions in this space after building and interacting with computational artefacts.
2. Workspace: Students build their computational artefact (e.g. algorithm, model, simulation) and view its output (e.g. graphs, data tables) in the workspace. The layout of the workspace depends on the computational tool(s) in each unit. In the example in Figure 2, the workspace contains a graphing tool ('Data' tab), a biologist's report ('Biologist's report 1' tab) and a concept mapping tool ('Model' tab).
3. Test function: Students receive immediate feedback on the quality of their computational artefact by using the test button. The exact form of feedback varies depending on the type of computational tool and artefact (e.g. visual feedback in a block-based programming environment). In this example, the data from the real phenomenon and from the students' model can be visualised and compared using a graphing tool in the 'Data' tab.
4. Examples: Students can view (and sometimes interact with) a functional and annotated solution to a similar task (see Figure 3).
5. Progression bar: The progress bar provides a visual cue to students about the number of items (light blue dots) in that specific phase of the unit and on the items that have been completed (darker blue dots).
6. Timer: A digital clock indicates the time remaining in each phase of the unit.
7. 'Submit' button: Students click here to submit their solution and move to the next item.

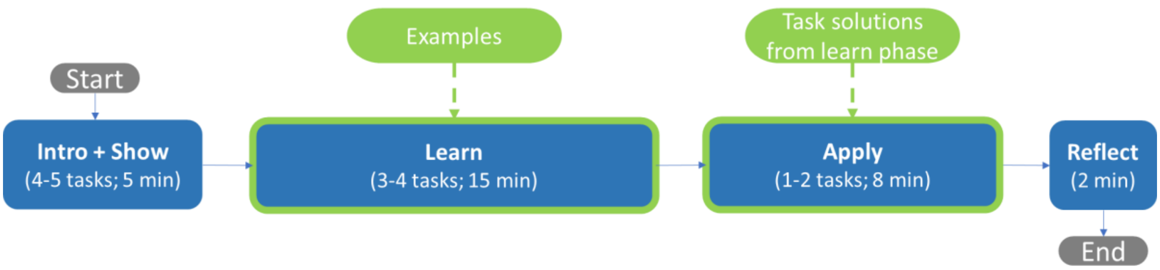
Figure 3. Worked example available to students in the Conservation unit



4.3.2. Sequence of tasks and task types

55. Nine test units, each composed of several tasks within a digital learning environment, have been carefully designed to elicit evidence about students' ability to engage in the learning in the digital world construct. While all units are based on different scenarios and contexts, and integrate different computational tools, they all share the same internal organisation. There are four main "phases" (see Figure 4): 1) a short introduction to the unit ("**Intro**") with discrete pre-test items for students to show what they already know and can do ("**Show**"); 2) a learning phase in which students work through an embedded tutorial and several interactive, scaffolded tasks ("**Learn**"); 3) an application phase where they must apply what they learnt in a more open, complex task ("**Apply**"); and 4) a short reflection phase with self-evaluation questions ("**Reflect**").

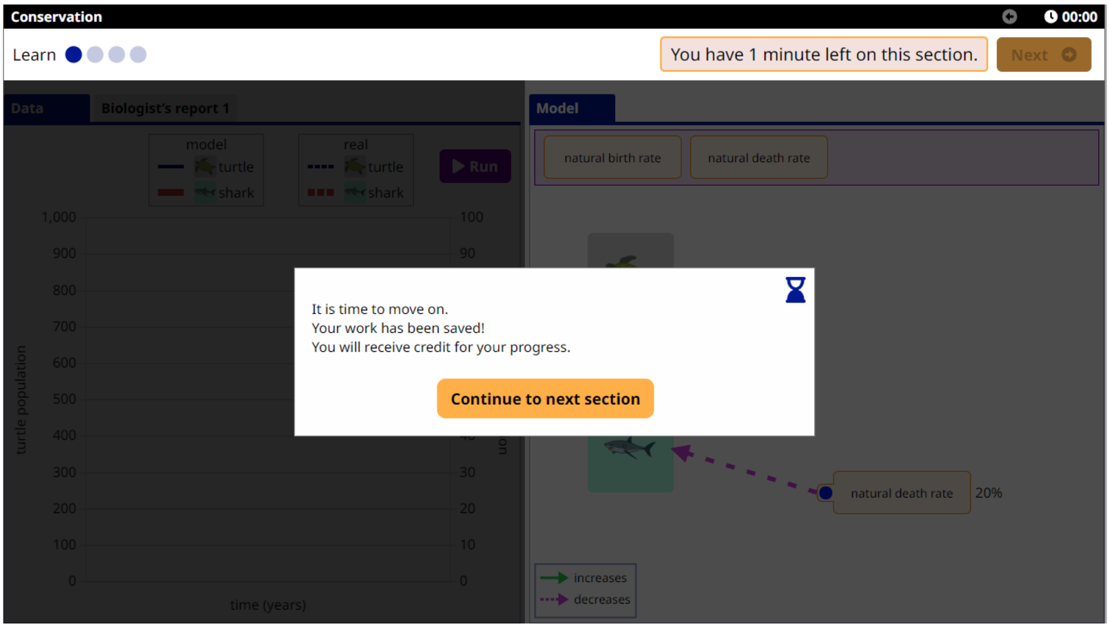
Figure 4. Organisation and flow of tasks within the learning in the digital world units



56. Students have an allotted amount of time to respond to the tasks in each phase. After students have completed each phase (or the maximum amount of time for that phase elapses), they progress to the next phase of the unit; students are given an unobtrusive one-

minute warning before the time runs out in each phase (see Figure 5). Any progress students make in the tasks in the previous phase will be saved and awarded credit.

Figure 5. Example of the forced move pop-up screen



57. The general sequence and type of tasks within each phase of a unit will be illustrated below using the released unit called Conservation. In this unit, students learn about a marine ecosystem using an executable concept map, a data exploration tool and information from an expert report. Students represent their emergent knowledge by building a computational model and use it to make predictions about the ecosystem in order to take appropriate conservation decisions.

Introduction and Show phase

58. Each unit starts with a static page (see Figure 6) that introduces the overall learning goal(s) of that unit and briefly describes the unit context and problem scenario. The page also introduces a gender-neutral computer agent who acts as a tutor throughout the unit (e.g. introducing the unit context and goals, asking students questions, guiding students through the interface, etc.)

59. The introduction is followed by four to five short pre-test items (“Show”) asking students to show what they already know and can do. This pre-test serves to measure students’ initial level of knowledge, which is essential for estimating how much and what they learn during the test. To assess students’ prior knowledge efficiently, item types in this phase include multiple-choice, true/false or simple interactive tasks (see Figure 7 for an example pre-test item). The items target the key concepts and practices that students will need to mobilise during the subsequent interactive phases of the unit. For example, in Conservation, the items measure students’ ability to read and understand graphs, draw inferences and make predictions from data. Students do not have access to learning resources or feedback during this phase.

Figure 6. Example static intro page of the Conservation unit

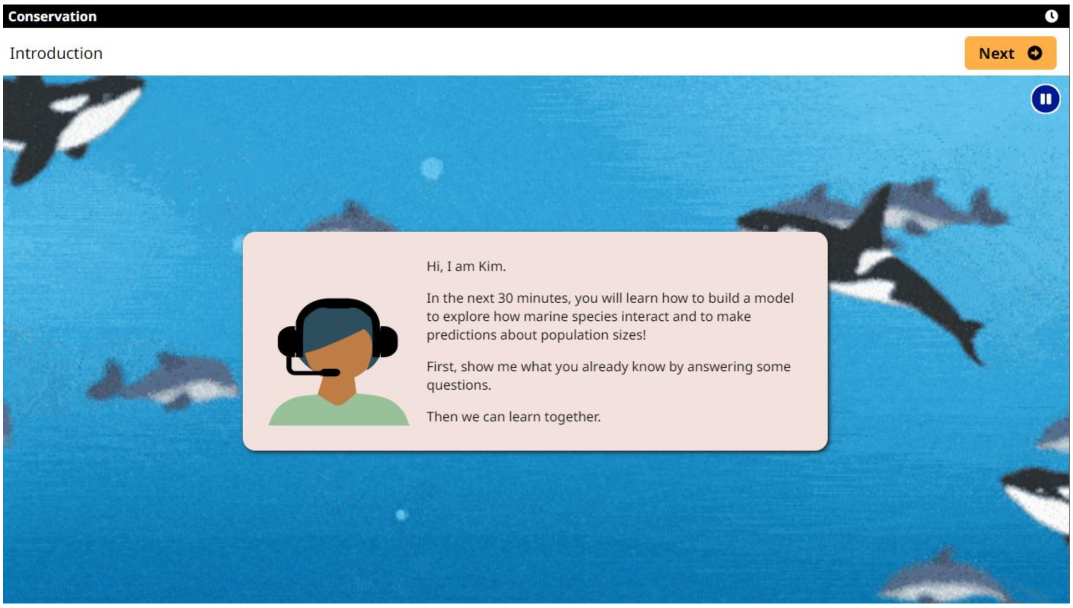
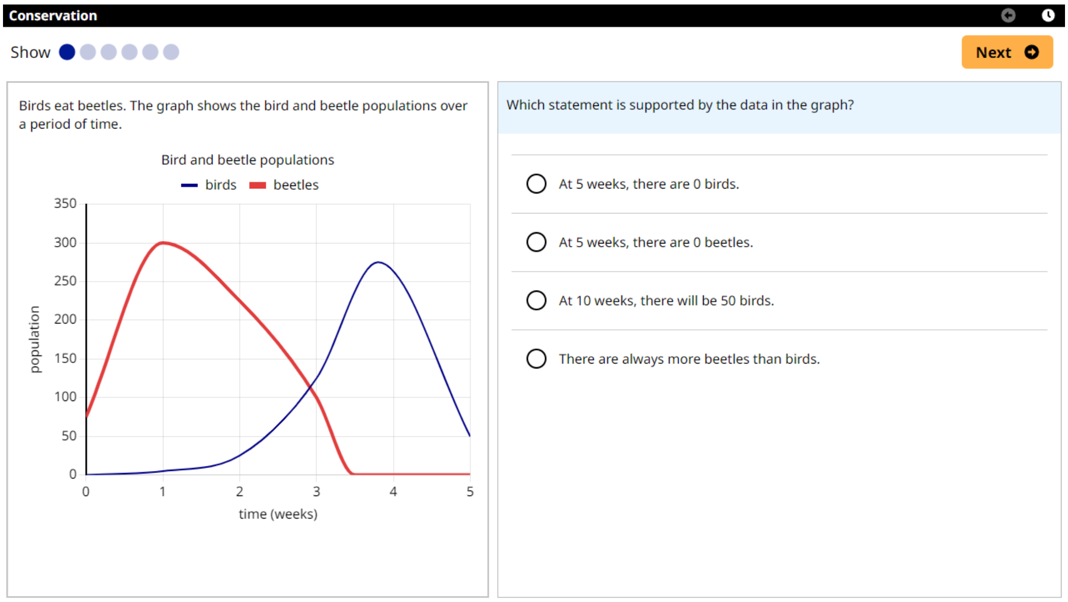


Figure 7. Example static, multiple-choice pre-test item on graph literacy



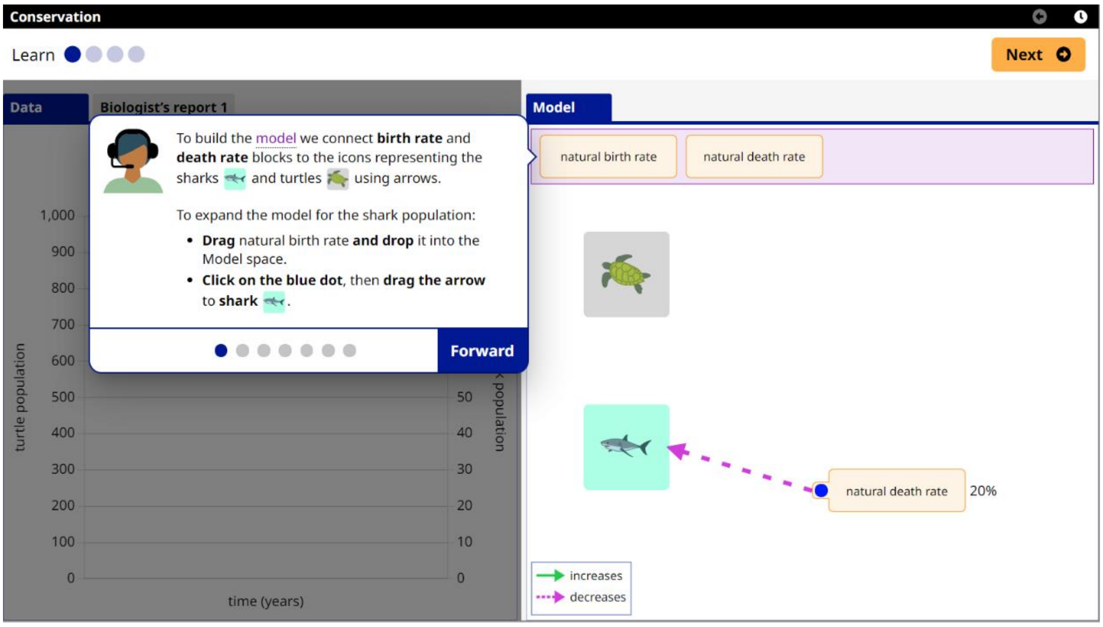
Learn phase

60. The "Learn" phase consists of a series of interactive open tasks in which students learn and practice the key concepts and skills related to the construct. The learning goals are specific, achievable and measurable: in the context of this unit, students have to learn how to integrate the information from the report into the computational model (simply connecting the variable blocks and changing their value), read and interpret lines in a time graph, and conduct multiple experiments until they get a model that fits the real data.

61. The "Learn" phase begins with a scaffolded and interactive tutorial by the tutor agent on simple tasks in the learning environment (see Figure 8). The main purpose of the

tutorial is to familiarise students with the interface, affordances and basic functionality of the computational tool(s) in the environment. In many cases, students view short videos to reduce their reading load and are instructed to perform certain actions (e.g. drag-and-drop a block into the workspace, access the example, etc.) by the tutor agent. If a student tries multiple times to move forward without carrying out an action, the system will automatically demonstrate the action to the student before moving them to the next step. Although the tasks in the "Learn" phase have been carefully designed to be intuitive and accessible, the tutorial tasks and assistive mechanism ensure all students have the minimum familiarity needed to engage productively with the rest of the tasks in the unit.

Figure 8. Example tutorial task from the Conservation unit



62. Following the tutorial tasks, students complete three to four open tasks using computational tools. The tasks include a range of problem types that are selected to cover all the learning goals in the unit. Students have the opportunity to practice at least once, but often multiple times, the key concepts and skills they will need to combine in the "Apply" task.

63. In the Conservation unit, for example, a simple "Learn" task (see Figure 2) asks students to complete a model of the turtle population by referring to observations from the biologist's report. The students must then respond to a simple question regarding the accuracy of their model. In the last task in the "Learn" phase for this unit, students investigate the effect of an external shock to the ecosystem (Figure 9). After each task in the "Learn" phase, students respond to a self-report item about their performance in that task. They also view the annotated solution to the task and can compare it to their own solution to support their learning (see Figure 10).

Figure 9. Last task in the "Learn" phase

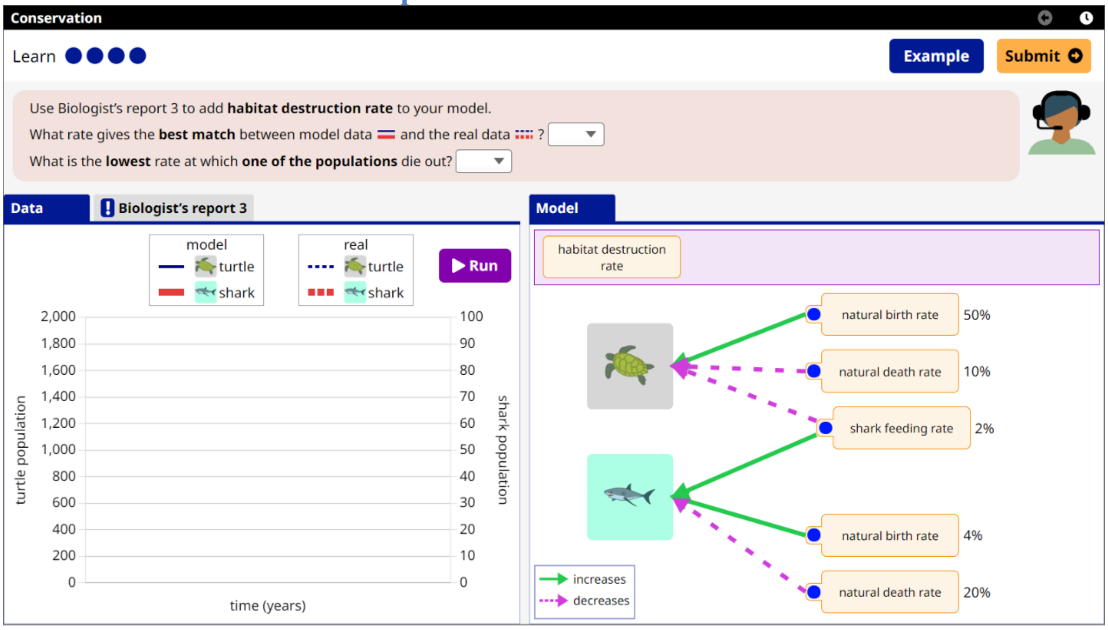
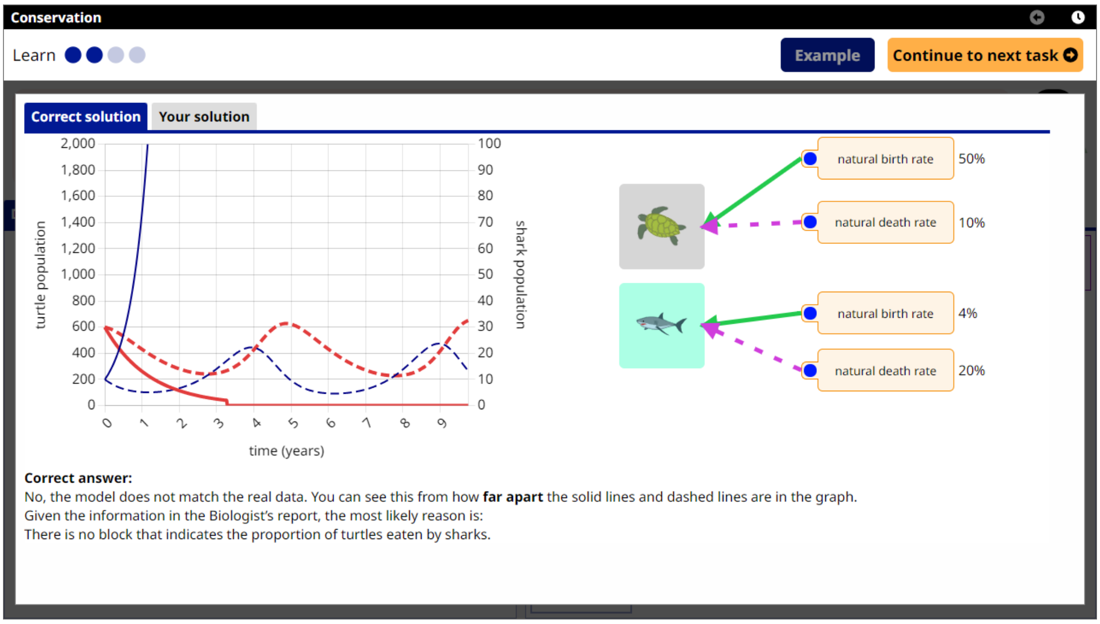


Figure 10. Example annotated solution after a task from the "Learn" phase



Apply phase

64. The final interactive phase of the unit asks students to apply the concepts and practices they have worked on during the "Learn" phase to an extended, open task. For certain units, this phase is structured in several sub-tasks to ensure students have sufficient opportunities to provide evidence of their ability to apply different practices. For example, Part 1 of the "Apply" phase in the Conservation unit asks students to build an accurate model for different underwater species (see Figure 11). They must acquire information from the biologist's report to identify variables to add to the model and set values for these

variables ("build and debug computational artefacts"), run the model to generate data ("conduct experiments and generate data") and check that the data are accurate compared to the real data ("analyse data and define relationships"). Students are exposed to all these practices in a simpler context in the first two "Learn".

65. In Part 2 (see Figure 12), students investigate how a new variable affects the system – something they have worked on in "Learn" task 3. All students start Part 2 with an accurate model even if they did not successfully complete Part 1 to reduce dependencies between sub-tasks. They must demonstrate all three sub-facets of the competency model for computational problem-solving practices by correctly adding the fishing rate variable to the model ("build and debug computational artefacts"), testing different rates ("conduct experiments") and identifying the highest fishing rate at which the coral population will survive based on their results ("analyse data").

66. These tasks have been designed with "low floors" and "high ceilings", meaning that all students should be able to make at least some progress towards a solution, but most will not be able to complete the tasks at first attempt. In the "Apply" phase, students can access annotated task solutions from the "Learn" phase (see Figure 10 for an example solution) to help those who were not able to correctly implement the required concepts and practices in the previous phase.

Figure 11. Part 1 of the "Apply" phase in the Conservation unit

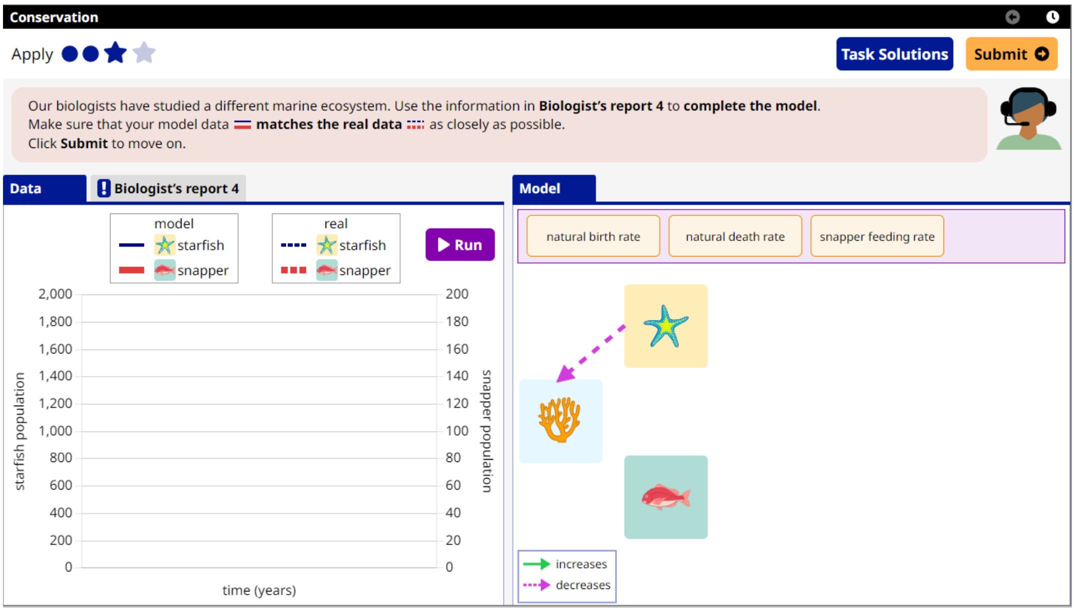
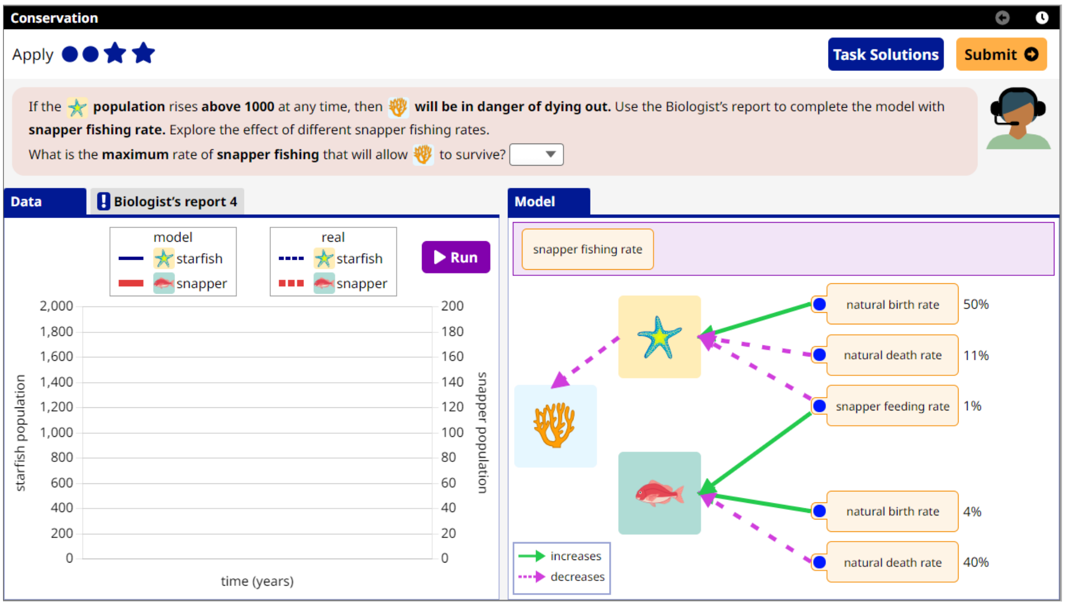


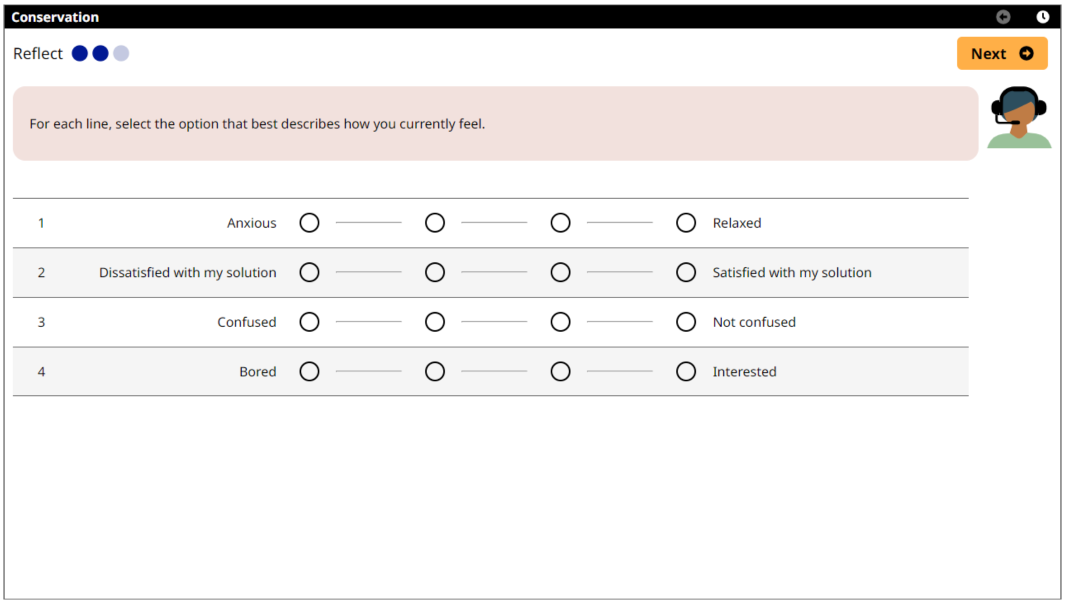
Figure 12. Part 2 of the "Apply" phase in the Conservation unit



Reflect phase

67. The final phase of the unit includes a set of situated self-report items aiming to gather evidence about students' self-regulated learning processes throughout the unit. In particular, students respond to questions about their performance in the task, their effort, and their affective states (see Figure 13).

Figure 13. Self-report item on students' affective states



4.3.3. Assembling the tasks

68. Students who take PISA in 2025 will spend up to one hour completing two units of the learning in the digital world assessment. The learning in the digital world tasks are organised into clusters of 30 minutes according to the above task sequencing. Each 30-minute cluster of tasks (i.e. one unit) will be placed in multiple computer-based test formats according to a rotated test design. Although some units do not provide evidence for all components of the competency model, the test will be assembled in such a way that there is an adequate coverage of the competency model at the population level. It is preferable that students complete two units that include different computational tools and learning goals (for example, one unit in which they work on data from a simulation and one unit in which they write a computer program).

4.4. Evidence model

69. Every task developed for the assessment has a detailed set of evidence rules describing how student responses and interactions with the digital test environment will be parsed into observables that are useful for analysis. The evidence model is derived from theory-based assumptions about what constitutes productive computational problem-solving practices and self-regulated learning processes. The evidence rules for each task have been refined through multiple cognitive laboratories and pilot studies and will be further validated through the full PISA 2025 Field Trial.

70. Evidence of student achievement, self-regulated learning behaviours and learning on the test will be aggregated across units for reporting. The reporting strategy is adapted to the intended claims of the assessment and intends to produce multi-dimensional information. Students' competency on computational problem solving will be reported using a scale, organised by achievement levels, as traditionally done in PISA. Beyond reporting on students' computational problem-solving performance, this assessment also aims to provide information on students' capacity to learn with digital resources. This second claim will be made by developing "profiles" of learners that uses information derived from indicators of their self-regulated learning processes, combined with evidence on students' learning during the test.

4.4.1. Evidence rules for computational problem-solving practices

71. Students' capacity to apply computational problem-solving practices will be measured on the basis of the progress they make through each of the units (i.e. the extent to which they successfully complete the tasks) as well as the quality of their computational artefacts with respect to the given task goals (for example, the completeness and accuracy of their models or the accuracy and generalisability of their algorithms). Indicators of student performance on these practices will be constructed using both response and process data collected throughout each unit.

72. The evidence rules for the open interactive tasks award credit for successfully solving the task as well as achieving or partially achieving the task's sub-goals. They specify the actions or behaviours students must demonstrate in the context of each task and sub-goal, how much credit they can earn for each sub-goal they achieve, and how these rules map onto the sub-facets of the competency model. This approach awards full credit to students who show mastery of the various sub-facets targeted in a task while also awarding partial credit to students who appear to be heading in a productive direction but did not produce a complete solution. This partial credit model can also be used to produce more diagnostic indicators on student understanding of important computational problem-

solving practices and concepts (for example, whether they are able to understand a data table or can use conditionals in a program).

73. The partial credit scoring approach is best illustrated through an example task. In the programming task shown in Figure 14, a student must build an algorithm to instruct the turtle-shaped agent to pick up and place stones in the middle of the grid-like world. A student who builds a program that achieves the goal state and correctly uses control flow structures (e.g. “while” loops) and functions to organise and increase the generalisability of their algorithm will receive full credit (see example, solution A in

74. Figure 15), whereas a student who does not manage to build a complete program that achieves the goal state but correctly uses while loops and/or functions (or vice versa) will receive partial credit (see example solutions B and C in

75. Figure 15). Depending on the complexity of the task, there may be several partial credit categories corresponding to different quality (partial) solutions.

Figure 14. Complex programming task in the Karel the Turtle unit

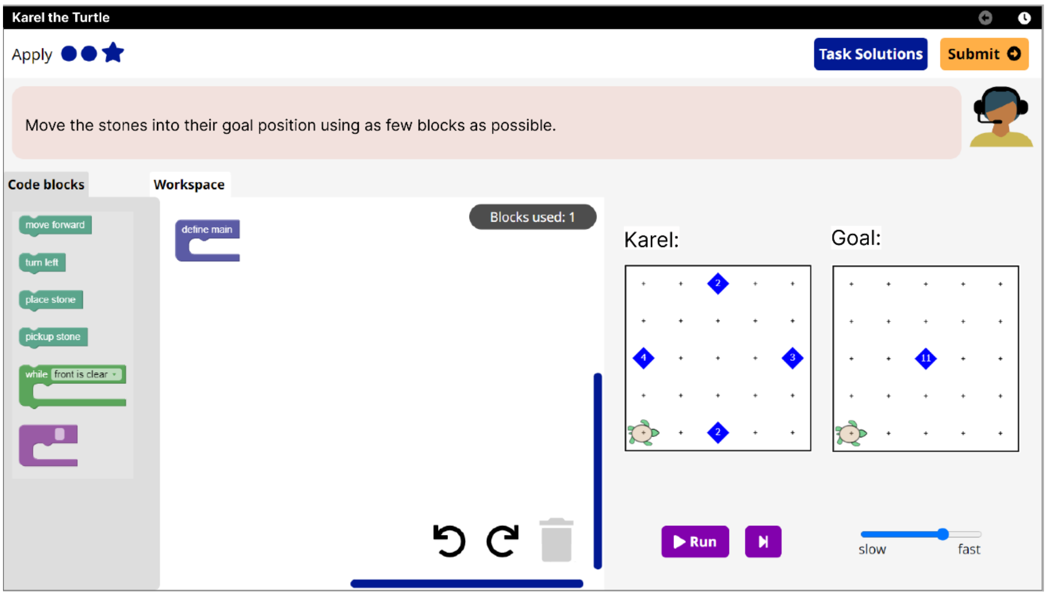
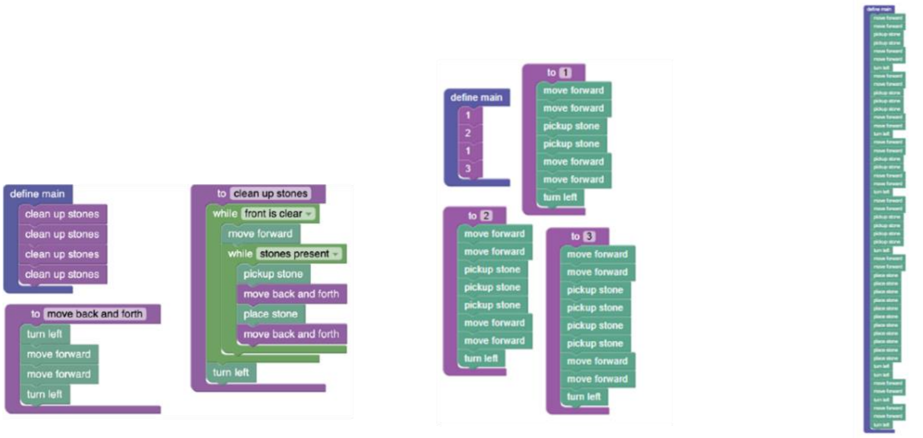


Figure 15. Example student solutions to the programming task in the Karel the Turtle unit



Solution A: Full credit – student achieved the goal state and used correctly while loops and functions

Solution B: Partial credit – student did not achieve the goal state (failed to place 11 stones), but correctly used functions

Solution C: Partial credit – student achieved the goal state but did not use correctly while loops or functions

4.4.2. Evidence rules for self-regulated learning processes

76. The purpose of this set of evidence rules is to describe the extent to which students adopt self-regulated learning behaviours such as checking their understanding and following up on feedback to make progress on the tasks. These rules will generate indicators that can be grouped into two classes: 1) indicators of self-regulated learning behaviours; 2) indicators of learning on the test. The first set of indicators are mapped to the three facets of self-regulated learning processes in the competency model (monitor progress and adapt, evaluate performance, and maintain motivation and task engagement). The indicators of learning on the test measure how students' knowledge and understanding of the target concepts increases as a result of working through the tasks in the unit.

77. The indicators are defined using a combination of theory-driven and data-driven analytical approaches. Theory-driven approaches are based on experts' judgements on what constitutes "productive" self-regulated learning behaviour in the context of LDW tasks. For example, for the facet "monitor and adapt", theory assumes that productive self-regulated learning would be demonstrated by students that check whether their work is correct or not. At the end of each learning task, students have the opportunity to compare their solution to an annotated expert solution. Theory suggests that students who do not feel confident about their solution, but who are good at monitoring their learning, would spend time reviewing their work. The time students spend comparing their solution to the expert solution can be estimated using information from process data (Figure 16).

78. Applying these rules is often complex because several of these adaptive behaviours depend on the students' ability level. Consider, for example, productive help-seeking processes. This important learning ability is defined by two distinct behaviours: the decision to seek help when needed, and the choice to follow up on the help received. Students who know how to reach the solution do not need to seek help, meaning productive help-seeking is not observable for these students and there is no evidence bearing opportunity. To develop an indicator of productive help-seeking, it is thus necessary first

to identify those students who are stuck and need help (Figure 17). This can be done by inspecting process data and identifying whether students get stuck or not during the task. This state could be indicated, for example, by a time interval or sequence of actions where no progress towards the task goal is observed.

79. However, interpreting the meaning of event sequences in the process data is not always straightforward: for example, when students do not take any actions (i.e. they do not interact with the learning environment) it is difficult to distinguish between those students who are taking a reflective pause and those who are simply disengaged. This means that all evidence rules and resulting indicators for self-regulated learning processes need to be extensively validated.

Figure 16. Example decision trees for theory-based indicators of self-regulated learning: checking expert solution

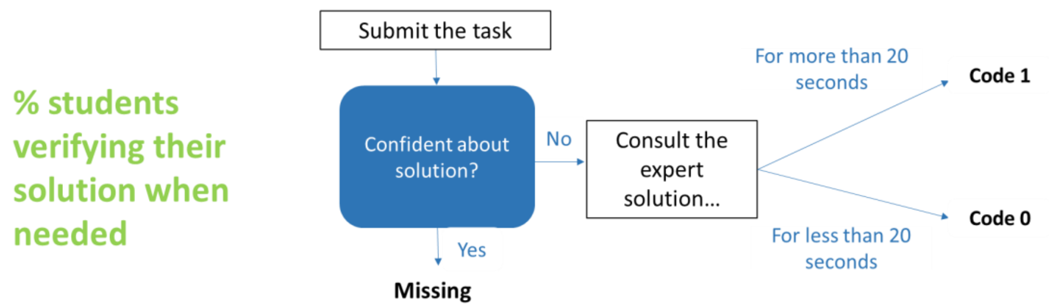
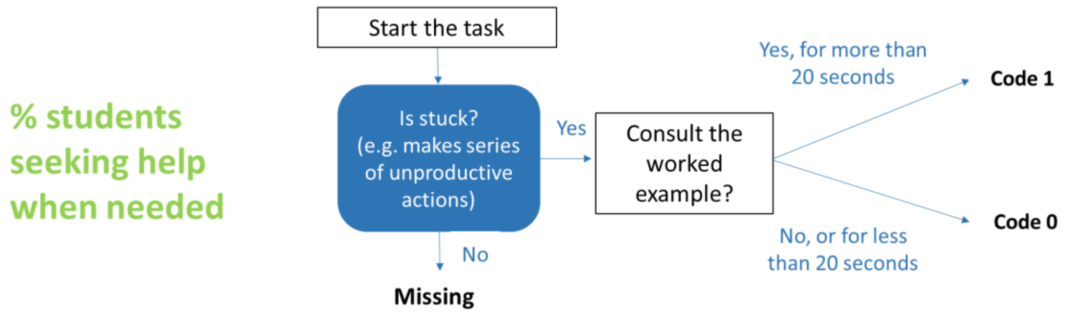


Figure 17. Example decision trees for theory-based indicators of self-regulated learning: help-seeking



80. In addition to theory-driven evidence rules, data-driven approaches can be used to create indicators of self-regulated learning processes. For example, contextualised sequence mining can be used to evaluate differences in learning strategies between types of learners. This approach filters out irrelevant actions and combines qualitatively similar actions into a limited number of distinct 'behaviour' categories. For example, for the Conservation unit, the task model indicates that students can engage in the following types

of actions: 1) obtaining information about the ecosystem consulting the biologist report; 2) constructing the model by either connecting the variables or changing values for the variables; 3) checking the correctness of the model by running the model and generating data; 4) seeking help by consulting the examples. Frequent sequences of these action types can be identified, which can either be characterised as "productive" or "unproductive" on the basis of their relationship with student performance and with learning gains over the course of the unit.

81. Indicators on students' motivational and affective states will be developed using information in the situated self-reports that are presented before and after the "Apply" phase. These situated self-report items ask students how they feel about their task performance, level of effort, and affective state(s). Simple indicators can be built based on the percentage of students reporting given responses (for example, the percentage of students who report they feel bored or confused). More complex indicators could also be derived by combining these data with process data, for example combining students' self-reported level of effort with their level of activity in the learning environment.

82. Different methods are being explored to derive estimates of students' learning on the tasks and throughout the unit. The simplest ones are based on a regression analysis of students' performance on the interactive "Learn" and "Apply" tasks on performance in the pre-test items: students who do better on these interactive tasks than predicted by their pre-test scores are expected to have learnt more during the unit. Other more complex approaches, such as Dynamic Bayesian Network (DBN) (Levy, 2019[71]) models, could be employed to model the mastery of different competencies at different time points (or between tasks in initial and later phases of the unit), with previous levels of ability modelled as influencing final levels of ability.

83. These indicators on self-regulated learning processes will be combined for reporting with the objective of shedding light on opportunities to improve how students engage in complex problem solving in digital environments. One option to summarise this complex information into a format that is accessible to policymakers and the general public is to develop several overall "student profiles". Students would be classified into profiles according to how much they learn during the unit and according to the self-regulated learning processes they demonstrate. For example, one such profile might represent "engaged learners" who make progress in their knowledge by using the learning resources and acting on feedback in an effective way. Other students might be grouped together because they share the characteristics of "confused guessers" who perform many actions with no logical connection and achieve no progress.

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