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Instructional support for learning with agent-based simulations: A tale of vicarious and guided exploration learning approaches

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ABSTRACT

Science content knowledge is essential for many applied practices within health-care professions. With this in mind, the current study seeks to promote in-depth conceptual understanding of science pharmacology content among students from health-care programs—nursing, nutrition, and health education—by introducing learning with agent-based models. While the literature shows that learning with agent-based models promotes better conceptual understanding than more traditional approaches, to achieve these potential benefits, instructional supports are needed. This study employed an experimental pre- and post-test design comparing two forms of instructional approaches for learning with agent-based models: one group learned with agent-based models using the vicarious approach, where pairs observed and collaboratively discussed recordings of others' learning with agent-based models; the other group explored agent-based models in pairs while collaboratively discussing a set of text-based prompts, the guided exploration approach. The results revealed significantly higher pharmacology learning gains following the vicarious instructional approach compared with the guided exploration of agent-based models. Thus, findings suggest that learning from observation can be comparable and even superior to the guided exploration approach with regard to the immediate knowledge gains when collaboratively dialoguing with a peer while observing dialogue of others takes place. Future research should evaluate this instructional effect on knowledge retention and with long-term interventions.

1. Introduction

Robust science content knowledge is central to many applied health professions. For example, physical therapists must know human anatomy and physiology in order to evaluate patient mobility and recommend sequences of rehabilitative exercises. Radiologists must know about electromagnetic radiation and how human tissue is affected by it in order to produce and read film. Nutritionists must know about digestive processes and how different food sources supply nutrients and serve daily health needs. Nurses, as a last line in the administration of in-patient medications, must understand some key ideas of how medication affects the human body and potential therapeutic or side effects for the patient. While specialized forms of knowledge may exist for each of these (e.g., Hoyles, Noss, & Pozzi, 2001), preparatory training for these professions requires exposure to and development of relevant science ideas.

One promising vehicle for increasing science content knowledge is the use of computer simulations. Much of the research on the

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effectiveness of computer simulations in science education has examined the impact on learning content knowledge in the physical, biological, chemistry, and earth sciences (Honey & Hilton, 2011; National Research Council, 2011; Rutten, Van Joolingen, & Van Der Veen, 2012; Smetana & Bell, 2012). These discipline-based simulations incorporate a variety of designs and modalities, from dynamic representations operated with mouse and keyboard controls (e.g., Physics Education Technology, 2011) to immersive, whole-body interactive astronomy simulations using an embodiment approach (e.g., MEteor; Lindgren, Tscholl, Wang, & Johnson, 2016). Computer-based simulations and models can provide excellent opportunities to promote deeper conceptual understanding of science content, especially when complex systems are involved (D'Angelo et al., 2014). Simulations of complex systems allow students to alter parameters for parts and observe how the system changes at the macro level. Of special interest to this study is agent-based modeling (ABM). Learning with agent-based models allows students not only to test their ideas, negotiate, compare, and repair understandings based on the dynamic feedback provided by the running simulation model but also, via a complexity approach, to understand the mechanisms driving the system's patterns (Dickes, Sengupta, Farris, & Basu, 2016; Wilensky & Reisman, 2006). Since human-body physiological and biochemical processes and various medical treatments are a prime example of a complex system, agent-based models that are modeled with a simple set of elements and rules might support the learnability of science content knowledge (Wilensky & Papert, 2010). Yet, to achieve these potential benefits of learning with agent-based models, there is a need for designed support and instructional guidance (see meta-analysis by Lazonder & Harmsen, 2016).

Although the effectiveness of learning with agent-based models has been established, currently there is a need for more research on how different forms of instructional guidance for learning with agent-based models best support different populations. For this study, we compare a vicarious-learning approach of collaboratively observing a dialogue between a learner and an instructor with an approach that involved guided exploration and explicit written prompts to have a dialogue related to a set of agent-based models. In this study, we aimed to outline the advantage of the vicarious learning approach as a benefit for immediate learning, and we discuss its implications for instructional design and further research.

1.1. Learning with agent-based models

ABM is a computational modeling paradigm that emphasizes multilevel examination of complex, multi-agent systems. Common systems include NetLogo, StarLogo TNG, and Agentsheets. The ABM methodology encodes the behavior of individual agents in simple rules so that we can specify and observe the results of these agents' individual actions and interactions. Learning through this approach focuses on entities and their actions (also called the micro level of the system), such as movement, interactions, and global flows (also called the macro level of the system) and allows students to comprehend parallel processes by which emergent phenomena form (Wilensky & Resnick, 1999). For example, in the biology domain, DNA and proteins at the molecular (micro) level result in an emergent phenotype at the cellular or organismic (macro) level (Wagh & Wilensky, 2018). In the chemistry domain, when gas particles have higher kinetic energy (i.e., they have increased speed), the measured macro phenomenon is an increase in temperature (Samon & Levy, 2017).

Exploration of agent-based models encourages causal emergent thinking in connecting individual behaviors with systemic patterns. Using this approach, students are able to understand the mechanisms of the complex systems driving these patterns (Dickes et al., 2016; Levy & Wilensky, 2008). For instance, ABMs have been used effectively to help students learn about population dynamics in simple ecosystems (Berland & Lee, 2012; Wilensky & Reisman, 2006), evolutionary processes (Wagh & Wilensky, 2018), electrical current and resistance (Sengupta & Wilensky, 2009), air resistance (Hirsh & Levy, 2013), and chemical phenomena (Stieff, 2005).

To achieve these potential benefits of agent-based-models exploration, students need support and guidance (Alfieri, Brooks, Aldrich, & Tenenbaum, 2011; D'Angelo et al., 2014; Kirschner, Sweller, & Clark, 2006). However, the educational literature presents varied types and levels of guidance, from prompts and cues to specific and direct explanations of how to perform an action (Lazonder & Harmsen, 2016). There is an ongoing debate, the "assistance dilemma," about what type of guidance is adequate and whom it fits (Koedinger & Aleven, 2007, p. 261). On one side of this argument are those advocating direct instructional guidance as beneficial for novice learners (Kirschner et al., 2006; Tuovinen & Sweller, 1999; Wood, Bruner, & Ross, 1976); on the other side are those suggesting that less heavily guided instructions may be more productive, encouraging concept learning and transfer (Bruner, 1961; Kapur, 2008; Koedinger & Roll, 2012; Loibl, Roll, & Rummel, 2017). Hmelo-Silver, Duncan and Chinn (2007) challenged this notion by suggesting that instead of relying on these dichotomous positions on the continuum of guidance level, the questions to be asked are "under what circumstances do these guided inquiry approaches work, what are the kinds of outcomes for which they are effective… and what kinds of support and scaffolding are needed for different populations and learning goals?" (p. 105). We share this position.

In fact, regarding exploration of agent-based models, it is still unclear how to organize and design instructional guidance for different learner populations. On one hand, agent-based models are exploratory models designed so that students can discover things by experimenting within a microworld; on the other hand, without providing explanations, understanding of complex systems won't become explicit but might remain implicit (Rieber, Tzeng, & Tribble, 2004). Vitale, McBride, and Linn (2016) compared two forms of automated guidance, direct explanations and prompts to motivate learners (knowledge integration guidance), to support learning of complex systems with agent-based models. They found that directed guidance for agent-based-models exploration produced higher immediate learning gains than minimal guidance did; however, Jacobson et al. (2017) and Levy et al. (2018, p. 2), studying agent-based models' exploration for complex-systems learning, suggested that minimal guidance, or a "constrained discovery," can be valuable to conceptual learning.

The aim of this paper on instructional support for learning with agent-based models is to add to our knowledge about how the type of instructional approach, and desired learning outcomes interact within the context of learning unit. In addition, being grounded in the cognitive load theory, which draws from models of cognitive architecture, we explore participants' mental effort, which reflects an individual's invested cognitive capacity while learning (Paas, 1992; Paas & Van Merrienboer, 1994) to compare two forms of instructional guidance. Here we propose vicarious learning as a novel instructional approach to support learning with agent-based models.

1.2. Vicarious learning

Learning from observing, or learning vicariously, was first proposed by social psychology research (Bandura, 1969, 1986) to evaluate learning by imitating and modeling someone else's behaviors and actions. Bruner (1986) stated that “most of our encounters with the world… are not direct encounters” (p. 122), which seems to imply that it is possible to learn through mechanisms other than primary or firsthand experience. Such social learning is effective without the need for the observer to experience feedback directly. Bandura's introduction of the idea—vicarious reinforcement—was based on classic studies in which children were seen to imitate the aggressive behavior modeled by adults as they assaulted Bobo dolls (Bandura, Ross, & Ross, 1963).

Vicarious learning has been also explored in the area of learning of cognitive behaviors as asking questions (Craig, Gholson, Ventura, Graesser, & the Tutoring Research Group, 2000; Rummel & Spada, 2005), doctor–patient communications skills (Stegmann, Pilz, Siebeck, & Fischer, 2012), and acquiring complex cognitive skills such as solving physics and chemistry problems (Chi, Roy, & Hausmann, 2008; Muldner, Lam, & Chi, 2014; Okita & Schwartz, 2006). Initial research that explored differences between direct participation in a task and simple observation of its being performed was conducted by Schober and Clark (1989), in which pairs of participants communicated about a task that involved sequencing figures correctly. Simply overhearing the dialogue, rather than participating directly, resulted in poorer performance, leading Schober and Clark to conclude that the direct participants had an advantage by being able to jointly construct a common ground of comprehension. However, in a replication of Schober and Clark's study (Chi et al., 2008; Chi, McGregor, & Hausmann, 2000), vicarious learners were required to be constructive and actively engaged by self-explaining aloud while overhearing a tutor–tutee interaction; as a result, the vicarious learners did just as well as the tutees who interacted with a tutor.

To further explore vicarious learning, Chi and her colleagues tested different conditions involving different vicarious aspects—observing monologue videos alone/observing dialogue videos alone/observing monologue videos collaboratively/observing dialogue videos collaboratively (Chi et al., 2008; Chi, Kang, & Yaghmourian, 2017). The results suggest that vicarious learning through observation does not have to be passive but might instead be considered interactive when the conditions of *collaboratively* overhearing and observing *dialogue* between a learner and an instructor are taking place. The advantage of designing vicarious learning with the dual-discourse approach, collaboratively observing a dialogue, is twofold. First, observing collaboratively facilitates interactions between peers that offer an opportunity for exchanges of ideas and argumentation processes which foster learning (Schwarz, Neuman, & Biezuner, 2000). Second, observation of dialogues over monologues makes it possible for vicarious learners to overhear the tutee's questions and struggles and to reflect on their own mental models using the tutor's feedback as well. As a result, learning gains from collaborative observations of dialogues were similar to learning gains from face-to-face human tutoring (Chi et al., 2017; Muller, Sharma, & Reimann, 2008).

In this regard, Chi and her collogues developed a cognitive theory that focuses on the extent to which the learning activity engages the cognitive system in four behavioral modes: interactive, constructive, active, and passive (ICAP; Chi, 2009; Chi & Wylie, 2014). The ICAP framework's modes, in decreasing order of expected engagement and learning, are Interactive (dialoguing and co-constructing; e.g., reciprocal teaching, debating), Constructive (generating knowledge; e.g., self-explanation), Active (manipulating information; e.g., verbatim note-taking), and Passive (receiving information; e.g., viewing a lecture). The ICAP theoretical framework defines joint dialoguing as the highest interactive level of cognitive engagement (Chi & Wylie, 2014).

This study is aimed at adding to the existing body of knowledge on vicarious learning by evaluating how it is possible to facilitate the active modes of cognitive engagement while learning vicariously, by comparing it with guided exploration of agent-based models within the antidiabetic pharmacology education context (Chi et al., 2018). In our guided exploration approach, pairs are also asked to actively talk with one another and to make sense of what they are seeing. However, they do not have access to a recording of a novice and advanced novice talking. They instead talk about what they are seeing and encountering as they explore the agent-based models. Building from prior experiences, students bring to bear ideas and emotional reactions that interact with instruction in ways that influence learning (Pekrun & Stephens, 2012; Sinatra, Heddy, & Lombardi, 2015). Thus, students' dialogue enabled us to pinpoint students' expressed ideas and emotions to illustrate the effect of instructional guidance on the learning process. In this regard we are using Fredricks, Blumenfeld, and Paris's (2004) definition of emotional engagement as encompassing feelings and attitudes about the learning task or learning context, such as feelings of interest in a particular subject (Renninger & Bachrach, 2015).

1.3. Agent-based models to support pharmacology learning

The current study focuses on science learning, particularly pharmacology learning, among health care professions in a higher education setting. Pharmacology as a content setting facilitates meaningful contexts and applications of both chemistry and biology concepts. Previous studies showed that such a use of pharmacology topics, which are inherently integrative, was associated with improved student performance in both biology and chemistry disciplines (i.e., Schwartz-Bloom & Halpin, 2003). Moreover, we aimed to support science learning within health-related education.

Pharmacology is a set of core content that includes knowledge of specific drugs, their generic name classes, specific indications of use, dosages and side effects, food and drug interactions, and some pharmacokinetic[1] and pharmacodynamic processes. Pharmacodynamic processes are presented as the mechanism of actions of the drug on the body within specific macromolecular components in tissues, such as receptors (Katzung, Masters, & Trevor, 2011). For instance, pharmacodynamics would address concepts such as maximum effect (point beyond which no further increment in response is achieved) and types of drug–receptor interactions (i.e., agonist or antagonist[2]). For example, Glibenclamide (Glyburide) is widely prescribed for treatment of diabetes mellitus type 2, which, binding to sulfonylurea receptors, inhibits the ATP-dependent potassium channels in pancreatic beta cells. This pharmacodynamic antagonist receptor–drug relationship leads to depolarization of the cell membrane, and as a result increases insulin secretion and hence decreases glucose blood levels.

Understanding of pharmacology concepts is crucial for health care practitioners. For example, consider how pharmacology is important for nurses. Registered nurses are accountable for the daily preparation and administration of approximately 7000 medication doses and devote 20–40% of their time to this task (Westbrook, Duffield, Li, & Creswick, 2011). Deep and resilient understanding of pharmacology concepts improves nurses' abilities to predict with greater accuracy the therapeutic or toxic effects of a given medication and guides nurses through dynamic, complex clinical setting (Boggs, Brown-Molnar, & DeLapp, 1988; Lim & Honey, 2006; Meechan, Mason, & Catling, 2011). Van Hulle Vincent and Gaddy (2009) reported that nurses demonstrated several misunderstandings in relation to pharmacology which could have prevented them from administering adequate analgesics to relieve postoperative pain in children. A cross-sectional study reported that “inadequate pharmacological knowledge was one of the human factors associated with medication errors” among nursing staff (Cheragi, Manoocheri, Mohammadnejad, & Ehsani, 2013, p. 230). Thus, in our previous and current studies (Dubovi & Lee, 2018), we aimed to improve pharmacology learnability by incorporating agent-based models in pharmacology education.

In other health-related fields, pharmacology plays a role and is introduced in preservice instruction. Nutritionists must consider how medicines affect nutrition and help patients plan accordingly (Mestres & Duran, 2009). Some foods disrupt the uptake of certain medications and either need to be eliminated from the diet or scheduled around dosages. Some dietary regimens are one part of holistic treatment that includes medication, such as managing hypertension through a combination of drugs and diet (as well as exercise; Huang, Hsu, Wang, & Shin, 2010; Spahn et al., 2010). Nutritionists must understand how much influence a medication has and how much diet must contribute to desired changes.

This paper presents the Deep Dive into Diabetes (DDD) agent-based learning environment, which was constructed with the NetLogo modeling platform (Wilensky, 1999). The proposed agent-based models that simulate biochemical processes representing the relevant anatomy of glucose equilibrium were constructed in our previous study (Dubovi & Lee, 2018). Two central representations were used: cell models (pancreas cells, muscle cells, and liver cells), and plots showing the numbers of various molecules (see Fig. 1). Each cell model includes the main organelles and molecules that participate in the metabolic processes and insulin mechanisms that maintain blood glucose equilibrium. The models are used to demonstrate the effects of various activities and diets on both healthy and diabetes type 1 or diabetes type 2 body functioning. Participants can add different types and doses of medications, manipulate multiple characteristics and habits (such as fasting or sports activities), and observe the subsequent body reaction. The plots show the number of insulin, glucose, and medication molecules in the various relevant body parts. The use of multiscale models enables participants to zoom in on each type of cell separately or to zoom out to view how the different types of cells work synchronously for a more comprehensive exploration of glucose equilibrium. To evaluate two instructional approaches, we constructed the DDD learning environment with two different levels of learning activities that support learning with agent-based models: collaborative observation of a video tutorial, a vicarious approach; and collaborative exploration and experimentation with agent-based models, a guided exploration approach (see Fig. 2, and “Methods” section for more details).

1.4. Research questions

In evaluating two types of instructional approaches during collaborative learning with agent-based models, we were guided by the following research questions:

(1) What impact does collaborative learning with the vicarious approach have on understanding of pharmacology compared with collaboratively guided exploration of agent-based models in terms of knowledge gain?
(2) How does the type of instructional approach affect the learning process in terms of the experienced cognitive load (using mental effort self-report), emotional engagement (in terms of verbal emotional expressions; Fredricks, Blumenfeld, & Paris, 2004), time on task, and the accuracy of ideas that were expressed during student dialogues?

[1] Pharmacokinetics is the study of drug concentrations during the processes of absorption, distribution, biotransformation, and two routes of drug elimination: metabolism and excretion (Katzung et al., 2011). Pedagogically, it is common to present these interactions as actions of the body on the drug.

[2] A receptor is a component of a cell or organism that interacts with drugs and initiates the chain of events leading to the drug's observed effects. Some drugs function as agonists by activating the receptor, other as antagonists by blocking the biological actions of other agonist molecules (Katzung et al., 2011).

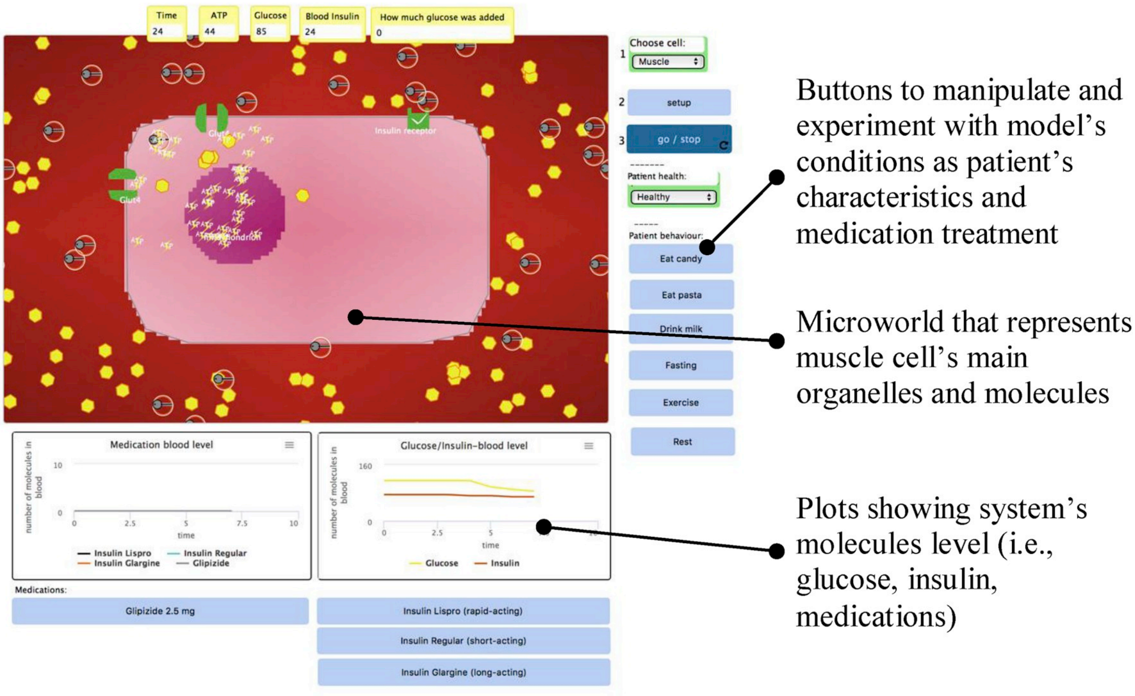


Fig. 1. Screenshot of agent-based model in the Deep Dive into Diabetes (DDD) learning environment. The model represents different cell types that are responsible for glucose equilibrium, plots to follow the system's changes, and buttons to explore.

2. Methods

2.1. Research design

This study employed an experimental pre- and post-test design with two comparison conditions to explore the effect of instructional approach on learning with agent-based models. We used a mixed-methods analysis approach: a quantitative analysis was conducted of questionnaires of all participants ($n = 70$), and a qualitative video analysis was conducted of 11 randomly selected student dyads ($n = 22$).

2.2. Participants

The participants were 70 health care undergraduate students (40 students from a nursing program; 23 from a nutrition program; and seven from a health education program) who volunteered to participate in this study. This diabetes pharmacology topic is an important one for the populations we studied, based on consultation with professors teaching the undergraduate students in the majors we sampled. Most participants were female ($n = 61$), and the average age was 23 ± 4.85 years. The ethnic makeup of the group of participants was comparable to that of the local rural population where the study was completed: 91% White, 4% Asian, 2% American Indian or Alaska Native, and 3% Other.

2.3. Procedure

All participants received some classroom instruction background related to diabetes and the underlying biomechanics as part of their training independent of the current study. Participants were randomly assigned to participate in random pairs (i.e., pairs from different programs could be assigned together) in one of two conditions (see Fig. 3): a collaborative exploration of agent-based models coupled with explicit prompts, the guided exploration ($n = 34$), or a collaborative observation of video tutorial, the vicarious condition ($n = 36$). Students were assigned to learn in pairs to promote discussion and thinking aloud to capture their interactions and discourses, and to apply a collaborative learning model used in other research on students using computer simulations (e.g., Parnafes, 2007). Moreover, the literature proposes that learning in pairs promotes argumentative discourse, debate, and self-generated explanations, which in turn influence learning outcomes (Chi et al., 2008; Damon, 1984; Schwarz et al., 2000). In both conditions, students were prompted to discuss the material in the learning modules with each other.

On average, students spent approximately 50 min learning with the vicarious-instruction and 52 min learning with the guided exploration-instruction method. Dyads were tested one at a time at the university lab while one of the authors was present in the room to take care of technological aspects. The timing of the experiment varied randomly among all days of the week and times of

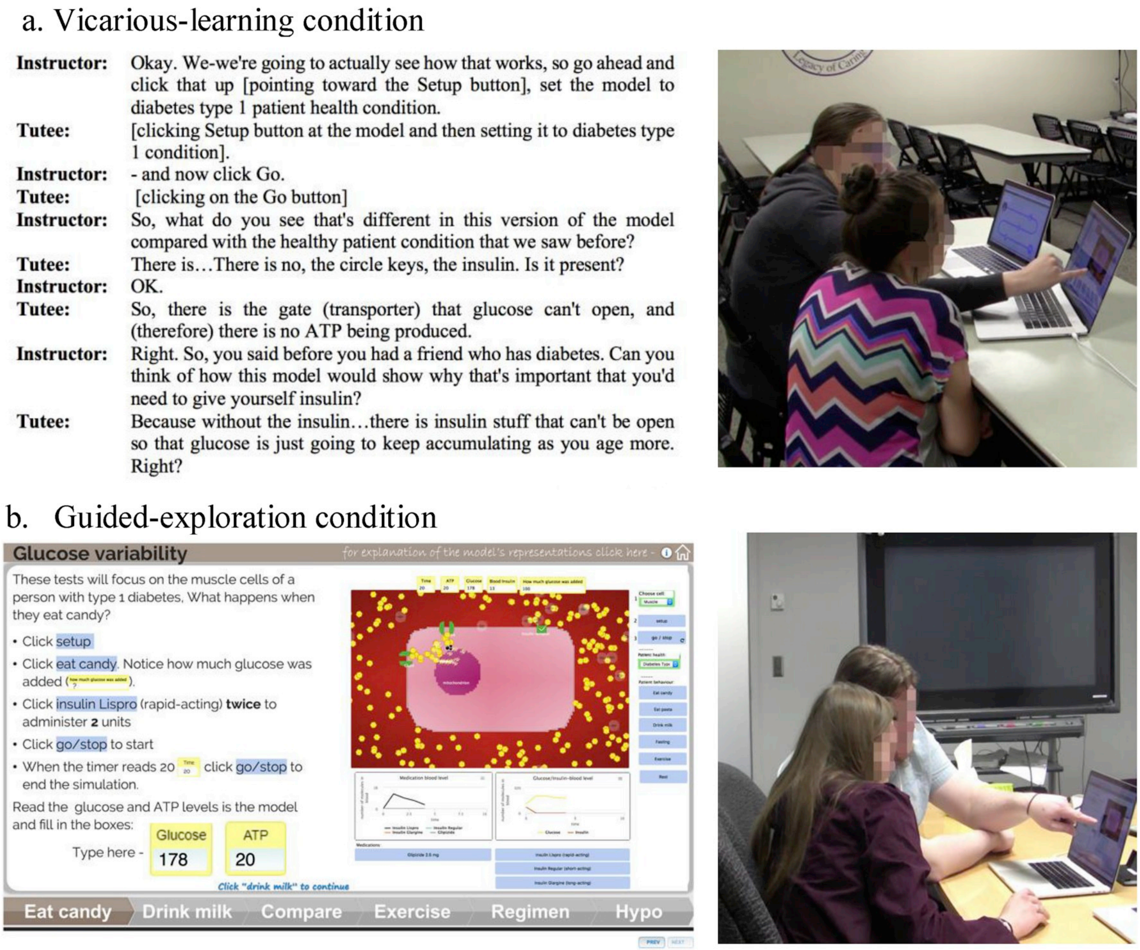


Fig. 2. Deep Dive into Diabetes (DDD) learning environment: (a) Vicarious condition: example of conversation that students were overhearing while learning with the video tutorial and photo of students learning with the environment; (b) Guided exploration condition: screenshot and a photo of students learning with the environment.

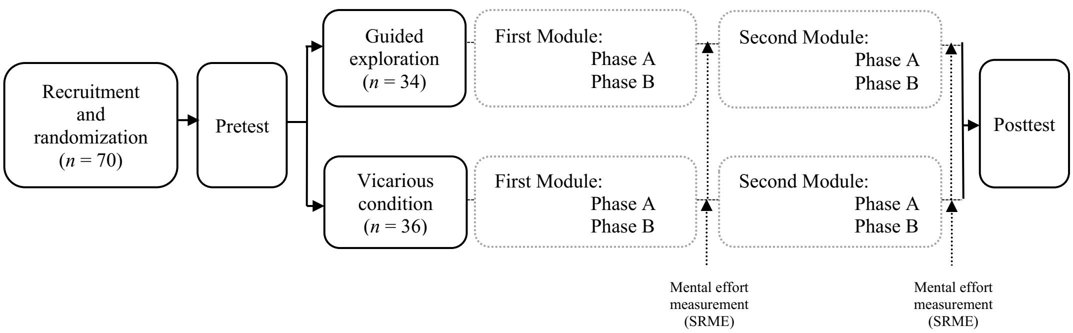


Fig. 3. Research design. SRME = Subjective Rating of Mental Effort.

day. To evaluate the applied science content knowledge within health sciences, we asked participants to complete individually the Diabetes Knowledge questionnaire (Dubovi & Lee, 2018) before and after the experiment. During the experiment, participants were asked at two time points to rate the level of mental effort (Subjective Rating of Mental Effort [SRME]; Paas, 1992) as individuals. There were no statistically significant differences in demographic characteristics such as grade point average (GPA) scores (χ^2 = 2.58, p = 0.46) or prior knowledge about diabetes (t = 1.36, p = 0.17) between the two conditions.

2.4. Instruction design and materials

While learning with the DDD environment, students in both groups were asked to use information from an agent-based model to solve diabetes and antidiabetic pharmacology related problems. The DDD environment was divided into two main modules (see Table 1). The first module was related to basic knowledge of glucose regulation, and the second module raised more sophisticated concepts of glucose dysregulation (e.g., insulin production and drug mechanism of action) building upon the knowledge derived from solving the problems in the first module. Each module was divided into two phases: in Phase A students were asked to solve the problems with minimal instructional prompts; in Phase B they received more detailed prompts (according to the condition they were assigned to) to discuss the concepts and problems that were raised in Phase A. Sequencing the learning process by introducing from the beginning (Phase A) activities with only minimal prompting was aimed at helping learners actively generate and differentiate their prior knowledge and then, in Phase B, contrast it with more detailed prompts (Kapur, 2008; Schwartz & Bransford, 1998). In all phases and across both conditions, students were prompted to discuss their ideas with each other. We theorized that this generative instructional design for both conditions, which is classified as “interactive” according to the ICAP framework, would be helpful for effective learning (Chi et al., 2018; Chi & Wylie, 2014). The learning sequence for the vicarious condition and the problems to solve were identical to the sequence and problems for the guided exploration condition; however, as described below, the exact scaffolding differed by virtue of one being in the form of a pre-recorded video and the other being in the form of textual prompts for manipulating the model.

Those in the *vicarious condition* received scaffolding through a video tutorial of an instructor and learner while exploring the agent-based models. A staff member at a university who was an advanced novice on diabetes and was familiar with the NetLogo modeling system served as the instructor, and a graduate student who had passing familiarity with diabetes and the modeling system was the tutee. This was a semi-scripted conversation. The study participants were able to overhear the dialogue between learner and instructor that included the instructor's explanations of the agent-based models' representations; what to pay attention to while the model is running and how to interpret the model's output; and questions raised by the student which were followed by the instructor's feedback (see short transcript from the tutorial video that students were overhearing in Fig. 2a). Similar to Chi et al.'s (2008) study, students could pause, reverse, and skip portions of the video. To enhance participants' active cognitive engagement while observing, we also followed Chi and her colleagues' vicarious-learning design by asking learners explicitly to discuss several problems which were deliberated on in the video and served as landmarks for the video and prompted interactive dialogue between the participants (Chi, 2000; Chi et al., 2008).

The *guided exploration condition* received scaffolding through textual prompts that provided guidance on how to operate the agent-based models and what to notice. Specifically, text would tell the students which graphs and monitors to pay attention to. These textual prompts were only available in the guided exploration condition. Just as in the vicarious condition, to facilitate dialogue among pairs, students were asked to talk with each other and to solve subproblems while exploring the agent-based models (see Fig. 2b). Their solutions to the problems were entered on a single shared computer. We used learning activities that we developed in a previous study (Dubovi & Lee, 2018).

2.5. Data collection instruments

2.5.1. Diabetes Knowledge questionnaire

The Diabetes Knowledge questionnaire was adapted from the pharmacology diabetes mellitus questionnaire (PDM) developed in our previous study (Dubovi, Dagan, Sader-Mazbar Nasar & Levy, 2018). The questionnaire was translated from Hebrew to English by a bilingual health professional using a forward-and-backward translation approach (Degroot, Dannenburg, & Vanhell, 1994). The questionnaire consists of nine questions (seven multiple-choice, two open-ended) and evaluates understanding of biochemical glucose equilibrium, glucose disequilibrium (i.e., diabetes type 1 and diabetes type 2), and medication actions (see Supplementary Material). Analysis of the Diabetes Knowledge questionnaire using Cronbach's alpha yielded an internal consistency score of 0.68, which was similar to our previous report ($\alpha = 0.71$) and can be considered acceptable.

Responses to the questions on the questionnaire (multiple-choice and open-ended) were coded as correct or incorrect, and the total score was calculated as the percentage of correct answers. Although students completed the pre- and post-test questionnaires as individuals, their learning process was nested within their collaboration as a pair. Prior knowledge varied greatly between students as individuals as well as within pairs. To account for these variations, the analysis involved multilevel modeling (Hox, Moerbeek, & van de Schoot, 2017). We used R and lme4 (Bates, Maechler, & Bolker, 2012) to perform a three-level hierarchical model. Owing to the pretest/posttest design used in this study, our data analysis encompassed repeated measures on individuals over time. Consequently, a three-level structure arose: both test times (Level 1) were clustered within students (Level 2), who were nested within dyads (Level 3). Although multilevel models quantified the variance across pairs, the focus of the study was on the individual student level.

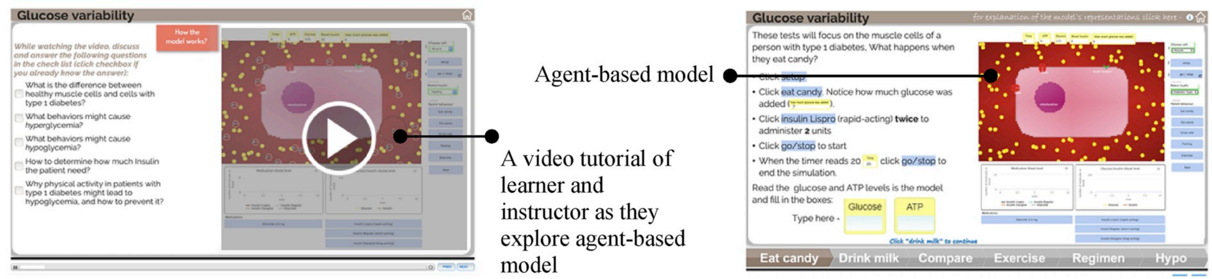
2.5.2. Subjective Rating of Mental Effort

The SRME, developed by Paas (1992), is a self-rating report that uses a single item to indicate the amount of mental effort invested in a learning activity on a 9-point Likert scale (1 = *very, very low mental effort*; 9 = *very, very high mental effort*). Although the SRME is only a unidimensional rating scale and can be completed in less than a minute, it has been used as an index of cognitive load that refers to the individual's cognitive capacity while working on a task (e.g., Lin & Cai, 2009; Paas, Ayres, & Pachman, 2008). Learners in the current study were asked to rate their mental effort at two time points: after solving problems in the first module, and after solving problems in the second module (Fig. 1). To evaluate SRME levels between the two time points for the two experimental groups,

Table 1
Short summary of Deep Dive into Diabetes (DDD) learning environment activities to explore the phenomenon of dynamic blood glucose regulation within healthy and diabetic human organisms.

Module	Activities Sequence	Example of Problems to Solve
Module 1:Glucose regulation	Phase A	• Discuss what patient behaviors may increase and decrease glucose levels (called glucose variability). • Propose an insulin regimen to better control blood glucose levels. Base your proposal on patient's lifestyle, address when different types of insulin should be used by a patient – Insulin Lispro (rapid-acting) and Insulin Glargine (long acting).
	Phase B	• How might different types of food affect blood glucose levels? • How does physical activity affect blood glucose levels? • How might exercising cause hypoglycemia? • What are the differences between healthy cell function, type 1, and type 2 diabetes? • How does one determine the amount and timing of insulin injection (insulin regimen)? • How does one keep blood glucose levels within a healthy range while ex- ercising?-

Vicarious Condition Screenshot: Guided-Exploration-Condition Screenshot:



Module	Activities Sequence	Example of Problems to Solve
Module 2: Glucose dysregulation	Phase A	• Discuss the differences between type 1 and type 2 diabetes. • Patients with type 2 diabetes are often treated with oral medications. Explain why patients with type 1 diabetes cannot be treated in the same manner as patients with diabetes type 2 and require insulin injections.
	Phase B	• Describe the mechanism of insulin secretion from beta cells (pancreas). • What influences the rate of insulin secretion? • How does insulin treatment regimen imitate insulin secretion from healthy beta cells? • What is the difference between type 1 and type 2 diabetes in relation to insulin secretion? • What does insulin resistance mean? • How does the mechanism of drug actions from the Sulfonylurea class define its prescription and possible side effects?

Vicarious-Condition Screenshot: Guided-Exploration-Condition Screenshot:

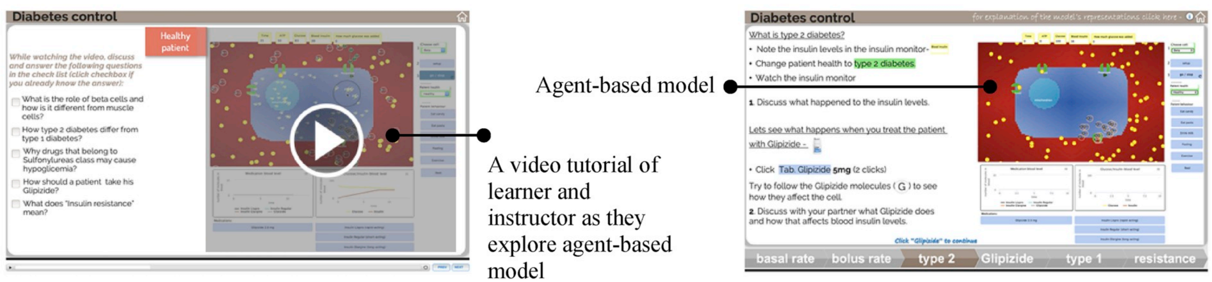


Table 2
Descriptive statistics for the Diabetes Knowledge questionnaire (N = 70)[a].

	Vicarious Condition (n = 36)			Guided Exploration Condition (n = 34)		
	Pre	Post	Learning gains[b]	Pre	Post	Learning gains[b]
Diabetes knowledge	34.56 ± 16.32	67.82 ± 22.07	33.25 ± 20.61	39.86 ± 16.66	61.47 ± 17.19	21.60 ± 16.7

[a] Data are presented in percentages: Mean ± SD, Range 0–100.
[b] Learning gains were computed as posttest score minus pretest score.

descriptive statistics (Means, SDs) and t-test analyses were used.

2.5.3. Demographic questionnaire

A sociodemographic questionnaire included information about self-reported gender, age, ethnicity, and GPA.

2.5.4. Video recordings

To assess the learning process, we recorded students' discourse and interactions with the agent-based models using screen-recording software and a separate standing video camera. We evaluated the learning process with the DDD environment for the following two variables: (1) time to complete the assignments (in minutes), and (2) frequency of accuracy of students' ideas as they learned with the DDD environment and a count of their verbal emotional expressions. For student's ideas and verbal emotion analysis, we randomly chose 11 pairs (n = 22 individual students); five pairs learned with the guided exploration condition and six pairs learned with the vicarious condition. To generate students' ideas accuracy their verbal emotional statements, we carefully transcribed, iteratively reviewed, and coded discourses and dialogues for ideas, explanations, and statements expressed. This approach to the selection of knowledge elements and ideas is comparable to the approach documented in Sherin, Krakowski, and Lee (2012) and Minstrell (1982). From this, we identified transcript excerpts to illustrate some of the dialogues and ideas expressed.

3. Results

Findings are presented for the following: Diabetes Knowledge questionnaire scores, mental effort levels, and the learning process.

3.1. Diabetes Knowledge questionnaire scores

Multilevel model analysis was conducted to determine the effect of pretest scores and experimental condition (vicarious vs. guided exploration) on post-test outcomes, both independently and through examining the interactions between them. Moreover, multilevel model analysis also considers the random effect of individual and pair characteristics on factors' interactions. As shown in Table 3, after adjusting for differences between individuals and dyads, the post-test Diabetes Knowledge scores were significantly higher than the pre-test scores (mean post-test scores, 64.74 ± 19.9 vs. mean pre-test scores, 37.14 ± 16.58). A significant interaction of Time × Experimental condition indicates that the vicarious-condition posttest to pretest learning gains were significantly higher than those for the guided condition (Table 3; for descriptive statistics, please see Table 2).

3.2. Mental effort

Mental effort evaluation using the SRME tool was conducted at two time points of learning with the DDD environment: after solving problems in the first module, and after solving problems in the second module (see Fig. 3). Results revealed that while solving the problems in the first module, participants in the guided exploration condition perceived a significantly higher mental effort (5.11 ± 1.60) than students who learned with the vicarious condition (4.22 ± 1.86; unpaired $t_{(68)} = 2.142$, $p < 0.05$). Interestingly, the mental effort while solving problems in the second module reported by participants in the guided exploration condition stayed relatively high, with a nonsignificant change (5.67 ± 1.24; paired $t_{(33)} = -1.926$, $p = 0.06$), whereas the mental effort reported by the vicarious-condition participants increased significantly (from 4.22 ± 1.86 to 5.19 ± 2.02; paired $t_{(35)} = -4.834$, $p < 0.001$). Thus, the mental effort for the second module was perceived by participants in both conditions, the vicarious and the guided exploration, as equally high (5.19 ± 2.02 vs 5.67 ± 1.24 respectively; unpaired $t_{(68)} = 1.206$, $p = 0.23$). No significant differences were found in students' mental-effort perceptions between nursing students and students from other health care programs[3] while solving the first module (nursing, 4.55 ± 1.88 vs. other, 4.80 ± 1.68; unpaired $t_{(68)} = 0.575$, $p = 0.567$) or while solving the second module (nursing, 5.50 ± 1.85 vs. other, 5.33 ± 1.49; unpaired $t_{(68)} = -0.404$, $p = 0.688$).

[3] Here we are differentiating between nursing students and non-nursing students, namely students from nutrition and health education programs, to evaluate the effect of professional identity. While both nursing students and students from other health professions were novices to pharmacology content, nursing students need this knowledge for actual future medication administration and management, whereas students from nutrition and health education programs need this knowledge only to account for patients' use of medications.

Table 3
Three-level nested random-intercepts multilevel model predicting student's Diabetes Knowledge questionnaire learning gains.

Fixed Effects	Null Model	Main Effects	Final Model
	Estimate (SE)	Estimate (SE)	Estimate (SE)
Intercept	50.942 (2.082)***	36.874 (3.206) ***	39.869 (3.386) ***
Time: Post vs. Pre (learning gains)		27.599 (2.328) ***	21.609 (3.187) ***
Experimental condition: Vicarious vs. Guided exploration		0.522 (4.165)	−5.301 (4.721)
Interaction:			
Time × Experimental condition			11.647 (4.444) **
Random Effects	Var	Var	Var
Dyads	28.173	66.173	66.173
Participants within Dyad	0	76.232	84.702
Residual	494.348	189.620	172.678
Model fit			
Log Likelihood	−636.472	−596.483	−593.208
AIC	1280.944	1204.967	1200.415
BIC	1292.710	1222.617	1221.007
Likelihood Ratio Test (Compared with the model to the left)		$\chi^2(2) = 79.977$, $p < 0.001$	$\chi^2(1) = 6.551$, $p < 0.05$

Note: Sample size is 35 dyads made up of 70 participants with 140 observations total. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

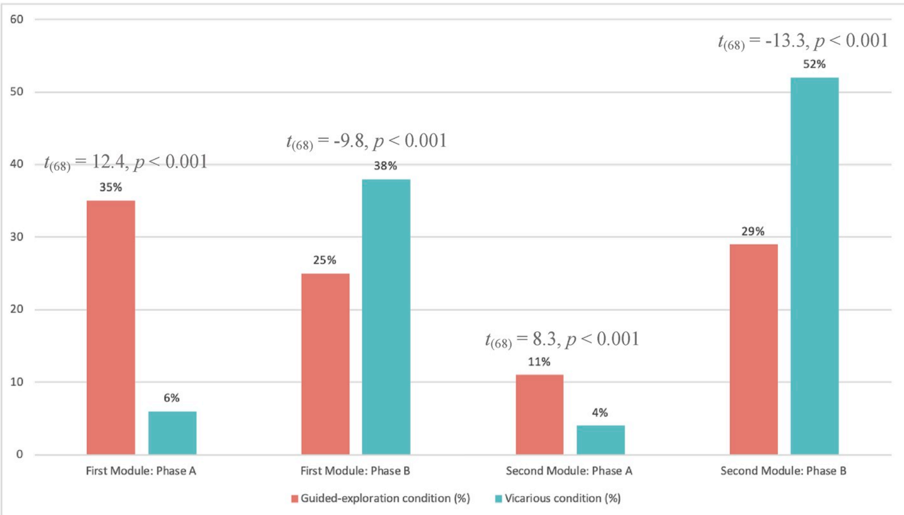


Fig. 4. The differences in time use (%) between the vicarious condition and the guided exploration condition while learning with the Deep Dive into Diabetes (DDD) environment.

3.3. Learning process

To further examine learning processes that characterized learning with the DDD environment, we analyzed the video-recorded data to evaluate students' time use and the quality of the different ideas exchanged between the partners. Analysis of students' time use (Fig. 4) reveals that students in the vicarious condition spent most of their time on solving Phase B of the second module (52%), which was more sophisticated but supported by detailed instructional prompts, whereas students in the guided exploration condition spent most of their time (35%) on solving Phase A of the first module, which demanded only basic understanding of glucose equilibrium mechanisms but was supported by only minimal instructional prompts. While the time devoted to each phase within the first and second modules was significantly different between the two experimental conditions (Fig. 4), only Phase B of the second module yielded a significant correlation with a medium effect size to the Diabetes knowledge posttest scores ($r(70) = 0.32$, $p < 0.01$).

Ideas expressed by 11 randomly chosen pairs of students shed light on the differences in time use between the experimental conditions. About 230 ideas and explanations were identified for five pairs who learned with the guided exploration condition (average number of ideas for each pair was 48) and 305 for six pairs who learned with the vicarious condition (average number of ideas for each pair was 51). To illustrate the process of coding ideas that participants expressed while learning with the DDD environment, we present the following short episode of a pair of students who were assigned to the guided exploration condition. This episode illustrates the expression of some accurate and less accurate ideas:[4]

Jessica:	Go. Now I click Go button. [setting the model to the diabetes type 1 condition].
Michelle:	So, we should have him eat candy.
Jessica:	Eat candy [clicking on the button which says "eat candy"]. It will be so much glucose.
Michelle:	So [observing the agent-based model], nothing is getting through [the muscle cell] at all.
Jessica:	Yeah, but, because there is no insulin.
Michelle:	Ahhh… there's no insulin. So, like, if they drink milk or eat pasta, or fasting, it won't matter, doesn't it?
Jessica:	There's nothing. So, you do not need to exercise. There's no insulin. They still need insulin to be alive.
Michelle:	Yeah, [without insulin] they are unable to make ATP.
Jessica:	Mm-hmm. So, there's no energy and then what?!

During this episode, Jessica and Michelle articulate three basic ideas that are critical to understanding the pathological processes related to glucose equilibrium as part of antidiabetic drugs action. The first is insulin's role in the regulation of glucose metabolism: if there is no insulin, then "nothing is getting in," meaning that without insulin, glucose can't enter the GLUT4 transporters on muscle cells' membrane. This idea is correct for the muscle and lipid tissues, where glucose metabolism is mediated by the hormone insulin. The second idea implicates the pathological definition of type 1 diabetes: "There is no insulin." Here Jessica expresses a nominal fact: in type 1 diabetes there is no insulin. Following that, a relationship between glucose molecules to ATP production is noted, namely the cellular respiration metabolic pathway (glycolysis). Jessica summarizes here her third idea, that when there is no glucose within the cells, ATP production process is impaired, which means that "there's no energy" production. This explanation is only partially correct because fatty acids and amino acids can be used for ATP production.

An analysis of students' ideas revealed that students who learned with the guided exploration condition (five pairs) expressed a total of 41 inaccurate ideas, whereas students who learned with the vicarious condition (six pairs) expressed only seven inaccurate explanations in total. Most of the inaccurate explanations (49%) with the guided exploration condition resulted from misinterpreting what to pay attention to while exploring the agent-based models. For example, the following episode represents a discourse typical of the guided exploration condition and related efforts to interpret muscle cell representations during Phase A of the first module[4:fn4]

Kate:	Okay. Glut4 channel is letting glucose inside.
Alex:	Glucose, yeah.
Kate:	Glucose or anything?
Alex:	Yeah,. . . . It makes ATP.
Kate:	And the insulin receptors are not really finding anything.
Alex:	Not a lot. It bounces [glucose molecules] off the insulin receptor. That's interesting.
Kate:	What's the—
Alex:	I don't know what those things are.
Kate:	"Time ATP glucose," "blood insulin" [reading from monitors' labels on the model interface]. Would it be blood insulin? Sounds strange.
Alex:	Maybe. Yeah.
Kate:	Oh. Hey, look. We've kind of a manual here [pointing toward the right side of the screen, beside the model].
Alex:	Oh. [laughs]

Kate and Alex were unsure what agents and their interactions represented until they finally noticed that the explanations for how to read the model were posted on the screen beside the model. Thus, in contrast to the vicarious specific guidance, which reduced the number of inaccurate ideas, the guided exploration condition was supported with less content-specific scaffolds, which, in turn, although it facilitated experiments and new discoveries, also made it more likely for inaccurate ideas to emerge. Moreover, the guided exploration condition was also related to stronger emotional expressions. More specifically, participants who learned with the guided exploration condition expressed 44 emotionally positive and negative verbal statements, whereas those in the vicarious condition presented only 19 emotional expressions. Thirty-two percent of the verbal expressions in the guided exploration condition were positive expressions such as "I like how the…, it really shows you like visually what is happening"; or, while making decisions about medication treatment, the following excitement was expressed: "They're going to die. We're killing him!" Here students projected life-like attributes onto the model even though there was no actual representation of a person. We believe that this empathic reaction to the computer model was induced by actions that students had to make, such as when and how much insulin should be administered; 68% of verbal expressions were more negative emotions such as "I don't know" or "I can't, I can't like wrap my head around it. It's so confusing. And this like thing is like confusing me more." Although the distributions of negative and positive emotions between the two experimental conditions were similar (64% vs. 36% for the vicarious condition; 68% vs. 32% for the guided exploration condition), the total number of verbal emotional expressions was higher for the guided exploration condition, suggesting a higher level of emotional engagement.

[4] All names are pseudonyms to protect participants' identities.

4. Discussion

Agent-based models are open-ended environments in which learners can explore different topics with the goal of understanding the underlying complex systems principles that govern the behavior of the agents and their emergent interactions. Those interactive simulations allow learners to conduct experimentation in which they have opportunities to engage with core concepts as equilibrium, set their own questions for exploration, and compare and contrast scenarios to make sense of the topic to be investigated. To promote health care pre-professionals' learning processes using agent-based models, we evaluated two instructional approaches. Our results clearly show that for immediate knowledge gains, the vicarious-learning approach was superior to the guided-exploration condition following a set of text-based prompts.

A theoretical surround for the current study is the ICAP framework, which predicts that the more that learners are cognitively engaged with their instructional materials, the better their learning outcomes would be (Chi et al., 2018; Chi & Wylie, 2014). Consistent with previous studies, our study shows that by optimizing learning from observation using collaborative dialoguing, the vicarious learners shift their cognitive engagement from passive mode to interactive mode, which in turn makes the vicarious approach for learning with agent-based models comparable to the guided exploration approach (Chi et al., 2017; Chi & Wylie, 2014). While the level of cognitive engagement in both study conditions seems to be comparable, students in the vicarious condition appeared to have greater learning gains. This raises questions about how that came to be.

We propose three possible explanations for the vicarious instructional approach advantage: less-inaccurate ideas involved in the learning process, better use of time, and lower perceived mental effort. Our analysis of the learning process proposes that students who learned with the guided exploration approach expressed more inaccurate ideas than the vicarious learners did. The inaccurate ideas among students who explored agent-based models using only textual prompts resulted from misinterpreting what to pay attention to while trying make sense of the multiple interactions and representations visualized by the agent-based model. We believe that those inaccurate ideas contributed to the significant difference in time on task between the two experimental conditions. Whereas students who learned with the vicarious instructional approach spent a major portion of their time (52% on average) on the most sophisticated phase of the DDD learning environment (Phase B of the second module), students who learned with the guided exploration condition devoted a major portion of their time (35% on average) to the introduction of basic concepts in the DDD learning environment (Fig. 4). Interestingly, our results showed that the more time that students devoted to solving problems in the most sophisticated section, the higher their knowledge posttests scores were. This effect of time-on-task on the academic performance of students learning in the computer-based learning environments was widely studied by researchers in the last decade (e.g., Krause, Stark, & Mandl, 2009; Louw, Muller, & Tredoux, 2008; Macfadyen & Dawson, 2010). Goldhammer et al. (2014) also showed that time-on-task increases with task difficulty and is positively related to students' performance. Following the notion that devoting more time to more sophisticated tasks is related to academic success, we can suggest that students who learned with the vicarious approach, though maybe unintentionally but as a result of the vicarious instructional design, made better use of their time than students who learned with the guided exploration condition.

Another factor that may have contributed to vicarious learning advantage is the level of perceived *mental effort* which reflects a difference in cognitive load associated with learning in novel, unfamiliar domains (Clark & Mayer, 2003; Paas & Van Merrienboer, 1994; Sweller, 1988). Our findings show that students who learned with the guided exploration condition reported higher mental effort following learning with the first module of the DDD learning environment compared to vicarious learners. As we suggested above, the higher mental effort might have derived from less efficient time use trying to make sense of higher amounts of their own inaccurate ideas.

Interestingly, while learning with the guided exploration condition involved more inaccurate ideas, it also triggered more emotional statements, both positive and negative. Emotions expression may suggest a higher level of engagement with the learning content, which in turn is associated with academic achievement (Pekrun & Linnenbrink-Garcia, 2012). Whereas learning-related enjoyment and positive emotions presuppose that the student has a sense of being able to master the material, negative emotions might be triggered by cognitive conflict and confusion, which in turn will either initiate deeper learning processes or, if appropriate scaffolds are not implemented, result in a sense of failure (D'Mello, Lehman, Pekrun, & Graesser, 2014). The emerging emotional disequilibrium that derives from the guided exploration instructional approach might be a precursor of deeper cognitive processing and thus should be further studied, specifically expanding knowledge evaluation for its retention.

4.1. Limitations

Given that our findings can contribute to science instruction, the study has several limitations, and further experimental studies are needed. Specifically, the current study evaluated only immediate learning effects followed by one short intervention, using a single population. It also involved applied health science content, which was pursued because of specific research interests related to students pursuing those fields. It remains an open question whether foundational disciplinary science content learning shows the same effects (e.g., kinetic molecular theory, predator–prey relations in ecosystems, evolution and natural selection). Therefore, the advantage of the vicarious approach over the guided exploration of modeling systems should be further explored by others in the field. Open exploration of agent-based models is important for concept construction, yet our findings suggest that we should do more to ask what conditions make working with and learning from agent-based models more or less challenging with different instruction types for different populations. Furthermore, although the subjective mental-effort measurement employed has been extensively and successfully used, showing good psychometric properties, some researchers raised concerns about its capacity to measure cognitive load due to many variations in how the measurement was applied (e.g., used with different labels or with fewer categories) and inconsistency in differentiating cognitive load types (De Jong, 2010; Leppink, Paas, Van der Vleuten, Van Gog, & Van Merriënboer, 2013; Sweller, van Merriënboer, & Paas, 2019). Therefore, further studies might use physiological techniques to increase cognitive load measurement reliability and validity (Antonenko & Niederhauser, 2010).

4.2. Conclusion

The main practical implication of this study suggests that learning with tutorials can be scaled up and maximized when visual displays entail dialogue between instructor and students and the learners solve problems while observing and overhearing this dialogue collaboratively. Most of the learning technologies or "edtech" systems that provide one-way, online lecture-based videos, according to the ICAP theoretical framework, are using a passive mode of engagement and thus encouraging minimal learning outcomes. We propose that this instructional approach can be generally shifted from passive to constructive and interactive modes by encouraging learners' dialoguing as they collaboratively overhear the videos. As we showed, by invoking an interactive level of engagement using dialoguing, vicarious instructional design can be at least as efficient as the guided exploration of simulations using agent-based models. Vicarious learning provides a unique modeling opportunity for students to learn how agent-based models and other simulation should be explored and enables them to reflect on their own process of learning.

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Appendix A. Supplementary data

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