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Students' actual purposes when engaging with a computerized simulation in the context of citizen science

Michal Dvir[1] | Dani Ben-Zvi[2]

[1]Faculty of Education in Science and Technology, Technion Israel Institute of Technology, Haifa, Israel

[2]Faculty of Education, University of Haifa, Haifa, Israel

Correspondence
Michal Dvir, Faculty of Education in Science and Technology, Technion Israel Institute of Technology, Eilat 12, Haifa, Israel.
Email: dvirmich@gmail.com

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Abstract: In today's information age, developing data science competencies has become vital to fostering responsible citizenry. However, the actual techniques learners need to become proficient in are still somewhat "in-construction", as the relatively new field of data science is constantly expanding to meet new data-related demands. Data science education needs to develop innovative means to keep up with this expansion that focus less on proficiency in specific techniques, but rather introduce novices to authentic data practices, and the authentic purposes directing the authentic practices. This paper focuses on a specific practice, the use of simulations to generate and examine data, in the context of authentic scientific Citizen Science research. We provide a case study of one pair of middle school students' engagement in an extended learning sequence including simulation activities inspired by authentic data practices, adapted to also be authentic for young students. While the simulation activity was inspired by the scientists' purposes, our findings illustrate four different actual purposes the students attributed to it. We also show that as the students deepened their engagement with the simulation, they gradually appropriated its intended purpose, alongside articulating more mature views of data-related concepts. The conclusions summarize the four different purposes the students expressed and identify aspects of design that contributed to the gradual re-shaping process of their actual purposes.

KEYWORDS

authenticity, computerized-simulations, data science education, educational technology, purposes

Practitioner notes

What is already known about this topic

- Introducing students to data science and statistics has become essential nowadays.
- Students need to be introduced to authentic data practices, but also to the authentic purposes motivating these practices.
- Utilizing computerized simulations is a common authentic practice in science and statistics.
- The pedagogical, intended, use of computerized simulations can be inspired by the authentic purposes but should also be adapted to be authentic for the students.
- Students may have actual purposes that differ from the authentic and intended purposes.

What this paper adds

- A case study of a pair of middle school students' engagement with a computerized simulation tool, as part of their participation in a Citizen Science project.
- The students expressed four actual purposes for the simulation.
- The students' initial purposes differed from the intended purposes, limiting their participation.
- Key aspects of the overall activity design ultimately supported the students to appropriate the intended purpose of the simulation and more deeply engage with the intended statistical notions.

Implications for practice and/or policy

- It is important to consider that students may attribute purposes that differ from those of the teacher or the activity designer, to any learning activity they engage in.
- Making the intended purposes more explicit may be helpful, but potentially not enough for students to appropriate them.
- Researchers' prompts, students' freedom to reshape their use of the simulation tool and productive discussion norms can be beneficial aspects.

INTRODUCTION

Learning as enculturation

As humanity moves into the data epoch, the need for a data literate citizenry has never been so vital (Finzer, 2013). Recent events, such as the COVID-19 pandemic, illustrate the need to consider complex factors as they unfold in the real world and how decisions based on vast, but limited data, can have dramatic consequences on human life, economics, social challenges, and democracy. Although the field of data science is rapidly expanding, it is struggling to keep up with the changing demands brought by the information age (Wise, 2020). Current research in data science education faces the challenging task of designing, implementing, evaluating and refining effective pedagogies, while the actual techniques learners need to become proficient in are still somewhat "in-construction" (Lee & Wilkerson, 2018). Adopting a sociocultural perspective of learning can help address this challenge. From a sociocultural perspective, learning can be seen as transforming participation in cultural activities (Rogoff, 2003), where culture is seen as "the constellations of practices historically developed and dynamically shaped by communities in order to accomplish the purposes they value" (p. 686, Nasir et al., 2006). Adopting this view reformulates the goal of teaching as supporting students' reshaping of the ways in which they participate in authentic disciplinary activities to more endorsed or culturally valued forms of participation, rather than develop technical proficiency (Hod & Sagy, 2019). This view also highlights the central role purposes hold in cultural and educational activities. Introducing students to a disciplinary culture therefore should also include introducing them to the purposes the disciplinary experts value or attribute to endorsed disciplinary practices.

Authenticity and multiple purposes

While some refer to authenticity as congruence with the practices of the community of expert practitioners of the targeted domain (Lave & Wenger, 1991), by importing such "authentic" activities into a classroom, underlying principles of the classroom or school culture are typically not accounted for (Linchevski & Williams, 1999). For an activity to be considered authentic to learners, it must also support inclusion of their previously cultivated dispositions and beliefs (Hod & Sagy, 2019) and thus be congruent with their pre-existing practices, interests and goals. An activity that would be *doubly authentic*, to the practice and the students, can potentially serve as a *gateway activity*: one which utilizes learners' existing resources and provides an experience through which they can engage with the underlying principles of the experts' practice. These experience-based insights can later be leveraged to foster engagement in the formal disciplinary culture's practices.

The way students participate in any classroom activity is influenced by the purpose they attribute to it (Lavie & Sfard, 2019). We view the notion of purpose similarly to Ainley et al.'s (2006) definition of a purposeful task as "one that has a meaningful outcome for the pupil, in terms of an actual or virtual product, or the solution of an engaging problem" (p. 29). However, in their discussion they restrict their use of the term *purpose* as one that strictly "refers to the perceptions of the pupil". Inspired by Lavie and Sfard's (2019) definition of task, we extend Ainley et al.'s use of the term, to refer to the potentially different purposes (ie, what would be considered a meaningful outcome or solution) of each of the interlocutors—be it those present in the room (eg, student, teacher) or those who design the activity and research students' engagement in it.

While the designed purpose of a gateway activity may be influenced by authentic disciplinary purposes, the purposes students attribute to it may vary greatly (Dvir & Ben-Zvi, 2021a). Even when an authentic disciplinary practice is adapted to a doubly authentic activity, students' personal purposes may be vastly different than the designed purpose of the task (Ainley et al., 2006), potentially hindering their adaptation of the authentic endorsed purposes and therefore the procedures promoting them that form the endorsed authentic practice (Lavie & Sfard, 2019). Furthermore, when specifically designed to have "a meaningful outcome for the pupil" (Ainley et al., 2006, p. 29), what students consider as meaningful can encourage them to act in a way that is at odds with the intended practice. For example, in the context of statistics or data science, students might consider the purpose, or meaningful outcome of a data investigation to be validating their conjecture (as opposed to examining or refuting it, Popper, 1963), and therefor would champion biased depictions of their data (Dvir & Ben-Zvi, 2018, 2021a). To attend to these potential discrepancies in purpose, authentic disciplinary purposes should be embedded in the design of a classroom culture, however one should also be mindful that the actual culture fostered in a classroom might be infused with additional or different purposes. Inspired by Hod and Sagy's (2019) distinction between authentic (eg, data science), intended (the designed classroom culture) and actual culture, in this paper we wish to explore students' personal or actual purposes, in relation to the designed intended and authentic disciplinary purposes, focusing on a pedagogical adaptation of one authentic disciplinary practice—using computerized simulations.

The practice of utilizing computerized simulations as part of authentic and intended cultures

While hands-on simulations have long been part of the scientific and statistical practice, technological advancements have enabled the proliferation of computerized simulations as a fully endorsed means to examine new, previously unaccounted for phenomena (Ahrweiler & Wörmann, 1998). In general, the role of a simulation is to provide often visual manifestations for unseen processes such as abstract notions (Segala & Lynch, 1995), or microscopic behaviour (Binder, 1995), that allow tinkering with and examining unfamiliar mechanisms, minimizing the need for approximations (Heermann, 1990). Although utilized in many disciplines, the purpose of a simulation may differ. For example, while in science "the main purpose of the simulation is insight [about scientific behavior], not data" (p. 2, Stoltze, 1997), in statistics the main role of simulations is indeed examining the *data* that an unfamiliar (or computationally complex) model can generate (Cobb, 2007), reflecting differences in the values and practices characteristic to each disciplinary culture. In data science, there is an additional layer of complexity to define the main role of the authentic use of simulations, as the data science culture is actually at the intersection of several disciplinary cultures, including statistics and the culture of the disciplinary context (eg, science) for which the data analysis is commissioned (Finzer, 2013).

Beyond authentic practice, simulation tools have been found to be beneficial in supporting students' scientific (Falloon, 2019) and mathematical (Hillmayr et al., 2020) reasoning, particularly when embedded in doubly authentic learning activities where the authentic practice is adapted to also be authentic for learners (Garfield et al., 2012; Hillmayr et al., 2020). Computerized simulations allow visual manifestations of abstract notions, and thus, afford more tangible explorations of them (Arcavi, 2003). Technological advancements can free the learner from focusing on mathematical procedures (Cobb, 2007) or laborious computations (eg, Rubin & Hammerman, 2006) related to the simulated phenomenon, as well as reveal naïve views they might hold (Liu & Lin, 2010). Furthermore, computerized simulations, as opposed to hands-on simulations, can provide the learner with a more extensive experience of the simulated process or notion (Garfield et al., 2012). The designed intended purpose of pedagogical utilizations of simulations therefor typically includes raising the accessibility to complex notions, thus might be different than what an expert would have employed it for (Budgett & Pfannkuch, 2018). Even doubly authentic simulation-based activities, inspired by authentic practice, are often infused with additional educational purposes (Manor & Ben-Zvi, 2017), pending on the designed intended culture and the general educational goals (Hod & Sagy, 2019). We describe now an example from data science education for such a doubly authentic design, and its intended purposes. Focusing on this design, this paper will explore the actual purposes students attributed to their simulation use.

Intended purposes of an integrated modeling approach

The integrated modeling approach (IMA, Manor & Ben-Zvi, 2017) is a doubly authentic approach to introduce young learners to the culture of statistics and data science, inspired both by authentic statistical practices, as well as students' knowledge, skills, interests and potential challenges. The approach is inspired by two authentic practices—investigating data to formulate statistical inferences (Makar & Rubin, 2018) and probability modeling (Pratt, 2000). While pedagogical adaptations of each of these practices have historically been researched separately (Makar et al., 2011; Mewborn et al., 2007), recent trends in statistics education have championed integrating the two, as is customary to expert practice, to support novices to relate probabilistic understandings to data-based inferences (Pfannkuch et al., 2018). While the IMA introduces learners to each practice separately, referring to each as a separate world of inquiry (the real and probabilistic worlds), it offers a unique form of connecting between them.

Learners begin by conducting "real-world" data investigations with the purpose of formulating "real-world" data-based inferences, facilitated by TinkerPlots (Konold & Miller, 2015), designed to accommodate young learners to easily construct a variety of data representations. Upon formulating inferences, students are encouraged to articulate and consider the uncertainty related to formulating claims beyond the data at hand. Having articulated uncertainty-related concerns (often informally probabilistic in nature, such as 'can I trust a sample of this size to represent a larger population?'), they are introduced to the probability world, as a realm to explore the concern they expressed.

Their probabilistic exploration begins with designing a model of their current inference utilizing various options of the TinkerPlots Sampler.[1] The model design is image-based and the model they create depicts their specific view of the investigated phenomenon. However, the Sampler model has a built-in probabilistic mechanism that allows learners to generate random samples from the population they designed. As students generate more and more samples, they experience the random sampling process and the sampling variability their model can generate. They ultimately utilize their experience with this simulation to formulate probabilistic insights about the samples' behaviour (eg, this sample size is too small to represent the population) and implement these returning back to continue their preceding real-world data investigation (eg, by collecting more data).

The intended purpose of the IMA simulation utilization is an adaptation of the authentic statistical use of simulations (eg, examining what data an unfamiliar model can generate). The intended purpose is introducing novices to the random sampling process and related statistical notions (ie, sample representativeness, sampling variability and sample-population relations) in a way that they can connect these to their real-world data investigation. However, learners often exhibit or articulate different purposes for the use of the simulation and the simulated samples they generate (eg, to learn about the real-world population, Dvir & Ben-Zvi, 2021a; to prove the simulation has been tampered with, Dvir & Ben-Zvi, 2021b), influencing their learning outcomes (eg, favouring simulated samples over real data, Dvir & Ben-Zvi, 2021a; disconnecting the probability-world insight from real-world sampling, Dvir & Ben-Zvi, 2021b). Although these discrepancies between the intended and actual purposes have been mentioned, they have not yet been thoroughly examined. Furthermore, the previous implementations of IMA-inspired simulations have focused on everyday contexts (Aridor & Ben-Zvi, 2019). Students might encounter additional challenges when the real-world context of inquiry is scientific in nature, as often is the case in authentic data science practice. Focusing on a recent implementation of an IMA-inspired learning sequence in the context of a complex scientific phenomenon, in this paper we examine: *What actual purposes can young students attribute to IMA-inspired simulation activities, and how can these change throughout their participation?*

METHOD

This study was conducted as part of the Connections project, a longitudinal design and research project (began at 2005), whose goal is promoting and examining young learners' statistical reasoning in a technology-enhanced, inquiry-based learning environment, currently collaborating with Taking Citizen Science to School (TCSS[2]) research center. TCSS examines the pedagogical potential of incorporating students as participants in Citizen Science projects, a genre of research incorporating the assistance of the public to collect vast amounts of data in less costly and time efficient ways (Kelling et al., 2015). Often, the nature of the scientific inquiry is closely connected to its participants' everyday lives (Jordan et al., 2015). Therefore, students' engagement in these projects has the potential of being doubly authentic—to the students, as well as to the culture of science characterizing the real-world ongoing research they contribute to. If the students have the opportunity to also meaningfully engage with the data they generate, their participation can also be authentic to the culture of statistics.

We employed an instrumental case study approach (Stake, 1995) to provide in depth accounts of the purposes young students attribute to their use of the simulation, and how these changed as they participated in the project's preliminary research. We chose a case study approach since our goal is to offer an in-depth, multi-faceted account of students initial and changing purposes for a simulation, a relatively complex yet nuanced process, as it occurred in the setting we designed. Customary to design research (Bakker, 2004) and due to the exploratory nature of this study, focusing on a previously untested novel learning sequence, this preliminary research focused on one pair of middle school students (ages 13 and 14), with the goal of later scaling up the design. The IMA-inspired learning sequence included both real-world and probability world activities, adapted to the scientific context of a citizen science project the pair contributed to. We open this section with information about the Citizen Science project and the learning sequence the pair engaged in. We then introduce the participating pair and describe the data collection and analysis we employed.

The Radon citizen science project

The pair participated in an eight 90-minute-lessons learning sequence[3] as part of the Radon ("the silent killer", an omnipresent inert gas, dangerous in high concentrations) TCSS project. As with other Citizen Science projects, the omnipresence of the Radon gas, and its health hazards, make its monitoring and exploration highly relevant to the project participants' everyday lives (Jordan et al., 2015). Participating in the authentic scientific Radon investigation offers authentic experience of the scientific culture, and the learning sequence we developed was particularly designed to also meaningfully engage the students with the data generated by their participation. The learning sequence opened with an introduction to the Radon project, and, in accordance with the IMA (Manor & Ben-Zvi, 2017), followed with three real-world data investigations leading to a subsequent probability world investigation.[4] The investigations were specifically designed as gateway activities inspired by one of the scientists' authentic purposes: modeling a behaviour that is unique to Radon and is currently un-explained, the Radon temporal variation (high, frequent, non-systematic, momentary fluctuations). An innovative measuring tool the scientists used and students were to utilize to collect data was also central to the activity design. The measurement given by this tool is the mean Radon Concentration Level (RCL) in four days, and the students were planned to ultimately examine the big data set collected by the project's participants. To scaffold their engagement with the latter data, thus make it authentic to the learners as well as to the practice, the students began by examining additional authentic data sets, collected by the scientists in their lab, originally intended for tracking the concentration of Radon gas to insure the lab adheres to health regulations. In accordance with the 'growing samples' heuristic (Bakker, 2004), the students gradually examined 24 (one day), then 48 (two days) and finally 72 (three days) of hourly Radon measurements. The designed purpose of their real-world data investigations was to "learn more about Radon", meaning, (1) to experience and model its temporal variation; and (2) to emergently consider the mean as a representative of Radon concentration.

Upon formulating an inference about the Radon's behaviour, the students were encouraged to articulate their uncertainty and its origins. Having experienced the temporal variation that was evident in their three-day data, both students expressed concerns about formulating general claims about Radon's yearly behaviour based only on three days of measurement. In accordance with IMA, the Sampler simulation tool was then introduced with intended purposes adapted to be authentic to the students' needs as well as the scientists' actual practices. The intended general IMA purpose was adapted to students' examining sampling variability to (1) discover that a four-day measurement is significantly more representative than a three-day measurement (aligned with the authentic use of the scientists' short-term measurement device); and (2) develop an estimation of the maximum error of a four-day mean measurement. While these were the intended purposes of the use of the simulation, the students articulated different actual purposes, which are the focus of this paper.

The participants

Liv (13-years-old, grade 8) and Yoni (14, 9) are articulate middle school students from a public school in northern Israel. Both had no prior experience with data investigations and were chosen as they agreed to participate in the study, were verbal and open, thus were able and willing to share and explain their thoughts, considerations and concerns. Furthermore, early in the learning sequence, the pair emergently mentioned simulations as part of what they believed the scientists utilize, thus infused simulations into the ongoing conversion. The accompanying researchers therefore had many opportunities to inquire about the students' views of simulations, resulting in an abundance of resources to deduce the purposes they attributed to it and how these changed throughout their engagement in the learning sequence.

Data collection and analysis

All of the participants' actions were videotaped by camera and Zoom,[5] concurrently documenting the students' computer screen and articulations. The data corpus was transcribed and analysed according to the interpretative microgenetic method (Siegler, 2006) by the two authors and at least one additional Connections research team member. The transcripts, generated by the entire research team, included any articulation expressed (by the students and the researchers), any actions taken (eg, changes to the data representation documented both verbally and visually via screenshots), along with any additional gestures (written in squared brackets to distinguish them from verbal articulations). The unit of analysis was a single full utterance (eg, a students' full response to the researcher's question, until completion or until interrupted by another speaker).

The analysis began by reviewing each utterance and interpreting any vague or unclear words (eg, what does "it" referred to), considering the context of the utterance, and the accompanied gestures and actions (eg, in the previous utterance the researcher asked what the Sampler simulation would generate, and in the student's response, while saying "it" she pointed towards the image of the Sampler model they created, currently visible on their computer screen). For each utterance initial interpretations of its general meaning were noted (eg, the student is expressing her view of the type of data the Sampler model would generate), again in consideration of its context (eg, prior articulations). The second stage of the analysis, in accordance with the goal of this study, focused on the students'[6] utterances that included explicit and implicit mentioning of the simulation tool (eg, "because we gave it [the Sampler model] a range … of 48% [in the second column], it increases the chances that they [sampled data] would be taken out form here [the second column]"), and the actions they took while utilizing the simulation tool. Utilizing our definition of purpose as a *meaningful outcome or solution* (Ainley et al., 2006), the interpretated general meaning of each relevant utterance was re-examined to suggest any implied possible purpose the students attributed to the simulation (eg, the student is running the simulation to generate samples she can use to further explore the phenomenon, expecting it would only generate data that is similar to the Sampler design, indicating she considered a meaningful outcome of the simulation to be generating similar data). If more than one purpose was implied, the full context of the utterance was again reviewed to determine the most probable purpose. Finally, the interpreted purposes were reviewed to identify commonalties, allowing to classify all of the relevant utterances into one of the following four broad types of purposes: (1) generating scientific (contextual) information; (2) generating identical or similar data; (3) examining the probabilistic nature of random sampling; and (4) examining the probabilistic nature of random sampling to inform the real-world data investigation. Key scenes were discussed and triangulated, by going back and forth in the data corpus, by examining various data sources and by discussing various possible interpretations among at least three researchers until reaching consensus (Schoenfeld, 2007b).

RESULTS

In this section, we illustrate the four types of purposes the students expressed for utilizing the Sampler simulation. These are described chronologically showcasing not only the various purposes they held, but also how these progressed as the students deepened their engagement with the simulation.

Simulations as a tool for generating scientific (contextual) information

During the real-world data investigations, the students were both hesitant to formulate any inferences beyond the three-day hourly data they were examining about the Radon yearly behaviour. The concern they repeatedly expressed was based on their view that the variation they observed in their data can be fully explained by environmental conditions, a cause-and-effect view, but they did not know what all the factors were or how they can affect the RCLs. In discussing their belief that the scientists have more knowledge than they do about the effects of environmental conditions, Liv emergently introduced the term "simulation" to the conversation:

1	L:	They [the scientists] can conjecture what might happen because they tested heat, for example … did a simulation, so they have more information about the quantity of radon in the summer as opposed to the winter, and we do not have that information, so we do not know how it [RCL] will change in different climates …
2	R1:	… Do you think scientists can check everything?
3	L:	Not everything, but they can do more than we can … That's why they need to make many conjectures … and make educated guesses …

4	R1:	And when they do not have the option of physically going to check something, do they have any additional options beyond just conjecturing?
5	L:	Try to do a simulation of it, like we see here [real sample]. These [the real data] are real things, but you can do it in laboratory conditions
6	R1:	What does simulation mean?
7	L:	A simulation is an un-natural thing they create, not a natural situation, in laboratory conditions
8	Y:	… Simulation basically will be not the real thing, as opposed to laboratory conditions that can be real but in controlled conditions, but it is still Radon, is still a phenomenon that happens in the real world and is even common, as opposed to simulation. It is like trying to do it in a less substantive way

Liv referred to "simulations" as one means the scientist has to obtain "more information" about the effects of environmental conditions, such as temperature [1], again implying the cause-and-effect view both students had earlier expressed. Building on the students' mentioning of the formal scientific practice, the researcher questioned if they believed scientists can "check everything" [2], referring to previous discussions about the multitude of potential impactful environmental conditions. In Liv's response she again implied how without "checking everything", one is left with only "conjectures" or "educated guesses" [3], reflecting the pair's full uncertainty with formulating any general claims. Implying that not everything can be "physically checked" [4], challenging Liv's claim, the researcher implied one of the benefits simulations can afford—something scientists can do beyond mere conjecturing. Liv's response acknowledged this benefit [5], but also conveyed her view of a simulation as means to generate information that is similar to the real-world data they were examining, but in restricted ("laboratory", "un-natural") conditions [7]. Yoni's view of simulations was likewise a tool to generate additional information, but he emphasized that this information would not be "real" and would be generated "in a less substantive way" [8]. Despite the different depictions, the pair's shared initial view of "simulations" was a scientific practice the scientists employ to generate more scientific information about the cause-and-effects of attributes.

Simulation as a tool to generate identical or similar data

The students continued their gradual real-data investigation and concluded it in the sixth lesson. Asked to formulate concluding inferences about the Radon yearly behaviour, Yoni again expressed his concern:

9	Y:	My conjecture was that according to these [real-world] data from one until eight [pm] there would be substantially less radon than other hours during the day, but it's a theory, we have no way of proving it in other days …
10	R2:	… Does this mean that we need to continue and examine theories?
11	Y:	Of course, every detail

Yoni's concern again implied the pair's uncertainty regarding their ability to confidently formulate general claims about the Radon's yearly behaviour [9]. It also echoed their previous discussion about simulations—he had now formulated a conjecture that cannot be proven [9], thus needs to be further meticulously examined [10, 11]. Building on the prior exchange, the researcher then introduced the Sampler as a means to "help you answer your questions" [12], and instructed the pair how to utilize it to design what they believed about the Radon's yearly behaviour, based on their three-day sample. The students ultimately created a Sampler model fully based on their real-world sample (Figure 1).

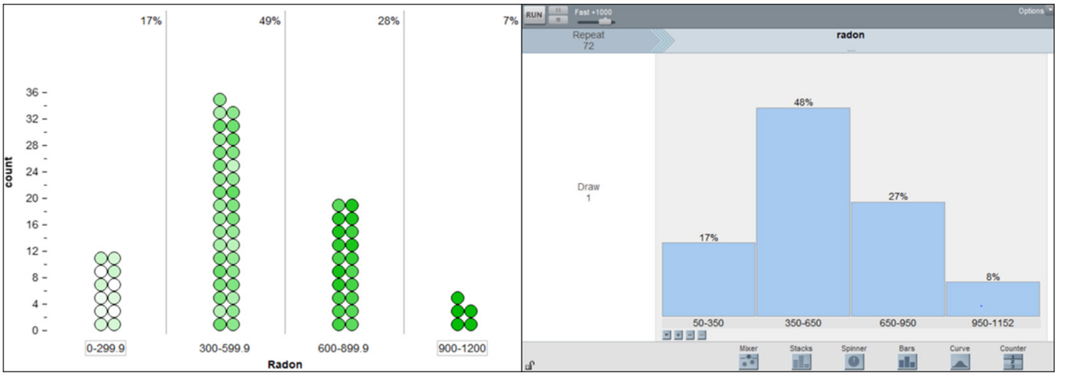

FIGURE 1 The students' sampler design (right) based on the real-world data (left)

Although the students complied with the researcher's instruction, in the next lesson it was evident that both students were unsure about the role of the Sampler model they designed (eg, “I have no idea what is the meaning of this model” [Yoni, 13]). Together with the researcher they recalled how they constructed the Sampler model based on the real-data. After recalling how the two were connected, the researcher encouraged them to consider the different role each of them had:

14	R:	So what is the difference [between the sampler model and the real sample]? Why are we moving to the simulation world[7]?
15	L:	Because we want to check a random sample, that it [the Sampler] will give us three random samplings [days] and not specific, so it will give us more information about one year
16	Y:	… I think that it is because we do not have a budget to measure every hour of every day … We are doing this to make the process more efficient, you can basically do this more accurately with real results but this makes the process more efficient, makes it simpler

Liv repeated in her response the role she previously associated with simulations, generating “more information” [1] but connected it to their current investigation, “more information about one year” [15]. Yoni added an additional real-world practical motivation for conducting simulations, efficiency [16]. Both students seemed to agree the simulation would substitute real data gathering, but the nature of the data they expected it to generate was unclear. To further understand the students' perceived role of simulation, the researcher inquired about what the students thought that can be *learned* from their simulation:

17	Y:	I am assuming that this software knows sort of what we know [about] how radon behaves, right?
18	R2:	It [the Sampler] knows what you … drew in the model, that is what it knows
19	Y:	So it [the software] will give us what was given in the model … What the software will give me will be based on this [the Sampler design] because this is the data we gave it
20	R2:	What does that mean?
21	Y:	That it [the software] will be accurate more about the laboratory itself, under the assumption that the data here [real sample] are accurate and the Radon behaves the same in the three really specific days [in the real sample]
22	L:	I think that because we gave it [the Sampler model] a range, that we thought that it was the range of RCLs … If I put here the range of 48% it increases the chances that they would be taken out form here? I think this is how it is supposed to be, because I said that there were a lot of cases where the Radon is like this [350–650], so it will take it out of here [the 350–650 column]

23	R2:	Yoni is saying that … because we built it [the Sampler] according to what we saw in the lab [real-world data], the sample we take out of the machine randomly will help us learn about the real world, about what happens in the lab … is that what you are saying?
24	Y:	A lot of options go through [my mind] about the sample that we see and many things [environmental factors] that can change it, so I think you can learn [from the Sampler] but it is very very very dependent [on environmental conditions]

In response to what can be learned from the Sampler, Yoni questions what the Sampler "knows", referring specifically to the scientific context of "how Radon behaves" [17]. When the researcher provided Yoni with the information he requested, restricting the software's "knowledge" to what the students had designed [18], not to scientific information about the Radon, Yoni then expressed a new expectation about the simulation: the data their model will generate will be identical to what was "given" (designed) in the model [19]. Prompted to elaborate [20], Yoni restricted what can be learned from the Sampler: one can only learn about about specific days that Radon behaves in "the same" way it did during the three days of real-world data collection and the location, "laboratory", they were collected from [21]. Liv too expressed an expected relation between the Sampler design (eg, "I put here" [22]) and the data it would generate, but one that was more probabilistic (eg, "increases the chances") than Yoni's, relating to the relative frequency in their designed model. The researcher re-iterated what she understood from what the pair, specifically Yoni, had articulated [23], asking if he considered the potential simulated data as a means to learn about the Radon's behaviour. Yoni explicitly re-iterated his hesitation connecting his current view of the role of the simulation and his view that all variation in the data can be fully explained by cause-and-effect: because the Radon's behaviour is dependent on many factors (not accounted for by the Sampler device) there is not much one can "learn" more generally from the simulation [24], still expressing the pair's full uncertainty in formulating general claims.

In the conversation that followed the latter exchange, Yoni again mentioned a real-world scientific motivation for simulations (eg, "it makes sense, it is even very very smart how we do this instead of waiting for a whole year" [25]) but also its limitations (eg, "because it doesn't take into account what can cause dramatic change" [26]). These indicated that while Yoni acknowledged the scientifically authentic justification for utilizing simulations, he restricted the potential knowledge gains of the simulation due to his view that variability can only (and fully) be explained by systematic sources, which he had insufficient information about. Challenged by the researcher to consider still what can be learned from the simulation, Yoni ultimately agreed that "because we gave it [designed the Sampler according to] three normal days, it will give us samples of additional three normal days" [27]. Liv shared similar concerns (eg, "[we need] to understand how the climate affects it [RCLs]" [28]), but was generally more open about what can be learned from the Sampler about the Radon's yearly behaviour (eg, "I can maybe see a little more how a year would look like" [29]). Both students therefor now considered the role of the simulation as providing identical or similar results to those in the Sampler model, as opposed to the initial expectations they attributed to the scientists' practice, of learning more about the effects of environmental conditions.

Simulations as a tool to examine the probabilistic nature of random sampling process

As the students generated the first simulated sample, they both agreed its results resembled greatly to their Sampler design, as they had expected (eg, "it will show that the machine builds a graph according to the data we give it and nothing more" [Yoni, 30]). Despite the similarities, both students were still reluctant to formulate any general claims as they explained the resemblance fully by what they had designed (eg, “I chose the chances, and I did not choose them based on knowledge about the effects of climate but on those three days” [Liv, 31]), reflecting their view of the simulation's role as generating data almost identical to the Sampler design.

The students generated a second simulated sample and were surprised to discover “Oh, the data have changed!” [Yoni, 32]. Although initially disappointed by the unexpected differences they were acknowledging, both students explained these by the real-world Radon behaviour they had seen in the preceding real-data investigation (eg, “it is reasonable that there would be days where the range is more towards the low side” [Liv, 33]), without considering sampling variability related to random sampling. When Yoni again articulated his cause-and-effect explanation for the variability (“where the cats sleep can affect the RCLs in the house” [34]), the researcher reminded the pair that they did not include the effects of environmental conditions in their Sampler design. In response, Yoni expressed, for the first time, a somewhat probabilistic expectation: “but this is probability … what are the chances that one of the samples would be between 50–350? 17% according to the percentages we gave it” [35], however claimed that “any one percent can still make drastic change” [36] reflecting an extreme view of sampling variability.

Yoni's reaction to the third simulated sample (Figure 2) was quite extreme, “drastic change!” [37]. Liv, however, began noticing that despite the changes in the percentages in each column, there was something shared by all of the samples they have seen so far. While Yoni was worried that the “quantity itself has changed” [38] Liv explained:

39	L:	Of course it [the percentage of a column] will change in terms of the concentrations because every day there is variation, but in terms of the ratio—that there is the fewest of this [lowest relative frequency, right bin, Figure 2] and then this one is next [second lowest relative frequency, left bin, Figure 2], the ratio stayed the same

The stable element Liv was now acknowledging was not the quantity or percentage within a single column but the relation between their relative frequencies [39]. Accepting Liv's

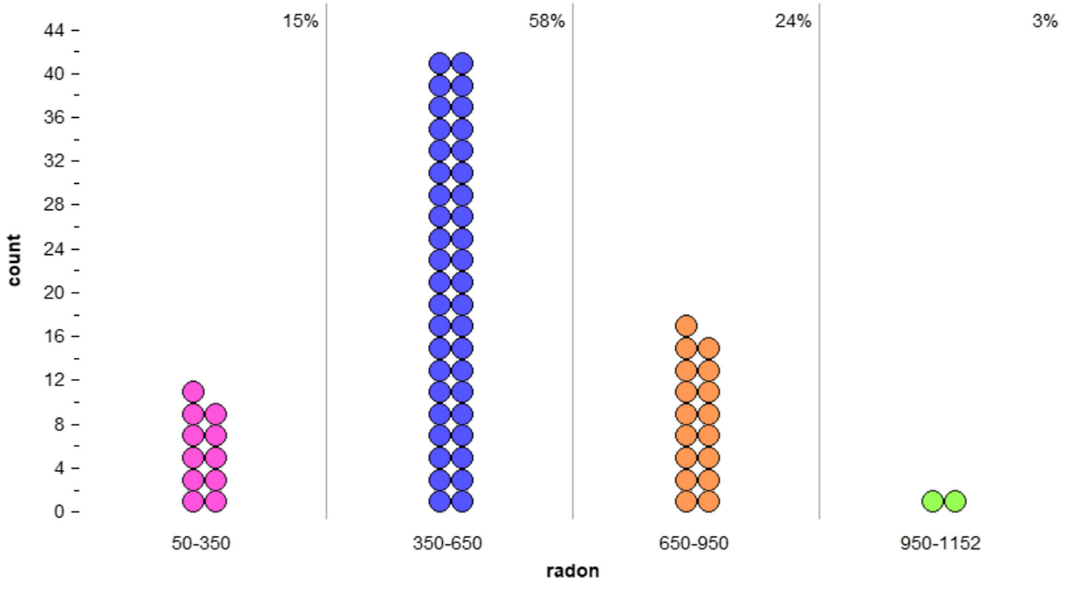

FIGURE 2 The third simulated sample the students were examining

claim, both students expressed a belief that this relation would also be found in the next simulated sample. Although the fourth simulated sample indeed adhered to their expectation, Yoni was still hesitant to infer more generally about samples' behaviour—"any sample that comes out, I don't trust it, because this is a limited software" [Yoni, 40]. Liv challenged Yoni's latter claim:

41	L:	It [the simulation] is effective because it can show you data about other 72 hours, It is effective in what it does, it just does not know Radon, and neither do we … We can learn [from the simulation] about options that can happen in the same three days

Although Liv was also restricting the Sampler's ability to explain the Radon behaviour, she did see it as a means to learn something about "options" of the data that can be generated by it [41], articulating for the first time the Sampler's utility in exploring sampling variability or in her words the various "options" of samples that can be generated from the population they designed. Yoni rejected this purpose re-iterating his extreme view of sampling variability (eg, "if it is based on probability then all the options that we gave it can happen" [42]). To support the pair in further elucidating what can be learned from the Sampler, the researcher suggested they invent a method to compare across multiple samples that would be more efficient. Liv suggested they write down the percentage of each column, using the TinkerPlots' pen that does not get erased upon generating new samples. The pair employed this method for four additional simulated samples, each time adding the notation of the respective percentages (Figure 3).

The pair were so engaged in the task that they continued it even when the researchers stepped outside the room. When they returned, the pair excitedly shared what they have learned: "that it is pretty consistent with what we said before, the hierarchy of the percentages" [Yoni, 43], and then elaborated on the various numerical results that supported this claim. The researcher then inquired what they have learned from this in regards to samples size 72, in accordance with the activity's intended purpose [44]:

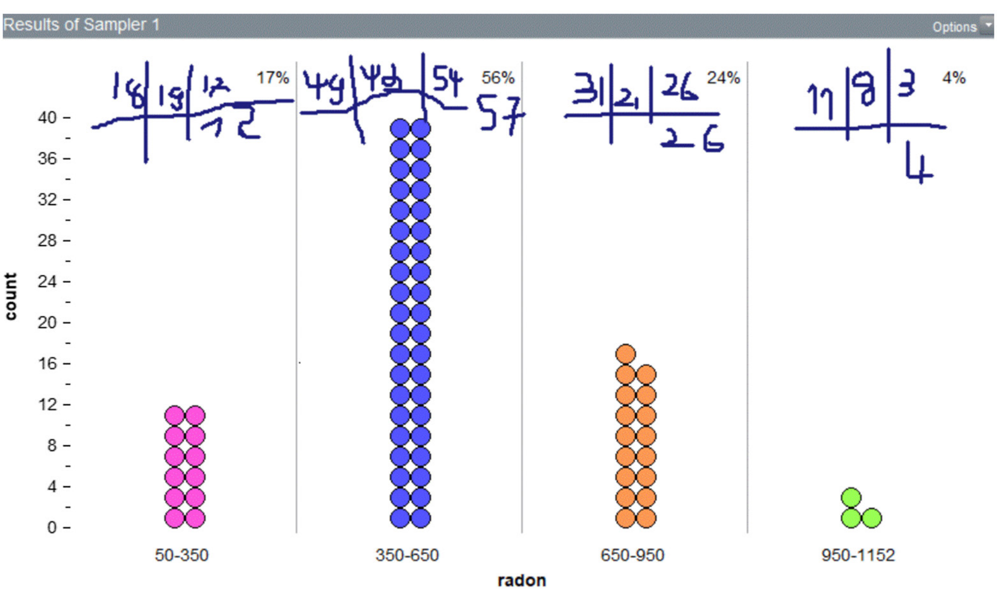

FIGURE 3 A random simulated sample with the pair's notations tracking the relative frequencies over four simulated samples

44	R2:	So what does this mean? Can samples size 72 represent a population that looks like this [sampler design]?
45	L:	Yes, for the same time period without changes
46	Y:	Yes, basically
47	R2:	That is different than what you [Yoni] said before … Alright how much? How much can it represent? Exactly? Would it come out exactly the same?
48	L:	You can see that it is not exactly the same, there are many differences, but it's the same ratio, it's sort of the same
49	Y:	It's still probability so there could be a week that everything rises
50	R2:	Yes? It could be? What are the chances that would happen?
51	Y:	Very very low, but it exists and if a chance exists it could still happen
52	L:	There is a chance that many things will happen, but a really small chance

While both students were still concerned with the potential effect of different environmental conditions, both were now willing to infer that a sample size 72, given similar conditions, would represent the population from which it was generated [45, 46]. Asked to quantify the extenet of the potential differences they now expected, Liv expected that the stable ratio they observed will persist [45], while Yoni, again claimed that any outcome would be possible [46]. However, in response to the researcher somewhat challenging their claims, posing an extreme what-if scenario [47] and asking about its likelihood [50], both students now agreed that the chances for a significant difference were low [51, 52], expressing a more mature view of sampling variability. Although not explicitly discussed in the latter exchange, the pair's focus on the behaviour of the samples they generated, as opposed to the scientific behaviour of Radon, indicated that the actual role they were utilizing the simulation for was examining sampling variability.

As the conversation continued, Liv suggested: “maybe we can take out many many many [samples] and see if it [the column with the lowest relative frequency] ever comes out more” [53]. They started generating additional samples, one after the other, focusing on the relation between the green (lowest relative frequency) and pink (second lowest) columns (Figure 3). Liv expected that “it will never come out [that the pink would be taller than the green]” [54], while Yoni was eager to prove differently. Although they did not explicitly articulate it, both students were fully immersed in examining sampling variability, without mitigating it by their contextual cause-and-effects views. They were extremely excited when finally, after many samples, the two columns they focused on came out with equal relative frequencies (eg, “Boom!!! It's the same!” [Yoni, 55]), the opposite ratio, and even one case where one of the columns was empty (Figure 4).

While both students acknowledged that this happened “very very few times” [Yoni, 56] Liv seemed to be a little discouraged, “this variability is sort of … there are cases that are really” [Liv, 57], explicitly referring to the sampling variability she observed, that exceeded her

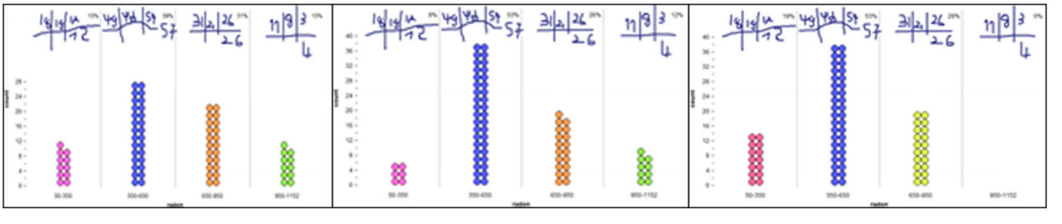

FIGURE 4 Samples in which the right and left bins had equal relative frequencies (left), the right bin had greater relative frequency (middle) and zero cases (right)

initial expectations. This motivated the pair to further their exploration of sampling variability, by formulating an expected range for the relative frequency of the mode ("39–68" [Liv, 58], "35–60" [Yoni, 59]. They again immersed themselves in generating additional simulated samples, jokingly keeping score (eg, "that's one for me" [Yoni, 60]). Yoni was excited to conclude that the range he suggested was "more accurate" [61], and the researcher seized the opportunity to connect his claims back to the issue of "trusting samples", in accordance with the intended purpose of the activity [R2, 62], implying that his choice of smaller range actually expressed a higher degree of trust in the samples' representativeness, expecting less sampling variability. The pair therefore were at this stage utilizing the simulation to explore the probabilistic nature of random sampling processes and develop estimations for the maximum sampling variability, or maximum error.

Simulation as a tool to examine probabilistic behaviour of random sampling to inform the real-world data investigation

In the next lesson the students summarized their use of the simulation and its role. Liv claimed, "I think I do have something to learn from 72 hours, and ultimately also that device that they [the scientists] want is only for 72 hours" [63], explicitly connecting the activity to the scientists' real goal of collecting data with their invented short-term measurement device. She then stated, "If I would have known more about the behavior of Radon, I could have learned more [from the simulation], but you can learn from this and off course there is a range of error" [64], connecting the ranges of sampling variability they previously examined to their meaning in the real-world scientific context. Yoni summarized what he had learned from the simulation also referring to the real-world scientific device and its goal: "That device is intended to say the room is dangerous or not dangerous, and for that [purpose]—72 hours are enough" [65].

When asked if a result of 80, using the scientists' device, would be considered dangerous or not, based on what they had learned from the simulation about the behaviour of Radon, Liv noticed that while the scientists' device provides a mean RCL, their Sampler model and the data they generated from it did not allow for exploring the mean. The pair therefore decided to construct a different Sampler model of the yearly RCLs that included their conjectured mean. They spent the remainder of their probability-world investigation utilizing the simulation to examine the sampling variability in relation to the mean of their simulated samples and concluded that 96 hourly measurements (4 day) would be more reliable than 72 (3 days). The connections the students articulated between the results of the simulation and the scientists' goals and devices, as well as adjusting their model to explore the behaviour of the type of measurement the scientists create and analyse, indicated the students were, at this point, utilizing the simulation to examine the probabilistic nature of the random sampling process to inform their real-world data investigation.

CONCLUSIONS

Adopting a socio-cultural perspective of learning (Rogoff, 2003) and considering purposes as an inseparable aspect of the students' actual culture, the designed intended culture and the authentic disciplinary culture (Hod & Sagy, 2019; Nasir et al., 2006), this research set out to explore their potential discrepancies. In accordance with this lens, we focused on a practice students engaged in, utilizing simulations, with the goal of examining a main aspect of their actual culture and enculturation to the target disciplinary culture: the actual purposes young students can attribute to IMA-inspired simulation activities, and how these can change as they engage with the simulation tool. The pair expressed four actual purposes, three of which were far removed from its intended purpose (Ainley et al., 2006). The first relates to a main authentic scientific purpose of deriving scientific insight (Stoltze, 1997), however reflectied more the students' perception of the scientific practice than the fully authentic scientific purpose (potentially introduced to the students through the science classroom culture they had experienced). The second reflects a more statistical purpose of randomly generating data (Cobb, 2007), but is infused with a naïve view of the data generating process, void of considerations of non-systematic sources of variability such as sampling variability. The third likewise reflects a statistical purpose of randomly generating data, but considers the role of the data generation as a means to examine the probabilistic nature of random sampling processes, accompanied with a more mature view of sampling variability. The final purpose was relatively aligned with the intended purpose of the IMA-inspired simulation use (Manor & Ben-Zvi, 2017) of connecting the experienced probabilistic behaviour of samples (sampling variability) with the real-world investigated context that instigated the need for the probabilistic investigation.

Overall, although initially attributing a different purpose to the simulation, as the students deepened their engagement with the simulation device they seemed to gradually and emergently appropriate its intended purpose. We refer to the process as emergent to reflect it was the students' choice to align their actual purpose with the designed intended purpose, but that is not to say they were not encouraged or scaffolded to do so. The main aspects of the overall activity design that facilitated the gradual appropriation process were: (1) the researchers' prompts (providing requested information [18]; asking to elaborate [20]; reiterating [23] or challenging the students' claims [4], [47], [50]; and referencing the intended purposes [44], [62]); (2) the freedom to reshape their use of the simulation tool (documenting the relative frequencies as in Figure 3, [53], [58–60]); and (3) the discussion norms between the students (eg, [21–22]) and with the researcher (eg, [23–24]). The latter was particularly consequential as Liv seemed to appropriate the intended purpose earlier in the learning sequence ([22]), and her disagreements with Yoni played a key role in his later appropriation of it [eg, [41], [44–51]).

These findings reify other studies that have pointed to the role of the overall classroom culture the simulation activities are part of (Garfield et al., 2012; Hillmayr et al., 2020), and extend them to show how these can contribute to students' developing the intended purpose even if initially they attributed to it other purposes. Beyond illustrating again the affordances of making abstract concepts and processes more tangible (Arcavi, 2003), our findings also show how students' use of the simulation revealed their initial naïve views (Liu & Lin, 2010) of relevant disciplinary concepts, and how these matured alongside their gradual appropriation of the purpose of the simulation activities. The gradual maturation process the students' actual purposes underwent is similar to Lavie and Sfard's (2019) depiction, implying how authentic disciplinary purposes, not just practices or procedures, often need to be nurtured and developed. Together, these highlight additional aspects of the pedagogical potential of doubly authentic simulation activities, as gateways to the authentic culture. These also suggest practical implications for supporting students' engagement in doubly authentic activities, including freedom to explore emerging concerns using the available tools, challenging naïve views or purposes they express and fostering productive negotiation norms. While further research is necessary to examine the generalizability of our results, the case presented in this paper, despite its idiosyncrasy, illustrates how building on students' personal purposes, even if they differ from those intended by design or those of the authentic culture, can support them to gradually appropriate the authentic practices, by means of developing the intended purpose inspired by the authentic purpose of the practice.

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CONFLICT OF INTEREST

There is no conflict of interest in the work reported in this manuscript.

DATA AVAILABILITY STATEMENT

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

ETHICS STATEMENT

This research was approved by the faculty ethics committee of the University of Haifa (approval number 16/102). The students and their parents were fully informed about the goals of this research and its implementation. The research was not conducted in the students' school and therefore they were not graded in any way on their participation. Students' real names were substituted by pseudo names to protect their privacy.

ENDNOTES

[1] The TinkerPlots Sampler allows students to design and run probability simulations, intended to expand the focus on data and statistics and incorporate probability.

[2] https://www.tcss.center/home-en.

[3] For more information about the Radon learning sequence, see: Connections 2020.

[4] The designed learning sequence included two additional investigation cycles, relating to the type of data that are generated in the Radon project. COVID-19 restrictions inhibited their implementation. A full implementation of the designed learning sequence is forthcoming. For an example for the written guidance the students received, see: Connections 2020.

[5] Although the students participated in-person accompanied by two researchers, additional 2–4 Connections researchers monitored each lesson and data collection remotely via Zoom.

[6] The researcher's utterances were carefully reviewed throughout the analysis, in accordance with the socio-cultural view that any aspect of the setting should be considered in interpreting the learning that occurred. However, as the goal of this study was to explore the purposes that the *students* articulate for the simulation (and not the purposes that the *researchers* articulate), in the second stage of the analysis included only the students' utterances were coded.

[7] A term the students chose for the probability world.

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