Journal of Physics: Conference Series

PAPER • OPEN ACCESS

High school students' epistemological approaches to computer simulations of complex systems

To cite this article: Eleonora Barelli *et al* 2019 *J. Phys.: Conf. Ser.* **1287** 012053

High school students' epistemological approaches to computer simulations of complex systems

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Abstract. The science of complex systems can provide not only scientist, but also professionals, policy-makers and citizens, with thinking resources to interpret and understand most of the modern global challenges. In this field, the widespread use of computational simulations, that are neither theoretical instruments nor laboratory experiments, has been contributing to the widening of the scientific skill gap between experts and citizens. The pilot study we present in this contribution aims at investigating high school students' approaches towards simulations of complex systems, by searching for the criteria they use to evaluate their explanatory power and the reliability of their results. Preliminary analysis of the paired interviews has shown that (1) rarely students are able to elaborate explanations of the simulated complex phenomena, and (2) their critical attitude and trust towards simulations are strongly affected by their epistemological background. We argue that these findings deserve to be furtherly investigated, to understand in more details the sources of students' difficulties in recognizing the epistemological and methodological value of simulations for scientific research and practice.

1. Introduction

In an increasingly complex world, our society is facing big global challenges – e.g. global warming, migrations, radical changes in the labour market dynamics, world populations growth – and most of them need STEM (Science, Technology, Engineering and Mathematics) knowledge and competences to be tackled and understood [1]. Indeed, innovations in the STEM research and application fields influenced so much the society in the last decades that, in order to rationally manage such issues, it is necessary to own specific thinking resources and to be aware of the connections between STEM and society, both in terms of possible dangers and of opportunities [2]. By contrast, we are facing a paradox [3]: never before in human history there have been so many scientists developing so many analytical tools, but they often do not reach the working knowledge of professionals, policymakers and citizens. Although they must deal first-hand with the challenging social and global problems, a growing distrust toward science and scientists has been reported [4]. In fact, the analysis and understanding of these issues would require scientific competences coming from the science of complex systems [5]. The widening gap between the expert knowledge of scientists and that of common citizens [6] is not only due to the conceptual difficulties of the topics but also to the epistemological and methodological novelties they introduce [7]. Indeed, complex phenomena like climate change cannot be investigated with the traditional experimental method [8], that is why most of the projections and elaborations of future scenarios that – should – inform policy-makers decisions are not based on experiments but rather on computer simulations. Although they have progressively flanked theories and laboratory inquiry in research practice and ranked as the third pillar of science [9, 10], simulations are usually not part of high school curricula. Indeed, even if many multimedia interactive tools have been introduced in the classrooms (e.g. the ones produced by PhET to illustrate

classical models like ideal gases, friction and electric circuits [11]), they are rarely simulations of authentic complex systems that cannot be investigated with the traditional experimental method.
Driven by these motivations, we decided to investigate the problem of high school students' trust towards computer simulations of complex systems and to look for implicit or explicit criteria they use to evaluate their explanatory power and the reliability of their results. This research problem lays its foundation on results of researches in STEM education about complex systems, i.e. the novices' difficulties in interpreting their simulations [12], in formulating explanations about them [13], and in dealing with causal reasoning [14]. In this paper, we present: i) the framework we chose for formulating our research problem, making explicit the factors we considered *a priori* relevant; ii) the methodology of the research we used in our pilot study, discussing its strengths and weaknesses; iii) some preliminary results that confirmed some of our hypotheses, but also led us to question the validity of some of other hypotheses and to refocus the problem.

2. Research framework

2.1. The science of complex systems, its relevance today and the difficulties in its learning
Since the second half of the 20th century, a new field of study has grown within the scientific community: the science of complexity. This discipline studies the so-called complex systems, constituted of a set of individual elements which, interacting with each other and with the environment according to non-linear relationships, give the resulting systems some properties that the classical ones do not have [15]. The main traits of most complex systems can be summarized in the following list: i) non-linearity of the equations that describe the macroscopic variables and of the rules for the local interactions among the agents; ii) high sensitivity to initial conditions or "butterfly effect"; iii) presence of feedback loops; iv) appearance of global properties that cannot be deterministically ascribed to the local rules which the individual agents obey but emerge from the self-organization of the system.
From the 1970s, many systems have been studied and modelled as complex, within a very wide range of disciplinary fields: to report few examples, cells, human brain, crystalline solids, social systems, cities and climate are considered and have to be studied as complex systems. Because of the increasing relevance of issues like climate change and urban planning at many decisional levels, the perspective of complexity is becoming more and more important to be embraced by the people involved in decision-making activities [5]. While this can be stated as an urgent goal to be achieved, the educational research about complex systems has shown strong and resilient difficulties in learning about complex systems, mainly due to the conflict between new complexity-related concepts and commonly held beliefs or learners' prior experience [16]. The main conceptual difficulties can be summarized in the following two points: i) difficulty in giving up a sense of centralized control and deterministic causality in favour of descriptions involving self-organization, stochastic and decentralized processes [17]; ii) difficulty in renouncing the conception of a linear relationship between the size of action and the corresponding effect, accepting the butterfly effect [16].

2.2. The simulations for the study of complex systems
Together with the set of new concepts introduced in the scientific community, the science of complex systems has developed specific methods of analysis, including computational simulations. Going beyond the traditional laboratory experiments and theories, simulations can be considered the third important tool of science [9]. When a simulation runs on a computer, it gives rise to empirical predictions that derive from the theoretical mathematical model of the phenomenon under exam, and it works as a virtual laboratory in which, just as in the real laboratory, the researcher monitors the phenomena under controlled conditions, manipulates these conditions and discovers the consequences of such manipulations. The simulations are becoming more and more important not only for the scientific community that uses them as a mean of inquiry but are also at the core of the communication of the scientific results to policymakers and citizens and are currently used to support policy formulation [18].

Philosophers of science have offered a number of definitions of simulations. For the purpose of this paper, we refer to the following one: "System S provides a simulation of an object or process B just in case S is a concrete computational device that produces, via a temporal process, solutions to a computational model that correctly represents B, either dynamically or statically. If, in addition, the computational model used by S correctly represents the structure of the real system R, then S provides a simulation of system R with respect to B" [19]. We think that this definition is particularly helpful in our framework because it allows to distinguish between three different levels: the real system (R), the model of object or process (B) and the simulating system (S). Even the categorization of simulations can be performed in many different ways, according to different criteria; following [18], we can distinguish equation-based simulations and agent-based ones. The first are simulations describing the dynamics of a target system with the help of equations that capture the deterministic features of the whole system: a set of differential equations is used to derive the future state of the target system, modelled as an undifferentiated whole, from its present state. The agent-based simulations, at the opposite, lack an overall description of the macro properties of the system and simulate it by generating its dynamics through the imitation of its micro constituents that behave as dictated by local rules.

Simulations are thus crucial in dealing with complex systems but their interpretation as authentic scientific tools is a delicate point. Many criticalities have been individuated from the literature in science education exploring novices' attitude toward simulations of complex systems; we summarize two of them. First, while experts are able to move from the agent-based description to the aggregate-systemic reasoning and vice versa depending on the target of the analysis, the novices often develop linear agent-to-aggregate inferences, contrasting with the authentic disciplinary concepts related to complex systems [20]. The second criticality has been highlighted in a study carried out with adult citizens in a context of citizenship education [7]: many participants harboured resistance when dealing with simulations that were perceived as mere games and seemed not to grasp their methodological and epistemological value.

2.3. Scientific explanations through simulations

The sciences use simulations for multiple purposes; among their uses there are proof, prediction, policy formulation and explanation of complex phenomena [18]. The issue of explanation in general is widely explored and precisely conceptualized by the philosophers of science. Conversely, within the science education community, there is much discussion about this issue with a still little consensus about the nature of explanation itself [21]. Indeed, the literature in science education refers, mostly implicitly, to many different conceptions of explanation. A synthesis of them is provided in [21]:

- *Explanation as explication*: explaining consists in providing clarification for the meaning of a term or explicating a reasoning about a problem.
- *Explanation as causation*: explaining consists in establishing a causal account referring to the mechanistic properties of the phenomena (mechanistic explanation), to the physical laws the phenomenon has to follow (covering-law explanation), to the final goal the phenomenon has to realize (teleological explanation) or, when humans are involved in the object of the explanation, to the intentions of the individuals to reach a goal (intention-based explanation).
- *Explanation as statistical justification:* explaining consists in justifying phenomena by using statistical-probabilistic analysis of large data sets.

For the purposes of this paper, we consider only the second and the third types mentioned above as proper scientific explanations. Going deeper into the causal explanations, research in science education has shown that the mechanistic explanations are those that most foster students' sensemaking about phenomena [22]. Indeed, it has been proved that, when students are able to provide a mechanism to explain a causal relation, they express more confidence in the validity of the causal relation itself [23]. The mechanistic explanations can be recognized by tracing the structural components of mechanism: description of the target phenomenon; identification of setup conditions, entities, activities, properties of the entities; chaining backward and forward; analogies [24, 25].

According to these results, we considered the possibility of understanding the mechanism and producing causal explanations as a potential source of reliability for students dealing with computational simulations. In general, since explanation is strongly linked to sensemaking [25] and causation, we hypothesized that the trust or mistrust of students in simulations as scientific tools could rely, at least partially, on the feeling that it is possible and meaningful to use them to explain real phenomena.

In most of the applications of simulations to explanations of complex phenomena, it has been noticed a gap between the simulation outputs and the model [26]. This gap is largely due to the fact that computer simulations are epistemically opaque [19], which means that they are sorts of thought experiments in which the consequences follow from the premises, but in a non-obvious manner which can be revealed only through systematic inquiry [27].

3. The pilot study: context, design and data collection

The goal of our work is to investigate the problem of high school students' trust toward computer simulations of complex systems and to look for the implicit or explicit criteria they use to evaluate their explanatory power and the reliability of their results. In our pilot study we were particularly interested in identifying the epistemological issues that the students mentioned when formulating explanations and reasoning about simulated phenomena and in investigating the factors that could influence students' attitudes toward computer simulations in terms of trust.

The pilot study consisted in performing 13 semi-structured paired interviews; we chose this method because we were interested in the interactions among students, that are frequent and rich when the pairs consist of schoolmates [28], as it was in our case. During the interview, the students were asked to discuss about four different computer simulations of complex systems, responding the questions of our protocol. We included an interactive multimedia tool about ideal gases in the set of simulations presented to the students in order to compare the answers in the classical and complex cases.

The group of people involved in the qualitative study consisted of 26 volunteer students (12 males, 14 females), aged 17-18, of 5 different high schools in Emilia-Romagna, Italy. They were recruited by their physics teachers, who collaborate with the research group in STEM education at the University of Bologna. The majority of the students (24 out of 26) were attending scientific lyceums; only two of them were attending a linguistic lyceum. The science of complex systems was not part of the background of any student, since ministerial programmes, in Italy, do not include such issues.

We collected data through the interviews and then we carried out a qualitative analysis of four selected cases, as we will explain in the following section. In the followings, we provide a brief description of each simulation and the main features of the model they refer to; for the purpose of the analysis we report in the next section, here we focus especially on two simulations of complex systems and provide only few details for the others. Then, we describe the structure of the protocol and some of the questions asked to students.

3.1. The models and the simulations

3.1.1. Social segregation. The first simulation is built on the basis of the Schelling model of segregation [29]. We decided to include it in our study since it can be easily described but displays one of the most characteristic features of complex systems: the emergence of global properties of the whole system starting from local rules for the minimal sub-components which, namely, self-organize. In this model, there are two types of individuals who tend to move if they find themselves in regions where the other type is present over a certain percentage (1/3 default). These agents, that are not created nor destroyed during the evolution of the system, evolve according to a simple rule on the basis of their level of satisfaction, which in turn is determined by the makeup of their neighbourhood. Starting from an initial mixed population, the time evolution leads to an environment in which there are separate groups of individuals of the same category: an even slight homophilic bias is sufficient to cause wholesale segregation of the two types of agents. The simulation we have chosen for this model is an agent-based one [30] where the agents (squares and triangles) share the same environment (a grid in which every element occupies one place). The user can modulate a parameter that indicates the protagonists' preference to live near similar individuals, observing, in a graph, the final rate of segregation of the simulated social system. Changing the percentage of preference, higher levels of segregation display, even if, over a certain threshold, it can be seen that the model does not converge, and the agents continue to move “forever”.

3.1.2. Predator-prey interaction. The second simulation implements a model of an ecological complex system: the Lotka-Volterra model [31]. It consists of a pair of first order, non-linear, differential equations used to describe the dynamics of biological systems in which two species interact, one as a predator and the other as prey. By numerically integrating the equations, the solution of the model is periodic and can be interpreted in terms of circular causality. The periodic growth of the prey population is followed by the growth of the predator population; the consequent reduction of prey population causes a reduction of predator population, since there is less food to eat; this reduction of predator population lets the prey population grow and this cycle continues forever. Most of the Lotka-Volterra model simulations are equation-based; the output of this type of simulations is a graph showing the periodic evolution of the system dynamics. Since previous studies showed that some students had difficulties with this genre of simulations, when requested to act on the values of the parameters and to interpret the changes in the graph [32], for this study we decided to use an agent-based simulation of the same model [33]. In this simulation, there are two types of agents that populate a grid – the Canadian lynxes (predators) and the snowshoe hares (prey) – and interact according to a set of few rules (e.g. if a lynx does not have at least three hares among its nearest neighbours, starves and dies; if a hare escapes the lynxes, it survives and reproduces once). The user observes the changes in hares and lynxes’ populations in the grid and after thirty generations, is displayed a graph representing the periodic evolution of the populations.

3.1.3. Ideal gases. The third simulation refers to the model of ideal gases and the kinetic molecular theory. With this simulation, developed by the PhET [34], the user can pump gas molecules to a box and see what happens by changing the volume, furnishing or subtracting energy in the form of heat, changing gravity; temperature and pressure can be measured, and the properties of the gas can be investigated.

3.1.4. Global warming. The last class of models we considered are the climate models and, in particular, their estimations for the possible changes in the temperature patterns throughout the 21st century. The models we refer to are those used in the last report from the Intergovernmental Panel on Climate Change [35] to formulate predictions about how the Earth might respond to four different scenarios of how much carbon dioxide and other greenhouse gases would be emitted into the atmosphere. For our study, being the simulations very technical and difficult to experience by a secondary-school user, we chose to include a video that shows the changes in temperature and precipitations through the 21st century, on the basis of the IPCC models [36].

3.2. The interview protocol

At the beginning of the interview, the interviewers described the main characteristics of each simulation to the pair of students, then they asked them to explore each simulation, by watching the space-time evolution of the systems and by modifying the values of the possible parameters. The interview protocol consisted of five sections, the first four designed to investigate different dimensions of the students’ reasonings on simulated phenomena that could influence their trust and the last one to explicitly ask the students what affected their perception of trust/mistrust. More specifically, the sections aimed at making the students: i) observe and describe the “surface” of each simulation, identifying the fundamental elements represented and those in the background; ii) attempt an explanation of a specific simulated phenomenon; iii) carry out a meta-reflection about the meaning of explanation; iv) compare the output of the simulation and the data obtainable from a laboratory experiment; v) express their perception of trust and confidence about the use of simulation for addressing concrete real-world problems. In table 1, we report some questions for each section.

Table 1. Sections of the interview protocol and some examples of questions.

Description of the surface of the simulations	Identify relevant and non-relevant elements, changes, processes, user's way of interactions. Identify which elements are models and which are elements of reality.
Explanation of simulated phenomena	Explain this phenomenon. How does this simulation help you explaining the phenomenon? - The environment is divided into quarters and segregation is realized. (Social segregation) - There are cyclic and periodic evolutions for the numbers of prey and predators. (Predator-prey interaction) - Given a certain state, during a volume compression, the temperature can be kept constant. (Ideal gases) - In 2089, the highest temperature anomaly, with respect to today, is going to be at the poles. (Global warming)
Meta-reflection about "explaining"	What are the differences, in your opinion, between describing, interpreting and explaining a physical phenomenon? Are there any "whys" you can answer using this simulation? How determinism and uncertainty are related to this simulation?
Simulations, laboratory experiments and reality	Which is, in your opinion, the relationship between the simulated phenomenon and the data that can be obtained with a lab experiment? Does the simulation explain a real phenomenon?
Perception of trust	Would you trust the results of the simulation to deal with a real problem?

4. Research methodology

The data analysis was carried out with a qualitative methodology, through a theoretically-oriented iterative process of analysis and interpretation, where the hypotheses formulation was progressively refined through an enlargement of the empirical base, until theoretical saturation was reached [37]. Focusing with respect to the wide spectrum of topics and simulations presented above, the analysis was designed to address the following research question: *What factors influence students' attitudes toward simulations of complex systems and their level of trust?*

In this preliminary study, we focus on two interviews (four students) and we compare them. All the students attended the same type of school – scientific lyceum – 13th grade, but a couple – Elizabeth and Anthony[1] – had a physics teacher who, across the whole curriculum, systematically stressed the epistemological role of models in science, while the other two students – Lily and Evelyn – did not have any specific "epistemological education". After a preliminary reading of the whole dataset of transcripts, we selected these two interviews because the first one was particularly rich from an epistemological perspective, while the second one seemed to represent the majority of the interviews. As a general comment, to answer our research question we looked at the complete transcript of each interview, since the nature of students' reasoning did not emerge by analysing isolated sentences.

According to the research framework outlined above, we hypothesised that the recognition of the explanatory power of the simulations could influence the perception of students' trust toward them. That is why the first step of the data analysis consisted in the exploration of students' explanations; to do this, we considered the framework outlined in 2.3 to distinguish between descriptive explications and proper explanations. In order to make this distinction more operational and use it as a lens to analyse students' discourses, we formulated five *a priori* statements about the four simulations. They were intentionally prepared as an explication and four different causal explanations (mechanistic, covering-law, teleological and intention-based). Table 2 includes the statements about the phenomenon of social segregation in the simulation of the Schelling's model. Not all these explanations are considered acceptable by scientists nowadays: in particular, the teleological and the intention-based one hide the false assumption that local rules directly lead to corresponding global behaviours. In this phase, we were also interested to check the presence in the interviews of the structural components of mechanism [24, 25], in order to investigate if and how they contributed to the development of causal explanations.

[1] To preserve anonymity, all the students' names used in this paper are gender-indicative pseudonyms.

Table 2. A priori explanations for the phenomenon of social segregation claimed in the second part of the interview *("the environment is divided into quarters: segregation is realized")*.

Explication		The squares and the triangles become divided in groups of the same type.
Explanations	Mechanistic	If at least the 33% of the nearest neighbours are of the same type, the individual is happy and does not move; otherwise, the individual tends to move and reach another position in which he has at least the 33% of neighbours like him; now we evaluate the satisfaction of another individual and he moves in the same way: he will be surely happy if he move near an aggregate of similar individuals. Continuing this way, it results that individuals are "attracted" by group of similar individuals: the so-called segregation is realized.
	Covering-law	The environment becomes segregated because the individuals have to satisfy their law of preference: having the 33% of their nearest neighbours similar to them.
	Teleological	The environment becomes segregated because this is the goal the individuals have to achieve.
	Intention-based	The environment becomes segregated because every individual wants to stay with similar ones.

The second phase of analysis aimed at investigating if any other dimensions impacted students' trust/mistrust toward simulations. To this purpose, we qualitatively analysed students' explicit responses to the questions of the fifth section of the protocol, identifying the factors they mentioned speaking of their perception of trust. After this step, we triangulated the previous analysis by looking back at the other parts of the interview searching for markers testifying that the factors we identified were not occasional but there were utterances of them in the previous students' discourses. Finally, we looked for possible relationships between their trust/mistrust, the typology of simulation under discussion and the kind of explanations they formulated.

5. Data analysis and results

5.1. Students' explanations about simulations of complex systems

The first part of the analysis showed that the identification of the components of a mechanism in each simulation was not sufficient to favour actual explanations. As an example, we report the case of Elizabeth's reasoning about the simulation of Schelling's model. When asked to describe what she sees in the simulation, she is able to identify elements of the mechanism behind it: *"It is presented a grid in which a half are squares and a half are triangles. These figures move on the basis of their preference and everyone tries to have a certain percentage of similar people. When the simulation runs, we notice that little tendencies of all the individuals lead to global tendencies"*. Indeed, she recognises the target phenomenon (the *global tendency* to segregate), the entities (*squares* and *triangles*), the setup conditions (*a grid in which a half are squares and a half are triangles*), the activities of the entities (their ability to *move on the basis of their preference* to fulfil the conditions of having *a certain percentage of similar people* as neighbours). Despite this, when requested to explain the phenomenon of segregation, she just explicates it, describing what she sees at the end of the space-time evolution of the system: *"At the end of the run, we notice that the figures are not mixed: they start from a mixed situation and at the end they are divided. This is the phenomenon of segregation"*. We categorize this one as an explication since the student just *notices* a behaviour of the system, without investigating the causes behind it. As a confirmation of this interpretation, when asked if this simulation could provide any explanation about why the phenomenon unfolded the way it did, Elizabeth answered that *"the simulations just says how, not why"*. Similar explications of complex phenomena can be found also in other interviews.

In only few cases the students appeared to be able to go beyond mere explications, toward proper explanations: this is the case of Anthony when reasoning about the Lotka-Volterra model and of Lily about Schelling's model. Anthony starts from the observation of the graph, rephrased with an explication (he uses the verb *notice*, as Elizabeth did before): *"From the graph we notice that prey* *increase exponentially, while a little increasing in the number of predators causes a dramatic decreasing of prey"*. Going forward with the interview, he gives an explanation about the emergent periodic phenomenon: *"There is a maximum of predators and a corresponding maximum of prey, but soon it falls down till zero. Here, naturally, the predators have to follow this tendency: since there are no more prey, they will die, and it will restart from a minimum of both"*. We categorize this explanation as covering-law, since Anthony ascribes the behaviour of the populations to a natural law expressed as a regularity, a t*endency* they *have to follow*: it can be noticed that the law that, according to this student, covers the phenomenon is not expressed in a symbolic form but this is not necessary in covering-law explanations, where "false-laws" and law-like statements, like the one expressed by him, are permitted [38]. Another covering-law explanation is that formulated by Lily about Schelling's model: *"Triangles and squares are forced to move in order to satisfy the rule of having one third of their neighbours similar to them; the lower is the tolerance, the more the individuals will be divided and grouped"*. The covering-law character of this explanation is given by the fact that Lily ascribes the cause of movement leading to segregation to the need of *satisfying the rule* of having a certain percentage of similar neighbours. This explanation is partial and does not really explain the final segregated state reached by the system, but just the local movement of the agents; anyway, considering it as an explanation we are able to identify its limits and its explanatory power, which, in the case of self-organizing systems, is weak.

5.2. Students' trust about simulations

Analysing the transcripts of the two interviews, we noticed differences in the approaches of students with different epistemological backgrounds. Elizabeth and Anthony, who had been taught science also from an epistemological perspective, seemed more aware, consistent, and able to critically evaluate the use of simulations. For instance, Anthony reflects about Schelling's simulation as follows: *"We don't have to take squares and triangles literally but like a social experiment which – through a totally mathematical, rigorous and deterministic simulation – becomes a possible model to understand how certain behavioural tendencies develop"*. Then, he expresses a robust confidence in simulations, according to a principle of similarity between the objects and processes represented in the simulations and the reality, but he remarks a need to interpret the results in particular cases, when there are constraints in the target dominium which are absent in the source one: *"In general, I trust simulations because they are models similar to reality, but they have to be interpreted in order to move to the right conclusions. If we think at the real case of 90% preference, we know that there cannot be infinite moves […]: people don't have even the money to move so many times!"*. On the opposite, Evelyn and Lily, two students with weak awareness of epistemological issues, did not trust simulations. The reason for this lack of confidence is expressed by Lily when she reasons about Schelling's simulation: *"I don't trust it because we are talking about a phenomenon regarding people, so I don't think it is possible to quantify scientifically everyone's tolerance. If I had a city with 120 individuals and I used a simulation like this, I wouldn't be sure to find the real result!"*. For her, the scientific character of the simulation could be recognized only if it provided predictions and explanations for the behaviour of each individual agent: since it is not possible, the simulation cannot be trustworthy. We suppose that her attitude finds its roots in her naïve belief about the meaning of model in general, that is considered reliable and well-posed to provide explanations if and only if it is substantially a copy of the real target system.

Such a naïve approach was accompanied also by other statements about the factors that the students considered important to make a simulation reliable, e.g. i.e. a simulation with a higher number of parameters, or one that takes as inputs "real data" could have been considered more accurate. We think that these criteria expressed by students deserve to be better investigated in further studies.

6. Discussion of the results

The data analysis allowed us to point out some preliminary findings that we can summarize in two main points that we are going to discuss. The first finding confirms the research results about the novices' difficulties in interpreting complex phenomena. Even if the students correctly identify the main components of the mechanism behind the simulations, most of them are not capable of formulating proper explanations about the complex simulated phenomena. In most cases the simulated phenomena are just explicated. We also noticed that in the cases of explanation, simulations of complex systems activate only covering-law, teleological or intention-based explanations, while there is not any trace of mechanistic explanations. Indeed, the students use a normative lexicon to describe individual agents that, via the rules they follow, are forced to lead to a higher-level configuration of the system. This finding is coherent with the previously cited literature in science education highlighting the novices' difficulties in renouncing the deterministic-centralized mindset typical of classical science.

A second relevant finding is that students' weak awareness of epistemological issues was linked to a lack of trust and confidence about simulations. The analysis of students' discourses showed that this sceptical attitude could be ascribed to naïve epistemological conceptions about, for example, the role of models in science and their predictive power. On the contrary, the students who had been taught science also from an epistemological perspective expressed more confidence toward the simulations. Their discourses revealed deeper reflections about the meaning of the simulations as well as critical and more aware evaluations about their possible uses and applications.

Alongside these two findings, this pilot study also revealed some methodological weaknesses. Even if the paired interviews allowed us to observe the rich and frequent interactions among students, they did not consent to obtain all the answers to the questions of the protocol for each simulation proposed. Indeed, in many cases one of the two students dominated, not giving to the other equal opportunities to express herself/himself, especially in case of disagreement. Since this result is consistent with the literature about paired interviews [39], we plan to revise the methodology of data collection for further studies, in order to be able to draft comparisons between the approach to simulations of classical vs complex systems for each student involved. In this way, we could investigate whether the classicality or complexity of the model behind the simulation is one of the factors influencing students' trust.

7. Conclusions

In this study we dealt with the issue of the scientific skill gap, investigating specifically the factors affecting high school students' trust in computer simulations as scientific tools that help in formulating possible explanations of phenomena.

We noticed that the students rarely appeared to be able to elaborate explanations by themselves using simulations. Furthermore, the students' criteria to establish their level of trust in simulations were scarcely based on scientifically significant arguments but in the case of the two students explicitly taught in epistemology of science within the ordinary science classes. We argue that this finding deserves to be furtherly investigated: that is, students at the end of their mandatory school curriculum, after having studied science for many years in the highest-level schools (*lyceums*), are not able to critically interpret the epistemological and methodological value of a scientific simulation.

For what concern the specific difficulties concerning complex systems and the lack of interdependence between mechanism descriptions and causal explanations, we hypothesize that the difficulties in generating mechanistic explanations about complex phenomena are linked to the difficulties in constructing autonomously a "mid-level" between the agent-based description and the aggregate one. This mid-level, that the literature in science education has claimed to be particularly relevant in the process of making-sense of complex systems [40], could be important also in formulating mechanistic explanations that have to connect individual behaviours to global properties, through intermediate involving little groups of agents.

We plan to develop further studies in which problematize the epistemology of simulations and include the features the students said to make a simulation more reliable, in order to investigate if and how these sceptical attitudes persist or give birth to more articulated reflections.

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