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Simulation-Based Learning: Open questions and guidelines for the instructionally effective use of simulation[1]

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Abstract

In his book "Visible Learning", Hattie (2009) assigned an effect size of d=0.33 to instructional simulation—i.e., below the d=0.40 hinge point considered to be of relevant practical value for instructional methods. Yet, how might this value be interpreted, in light of studies conversely highlighting the instructional potential of simulation as a teaching and learning method? One way to explore this apparently conflicting evidence is to examine the misconceptions and methodological flaws that are frequently encountered in this research field, which make it difficult to collect a coherent base of evidence on simulation's instructional effectiveness. Some factors potentially influencing this type of effectiveness are: students' prior domain-knowledge, degree of cognitive scaffolding, and the "opacity" of the underlying simulation model. Moreover, the nine meta-analyses that Hattie examined, and for which he calculated a d=0.33 effect size, did not differentiate between simulation-*using* and simulation-*building* learning scenarios.

Keywords: simulation, evidence based education, cognitive load, instructional strategies, instructional methods.

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Introduction

After decades of debate and reforms influenced by a variety of learning theories and cultural perspectives, the world of instruction is currently being impacted by a new research trend proposing to evaluate the relative effectiveness of different factors contributing to school achievement as objectively as possible. In fact, ever more numerous studies aim to find evidence of learning; these therefore originate from the research field of Evidence-Based Education, or EBE (Calvani, 2012). Specifically, in his book Visible Learning, Hattie (2009) synthesized data from 800 meta-analyses on achievement, by examining fifteen years of research involving millions of students and by calculating the overall effect sizes of a large number of variables that influence learning. Among technology-based instructional methods, Hattie also examined the method of simulation.

Based on the results of nine meta-analyses conducted between 1981 and 2002, Hattie (2009, p. 230) calculated an overall effect size of 0.33 for simulation. Although this value was not among the lowest, it is not considered of great practical value (see below), because it was lower than expected for the instructional effectiveness and degree of innovation that are typically associated with this instructional method (Papert, 1982; Jonassen, 2000; de Jong, 2012; Landriscina, 2009, 2013).

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The barometer of influences

A frequently used method in the field of EBE is effect size calculation: This statistical measure shows the strength of the relation between two variables and is used on a large scale in medicine and in the social sciences. In Education research, the dependent variable is typically that of achievement level, and the independent variable consists in a factor requiring quantitative effect investigation. Studies of this type are conducted by comparing the outcomes of an experimental group and those of a control group, or in studies examining a single group, between an initial condition and a final one. Effect size is calculated as the difference between the two groups' means, divided by the mean of the standard deviations. The statistical methods of meta-analysis can be used to combine the results of single experimental studies yielding comparable data, which allow for the synthesis of different study outcomes into a single overall estimate.

Hattie (2009) used the statistical distribution of these effects on all of the meta-analyses examined in his study to establish a "hinge point" of d=0.4. He held that this value corresponds to the level above which improvement in achievement effects are of great practical value. Moreover, he developed a scale, the "barometer of influences", subdivided into 4 zones: The interval of d=0.4 to d=1.2 is the *Zone of desired effects*, as these are the influences that have the greatest impact on student achievement outcomes. Factors with an effect ranging between these two values should therefore be considered a priority in teachers' instructional methods decisions. Just below that lies the interval of d=0.15 to d=0.4, called *Teacher effects*, i.e., learning resulting from the activity of teachers in a typical school year. The range of d=0.0 to d=0.15 corresponds to *Developmental effects*--student maturation, as would occur with no schooling. Lastly, the area below d=0.0 is that of *Reverse effects* on learning, which diminish learning and should therefore not be implemented.

In some instances Hattie's data reflect practices commonly associated with effective teaching, such as the high effect sizes reported for student-teacher feedback (d=0.90 for student feedback to teachers, d=0.73 for teacher-to-student feedback). Other times, the data conversely underscore doubts about consolidated practices, such as homework, whose overall effect on learning has been found to be very low (d=0.29). In terms of instructional methods, the barometer needle strongly favors ones involving the clear-cut structuring of content and direct instruction, with special focus on models developed in the 1960's and 1970's, such as Mastery learning (d=0.58) and Keller's PSI Method (d=0.53). The effectiveness of other methods, such as discovery learning methods, has been questioned, however. Examples are Inquiry-based learning (d=0.31) and Problem-based learning (d=0.15) (not to be confused with Problem-solving teaching, based on the explicit teaching of heuristics for solving problems and yielding an effect size of d=0.61).

One aspect that clearly emerges is a re-evaluation of the teacher's role, considered to be the most important agent in the instructional process. Teachers are not only a source of knowledge and facilitators of student activity; they are also change agents, who must decide *what* and *how* to teach in a given moment, based on an evaluation of a student's progress. From this perspective, the main message of the

Visible Learning approach (and of EBE in general) is an appeal to teachers and to policy-makers to be more aware of the need to measure their own instructional methods' effectiveness, rather than base their decisions on ideas and conclusions traditionally considered to be valid, or because they are new or popular.

A note of attention

In his approach to evaluating instructional methods, Hattie did not limit himself to drawing up a classification based on a series of numeric values. He aimed to untangle the web of causal influences emerging from combining results from the studies examined, by investigating reasons that might underlie differences in outcomes, conducting a second level meta-analysis thereby (Pawson, 2006, p. 56). This type of meta-analysis calls for a careful examination of the role of moderating variables, i.e., of those independent secondary variables that contribute to reducing or intensifying the influence of primary independent variables (e.g., age, gender, social class). For example, with respect to the variable homework, Hattie (2012, p. 12) did not interpret the corresponding low value of d=0.29 as a reason to abandon that activity, but as a starting point for identifying the reasons why homework was not found to be particularly effective. A more detailed analysis, subdivided by age group, revealed that the effect size diminished to d=0.15 in primary school and rose to d=0.64 in secondary school—a finding that made it possible to hypothesize the moderating effect of student age. Hattie (2012) cited the case of a school in New Zealand, which proposed that a remedial action might be that of creating a website in which homework is presented in the form of “home challenges” and of measuring the impact of the initiative on the students’ results and parental involvement. This perspective suggests that over-emphasis on the numeric values of effect sizes can risk overlooking improvement deriving from even small changes.

The case of simulation

With respect to simulation, the value of d=0.33 calculated for this method (2009, p. 230) is close to the hinge point (d=0.4), which separates the teacher effects zone from that of desired effects. Although yielding a significantly higher effect size than other methods, e.g., Web-based learning (d=0.18) and Distance education (d=0.09), this value was not particularly significant on the barometer of influences. It must be noted, however, that it reflects the existence of several critical points that have not yet been resolved, and specifically, different ways of using simulation and measuring its effectiveness. For example, according to the National Research Council (2011) report entitled *Learning Science Through Computer Games and Simulations,* “several barriers slow large-scale development and use of games and simulations for science learning in K-12 and higher education” (p. 175). The same report states that “there is moderate evidence that simulations motivate students’ interest in science and science learning, and less evidence about whether they support other science learning goals” (p. 2) An important aspect of the EBE perspective is that: “The many gaps and weaknesses in the body of research on the use of simulations and games for science learning make it difficult to build a coherent base of evidence that could demonstrate their effectiveness and inform future improvements. The field needs a process that will allow research evidence to accumulate across the variety of simulations and games and in the face of the constant innovation that characterizes them" (p. 55).

This reference to research gaps and the lack of a coherent evidence base is particularly pertinent to the meta-analyses Hattie used to calculate the overall effect size of simulation. A first critical point is that in some of these studies (VanSickle, 1986; Remmer & Jernsted, 1982), simulations and games were examined as a single category. Hattie (2009, p. 230) himself used the two terms interchangeably. These activities, however, present key differences from an instructional perspective, due to the different cognitive processes they involve; thus, not distinguishing between them can lead to confounding (Landriscina, 2013, p. 4). By definition, a simulation is based on the imitation of a system or a situation, whereas a game is not bound by this constraint, but exclusively follows its own rules. Moreover, in simulations the element of competition is not necessarily present, but conversely is a typical component of games. (An overlapping area exists for simulation games, but these have been developed more thoroughly in the videogame sector than for instructional purposes.) Furthermore, it is important to preliminarily distinguish between two types of computer simulation:

- *model-based simulations*, which are based on the construction of a system's theoretical model (also known also as "theoretical simulations");

- *experiential simulations*, based on the creation of a virtual event to be experienced by one or more participants.

In both cases, the instructional goals and learning processes involved are quite different, and combining data from one or the other type of simulation to draw general conclusions about the effectiveness of simulation as an instructional method can be methodologically misleading.

Moreover, many studies examined in meta-analyses do not clearly define learning goals: At times they concern the learning of facts and concepts, at others, the learning of processes or procedures; at even others, they involve the development of thinking skills (e.g., critical thinking, problem-solving, scientific reasoning). Other times, moreover, the only purpose of simulation is motivational (e.g., increasing students' interest in science, or in using scientific language), with no clearly defined learning goal.

Moderating effects

With respect to the differences that emerged among the various studies examined in Hattie's meta-analyses, the existence of categorical variables that can moderate the efficacy of simulation in one direction or another must be considered, including:

- students' prior knowledge;
- support provided to students;

- simulation model “opacity”.

With respect to the first factor, simulation-based learning environments are frequently characterized by dynamically changing multiple representations of information (images, animations, graphs, levers, numbers), and students must mentally integrate these while carrying out complex tasks, such as testing hypotheses or exploring alternative courses of action. These types of environments are typically characterized by a high number of interacting elements requiring simultaneous processing in working memory and producing a high intrinsic cognitive load thereby (Plass et al., 2010; Sweller et al., 2013). Moreover, if the interface’s cognitive ergonomy is not well-designed, the extraneous cognitive load involved may also be very high. In these situations, a student’s domain knowledge will be a key learning factor. This view is in line with Ausubel’s “assimilation theory of learning”, which holds that “the most important single factor influencing learning is what the learner already knows” (Ausubel, 1968, p. vi). From this perspective, it is important to remember that simulation can also be used to transfer completely new content(s) to students. At other times, it can be implemented as a kind of practice that is similar to laboratory activity, with the aim of applying and reinforcing knowledge acquired through other means. Thomas and Hooper (1991) distinguished between *pure simulation* (i.e., practice only features) and *impure simulation* (i.e., practice and presentation features). Along the same lines, Brant et al. (1991) investigated whether it is more effective to use simulation before or after lessons: Their participant students receiving simulation as a framework for understanding prior-to-formal classroom instruction scored significantly higher on an applications post-test than did students using simulation as an integrating activity following formal instruction.

Another factor that notably influences the effectiveness of simulation is type of cognitive support provided. Simulation has been frequently presented as an example of exploratory learning strategy, in line with constructivist pedagogy (Tobias and Duffy, 2009). Nonetheless, a closer look at different simulation use contexts reveals that there are several options open to teachers and researchers:

- in the exploratory learning strategy, general learning goals are presented, and students may choose sub-goals, methods, and activities;
- in guided discovery, each learning step's goals are presented, and students are free to explore the learning environment, but are given guidance and help at each stage;
- in programmed discovery, examples are given, and students must discover the underlying rule(s) by following a sequence of carefully programmed steps.

In one study examining the effects of simulation on high school biology students' problem-solving skills, Rivers and Vockell (1987) divided simulations into two categories—guided and unguided. Results showed that students using the guided version of the simulations outperformed the other students on tests of scientific thinking and critical thinking. This finding suggests that students perform better when some form of guidance is provided, i.e., in a guided study or programed study environment rather than in one of free discovery. As reported by de Jong (2012), this hypothesis found confirmation in other studies, because “large-scale evaluations of carefully designed simulation-based learning environments show advantages of simulations over traditional forms of expository learning and over laboratory classes” (p. 458).

In further consideration of the support-provided-to-students factor, it is important to distinguish between simple simulation programs, which allow students to change only a few variable values and view the consequences of their decisions in a graph, and more structured simulation-based learning environments. The latter also feature instructional supports and resources aimed at facilitating and enriching the students’ learning experience, such as background information, questions, hints, explanations, exploration guides, exercises, graphing tools, and planning tools.

The use of these supports has been investigated by a group of researchers who developed the SimQuest program (de Jong, 2006; de Jong and van Joolingen, 1998) to mitigate and solve some of the problems that students typically encounter in discovery based learning. In fact, some types of simulation had initially been presented by their proponents as exploratory learning environments, on the foundation of constructivist or inquiry-based premises, but in most instances, these environments gradually developed guiding and support functions for students (Horwitz and Christie, 1999; Nelson, 2007; Stieff and Wilensky, 2003). These more recently developed guidance modes can be considered to be “cognitive scaffolding”, i.e., the support structure provided to students in an initial learning phase. Cognitive scaffolding allows students to carry out a task that would otherwise be too difficult for them to do alone; it is then successively removed as students become capable of doing the task autonomously.

Another factor that can significantly increase or diminish the instructional effectiveness of a simulation is the underlying model's degree of opacity. For example, in "black-box model" simulations, students can explore a system's behavior, but the underlying conceptual and/or computational models remain hidden and can only be inferred by what is viewed on the screen (Landriscina, 2013). City-building simulation games present thousands of scenarios, but do not show the rules constraining these scenarios, as established by the game's creator(s). When students observe events that occur as a consequence of their decisions, they automatically tend to attribute rules to the system, which may or may not coincide, however, with those actually present in the model. Erroneous or incomplete inferences can interfere with learning and can render simulation less effective or even misleading. Yet, if utilized as a source of cognitive dissonance, and transformed into correct inferences, this process can be useful for a deeper understanding of the system or phenomenon under study.

Scientific research and open questions

The meta-analyses examined in Hattie's (2009) book refer exclusively to the use of previously designed simulations, not to student construction of simulation models. In the latter case, students utilize a programming language or a modeling software to construct a simulation together with their teacher—a highly different process!

Research findings in the field of Model-Based Learning and Teaching highlight the great instructional value of having students build, evaluate, revise, and elaborate their own visual or material models (Gobert & Buckley, 2000). According to Seel (2012), this dynamic type of modeling provides a new perspective for students in which “Learning occurs by comparing the expected results of operations on a system with the observed consequences of transformations. In the case of gaps between expectations and observations, the outcomes are used to update or revise the mental model” (p. 1053). From this perspective, learning occurs through a *learning pathway*, which leads from an initial state characterized by the student’s preconceptions, to a desired final state, of causal explanation. This type of pathway can be decisive when the learning goal does not concern basic facts and concepts, but requires a restructuring of students’ individual mental models, e.g., the pre-conceptions with which students may typically begin learning scientific concepts.

In teaching contexts, simulation can be integrated synergistically with other instructional techniques. A potentially productive method is that of reciprocal learning (Iserbyt, 2012), which requires students to work in pairs: While one student (the “doer”) interacts with the program, the other (the “observer”) observes and takes notes. Reciprocal learning allows a pair of students to process specific information with an extraneous cognitive load that is lower than what they would experience individually by interacting with the same simulation exclusively on their own. Another research area meriting investigation is that of students' study strategies, i.e. the repertoires of methods and techniques they apply when using a simulation or building a simulation model. Examples of these strategies are: brainstorming, note-taking, visually structuring information (e.g., using charts, maps, diagrams, timelines), summarizing, self-questioning, self-monitoring, creating sub-goals, and managing time.

Conclusions

Any evaluation of the instructional effectiveness of simulation must be based on an accurate examination of the different types of activity simulation requires of students, to characterize significantly diverse situations. The role of variables such as students' prior knowledge, support provided, and underlying model opacity, must also be considered. An analysis of this type can help specify the appropriate conditions for an instructionally effective use of simulation. Lastly, significant learning impact can derive from the combination of simulation with other instructional methods and study strategies.

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References

Ausubel, D. P. (1988). *Educazione e processi cognitivi. Guida psicologica per gli insegnanti*. Milano: Franco Angeli.

Brant, G., Hooper, E., & Sugrue, B. (1991). Which comes first the simulation or the lecture? *Journal of Educational Computing Research*, 7(4), pp. 469–481.

Calvani, A. (2012). *Per un'istruzione evidence based*. Trento: Edizioni Erickson.

de Jong, T. (2006). Technological advances in inquiry learning. *Science*, 312, pp. 532–533.

de Jong, T. (2011). Instruction Based on Computer Simulations. In R. E. Mayer & P. A. Alexander, (Eds.), *Handbook of Research on Learning and Instructio*n. New York and London: Routledge, pp. 446-466.

de Jong, T., & van Joolingen, W. R. (1998). Scientific discovery learning with computer simulations of conceptual domains. *Review of Educational Research*, 68 (2), pp. 179-201.

Gobert, J. D., & Buckley, B. C. (2000). Introduction to model-based teaching and learning in science education. *International Journal of Science Education*, 22(9), pp. 891-894.

Hattie, J. (2009).*Visible Learning: A Synthesis of Over 800 Meta-Analyses relating to Achievement*. London and New York: Routledge.

Hattie, J. (2012). *Visible Learning for Teachers. Maximizing Impact on Learning*. London and New York: Routledge.

Horwitz, P., & Christie, M. (1999). Hypermodels: Embedding curriculum and assessment in computer-based manipulatives. *Journal of Education*, 181(2), pp. 1-23.

Iserbyt, P. (2012). Reciprocal Learning. In N. Seel (Ed.), *Encyclopedia of the Sciences of Learning*. New York, NY: Springer, pp. 2785-2787.

Jonassen, D. H. (2000b). *Computers as Mindtools for Schools: Engaging Critical Thinking*. Upper Saddle River, N.J.: Prentice-Hall.

Landriscina, F. (2009a). Simulation and learning: the role of mental models. *Journal of E-Learning and Knowledge Society*, 5(2), pp. 23-32.

Landriscina F. (2009b). *La simulazione nell'apprendimento. Quando e come avvalersene*. Trento: Edizioni Erickson.

Landriscina, F. (2012). Simulation and Learning: The Role of Mental Models. In N. M. Seel (Ed.), *Encyclopedia of the Sciences of Learning*. New York, NY: Springer, pp. 3072-3075.

Landriscina, F. (2013). *Simulation and Learning. A Model-Centered Approach*. New York, NY: Springer.

National Research Council (2011). *Learning Science Through Computer Games and Simulations*. Washington, DC: the National Academies Press.

Nelson, B. C., (2007). Exploring the use of individualized, reflective guidance in an educational Multi-User Virtual Environment. *Journal of Science Education and Technology*, 16(1), pp. 83-97.

Papert, S. (1982). *Mindstorms: Children, Computers and Powerful Ideas*. New York, NY: Basic Books.

Pawson, R. (2006). *Evidence-Based Policy: A Realist Perspective.* London: Sage Publications.

Plass, J.L., Moreno, R., & Brünken, R. (Eds.) (2010). *Cognitive Load Theory*. NY: Cambridge University Press.

Remmer, A. M., & Jernstedt, C. (1982). Comparative effectiveness of simulation games in secondary and college level instruction: A meta-analysis. *Psychological Reports*, 51, p. 742.

Rivers, R. H., & Vockell, E. (1987). Computer simulations to stimulate scientific problem solving. *Journal of Research in Science Teaching*, 24(5), pp. 403–415.

Seel, N. M. (2012a). Dynamic Modeling and Analogies. In N. Seel (Ed.), *Encyclopedia of the Sciences of Learning*. New York, NY: Springer, pp. 1051-1054.

Stieff, M., & Wilensky, U. (2003). Connected Chemistry - incorporating interactive simulations into the chemistry classroom. *Journal of Science Education and Technology*, 12(3), pp. 285–302.

Sweller, J., Ayres, P., & Kalyuga, S. (2011). *Cognitive Load Theory*. New York, NY: Springer.

Thomas, R. A., & Hooper, E. (1991). Simulations: An opportunity we are missing. *Journal of Research on Computing in Education*, 23(4), pp. 497–513.

Tobias, S., & Duffy, T. M. (Eds.) (2009). *Constructivist Instruction: Success or Failure?* New York, NY: Routledge.

VanSickle, R. L. (1986). A quantitative review of research on instructional simulation gaming. *Theory and Research in Social Education*, 14, pp. 245-264.