Chapter # 25

USES OF ARTIFICIAL INTELLIGENCE IN INTELLIGENT TUTORING SYSTEM

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ABSTRACT
This article aims to present the operation of an Intelligent Tutoring System exploiting artificial intelligence to personalize the learning of the learner and to automate certain tasks of the teacher. All the resources consulted and the educational objectives achieved by the learner will be processed using the TinCan API and the limitation of the amount of sensitive data sent to the cloud will be ensured by the use of peripheral artificial intelligence. We start by defining the concepts of artificial intelligence and Intelligent Tutoring System, then we focus on the implementation of machine learning in such a system and the advantages that this technique brings. Finally, we describe the limits of such a technology and the possible solutions to it.

Keywords: intelligent tutoring system, edge computing, Artificial Intelligence, pedagogical resources, semantic technologies.

1. INTRODUCTION

For several years, the increase in the volume of data produced and progress in understanding the human brain have enabled engineers to create machines capable of simulating certain aspects of human intelligence. One of these aspects, the simulation of learning, has allowed the birth of machines capable of perceiving, learning and optimizing: this is machine learning, also called artificial intelligence (Hofstadter, 1979). This technological evolution is perceived as a disruptive innovation that will upset our society, due to its possibility of interacting and helping humans in high-level tasks. However, the appearance of a powerful tool for processing information does not induce profound changes in learning practices: the practices of teachers and learners must evolve in order to use technology in an optimal in view of the targeted objectives (Dai et al., 2020). This tool, which is extremely powerful in certain tasks, however comes up against limits intrinsic to human intelligence such as its ability to adapt to the unexpected or its ability to generalize from an extremely small set of data: it can therefore not replace human decision-making capacity and must remain a tool. Loeckx (2016) maintains that artificial intelligence can prove to be an effective device for learning through its ability to personalize the learner's learning experience but also through the possibilities of automating tasks and summary of the results for the teacher. The increase in resources available online, the democratization of online learning and the development of this technology have allowed the development of tools allowing the construction of personalized learning environments: the Intelligent Tutoring System (ITS). These systems make it possible to personalize the learning on several axes such as the follow-up of the evolution of the learner and the achievement of his objectives, the adaptation of the educational resources proposed according to his style of learning or even the generation of personalized feedback in different formats (e.g., alerts, graphs, report). Some fear full automation of the teacher's role, but numerous studies show that human intervention cannot be completely replaced. On the other hand, IA and ITS will change the existing pedagogical relationship between knowledge, teacher and learner by adding an aspect of mediation between these entities, leading de facto to profound organizational changes in traditional teaching, both in terms of teaching and student practices: while teachers will see their roles and practices evolve, students will have to learn how to make optimal use of AI to enhance their learning outcomes (Seldon & Abidoye, 2018). However, it will be necessary to ensure that students are educated on the use of such a tool, because even if the mathematical concepts underlying AI begin to be integrated into school curricula, a poor understanding of this technology will inevitably lead to a decline of the effectiveness of the tool, or even a negative effect on the quality of learning (Ijaz, Bogdanovych, & Trescak, 2017). In addition, other problems must also be studied upstream such as learning biases or the management of sensitive data. In summary, this chapter will focus on the representation of a field of knowledge and the modeling of a student, on the various opportunities linked to this technology but also on its limits and the means of overcome them. The research questions we will try to answer are the following:

- How does artificial intelligence serve the personalization of learning?
- What are the intrinsic limits of this type of technology?

2. METHODS

This article is a literature review aiming to analyze the design and impact of an ITS on the learner and the teacher with a view to creating an intelligent semantic learning support system. Searches on ResearchGate, ScienceDirect, arXiv and Google were made using the keywords “artificial intelligence”, “education” and “intelligent tutoring system”. This research includes questions about learning and these cognitive mechanisms, skill-based learning, e-learning, AI and its techniques, semantic technologies and standardized object descriptions, the functioning of intelligent tutors in the education, the technical and ethical limits of these tools. Other topics were also discussed such as the use of Natural Language Processing, recommendation systems, computational thinking, logic programming, theories of brain processes of information processing or even reflections and debates on the evolution of technology, education and society. For all searches, the keywords were searched in the titles and abstracts of the articles present in the aforementioned databases. The research protocol has been restricted to articles meeting various inclusion criteria: the article must be published in a peer-reviewed journal between January 2010 and December 2021 and must report on at least one analytical or empirical study. Dissertations and secondary data analyze were excluded. Study observations must be based on students in grades K-12 and must include a control group in order to be able to make a comparison (e.g., teacher-led class, human tutoring). The measure of the effectiveness of the system must be measured using standardized tests, and the study must provide the information necessary to consider the effect size. Finally, duplicate studies were excluded, and a review of the references used in the selected articles was made, but no further publications were added during the process.

3. DISCUSSION

3.1. Architecture of an ITS

Even if ITS have different approach models, they all share a common architecture by having three main types of knowledge: knowledge related to the domain to be studied (stored in the domain model), knowledge about each learner in order to personalize the transmission of knowledge (stored in the student's model) and pedagogical knowledge allowing the tutor to make decisions on the resources to be offered and on the help to be provided to the learner (stored in the tutor's model). According to Vanlehn (2006), there are two main loops in the latter, where one aims to determine the order of future tasks to be given to the learner according to the knowledge acquired (outer loop) and the other aims to follow the learning of the live student to bring him help in case of blockage (inner loop). This help can take different forms, depending on the type of model chosen during the designs. This system can be enriched using a Learning Record Store (LRS), which allows the storage and manipulation of data of the learner's learning experiences on different types of web resources.

3.1.1. Knowledge Model

The knowledge model, also called expert model or knowledge expert, contains the concepts, facts and rules of the domain targeted by the learner. Typically produced using the knowledge of experts in the field, it provides the ITS with a source of knowledge to present to the learner while serving as an assessment tool by comparing the learner's responses to their own. domain knowledge model. Among the most common knowledge base design approaches, we can cite the Cognitive Model which is based on the ACT-R theory of cognition and learning (Desmarais & Baker, 2012), a cognitive architecture aimed at defining the bases cognitive and perceptual operations governing human thought. In this vision of cognition, knowledge can be declarative (composed of facts) or procedural (composed of actions). These two types of knowledge are only accessible through the use of buffers, the content of which varies depending on the moment and represents the state of the rational thought controller. We can also cite the constraint-based model, where domain knowledge is represented in the form of rules not to be broken (e.g., “If the relevance of the answer is true, then the answer must be correct”). According to Mitrovic (2012), this approach, more mathematical than the previous one, maintains that each decision is made according to a certain number of limits not to be crossed while having to have solutions respecting the constraints posed. More easily implementable by computer, this vision of cognition is however defined as a vision not guided by the emission of hypotheses, which prevents the prediction of the entire model in advance: a solution allowing complete modeling tends to show that the system is not entirely constraint based. Concerning the modeling of knowledge, we observe two major forms which are inspired by semantic technologies by their capacities to offer an ontological language operable by humans and machines (Héon, 2016). The first is based on ontologies, allowing the description of a structured set of concepts representing a field of information as well as the relationships between these concepts. Mainly used in the semantic web, ontologies make it possible to create taxonomic links and semantic links in order to connect knowledge by their meanings and their hierarchies in this field. This representation can take the form of a heuristic tree, which is a diagram intended to reflect the path of thought and the associative nature of it by visually presenting the existing links between concepts. The second form is based on the Knowledge Graph, and represents a network of concepts linked together by descriptive verbs. This representation adds an additional dimension by clarifying the relationships between concepts: using the Subject-Verb-Predicate triplet, it facilitates the creation of data models representative of a set of additional concepts. to explain the relationships between these concepts, which allows an intelligent processing of these resources in addition to facilitating the inference capacity of the system (du Château, Mercier-Laurent, Bricault, & Boulanger, 2020).

3.1.2. Learner Model

The student model represents their characteristics, knowledge, and skills to provide the ITS with a source of information about it, allowing it to infer aspects of the learner's behavior. The system will then be able to compare the state of the learner's knowledge with that of the field in order to identify possible misconceptions and adapt the exercises in order to work on the weaknesses of student's skills. Two types of information must be processed to have a relevant model of the learner: their fixed characteristics (e.g., gender, mother tongue, level of study) and their dynamic characteristics (e.g., knowledge, emotional state, level of attention, problem-solving skills). This information allows the knowledge modeling of the learner on a domain, which can take different forms. Among the most frequent, we find the Overlay type modeling, where the knowledge of the learner is a subset of the knowledge of the expert system. The goal of the system is then to broaden the set of knowledge of the learner so that it completely covers all the expert knowledge. Its main weakness lies in the fact that each knowledge of the learner different from the expert is considered as a strategic error, while the error can also be in the operational domain (e.g., the learner may have understood the rule but mislead in the execution thereof). To overcome this problem, there is another more complex model to implement: the disturbance model, which consists of defining the knowledge that the learner has, and that the system does not have as errors. The goal of the tutor is then to reduce the scope of the learner's knowledge so that it no longer exceeds this expert knowledge. However, this system requires much more design time, insofar as it uses a library of erroneous rules which must be considered upstream by the designers. We can also cite the model based on stereotypes, where learners are grouped into pre-constructed archetypes, quick to set up but whose representation of knowledge is partial and dependent on the richness of the archetypes constructed. We can also cite the fuzzy modeling where subjective variables of the good or bad type are used to define the student, which allows greater flexibility of the system to the detriment of a share of precision in the measurement of knowledge. Finally, there are forms of modeling using Artificial Intelligence techniques to describe the learner's knowledge, through the use of Bayesian Neural Networks using Hidden Markov Model or Recurrent Neural Networks boosted via the use of LongShortTermMemory (LSTM) for better efficiency: we are talking here about Learner Knowledge Diagnosis (LKD). All these types of student models can be enriched by using a Learning Record Store (LRS), which makes it possible to precisely follow the progress of learners on various educational supports by storing data on the learning experiences emitted by them. This technique makes it possible to capture the informal aspect of the flow of learning and to formalize this data in the form of xApi instructions adopting the form “User + Verb + Object” (e.g., User read this article, User played this game, User participated in such activity). In addition to allowing the storage of less formal learning data, LRS allow data analysis and exchange with other systems: this is valuable information for ITS because it provides additional for monitoring learner learning (Bealink.io, 2020).

3.1.3. Pedagogical Model

The tutor model, also called the pedagogical module, is the engine of the system. He acts as a tutor in charge of choosing “what to teach, how and when”, evaluating the learner's knowledge and adapting the proposed content to his preferences, answering questions or even generating feedback. in case of error or misunderstanding (Bourdeau & Grandbastien, 2010). These actions are based on the pedagogical content stored in the domain knowledge model and the characteristics of the learner stored in the learner model, and are intended to encourage the learner to build himself even knowing her rather than following chain instructions. There are already semantic active learning systems (e.g., SASA) capable of enriching and personalizing the learner's experience, by exploiting a reasoner using the calculation of first-order predicates and ontologies modeling the entities participating in the process learning (Szilagyi & Roxin, 2012). The addition of artificial intelligence in such a semantic system allows the realization of a personal intelligent learning agent, which will aim to optimize the learning of each learner according to the model drawn up of this one and the knowledge to be transmitted through of the various educational resources available. To do this, the intelligent tutor must be able to answer three questions: Who, What and How. The first question concerns the learner and his characteristics (e.g., age, level of study, knowledge acquired, objectives, motivation). This information is essential in order to personalize the learning path, but also makes it possible to adapt the pedagogical choices inducing the cognitive states sought in the learner. These states bring together different cognitive processes, such as attention and reasoning, requiring cerebral resources in the learner in order to learn new knowledge or solve a complex task. The second question (What?) concerns the area of knowledge to be transmitted. Using the domain knowledge model, the tutor must be able to navigate between the characteristics of the domain to be learned (e.g., geography, history, foreign language), the subjects of the domain (e.g., concepts, rules) as well as the skills to be learned. work (e.g., communication, comprehension, writing, problem solving). The last question concerns the pedagogical aspect of tutoring, by understanding the strategies for approaching the subjects to be studied (e.g., reading, writing, arithmetic) as well as the effectiveness of these approaches according to the situations, the subjects to be studied, the profile of the learner and his motivation or of the context of use. To answer these questions, the paradigm of procedural programming, whose belonging to the field of Artificial Intelligence, allows the creation of a computer tutor capable of following and/or changing routines. This style of programming offers the program better efficiency and increased modularity compared to sequential programming, due to the division of the program into sub-parts thus limiting the side effects between the functions. These functional units, similar to small modules, each fulfill a specific task and can then be assembled together to form libraries. These libraries then fulfill a defined role (e.g., the cross product of 4 variables) and can be called at appropriate times in the learner's learning path. Since the tutor makes the link between the learner and the system, the use of Natural Language Processing (NLP) makes it possible to improve the construction of the learner's knowledge through a more natural dialogue as well as clearer and clearer indications and relevant aids (Rus, Niraula, & Banjade, 2015)

3.2. Advantages and limits of AI in an ITS

From a learner's point of view, AI acts as an intelligent tutor in a virtual environment to personalize the educational resources offered according to its learning style (Messika, 2019). All the data transmitted will be stored, analyzed and processed in order to improve the representation of the learner's knowledge and skills. This precise representation improves the system's ability to infer the pedagogical content to be favored according to the profile of the learner and allows the personalization of his learning path through the choice of different pedagogical strategies according to each profile. The precise monitoring of the evolution of the learner's knowledge facilitates the production of feedback to be provided to him, through the synthesis of his progress and the achievement of the set educational objectives (Alkhatlan & Kalita, 2019). In addition, the use of artificial intelligence facilitates the processing of information by allowing the highlighting of the different ways in which learners interact with resources and the effect that these have on the quality of learning, data who then assist the teacher in making decisions about the usefulness and impact of the educational objects used. The ability to extract statistical regularity and synthesize the system also allows the teacher to have a summary of the evolution of each learner, both on the achievement of educational objectives and on the evolution of the style of teaching, learning or motivation (Franzoni, Milani, Mengoni, & Piccinato, 2020). This analysis makes it possible to detect the difficulties specific to each learner but can also infer potential dropouts, reducing the digital divide linked to the use of a virtual tutoring system (Pitchforth, 2021). Finally, this technology offers the possibility of aggregating educational objects from a domain through the use of semantic technologies and metadata. Properly described pedagogical resources make it possible to drastically increase the amount of relevant pedagogical resources available to the teacher because they are processable and categorizable by machines, which facilitates interoperability between different learning systems (Apoki, 2021). One of the standards that can be used is LOM (Learning Object Metadata), which is a description scheme for digital or non-digital educational resources using several categories (e.g., general, life cycle, rights, relationship, classification) to describe a resource. However, the use of AI in a tutoring system brings several constraints to take into account. The first notable problem concerns learning biases during the training phase of the pedagogical model. This bias, coming from a biased data set, introduces a distortion in the training process which results in a systematic deviation of the model results. This bias can come from a confirmation bias, i.e., from cognitive biases of the designer, but can also be a statistical bias, i.e., from non-representative training data or statistical algorithms used inconsistent with the objective of the system (Mélot, Ris, & Briganti, 2021). To limit them, it is necessary to define upstream the precise needs of the users, to control the coherence of the methods used according to the desired results and to surround oneself with experts of the subject to be treated to limit the impact of one's own cognitive biases. Another problem is that of poor understanding of the technology, which can occur on the designer and user side. The main problem for the designer is the systemic problem of the black box: we know the input data; we observe an output result, but it is complex to explain what is happening between the two. This problem sometimes makes it difficult to explain on what elements the model is based to produce the result, which de facto complicates the explanation of the feedback produced, the debugging of the system in the event of inconsistent output or the granting of confidence to a system whose operation escapes human comprehension. There is currently no universal answer to this problem, with easily explainable algorithms having lower performance than algorithms using multiple layers of learning (Villani, 2018). Research continues to improve the transparency of these algorithms, even if this problem of algorithmic decisions may be more about the contestability of the results than the explainability (Abiteboul, 2017). On the user side, the poor understanding of technology is rooted in the lack of education on this subject. Currently, at a low level of study, IT is only office automation. We must demystify this technology by learning the basic algorithms and techniques for the operation of artificial intelligence (e.g., linear regression, decision tree, deep learning). The population must also be accustomed to using this tool in order to reduce use bias, better collect data and better understand the limits of the technology (O'Neil, 2016). Finally, it may be more appropriate to speak of machine learning than artificial intelligence because intelligence is a fairly strong term and ultimately quite incorrect in view of the degree of intelligence that AI really demonstrates. Finally, one of the last important points is that of the processing of sensitive data. The Internet of Things makes it possible to use several different connected objects as learning media, which involves data transfers between devices. In addition, collecting as much information about the learner as possible is necessary to design a model of their knowledge and skills, which involves collecting all the data they emit in addition to pre-filled information (e.g., sex, age, level of education). All these data are essential to have an accurate and relevant model of the learner but are extremely sensitive. One of the solutions to avoid having them transit through the cloud is to use peripheral artificial intelligence, a method combining machine learning and cloud computing to process the data as close as possible to the source of transmission in order to avoid the transmission large amounts of data in clouds. Peripheral computing is a technique aimed at synchronizing on a server only relevant and pre-processed data (Ismael, 2018). This technique applied to artificial intelligence works in two stages: first a local learning where each device adjusts its learning model, followed by a global aggregation where the main server defines the weights of the new model and updates it on the various connected objects (Li, Zhao, Lu, Liu, & Shen, 2019). Data are not transferred between devices, only models are transferred. Thus, time and bandwidth are saved and the private aspect of the data is protected (Hosseinalipour, Brinton, Aggarwal, Dai, & Chiang, 2020). This technique also has its limits but remains a feasible and relevant solution for the processing of sensitive data.

4. FUTURE RESEARCH DIRECTIONS

This bibliographical review presented only part of the concepts related to intelligent tutoring systems. Certain cognitive theories, learning theories, IT development possibilities or even the use of big data and learning analytics have not been addressed for the sake of non-exhaustiveness. Many areas still remain to be explored, and field experiments are necessary to confirm or invalidate the different ideas defended in this article. These experiments are planned for the near future and will be the subject of another publication.

5. CONCLUSION

Given the constant evolution of AI, it is important that students and teachers learn to master the technology in order to maximize its positive impact. ITS possible contributions are not negligible: better personalization of learning, better generation of feedback, powerful tool for statistical inference and aggregation of relevant content. Like any technology, however, AI has limitations such as learning biases, usage biases or securing the large amount of sensitive data retrieved. We must continue to work on these risks in order to avoid falling into a technological dictatorship where the tool becomes a constant monitoring instrument whose operation escapes the understanding of its users. It is certainly a powerful tool, but to be handled with care due to its various ethical and technological implications. Finally, it is important to say that Artificial Intelligence will never completely replace human decisions because certain characteristics of human intelligence (e.g., empathy, adaptation to the unexpected, data-efficient learning) cannot be transposed to the machine. In the history of human communication, evolution has perfected the transmission of information through the analysis of the face, the appreciation of attention or the consideration of emotions and other external parameters. Since humans are social animals who learn better from their peers, it is essential to retain humanity in one of the greatest strengths of our species: the ability to learn. Through an individualization of the learning path and associated with the look and decisions of the teacher, the smart tutor therefore seems to be a promising tool combining personalization and automation in order to support (and not replace) the teacher in his work, which remains and will remain essential due to our biological evolutions with regard to learning efficiency and transmission of information from human to human.)

REFERENCES

Abiteboul, S. & Dowek, G. (2017). *Le temps des algorithmes* [Time of algorithms]. Paris, Le Pommier.

Alkhatlan, A. & Kalita, J. (2019). Intelligent Tutoring Systems: A Comprehensive Historical Survey with Recent Developments. *International Journal of Computer Applications*, *181*(43), 1-20. https://doi.org/10.5120/ijca2019918451

Apoki, U. (2021). The Design of WASPEC: A Fully Personalised Moodle System Using Semantic Web Technologies. *Computers*, *10*(5), 59. https://doi.org/10.3390/computers10050059

Bourdeau, J. & Grandbastien, M. (2010). Modeling tutoring knowledge. In R. Nkambou, J. Bourdeau, & R. Mizoguchi (Eds.), *Advances in Intelligent Tutoring Systems* (vol. 308, pp. 123-143). Berlin, Heidelberg: Springer. https://doi.org/10.1007/978-3-642-14363-2_7

Dai, Y., Chai, C., Lin, P., Jong, M. S., Guo, Y., & Qin, J. (2020). Promoting students' wellbeing by developing their readiness for the artificial intelligence age. *Sustainability*, *12*(16), 1–15. https://doi.org/10.3390/su12166597

Desmarais, M.C., & Baker, R.S. (2012). A review of recent advances in learner and skill modeling in intelligent learning environments. *User Modeling and User-Adapted Interaction*, *22*(1-2), 9–38. https://doi.org/ 10.1007/s11257-011-9106-8

du Château, S., Mercier-Laurent, E., Bricault, L. & Boulanger, D. (2020). Modélisation des connaissances et technologies du Web sémantique: deux applications au patrimoine culturel [Modeling knowledge and technologies of the Semantic Web: two applications to cultural heritage]. *Humanités numériques*. https://doi.org/10.4000/revuehn.510

Franzoni, V., Milani, A., Mengoni, P. & Piccinato, F. (2020). Artificial Intelligence Visual Metaphors in E-Learning Interfaces for Learning Analytics. *Applied Sciences*, *10*(20). https://doi.org/10.3390/app10207195

Héon, M. (2016). *Le web Sémantique en 10 minutes* [Semantic Web in 10 minutes]. Retrieved from https://www.youtube.com/watch?v=r795n3AffgA

Hofstadter, D. (1979). *Gödel, Escher, Bach: An Eternal Golden Braid*. Basic Books.

Hosseinalipour, S., Brinton, C. G., Aggarwal, V., Dai, H., & Chiang, M. (2020). From Federated to Fog Learning: Distributed Machine Learning over Heterogeneous Wireless Networks. *IEEE Communications Magazine*, *58*(12), 41-47. https://doi.org/10.48550/arXiv.2006.03594

Ijaz, K., Bogdanovych, A. & Trescak, T. (2017). Virtual worlds vs books and videos in history education. *Interactive Learning Environments*, *25*(7), 904–929. https://doi.org/10.1080/10494820.2016.1225099

Ismael, K. (2018, August 14). Edge Computing vs. Fog Computing: What's the Difference? *CMSWire*. Retrieved April 13, 2023, from https://www.cmswire.com/information-management/edge-computing-vs-fog-computing-whats-the-difference/

Li, G., Zhao, P., Lu, X., Liu, J. & Shen, Y. (2019). Data Analytics for Fog Computing by Distributed Online Learning with Asynchronous Update. In *ICC 2019 - 2019 IEEE International Conference on Communications* (pp. 1-6). Shanghai, China. https://doi.org/10.1109/ICC.2019.8761303

Loeckx, J. (2016). Blurring boundaries in education: context and impact of MOOCs. *The International Review of Research in Open and Distributed Learning*, *17*(3), 92–121.

Mélot, H., Ris, L. & Briganti, G. (2021*). De l'intelligence humaine à l'intelligence* artificielle? [From human intelligence to artificial intelligence?]. Retrieved from https://www.youtube.com/watch?v=t2_poAVaiQ0

Messika, E. (2019). L'Enseignement Supérieur a L'Ere De L'Intelligence Artificielle [Higher Education in the Age of Artificial Intelligence]. *Forbes*. Retrieved April 13, 2023, from https://www.forbes.fr/technologie/7-recommendations-pour-l-enseignement-superieur-a-lere-de-lintelligence-artificielle/

Mitrovic, A. (2012). Fifteen years of constraint-based tutors: what we have achieved and where we are going. *User Modeling and User-Adapted Interaction*, *22*(1-2), 39–72. https://doi.org/10.1007/s11257-011-9105-9

O'Neil, C. (2016). *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*. Crown Publishing Group, USA.

Pitchforth, J. (2021) Et si l'Intelligence Artificielle était source d'égalité dans l'enseignement supérieur? [What if Artificial Intelligence was a source of equality in higher education?] *ActuIA.com*. Retrieved May 3, from https://www.actuia.com/contribution/jamiepitchforth/et-si-lintelligence-artificielle-etaitsource-degalite-dans-lenseignement-superieur/

Qu'est-ce qu'un Learning Record Store (LRS)? [What is a Learning Record Store?] (2021). Retrieved April 13, 2023, from https://bealink.io/a-quoi-sert-un-learning-record-store-lrs

Rus, V., Niraula, N., & Banjade, R. (2015). DeepTutor: An Effective, Online Intelligent Tutoring System That Promotes Deep Learning. *Proceedings of the AAAI Conference on Artificial Intelligence*, *29*(1). https://doi.org/10.1609/aaai.v29i1.9269

Seldon, A. & Abidoye, O. (2018). *The Fourth Education Revolution, will Artificial Intelligence Liberate or Infantilise Humanity.* London, UK: University of Buckingham Press.

Szilagyi, I. & Roxin, I. (2012). Learner Ontology for the Active Semantic Learning System. In I. Aedo, R. M. Bottino, N.-S. Chen, C. Giovannella, Kinshuk, & D. G. Sampson (Eds.), *Proceedings of the 12th IEEE International Conference on Advanced Learning Technologies* (pp. 393-394). Rome, Italy. https://doi.org/10.1109/ICALT.2012.162

Vanlehn, K. (2006). The behavior of tutoring systems. *International journal of artificial intelligence in education*, *16*(3), 227–265.

Villani, C. (2018). Donner un sens à l'intelligence artificielle [Make sense of artificial intelligence]. *AI for Humanity Rapport*. Retrieved from https://www.aiforhumanity.fr

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