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New Forms of Alliances Between Humans and Technology: The Role of Human Agency to Enhance the Design and Setting Up of Artificial Intelligence Based Learning Tools

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ABSTRACT

The aim of this paper in to investigate how new forms of alliances between humans and machines can be formed in the context of interaction and collaboration between human and artificial intelligence (AI), for the adoption of artificial intelligence-based learning tools (adaptive learning). The proposed approach is to analyse the cybernetics theory as a framework to define alliances between humans and AI-based tools. Different types of interactions between humans and machine learning algorithms taking roots from the theory of cybernetics are presented. This research will further extend to analyse how human-AI interaction design approaches can address risks and challenges associated with the adoption of adaptive learning tools and to show the need to focus on human agency throughout the design and running phases of these tools, where learners and instructors are required to be actively involved.

Keywords: Adaptive learning, Human-AI interactions, Participatory design, Education, Cybernetics theory, Cybernetics as framework

INTRODUCTION

The adoption of AI based learning tools, defined as adaptive learning tools, has evolved with the development of new forms of AI. Adaptive learning refers broadly to a learning process where the content taught or the way such content is presented changes, or “adapts”, based on the responses of the individual learner (Oxman and Wong 2014). Adaptive learning has the potential to improve learners’ and instructors’ experiences and make an important impact on education while raising risks and challenges that can be framed on human life, both in individual and societal level. According to interviews conducted with AI-based tools practitioners, these risks and challenges can be grouped at three level; i) ethical (related to the usage of learning data without the consent of users), ii) educational process (difficulty to integrate AI into the learning processes), iii) implementation at scale (shortage of skills).

In today’s environment, adaptive learning tools are being implemented to support instructors in content delivery and to provide learners withpersonalised learning, without necessarily involving them throughout the design and execution phases of these tools.

This paper investigates whether the development of new forms of interaction and collaboration between AI-based learning tools and its users, based on participatory design, would address risks and challenges linked to the adoption of these tools. The proposed approach is to analyse the cybernetics theory as a potential framework for analysing human-AI interactions and augmenting designers in creating human-centred interactive AI-enabled products. Cybernetics is defined as the science of feedback, and appears as part of the earliest study on human-machine interactions (Wiener, 1960).

Participatory design, with a need to focus on human agency in the design and running of AI-based learning tools is presented as primordial, to address risks and challenges related to the adoption of these tools. In the context of human-AI alliances, designers can embed participatory design approaches into tools -as AI subsystems- that can interact with humans (Dubberly 2015). This interaction can then support the AI subsystem to further learn and adapt to the user.

The methodology used for data collection is based on extensive literature review on cybernetics theory, education technology and adaptive learning; supported by interviews conducted with different group of AI based-tools practitioners and analysis of case-studies of organisations in the process of adoption of adaptive learning systems.

NEW FORMS OF ALLIANCES BETWEEN HUMAN AND TECHNOLOGY

Adaptive learning tools, based on new forms of AI technologies, can be of various types, ranging from simple systems with preconceived set of rules to complex systems with self-learning algorithms (Brinton et al. 2015). These tools are designed and developed by experts, without necessarily the involvement of learners and instructors. The findings indicate that a focus on human agency throughout the design and running phases of adaptive learning tools where learners, instructors and other education stakeholders are actively involved can have an important impact in addressing the risks and challenges associated with the adoption of AI-based tools (Osmanoglu 2022). Hence, the concept of participatory design for AI-based tools plays an important role in the development of adaptive learning systems. The analysis of participatory design requires a focus on forms of human-AI interactions and collaborations, that involve embedded feedback systems within adaptive learning tools. The following section presents various forms of alliances between humans and AI that can support participatory design. The approach adopted is to present cybernetics theory as a framework that can be used to support research and development on new forms of human-AI alliances.

CYBERNETICS

The notion of cybernetics has been introduced by Norbert Wiener, as as "the scientific study of control and communication in the animal and the machine", marking the early studies on human-machine interactions (Wiener 1961). The theory of cybernetics introduces the idea to control entropy in a system through feedback (Wiener 2019). In other words, cybernetics is the science of feedback, a response within a system that influences the continued activity or productivity of that system (Wiener 1961). The information travels from a system through its environment and back to the system, where feedback reports the difference between the current state and the goal, and the system acts to correct differences (Wiener, 2019). This process helps to ensure stability when disturbances threaten dynamic systems, such as machines, software, organisms, and organisations (Dubberly 2015).

The contribution of cybernetics theory to the idea of feedback is that any feedback system is automatically goal-directed, where both animals and machines fall into a new, wider class of objects that is characterised by the possession of control systems. Cybernetics not only draws analogies between animals and machines, but also studies the questions of system development at an abstract level. In other words, it provides a common ground to talk about living organisms, including humans, and machines, in a language suitable for a description of any goal-directed system. This last assumption has essentially determined the specific means and methods used in cybernetics (Valée 1995). In a broad sense, cybernetics involves the study of how systems regulate themselves and act toward goals, based on feedback from the environment. These can be biological (maintaining body temperature), mechanical (governing the speed of an engine), social (managing a large workforce), and economic (regulating a national economy), and not just computation (Wiener 1961).

According to Walter Canon, a frontrunner researcher in biological cybernetics, who studied mainly in mammals, and demonstrated the ability to compensate for an environmental perturbation by an internal modification rather than by an action on the environment, a feedback model that is conceptually explicit is called 'self-regulation' (Cannon cited in Parra-Luna, 2019). Control and communication play a fundamental role in cybernetics. Control is to be understood mainly as retroactive control, more precisely as negative feedback for self-regulation. In these regulation problems, the purpose is to maintain an essential parameter of a dynamical system at a chosen value (Wiener 1961).

Cybernetics offers the language (both vocabulary and frameworks) that enable scientists and designers from different domains of knowledge and practice to communicate, to describe the structural similarities of systems and to recognise patterns in information flows (Dubberly 2015). This shared language is especially useful in analysing, designing, and running complex, adaptive systems.

The use of the cybernetics vocabulary (formal concepts and associated terminology) is supporting integration through interdisciplinarity and transdisciplinarity. Its usage build bridges between different knowledge domains and allows to cross many disciplinary boundaries to create a holistic approach (interdiscipline). An example is the concept of control by feedback and the associated terminology. The concept can be applied in many different domains, where engineers, anthropologists, neurologists, psychologists and economists (and others) are constructing "similar" models, with different domains of application and terminology, where they can share information based on common ground for modelisation. Thus, cybernetics serves to facilitate communication between discipline areas (Parra-Luna, 2019). The concepts, models and terminology of cybernetics become systematised as a set of inter-related concepts (transdiscipline). The impact of cybernetics as a transdiscipline is that it abstracts from many domain models of great generality. Such models bring order to the complex relations between disciplines, and provide useful tools for ordering the complexity within disciplines (Ross 1956, cited in Parra-Luna 2019).

Practitioners of cybernetics see the ubiquitous phenomena of control and communication, learning and adaptation, self- organisation and evolution, when looking at the world. Cybernetics is the science of human-machine interaction that employs the principles feedback, control and communication. Therefore, the theory of cybernetics can be used to propose a framework for the development of forms of human-AI alliances (Osmanoglu, 2022). The following sections present different human AI interaction approaches that find root in cybernetics.

HUMAN IN THE LOOP APPROACH

New types of interactions between humans and machine learning-based AI models are grouped by researchers under the umbrella term of human-in-the-loop machine learning. Different approaches of human-in-the-loop are defined based on who is in control of the learning process. These can be identified as: active learning, in which the system remains in control; interactive machine learning, in which there is a closer interaction between users and learning systems; and machine teaching, where human domain experts have control over the learning process (Munro 2020). Aside from control, humans can also be involved in the learning process in other ways. In curriculum learning, human domain experts try to impose some structure on the examples presented to improve the learning; in explainable AI the focus is on the ability of the model to explain to humans why a given solution was chosen (Mosqueira-Rey et al. 2022).

Human-in-the-loop allows to leverage the power of the machine and human intelligence to create machine learning-based AI models. In traditional approaches, humans are involved in a virtuous circle where they train, tune, and test a particular algorithm. In other words, Human-in-the-loop describes the process when the machine or computer system is unable to solve a problem, and needs human intervention, which can involve in both the training and testing stages of building an algorithm, for creating a continuous feedback loop allowing the algorithm to give every time better results (Munro 2020).

INTERACTIVE MACHINE LEARNING

Interactive machine learning (IML), as a type of human in the loop approach, is an iterative learning process where humans and AI are interacting based on algorithms and frameworks that facilitate machine learning with the help of human interaction (Jiang et al. 2019).

Machine learning is more and more used for AI systems. The design and implementation of machine learning algorithms are developed mainly by skilled experts. The iterative approach adopted by these experts for machine learning development process involves the collection of data, construction of the model, and assessment of the quality of the model. Potential end users, who are often domain experts for the machine learning based tool, have limited involvement in this development process. They are consulted by the experts in providing data, or giving feedback about the learned model (Amershi et al. 2014). With this traditional development and running process, the end users' ability to directly affect the resulting model is limited.

Interactive machine learning addresses the question of how end users' involvement can be embedded in AI enabled tools, by defining AI subsystems that interact with humans. Caruana and colleagues brought the idea of creating a new cluster in the AI cluster that can allow interactions with end users, and they developed algorithms that enable interactive exploration of the clustering space and incorporation of new clustering constraints (Caruana et al. 2006). This approach enables everyday users to interactively explore the model space and drive the system toward an intended behaviour, reducing the need for supervision by practitioners. By allowing users to train, classify, view, and correct data through a feedback mechanism, interactive machine learning empowers them to create sub systems within machine learning for their own needs and purposes (Amershi et al. 2014).

DESIGN FOR AI ENABLED TOOLS

Both iterative design processes and cybernetics are based on learning and adapting to the needs of a system. In that matter, cybernetics can provide a useful framework for augmenting designers in creating human-centred interactive AI-enabled products (Dubberly 2015). Feedback loops defined within the framework provided by the cybernetics theory can be used by designers in embedding them into AI-subsystems to allow interaction with users, that can enhance the AI subsystem to further learn and adapt to the user.

Researches conducted on human-in-the loop design approaches, and particularly on interactive machine learning, show these share a common principle; that intelligent systems are designed with the goal to enhance or augment the human, and to evolve through human interaction. The Stanford University human-centred artificial intelligence working group reframed 'the human-in-the-loop' design approach as human-computer interaction (HCI) design problem, based on defining a selective inclusion of human participation in the intelligent automation as input, where the result measures the efficiency of intelligent automation while accommodating human feedback and remaining pertinent (Stanford HCI, 2022). In this approach, each step that incorporates human interaction expects the system to be designed in a way that before taking the next action these steps are understood by humans, and the critical steps are determined by human agency. This design approach is expected to bring transparency, while incorporating human judgment in effective ways. AI systems are built to support humans. The value of such systems lies not solely in efficiency or correctness, but also in human preference and agency.

According to researches, it is important to focus on the information flows existing in AI systems during the design phase, in a way to make operations more efficient and user experience more meaningful by creating opportunities for learning through feedback (Martellato and Ju 2018). Knowledge of cybernetics can support these processes.

The necessity of human agency in participatory design within a cybernetics-based framework, is further enhanced by designers. Medich, states that 'AI based tools are designed to extend the human ability to think, and cybernetic models are created with an emphasis on the human to maintain the system and encode the exchanged information into computer language'. He then follows that 'the technological side of the cybernetic system tend to adapt and learn fast from the human side, except in the encoded translated format, highlighting the importance on fluency of the human in technology to achieve more powerful things together'(Medich cited in Martelaro and Ju 2018).

HUMAN – AI INTERACTIONS IN THE CONTEXT OF ADAPTIVE LEARNING

Adaptive learning tools are developed by humans, however according to conducted interviews and researches, learners and instructors are not sufficiently involved throughout the design and running phases of these tools. Risks and challenges associated with the adoption of these tools can be addressed with a 'human in the loop approach' based participatory design, where the end users would interact with AI algorithms to contribute to the outcome.

Learners and instructors can be involved in participatory design in self-managing their own learning data used for training algorithms, to avoid the concerns for example at the ethical level over the usage of their data without their consent.

Extensive interactions of learners and instructors with AI algorithms can also support the integration of technology into educational processes (pedagogy) and better adapt better the technologies to educational processes. The interactions between AI-based tools and users can also help to develop new skills, to address the skill gap issue related to implementation at scale of adaptive learning tools. These hypotheses require to be supported by further researches.

Through the participatory design approach based on cybernetics, more agency is delivered to learners and instructors, at the different stages of adaptive learning tools' lifecycle (design, development, set up and running). Learners and instructors, by providing constant feedback, are expected to improve the capacity and the effectiveness of adaptive learning tools, consequently the educational system.

CONCLUSION AND FUTURE WORK

Different human-AI interaction approaches that find root in cybernetics have been presented.

The theory of cybernetics, as the science of human-machine interactions through feedback, is proposed as a framework to develop further human-AI alliance approaches.

This paper analysed whether a participatory design, focussed on human-AI interactions, can help to address risks and challenges related to AI-based tools adoption, particularly for adaptive learning tools.

The importance of human agency, as the involvement of learners and instructors, in the context of participatory design, to enhance the design and running of AI-based learning tools, has been highlighted. The involvement of users can be overcoming risks and challenges related to the adoption of these tools, by in addressing issues related to ethics, as to the usage of data, integrating AI and educational processes, and overcoming skills shortage for implementation at scale. However, these hypotheses remain to be tested as part of future researches.

This research will be further followed up with extensive research on cybernetics theory to develop new human-AI alliances taking into consideration new developments on AI.

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