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Unleashing the power of Open Educational Practices (OEP) through Artificial Intelligence (AI): where to begin?

Ahmed Tlili & Daniel Burgos

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EDITORIAL

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Introduction

The term Open Educational Resources (OER) was first coined at UNESCO's 2002 Forum on Open Courseware, and it was defined in the recent UNESCO recommendation on OER as "learning, teaching, and research materials in any format and medium that reside in the public domain or are under copyright that have been released under an open license that permit no-cost access, [reuse], [repurpose], adaptation, and redistribution by others" (UNESCO, 2019a). With the rapid evolution of the open education concept, researchers have shifted their focus from content-centered approaches, which mainly focus on OER, such as creation and sharing, to more practice-centered ones that foster collaboration between learners and educators for creating and sharing knowledge (Zhang et al., 2020). In other words, researchers and educators have shifted their focus from creating and publishing OER to practices that can be implemented using OER for education; these are referred to as Open Educational Practices (OEP). From the pedagogical perspective, Downes (2019) stated that the learning process occurs not through the consumption of the OER content, but through the ways of using it.

However, designing OEP can be challenging as many issues could be raised, such as culture tension in open courses, where learners can be from various countries with different cultural backgrounds and beliefs. Therefore, more research should be paid to enhance the adoption and design of OEP. Downes (2019) claimed that the evolution of technology could also impact the evolution of OER and OEP, since the nature of educational content changes with technology. In this context, several leading organizations have focused specifically on the use of Artificial Intelligence (AI) technology to unleash the power of OEP. For instance, UNESCO (2019b) created a workshop on how to combine OER and AI for better learning practices. This workshop focused on two areas, namely: (1) the policy solution to support adopting OER and AI; and, (2) technical solutions which focuses on using open algorithms and open data to provide smart OER repositories and platforms that can help learners learn in a way most suited to them. Another pioneer of open education, namely Creative Commons (CC), set up four working groups focusing on the future of openness where one of the groups is dedicated to AI and open content (AI@School, 2021). This shows that AI technologies play a core role in the future of OER and OEP.

Despite the increased attention towards harnessing the power of AI to enhance OEP, applying them both could be "tricky" as each area (namely AI or OEP) has its own challenges to be considered, and combining them together could be a "blessing and a curse" at the same time. A blessing, as AI-based OEP will help provide more adaptive and engaging learning and teaching experiences; while a curse, as researchers and practitioners need to pay an extra eye to the challenges merging from both areas together (i.e. copyright, privacy, and data normalization). For instance, learners might be treated unfairly by the system due to not considering some individual factors like culture, background or language in open education. This further might stress the risks of AI to reproduce some injustices of similar experiences. To extent the understanding of this topic, this collection (still in progress) specifically focuses on how Artificial Intelligence (AI) technology could reshape OEP, for better teaching and learning experiences. In this context, several case studies are reported (see section *Collection in Progress – Papers in this collection*). This collection also calls for more research to help better understand how AI and OEP could be combined for better future open education (see section *Call for papers*).

Open Educational Practices: from OER to OEP

Open Educational Practices (OEP) have emerged as innovative practices that could help in enhancing learning experiences and outcomes through the use of Open Educational Resources (OER). Huang et al. (2020a) conducted a comprehensive review of the OEP definitions in the literature and identified four main dimensions that should be covered under OEP, namely: (1) OER which are educational resources that are shared under an open license and can be used within a given OEP-based course; (2) Open teaching implies that educators should implement teaching methodologies that can allow learners to actively contribute to the co-creation of knowledge and be self-regulated; (3) Open collaboration implies that educators should build open communities to foster teamwork (e.g. editing a blog, creating a Wikipedia page) and social interaction; and, (4) Open assessment implies that educators design learning tasks that foster not only teacher assessment, but also peer assessment. This can emphasize reflective practices and improve learning outcomes, along with their attendant methodologies, pedagogies, and practices. All these dimensions are enabled by several technologies, such as social networks, and collaborative editing tools.

Despite that several studies have reported that OEP will be part of future education even in uncertain times (Huang et al., 2020b), several questions remained unanswered (Koseoglu et al., 2020). One possible question is how educators can monitor their learners and assess their learning progress and achievements in open learning environments where, unlike the traditional learning, the learning activities are self-regulated and learner-centered, such as editing blogs or searching and summarizing reports under an open license from disaggregated sources (e.g. open textbooks). Jivet et al. (2020) stated that one of the challenges reported by educators in OEP is the fear of losing control over the learning process, which can be extended to the hard tracking of outcomes, assessment, and progress indicators. In addition, in open learning environments, such as open communities on social networks, learners could be from various background, languages, and cultures. Zhang et al. (2020) stated that open learning environments could be inconvenient for some learners, such as those who are shy, therefore personalized OEP should be provided for them. Liu et al. (2016) further mentioned that new issues could be raised, such as cross-cultural tensions, in open online courses. Additional potential issues emerge in these settings, such as, a more restrictive interaction style from a learner, a less integrative teaching style from a docent, or a contextualization of demographic indicators.

To enhance OEP design and adoption, the Open Education Policy published in 2017 by Universidad International de La Rioja (UNIR) highlighted the crucial role of emerging technologies and acquiring digital skills in future open education strategies and policies (Burgos, 2017). It focused on five dimensions, namely: (1) having the variety of skills required to find, understand, evaluate, create, and communicate digital information in a wide variety of formats; (2) being able to use various technologies adequately and effectively to search for and retrieve information, interpret search results, and judge the quality of retrieved information; (3) understanding the relationships between technology, lifelong learning, personal intimacy, and proper information management; (4) using digital skills and appropriate technologies to communicate and collaborate with peers, colleagues, family, and sometimes the general public; and (5) using these skills to actively participate in civil society and contribute to a vibrant, informed and committed community

Similarly, the Cape Town Open Education Declaration (2007) further stated that "Open education is not limited to just open educational resources. It also draws upon open technologies that facilitate collaborative, flexible learning and the open sharing of teaching practices that empower educators to benefit from the best ideas of their colleagues" (p. 4). This implies that the Cape Town Declaration also encourages utilizing emerging technologies, such as Artificial Intelligence (AI), to facilitate open formats in teaching and learning, through open, yet safe sharing of best practices. However, these technologies should also be carefully utilized as they might have a counterproductive implication, such as a potential bias. In this context, the ART (accountability, responsibility, transparency) principles for responsible and trustworthy AI have been proposed by Dignum (2019).

Harnessing the power of AI to enhance OEP

Artificial Intelligence (AI) has emerged as a crucial technology to enhance the learning experience online by, for instance, analyzing learners' data automatically or personalize the learning process (Lynch et al., 2020). Baker and Smith (2019) defined AI, from a broad perspective, as "computers which perform cognitive tasks, usually associated with human minds, particularly learning and problem-solving" (p. 10). This definition implies that AI covers a range of technologies and methods, such as machine learning, Natural Language Processing (NLP), data mining, neural networks or various algorithms.

When discussing the future of open education, Tlili et al. (2021a) mentioned that AI could play a vital role in enhancing both OEP-based teaching and learning experiences at different stages. For instance, at the first stage when creating OER to be used when implementing OEP, to facilitate finding OER, it is possible to apply AI, specifically machine learning and NLP techniques, to analyze the OER created and generate automatic tagging of metadata. This could result in an OER with rich and more accurate metadata that can be found and used easily by learners and educators.

At the second stage of learning, machine learning and NLP techniques could be used to develop smart virtual agents who are responsible for answering learners' questions provisionally in open learning environments, when educators are not available. They can also be used to analyze learners' log data in open environments and provide adaptive learning accordingly. In online situations, especially with a large number of learners, groups, or courses, the ability of AI to categorize learners' behaviors to uncover patterns that allow targeted responses that drive academic performance is invaluable (Burgos, 2020). Additionally, AI can be applied to classify the quality of OER based on different factors (e.g. learners' feedback, number of downloads, or ratings by applying ranking algorithms). This means that the users (e.g. learners or educators) will get to see more highly valued OER ahead of poorly published OER, hence have more quality designed OEP. Moreover, text-mining techniques can be applied to collect and analyze the feedback of users about a particular educational resource in order to draw conclusions about its quality to other OER users.

Furthermore, mapping OER together for remixing OER-based teaching materials or for OEP-based self-directed learning could be very challenging for both educators and learners. This is because OER are stored on different repositories across different countries or states, and there is no communication between these repositories (Drabkin, 2016; Muganda et al., 2016). Therefore, it is possible to use sophisticated machine learning and NLP techniques to analyse the generated metadata of the published OER to map all of these resources together and build OER recommender systems. For instance, after a learner or an educator finishes reading an OER about "Introduction to gamification" published by educator A on repository X, the system recommends that they next read about "designing gamification in learning environments" published by educator B on repository Y. This generates automatic learning and teaching paths for both learners and educators, and facilitates the finding of adequate OER for better OEP-based learning or teaching outcomes.

Furthermore, Downes (2019) stated that open AI and open algorithms can also contribute to enhancing OEP. For instance, Zhang et al. (2021) integrated Jupyter, an open-source web-based interactive development environment that can support a wide range of workflows in data science, scientific computing, and machine learning, with an open e-book to help learners learn about AI. Through the virtual containers designed with Jupyter, the learners can collaboratively practice programming together. They can also reuse their peers' programming code to test it out or also to modify it and create other versions out of it. They can also remix their peers' programming code and redistribute it on other platforms. Downes (2019) also reported another open Azure AI service which is used to automatically add a description of an image, the alt tag, which can make the image accessible to those who can not see the image, as the alt tag can be read by a screen reader. Downes (2019) stated that this platform can be used to create automatic tag of OER, hence make them more discoverable online or also to create accessible OER.

On top of the traditional AI-supported areas like learning analytics and automated course generation, AI should be implemented to support interactivity and community-based creation of OER (Downes, 2019). For instance, Cognii (http://www.cognii.com/) allows open response assessments, while X5GON (https://www.x5gon.org/) fully automates the creation of OER-based courses. On the other hand, some authors warned about some potential downsides in the use of AI. For instance, Dignum (2021) stated that to ensure safe implementation and use of AI, its development should go beyond the technical and common privacy concerns to cover socio-cultural and human values, as well as ethical principles. Askell et al. (2019) considered responsible AI development as the step needed to ensure that AI systems have an acceptably low risk of harming users or the society and, ideally, to increase their likelihood of being socially beneficial. Therefore, responsible AI is concerned with the design, implementation and use of ethical, transparent, and accountable AI technology in order to reduce biases, promote fairness, equality, and to help facilitate interpretability and explainability of outcomes, which are particularly pertinent in an educational context in general and in an open educational context in particular, as learners could be from all over the world with different cultures, beliefs, and background. This is a task that involves every step in the process and every user in the information chain, form the AI designed, to the user, through the data holder.

What should be changed?

Harnessing the power of AI to enhance OEP is not the simple combination of open content or resources with AI techniques and algorithms. It is more complex than that and it is a whole ecosystem that should be studied carefully and changed to endorse "openness" and "intelligence" together for better teaching and learning experiences.

As a first layer, the mindset and personality of learners and educators, the main actors within this ecosystem, should also be "open" to adopt this change in future learning and teaching process, as different cultures may perceive OER and technology adoption like AI differently (Hodgkinson-Williams & Trotter, 2018). Social challenges can also limit the adoption of AI-based OEP. For instance, the provided learning content is now open to everyone and AI-based techniques and algorithms can help report the limitations of a given content, as a way for future improvements, if other users are interested to further revise this content. However, this can make educators uncomfortable, since they are not accustomed to learning criticism in traditional learning (Tlili et al., 2021a).

As a second layer, the learning environments, platforms, and repositories should be changed in design from static and black box (i.e. not open and cannot see what is happening) systems to more open and dynamic systems that could be customized and adapted easily (Downes, 2019). In this context, Tlili et al. (2021a) stated that to develop intelligent OER repositories that could provide learning recommendations accordingly, the OER repositories themselves (not only the resources) should be intelligent and open so others can access their metadata and make good use of it to recommend the resources they have. Therefore, when designing these learning environments and repositories, designers should think from the users' experience perspective rather than from the content experience. Additionally, the designed learning environments should go beyond the common concerns related to AI in education, such as privacy, security, and the appropriate uses of personal data (Dignum, 2021) to also cover affective privacy (e.g. the right to keep your thoughts and emotions to yourself), emotion induction (e.g. changing how someone feels), and virtual relationships where learners enter a relationship with virtual agents (Hudlicka, 2016).

As a third layer, the implemented AI algorithms and systems as well as the generated log data should be open so it can be reused in different contexts. Atenas and Havemann (2015) stated that open data are "openly licensed, interoperable, and reusable datasets which have been created and made available to the public." Downes (2019) further stated that future open education in the era of AI should be more decentralized encryption-based ledgers with cloud and AI assisted services. Besides, the rise of responsible AI in (open) education was not meant to give machines some kind of "responsibility" for their actions and decisions. On the contrary, the development of responsible AI algorithms and systems entails a long list of societal, legal or ethical decisions by designers, developers, and other stakeholders.

As a fourth layer, to better adopt AI-based OEP and manage smart and open learning environments and platforms, educators and learners should have the needed competencies (e.g. ICT, pedagogical, etc.) to do that. In this context, Nascimbeni et al. (2020) proposed a competency framework that users should adopt for better application of OEP. This framework could be further extended to cover the AI competencies as well.

Finally, the fifth layer which could support serving all the aforementioned four layers is policy. The policies could be laws and regulations to protect users' privacy and copyright in open learning environments, and when designing and using AI-based educational systems. This can give them more confidence to adopt AI-based OEP. The policies could also be trainings or workshops to help various stakeholders better design their courses and implement open pedagogies. They could further be encouragements to help educators explore AI and OEP. For instance, bonuses from universities could be provided for educators who are willing to harness the power of OEP through AI.

Collection in progress – papers in this collection

This collection begins with a paper titled "The evolution of sustainability models for Open Educational Resources: Insights from the literature and experts", discussing how emerging technologies have changed the sustainability models for OER. In this context, Tlili et al. (2020) applied the triangulation method, where they started first by collecting the available sustainability models for OER via a systematic review. They then validated these models through a two-round Delphi method with thirty OER experts. The obtained findings identified and analyzed ten OER sustainability models, where public and internal funding are the most established ones.

The next paper titled "Impact of cultural diversity on students' learning behavioral patterns in open and online courses: A lag sequential analysis approach" highlighted the potential conflicts that could be raised in open courses due to learners being from different cultures. In this context, Tlili et al. (2021b) applied Lag Sequential Analysis (LSA) to investigate how students from China, Tunisia, and Serbia behave in an open course on Moodle based on the theoretical framework of Hofstede's National Cultural Dimensions (NCD). The obtained results highlighted that students from each culture behave differently due to several interconnecting factors, such as educational traditions. The results also pointed out that culture is a complex dimension, and further investigation is needed to understand the other dimensions that may affect online and open learning behaviors.

In the paper titled "Understanding user behavioral patterns in open knowledge communities", Yang et al. (2018) also applied LSA to investigate how users collaboratively create and share knowledge in Open knowledge communities (OKCs). The obtained findings revealed that content editing and commenting were the most frequently occurred behaviors. On the other hand, uploading material, inviting collaborators, and credibility voting were the least occurred behaviors. The findings can help in improving OKCs, particularly for the communities in the early stage of development.

Finally, the three set of papers titled "Predicting completion of massive open online course (MOOC) assignments from video viewing behavior", "Subgroup discovery in MOOCs: a big data application for describing different types of learners", and "Applying learning analytics for improving students engagement and learning outcomes in an MOOCs enabled collaborative programming course" focused on analyzing students' behaviors in Massive Open Online Courses (MOOCs) based on big data and Learning Analytics (LA). For instance, Luna et al. (2022) applied Subgroup

Discovery (SD), specifically the Subgroup Discovery using Distributed FP-Trees algorithm, to describe learners in MOOCs based on their behaviors. Lemay and Doleck (2020) used machine learning techniques to analyze video logs in MOOCs and identify students' course completion rate. Specifically, nine video viewing behaviors (e.g. videos watched per week, total number of pauses) were collected and analyzed. The obtained findings showed that the features collectively explain only a small to moderate amount of variance in assignment completion. Lu et al. (2017) relied on the power of big data and learning analytics to increase students' engagements and performance in MOOCs. Specifically, the authors collected the log data of students from the edX platform and used a parallelized action-based engagement measurement algorithm (PAbA) to measure the engagement level of students. Based on the engagement level results, a notification is sent to the teachers notifying them about those at-risk (i.e. having low engagement level).

Call for papers

Despite that masses of research has been conducted on how AI should be designed and integrated in traditional e-learning systems, little is known about how AI could be embedded within open learning environments or used to enhance the open learning experience, including providing automatic open assessment and modeling, as well as personalized OEP. Additionally, no study in the literature, to the best of our knowledge, investigated how responsible AI in open education (i.e. the use of AI with OEP) should be designed and developed.

Therefore, given the background above, this collection further calls for applied findings related to the innovative use of AI in open learning environments to enhance the provided OEP, the ethical concerns of AI in open education, as well as the services provided for both educators and learners in these open learning environments. In doing so, the papers must have theoretical and practical approaches towards effective implementation of (responsible) AI and OEP, combined, for the improvement of the educational setting, whether focused on learners, educators, academic managers or institutions. Any potential target group might be addressed to this extent. The topics for this collection are varied and include, but are not limited to:

- Smart open learning environments
- Personalized open educational practices
- Automatic open modeling and assessment
- Open learning analytics
- Smart open teaching/learning services
- Open behavior analysis
- AI applied to learner performance in informal and open settings
- AI applied to teacher mentoring in open education contexts
- AI practically implemented towards personalized e-assessment in open education
- Responsible AI in open education
- Learner bias and injustice in open education
- Ethical and regulatory frameworks of AI-based OEP

Please note that all articles submitted to this collection will go through a regular blind review process, and appear online upon acceptance. When submitting a paper to this collection, please select the paper type "collection" on the journal system. If you have any questions, please feel free to email the guest editors of this collection.

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ORCID

Ahmed Tlili http://orcid.org/0000-0003-1449-7751
Daniel Burgos http://orcid.org/0000-0003-0498-1101

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Ahmed Tlili
Smart Learning Institute of Beijing Normal University, Beijing, People's Republic of China
ahmed.tlili23@yahoo.com http://orcid.org/0000-0003-1449-7751

Daniel Burgos
Research Institute for Innovation & Technology in Education (UNIR iTED), Universidad Internacional de La Rioja (UNIR), Logroño, Spain
http://orcid.org/0000-0003-0498-1101