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ARTIFICIAL INTELLIGENCE ENABLED FRAMEWORK FOR QUALITY EDUCATION: A MECHANISM TO LEVERAGE SDG APPLICATIONS

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ABSTRACT

PURPOSE: The continuously evolving Artificial Intelligence (AI) oriented artefacts are transforming every facet of daily life, including the education sector. Recognising education's critical role in enhancing citizens' quality of life, it becomes essential to explore how AI can revolutionise education, including learning and teaching processes, educational settings, learning outcomes, among other components. However, the complexity and scale of AI developments pose significant challenges to its effective implementation in educational contexts.

METHOD: Integrating AI in education has substantial implications on learning and teaching. On the one hand, AI might increase the accessibility to personalised and satisfactory learning experiences. On the other hand, challenges such as bias, privacy and digital divide, exacerbate the difficulties associated with deploying AI effectively in educational settings. A detailed qualitative analysis of principal AI frameworks, models and theoretical foundations has been undertaken to identify and assess factors influencing these challenges.

FINDINGS: This study presents an holistic examination of AI in education, focusing on theoretical frameworks, models and practical implications. It derives a conceptual framework aimed at promoting high-quality education, thereby supporting the achievement of Sustainable Development Goal (SDG) 4, which emphasises Quality Education.

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ORIGINALITY: This conceptual framework uniquely addresses the gap between the efficient use of AI in education and the attainment of SDG 4. Furthermore, it lays the groundwork for combining research efforts to address the ever-expanding research gap concerning effective employment of AI in education and broader life contexts. The study also suggests several directions for developing contextualised strategies for the implementation of AI in education.

RESEARCH LIMITATIONS: This study aims at gaining meaningful insights from the application of AI in education; however, it cannot accommodate every single educational or learning approach. Therefore, testing this framework with real world contextualised scenarios remains essential to avoid abstract outcomes.

KEYWORDS: *Artificial Intelligence; Education; Quality Education; Sustainable Development Goals; Technology Enhanced Learning; SDG 4*

INTRODUCTION

The utilisation of technology has transformed the shape of our societies over time, stretching from old inventions, e.g., Pascaline and Telephone, through recent breakthroughs, e.g., AI and quantum computing (Mungoli, 2023). The overall aim of using technology across various domains is to improve the quality of life for individuals and societies. For instance, advanced healthcare technologies, such as robotic surgery, gene technology, pocket-size ultrasound devices to mention but a few, have saved lives and improved healthcare services provided to citizens across the globe (Dash, 2020). Improving learner's experience remains at the core of the high demand to apply Artificial Intelligence (AI) in education, despite the existence of other factors such as cost effectiveness (Hammad *et al.,* 2020). Considering the critical role of education in enhancing citizens' quality of life, this paper aims to unleash the potential of AI in revolutionising the education system worldwide. This includes leveraging learning and teaching processes, educational settings, learning outcomes, among other components. However, the complexity and the scale of AI developments pose significant challenges to its effective implementation in educational contexts.

National, regional and international strategic plans and reports released in recent years highlighted the gaps to be addressed in sectors such as the economy, education, health, etc. The United Nations (UN) capitalised on these plans as well as lessons learnt from the progress of the Millennium Development Goals (MDGs) (Ahmed and Cleeve, 2004) and published its visionary report titled "Transforming our World: The 2030 Agenda for Sustainable Development" (UN, 2015). This report sets out an ambitious global agenda that has 17 integrated and indivisible Sustainable Development Goals (SDGs) in addition to 169 targets[1]. The scale and complexity of such a plan intensified the need to effectively exploit available resources, including technology and more specifically, artificial intelligence to achieve success. For instance, AI has been used to achieve SDG 7 on renewable energy (Fan *et al.,* 2023),

[1] https://sdgs.un.org/2030agenda

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SDG 16 on peace, justice, strong institutions (Dasandi and Mikhaylov, 2019), and other SDGs. It is beyond the remit of this paper to delineate the application of AI in all SDGs; therefore the focus will be given to SDG 4: Quality Education and its constituent targets. The rest of this study is structured as follows. The next section presents related work in both AI for education and AI for SDGs in general, while the third section presents the intended framework. The fourth section discusses the key concerns associated with the proposed framework, and the fifth, final, section concludes the paper and presents some research directions.

RELATED WORK

This section describes key progress in the domain of AI and its sub-domains in education. The section cannot cover all AI aspects, so only a few directions will be highlighted.

AI in Education

The continuous evolvement of technologies, including machine learning, big data, neural networks and AI has led to developing various artefacts that have the capability to simulate human intelligence. Among various AI definitions in literature, this paper uses AI to refer to machines that are capable of perceiving, recognising, learning, reacting and solving problems and dealing with challenges faced by humans (Kumar and Thakur, 2012). On the one hand, education is a very rich domain, and it entails a wide range of contextualised processes that require different engagement strategies. On the other hand, education impacts our lives and more specifically, every single sustainable development goal. For instance, quality education can help in combatting climate change (Mochizuki and Bryan, 2015), meaning leveraging our educational systems will get the whole world closer to achieving the above-mentioned SDGs. It is also connected to all stakeholders, including students, teachers, head teachers, policy-makers and leaders. For instance, teachers need to be, at least, aware of AI artefact capabilities to identify its impact on their students, learning deliverables and potential changes that might happen in the future.

There is no generic formula to assess the quality of education in a certain institute, district or country. However, there are various factors or indicators that can be considered in this regard, including: (i) learning and teaching methods, (ii) educational contents, (iii) learning environments, (iv) management teams, (v) quality of infrastructure (Burbules *et al*., 2020; Sharma and Singh, 2024). The lack of generic quality education frameworks can be attributed to various factors, but is mainly due to the variety of education levels, that is primary, secondary and higher education, culture and other contextual factors (Balzer, 2020). This complexity is the key reason why artificial intelligence can be useful in ensuring the quality of education: below are examples of where AI has been used in education:

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Personalised and Adaptive Learning

Personalised learning represents a paradigm shift in learning and teaching. It replaces the one-size-fits-all model with a new approach where the learner's preferences and needs are considered during the design and the delivery of the educational process (Walkington and Bernacki, 2020). Personalised learning and adaptive learning terms are used interchangeably in literature; however, according to Taylor *et al.* (2021), adaptive learning provides personalisedlearning at scale by assessing an individual's skills and knowledge, monitoring their learning journey and providing tailored feedback. Effective personalised/adaptive learning artefacts must employ the following four pillars: (i) taught domain knowledge, such as maths and history, (ii) pedagogy that guides learning based on the application of suitable theories of learning and teaching, (iii) human factors that include the ability to assess students' progress and needs, and (iv) AI techniques that refer to algorithms utilised for presenting contents and interacting with learners (Zhai *et al.,* 2021).

Personalised or adaptive learning is based on well-known pedagogical theories, and can be traced back to John Dewey who stressed the necessity of individualised instruction. This has been linked, at a later stage, with constructivist learning theory, and more specifically Self-Regulated Learning, Self-Directed Learning, to mention but a few (Hammad *et al.,* 2020). Both personalised and adaptive learning emphasise moving from the instructor-centred approach to the newly embraced student-centred approach. Such an approach allows students, especially in higher education, to improve their engagement with their learning, increase their satisfaction and retention rate, and finally focusing on developing their critical thinking and problem-solving skills. However, the complexity of effective implementation of adaptive or personalised learning remains a challenge as it is associated with higher budgets, complex development processes and privacy and data security concerns. Finally, intelligent mechanisms, such as big data analytics and rule-based AI, are utilised to develop personalised and adaptive learning systems. For instance, the interaction data between the system and the student will be collected and analysed to tailor and customise the future learning journey for a particular student (Ali *et al.,* 2024).

Intelligent Tutoring Systems

Intelligent Tutoring Systems (ITS) represent a category of AI-based systems that are designed and developed to provide learning using complex computational models of student behaviour and cognitive states (Xu *et al.,* 2019). A key feature that distinguishes ITS from other AI-based educational systems is that they specify what to teach (i.e., lessons to be taught), and how (i.e., teaching strategies). ITS captures the whole learning process and therefore consists of the following four core components: (i) domain model to model the subject being taught, its concepts and relationships (e.g., topics and subtopics), (ii) learner or student model to model student's learning, skills,

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understanding to mention but a few, (iii) teaching model to capture various methods of teaching (e.g., problem-based learning), and (iv) user interface to lead the interaction between the student and the ITS (Hammad, 2018). Understanding the underpinning mechanisms of ITS can be clarified by scenarios as follows. First, the student needs to log into the system where their credentials will allow extracting their behaviour, preferences, etc. This allows ITS to customise a learning process that best suits the learners. Second, the student requests a topic to study, e.g., how to calculate the area of a rectangle. The system has full ability to further analyse the request and suggest a way to teach the topic. For instance, the student might be asked to study a prerequisite skill if their student model does not show that they master this prerequisite skill (i.e., the student has a missing conception or misconception). If the student has already passed all the prerequisite requirements, then the teaching model can suggest teaching this student using the best pedagogical process, such as self-directed learning, direct instruction or others. Third, the lesson will be presented to the student and interaction will take place before presenting a specific assessment element to test their mastery of the topic. Fourth, the outcome of the assessment will be used to update the student's model to ensure capturing their new learning experience.

One practical example of ITS is the Knowledge Acquisition System (KAS) that targets high school students and offers content and interface adaptation based on: (i) student preference and (ii) student level (Li and Zhou, 2015). In this system, suitable content is offered to a student based on their performance as well as understanding level. Students can also select certain interfaces from a group of interfaces that are available. The Mathematics Intelligent Tutoring System is another ITS example that aims at teaching mathematics to all levels and ages (AbuEloun and Naser, 2017). The system relies on test results and the student needs to achieve 75% to move to the next lesson, otherwise they need to take the lesson again. It is clear from the above examples that different strategies are used to achieve student's learning outcomes based on context.

Generative Artificial Intelligence

Generative Artificial Intelligence (GenAI) refers to a technology that utilises deep learning models to generate human like responses based on complex or simple prompts. Such responses might be text, images, voice, etc., based on the tool and the prompt itself (Lim *et al.,* 2023). Large Language Models (LLM) is another term that has emerged recently, focusing on language modelling. Such models are trained on a large amount of text data to be able to respond to a prompt. ChatGPT (Chat Generative Pre-Trained Transformer) is one of the most recognised GenAI tools at the time of writing this paper. ChatGPT provides responses to user prompts that can be zero shot or a few shots. GenAI tools generate different types of output; it generates text (e.g., ChatGPT), video (e.g., Fliki), code (e.g., Durable), images (e.g., DALL – E3), to mention but a few. Since the

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introduction of GPT, various concepts have emerged, such as prompt engineering and fine tuning, which allow end users to generate quality outputs. For instance, users can get more accurate results if they fine tune ChatGPT 3.5 than using ChatGPT 4.0. So, it is not about using a paid or free version of the tool; it is about the skills required to deal with these tools. ChatGPT is not the only player in the market, there are many, including Microsoft Copilot tools and they are quite dynamic. For example, Copilot used to be named Bing Chat.

Utilising GenAI in education is associated with a positive and negative impact. On the one hand, students can use GenAI tools to formulate some ideas about a certain topic, paraphrase written text or provide feedback on an essay. On the other hand, staff can use the same tool to draft ideas for lesson plans, provide custom feedback to students, or help designing a quiz or learning activities (JISC, 2024). Miao and Holmes (2023) delved into details and identified further concerns and risks associated with using GenAI in education. Such concerns include the following: (i) use of content without consent, (ii) worsening digital poverty, (iii) relying on unexplainable models to generate outputs, (iv) generating deeper deepfake and reducing the diversity of opinions, and further marginalising the already marginalised voices. These are all genuine concerns that might negatively impact the educational process overall. Therefore, a regulation initiative must be in place to support GenAI stakeholders, including students, staff, management, market representatives, etc.

Summary and Reflections

Artificial Intelligence is becoming embedded in every single aspect of daily life. One additional domain that education will make a good use of is Multimodal Learning Analytics (MMLA). MMLA refers to utilising advanced computational analysis on data coming from different sources, e.g., learning management systems and sensors, to understand more how human learn and enhance their capabilities (Giannakos *et al.,* 2022). Such multimodal data require complicated frameworks and processes to handle them effectively. There will be an additional layer of complexity when AI systems and algorithms are required to accommodate contextual factors such as pedagogy of learning (Hammad *et al.,* 2022). Furthermore, planning and delivery of education in the age of technology must wisely consider the wider educational context. For instance, MMLA, and its sub-domain learning analytics, can be applied for various reasons, such as discovering students' patterns or predicting students at risk. Such objectives must be considered to align technologies (e.g., AI, voice assistant, extended reality, etc.) with learning and teaching strategy and objectives (Bahja *et al*., 2021).

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Artificial Intelligence for Sustainable Development Goals

Various attempts have been made in literature to use the power of AI to achieve sustainable development goals. For example, Berendt *et al*. (2020) examined the benefits and risks of AI in education in relation to fundamental human rights. The key objective was to utilise AI and big data to provide more effective monitoring of the education system in real-time and test the impact of this process on the human rights and freedoms for both teachers and learners. The study underlines the need to balance the benefits and risks of AI tools. Moreover, it insists on answering questions about governance and responsibility, who makes decisions, and which individual/organisation must be held accountable for regulating AI in education, especially when it comes to data protection and privacy and whether these questions need to be answered nationally or trans-nationally.

In addition, Berkat *et al.* (2024) aims at analysing the role of using big data and AI in enhancing the quality of education management in Indonesia. The researchers followed a quantitative approach based on empirical data they collected. The findings reveal that the use of big data had an impact on quality education management as well as school sustainability. Nonetheless, their study was limited to the survey used to collect the data with no way to operationalise their vision or plans. Other researchers such as Wu *et al.* (2020) proposed a framework that is built using big data and cloud-based services that integrates crowdsourcing and public Earth observation data products to provide cost-effective solutions for monitoring and tracking the achievement of SDGs, especially in low-income countries. Finally, Holmes *et al.* (2022) presented a framework to handle common ethical AI issues in education. They suggested a community-wide framework that focuses on (i) ethics of algorithms, (ii) ethics of data used in AI, and (iii) ethics of learning analytics. These are all big titles that hide many details underneath them that require further investigation.

To conclude, we are in the process of implementing the SDGs but a substantive challenge is to monitor our progress; this requires high quality data to determine the actual size of the problem and the population impacted. Unfortunately, there have been limited efforts in this direction, and therefore a mechanism for broad and high-quality data collection is needed to ensure effective SDG implementation and evaluation. Data are the main tool we provide to decision-makers to maximise the effectiveness of their intervention, but this cannot be achieved unless we have good data (UN, 2015).

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AI-Enabled Framework for Quality Education

As introduced above, there is a research gap in maintaining good quality data about sustainable development goals. This section proposes a framework utilising AI and big data analytics to collect, monitor and maintain SDG data and therefore help in achieving SDGs nationally and globally. Figure 1 visualises data according to each sustainable development goal and its indicators: red means no monitoring at all, yellow means incomplete or outdated data available, and green means official metrics are available. This figure reflects the low quality and the need for a more effective approach.

To respond to the above research gap, we are proposing a framework that considers the following principles:

1. Co-approach: this refers to "co-design, co-develop and co-consume". The framework must be developed collaboratively with communities, societies and citizens bottom-up to capture and accommodate requirements for countries, institutions and their units.
2. Micro-Macro approach: data must be collected, standardised and improved locally first, at unit level and institutional level considering stakeholder's requirements as well as suitable modelling techniques, e.g., metadata, master data and others, if needed based on context. Once this micro level is built, a macro level on a larger scale can be developed and presented on both descriptive and predictive levels. For instance, micro data can be about institutional educational assessment, while macro represents country or regional data.
3. Separation of Concerns: components and modules must be designed, developed and deployed in ways that maintain individualised views for each SDG, and indicate the impact of progress in a certain SDG on other SDGs or indicators.

The framework, depicted in Figure 2, is composed of the following elements:

1. *Institution:* to define the entirty per country, their roles, responsibilities and structure.
2. *Processes:* to list key process areas, business process architecture as well as business process models to ensure well documented and aligned business processes.
3. *People:* to view the resources required to implement the early identified processes in their own organisations according to roles and responsibilities.
4. *Technology:* to describe digital solutions required by people to implement the early-identified processes.
5. *Data:* to represent the core component of this framework that has been described above in order to maintain high quality data in the best form that suits institutions and their units.

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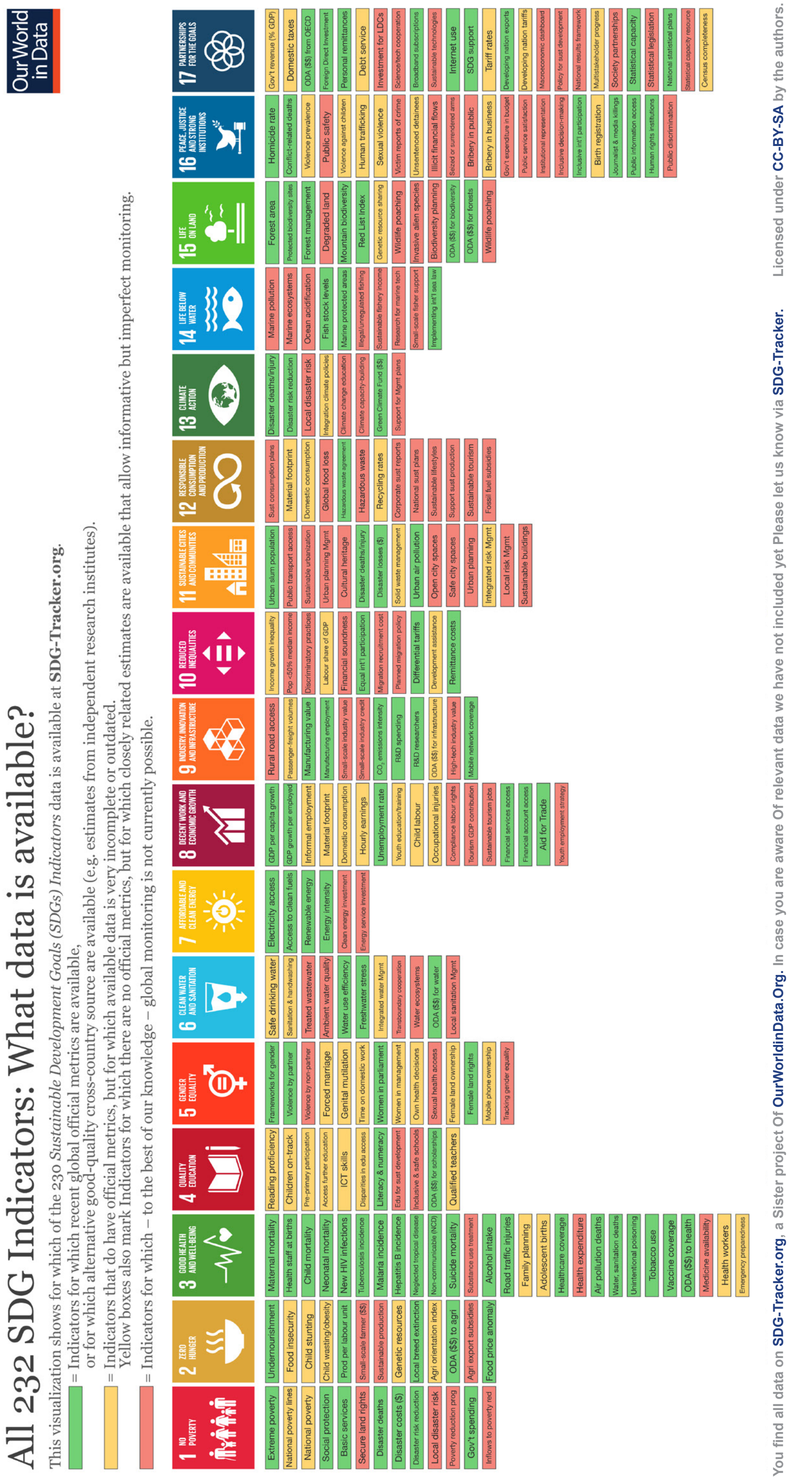

Figure 1 SDG data visualised

Source: Our World in Data

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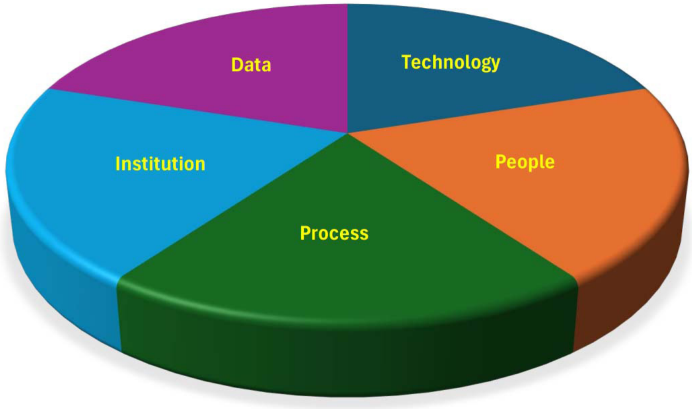

Figure 2 AI-enabled framework for sustainable education

Source: Developed by the author

It is very important to recognise that the above elements from data to institution do not represent a static snapshot. They are dynamic and there should be a mechanism to capture these changes and propagate them across the whole framework. It is also substantial to recognise the need for developing a flexible governance model for this AI-enabled framework. This governance model should be human centric, where every single feature in this framework is designed to promote human well-being and increase citizens' quality of life by following the relevant guidance, such as human-centred AI or human-centred design.

DISCUSSION

The above-presented framework captures the need for developing high-quality data so it can be used to provide evidence to decision-makers institutionally and globally. However, there are various concerns that need to be discussed based on the context of each country. Such concerns include, for example, bias where data scientists need to look into their data and suggest mechanisms to deal with this concern to avoid the negative impact on citizens. Second, such a framework might increase the digital divide between citizens based on their contexts. Therefore, it is highly recommended to pilot this framework and review its implementation and keep that learning cycle until we get satisfactory results reported by citizens, not only data scientists. Third, ethical concerns that might lead to a significant increase in the diversity and equity between citizens. It is recommended to follow the ethical approach to design AI-enabled systems and minimise ethical concerns associated with deploying AI artefacts that can make decisions on behalf of humans in an autonomous way. Finally, it is recommended to make good use of the recent innovative schools of artificial intelligence such as explainable and

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trustworthy AI. such as explainable and trustworthy AI. Such mechanisms allow humans to oversee the process and avoid looking at AI solutions' black boxes. This will allow humans to learn how to develop effective AI solutions as we are still at the beginning of a remarkable era where more innovative AI solutions will be developed to change people's lives for the better. Explainable AI cannot be separate from software engineering best practices such as human-centred design where humans are kept in the loop of every single activity we do.

CONCLUSIONS

This paper examines a significant global problem that impacts monitoring the worldwide progress towards achieving the 17 SDGs across the whole world. It focusses on SDG 4, Quality Education, as a case study, and highlights the key shortcomings in the current UN reporting system. It proposes a framework that utilises the power of AI to monitor the progress in a slightly different way from available solutions. Principles adopted, such as separation of concerns and co-approach, should allow more smooth development for such frameworks and effective learning cycles, where data scientists are expected to learn how to develop and deploy effective AI solutions at scale. It is inevitable to highlight that this framework retains the role of humans throughout the process: the role of humans is critical in every single stage of AI artefact development. Finally, the above framework represents a step towards achieving a better data-driven system that can help policy-makers in making decisions that improve citizens' quality of life. Nonetheless, this framework needs to be further developed and tested in real contexts with the comparative studies to fully capture its limitations and shortcomings.

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SUSTAINABLE DEVELOPMENT GOALS

BIOGRAPHY

Dr Rawad Hammad has a PhD in Software Engineering from the University of the West of England, and an MSc in Cognitive Computing from Goldsmiths University of London. He is Co-Director for Smart Health Centre, Programme Leader for MSc Digital Education Course, MSc AI and Data Science, Technology Enhanced Learning Research Group Leader at the University of East London. Rawad has extensive experience in Software Engineering, Technology Enhanced Learning (TEL), Artificial Intelligence in Education and Smart Health research and practice. He has contributed to and led various international projects, published research articles and has been involved in various conference programme committees, including EC-TEL, LAK, AIED and BUSTECH. Rawad is currently supervising five PhD students in addition to a number of MSc students. Rawad is an executive committee member of the International Society of Artificial Intelligence in Education (AIED) and a committee member of different research bodies..

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