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# The Sustainable Contribution of Artificial Intelligence to Higher Education - Results of a Pilot Study

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The past year has seen revolutionary breakthroughs in the development of artificial intelligence-based (AI) products that can impact almost every aspect of life. The change raises the question of the sustainability of education and how technology will transform the way we currently teach. This study aims to develop a model and its hypothetical adaptation that can be used to analyse the adoption and use of artificial intelligence in university settings. The importance of AI in education can be captured in its ability to personalise learning pathways, improve teaching methods and automate related administrative tasks. AI technologies are able to adapt to the needs of individual learners, providing personalised instruction and improving learning outcomes. AI can also help educators by automating routine tasks, allowing them to focus on individualised instruction and create a more engaging and effective learning environment. Based on the accepted results of exploratory factor analysis as the applied method of this paper, the research concludes that the model adaptation is feasible, but it is worth considering changing the variable reflecting implementation to one that is accepted by educators as the concrete institutional implementation of AI is still a very distant scenario in higher education. Future research should incorporate these findings into the design of possible structural models, as this area of AI research has the potential to bring significant social science and educational benefits.

## 1. Introduction

Artificial intelligence (AI) has become the subject of much scientific and non-scientific literature, as it is gaining ground faster than humanity can possibly handle. Data-analysis software and methods need to handle the exponentially increasing amount of data (Big data); thus, AI has a significant role nowadays in many fields. In 2023, AI's global market value is estimated at 196.63 billion USD, and 1811.75 billion USD market value is foreseen by 2030 (GVR, 2023), making the economic impact undeniable. AI can be defined more as an umbrella term for a combination of many different technologies. Fields such as deep learning, machine learning, and neural networks all rely on algorithms to process data but at different levels of complexity and abstraction (LeCun et al., 2015). According to Wang (2019), there are several problems in defining artificial intelligence because there is no widely agreed definition, and it is used with many different senses. The definition of difficulties is not part of this publication; however, it is important to mention. The definition by Chen and Wong (2019) is considered the guiding definition of AI in our paper: "Artificial Intelligence is generally defined as the property of machines that mimic human intelligence as characterised by behaviours such as cognitive ability, memory, learning, and decision-making."

As an extremely expanding area, it includes numerous fields such as language learning, medical science, navigation, customer service, unmanned shopping, robotics, and self-driving cars. Artificial Intelligence in Education (AIED) is a further area that offers a wealth of opportunities but also raises many questions. Education is an important area for both social and sustainable development. One of the key definitions promoted by the Fourth Industrial Revolution is the concept of sustainability in various aspects of modern society (Konečná et al., 2021). The Global Sustainability Agenda 4 aims to ensure access to equitable and quality education for all ages. The goal also envisages the elimination of gender and income inequalities in access to education (United Nations, 2023). Studies have drawn attention to research on AI and educational sustainability from both social

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and economic perspectives. The importance of this research is underpinned by the fact that AI will change the way higher education functions and its market situation in the future (Aviso et al., 2020), including the role of educators. Business actors at all levels and in all fields are using or will soon use AI solutions, so it is essential to have empirical results on the adoption or rejection of the technology (Dignum, 2021). A key issue for the future of education is that teachers, learners and education professionals understand the responsibility of using AI and are confident in using advanced technologies (Shenkoya and Kim, 2023). Evidence is available that the digital transformation of higher education is leading to increased innovation and improved student performance. This is explained by the fact that these advanced technologies provide students and teachers with more personalised resources that guarantee better educational services, ensuring a seamless transfer of knowledge (Dignum, 2021). Advanced technologies are also transforming the business model of higher education institutions as innovation and technology enhance online learning. Consequently, AI-based systems make learning more flexible, reduce the cost of education compared to traditional education models, diversify the types of courses available to students, and improve access to education (Shenkoya and Kim, 2023). For AI solutions to serve education in a sustainable way, rather than being seen as a threat, advanced use by educators is necessary and represents the future of this innovation. Research by Kuleto et al. (2022) has demonstrated that the higher the awareness and knowledge of teachers, the easier it is for them to identify opportunities for AI adoption and to actively participate in the process. The complex nature of AI, and in particular the 'black box' problem, is a barrier to a proper understanding of AI applications and how they work. Mutual understanding of the technology is one of the main challenges in terms of potential applications (Reim et al., 2020).

Research on the relationship between higher education and artificial intelligence can be grouped around different themes, with emerging themes including. Holmes et al. (2019) defined six areas in AIED: (1) collaborative learning, (2) student forum monitoring, (3) continuous assessment, (4) AI learning companions, (5) AI teaching assistant, (6) a research tool to further the learning sciences. In their study, they distinguish tools for students and teachers. Crompton and Burke's (2023) research related to the application areas summarised the applicability of AI in higher education, which, in their view, covers (1) assessment, (2) prediction of student performance, (3) application of AI assistants and (4) intelligent tutoring system, and (5) the process of managing student learning. On the other hand, the scholars analysed the educational use of AI from a disciplinary perspective, focusing on a specific topic. For example, Shukla et al. (2019) focused on the potential of AI use in engineering, while Hwang and Tu (2021) conducted a bibliometric analysis of the role and trends of AI in mathematics education. Extensive research has been published on the potential and experience of applying artificial intelligence to learning analytics. Learning analytics encompasses the areas of student performance prediction, automatic assessment and improvement of learning outcomes. The researchers believe that an integrated approach to future teaching, education management and AI is needed, with the aim of using AI to organise, analyse and understand data to support student success and inform decision-making. Research findings have shown that the application of this integrated approach provides competitive advantages in terms of learner engagement, performance, and learning perceptions (Ouyang et al., 2023). Similarly, the results of Pinto et al. (2023) confirm the need for an integrated approach to learning analytics. Their findings suggest that AI can provide real help in identifying students at risk of dropping out and can provide more reliable results in identifying at-risk learners than if a human were to perform this task. The literature review concluded that there is little research available on the adoption and use of AI by university teachers. There are no empirical results on how they perceive the use of AI in their teaching and especially in their research processes. Theoretical models have typically been developed for primary and secondary school teaching roles, with limited models available for higher education. This study aims to fill this gap aiming to develop a model and its hypothetical adaptation that can be used to analyse the adoption and use of AI in university settings by answering the following research question: Is it possible to adapt the model that was created for LEA institutions to a university environment?

## 2. Methodology and Theoretical Framework

The present research methodology is based on the model of Kuleto et al. (2022), which included the study of the teachers of the LINK Educational Alliance (LEA) at the levels of primary and secondary education (K-12). It explored the potential for artificial intelligence in administrative and pedagogical processes through a representative analysis (n = 109) of primary and secondary schools and people in LEA institutions. In order to identify two formative and one reflexive variable, the study used structural modelling (PLS-SEM). The questionnaire used in the modelling for the analysis was designed on the basis of the McKinsey (2017) Global Teacher and Student Survey, as K-12 institutions and artificial intelligence were also the focus of this analysis. This paper presents a hypothetical adaptation of the model, which, in order to ensure the validity of the methodology (questionnaire), has been supplemented with frameworks and variables from survey research (e.g., Heng et al. 2020) already identified through analysis, justified on the basis of previous research. The adaptation requires a modification of the model on which the analysis of this paper is based for use in a university environment. In addition to teaching and administrative tasks, research plays an important role in the university (Heng et al. 2020), and artificial intelligence can contribute to this. As a consequence of the rework, the formative variable opportunity has been examined in three forms (Figure 1): opportunity for education, opportunity for research, and opportunity for both education and research. The IBM SPSS Statistics 25 software package was used for the exploratory factor analysis presented in this study, which should precede structural modelling.

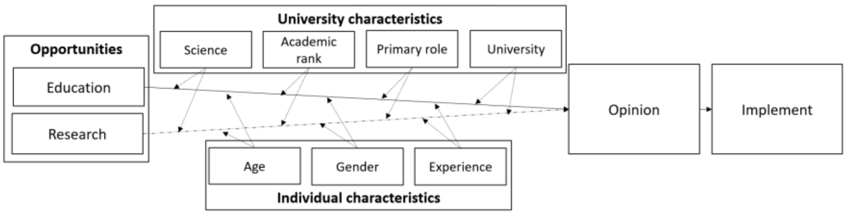


*Figure 1: Hypothetical adapted model from the model of Kuleto et al. (2022)*

The model on which the adaptation is based (Kuleto et al. 2022) did not use moderating variables, but their use may be important in the adapted model. Models that have been developed to measure the impact of digitalisation (e.g., UTAUT, UTAUT2, TAM) make use of moderating variables such as gender, age and experience (Sohn and Kwon, 2020). It became important to include these moderating variables (individual characteristics) in the hypothetical model but also to add university moderating variables (university characteristics) to the concept. A questionnaire survey is the most appropriate way to carry out the analysis, but it needs to be considered that this is limited by subjective scoring and the expected sample size in the final structural model to be developed based on the results of this analysis of at least 100-150. The ordinal questions of the questionnaire were answered on a 5-point Likert Scale, which is the best way of information processing (Chen et al. 2015). The questionnaire consisted of 4 main parts: general questions (e.g., The use of AI in my courses at university could help me to develop teaching materials.), research relevance (e.g., The use of AI in my research at university could help me to choose the topics of my researches.), educational relevance (e.g., The use of AI at university level in my educational work may help me to identify problems with educational materials), exploratory questions that may help me to ask further open questions (e.g., In addition to the above, what do you think are the general benefits of using AI at university?) and demographic questions (e.g., gender, age, field of research). The questionnaire was sent to as many lecturers as possible from a wide range of disciplines at the higher education institutions involved in the university research network during the period covered by the questionnaire. Consequently, during the completion period (10 June 2023 - 10 July 2023), only university lecturers were included in the online survey in order to meet the research objective (validation), resulting in a total of 54 respondents. The demographics of the university lecturers are as follows: academic rank (PhD student (9.26%), assistant lecturer (7.41%), senior lecturer (33.33%), associate professor (46.30%), professor (3.70%), field of science (agricultural sciences (5.56%), engineering sciences (3.70%), social Sciences (87.04%), natural Sciences (3.70%). The hypothetical model can be tested by exploratory factor analysis, which can be used to demonstrate the operation of formative and reflexive variables with sub-factors. This type of factor analysis can be used for the identification of the smallest number of hypothetical structures (factors, dimensions) and for the identification of structural differences between the variables to be measured (Watkins, 2018). A maximum of 5 sub-factors per factor could be included in the factor analysis due to the number of respondents (n=54) and the sample size rule (in structural modelling based on exploratory factor analysis) of Hair et al. (2011). Applied to the social and behavioural sciences, some research (e.g., Tucker and MacCallum, 1997) believes that it analyses the subjectively measured scoring of unobservable characteristics of people. This limitation, which means that only a cross-sectional analysis can be carried out for a given point in time, must always be taken into account in multivariate statistical methods. In light of the above, the method is, of course, suitable for the testing of the formative and reflexive variables of the hypothetical model of this study. Obviously, in this paper, many factor analyses were performed on several combinations of variables to determine the best-fitting sub-variables to include in the final analysis on the basis of the set of criteria used for exploratory factor analysis. It is important to note that moderating variables are not appropriate to test in exploratory factor analysis but should be tested following successful pretesting. It may be important to study their impact in the future by using the final structural model, as they may influence a number of factors (e.g., Can academic rank have an impact on the perception of AI in research?). The prerequisites for the factor analysis were as follows: Correlation>0.3, Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO): >0.5, Bartlett's Test sig.: <0.05, Communalities: >0.25, Goodness of Fit Test: >0.00, Total Variance Explained: > 33 %, Factor Weights: > 0.25 (Barna and Székelyi, 2008). The following settings were used for the analysis: Maximum-likelihood method, Varimax-rotation (variance maximalization).

## 3. Results

The exploratory factor analysis was conducted in several structures: opportunity for education, opportunity for research, and opportunity for both education and research. The results show that the first two solutions are only feasible by the exclusion of sceptical respondents (who gave a score of 1 for almost all variables), which would partially violate the preliminary model concept. For this reason, it is not presented in detail. The third alternative gave satisfactory results both when the sceptics were excluded (subsampled) and when the full sample was used. The correlation conditions were not fully met in any of the cases, mainly due to the sub-variables that are part of the implementation reflective variable (correlation value between 0.004 and 0.667). The appropriateness of the correlation conditions is important for performing factor analysis, as we create a principal component or several factors from sub-variables in order to explain as much as possible the total variance of them. Therefore, the existence of significant correlations between the sub-variables is important because of the commonalities (weights of sub-variables within factor analysis), taking into account the thresholds already described. Through the combined use of education and research, two formative (education-research, opinion) and one reflective (implementation) variables have been constructed (Table 1). The first element of the variable codes represents the factor name, but in the case of the opportunity, it is split in two: education (OE) and research (OR).

*Table 1: variables included per factor based on exploratory factor analysis*

| Factor name | Variable name | Code | Literature source | α | KMO |
|---|---|---|---|---|---|
| Opinion | student performance | O_4 | Kuleto et al. 2022 | 0.726 | 0.743 |
| | quality of researches | O_6 | Heng et al. 2020 | | |
| | quantity of researches | O_7 | Heng et al. 2020 | | |
| | time-saving | O_8 | Kumar, 2023 | | |
| Opportunity Education + Research | problem detection | OE_3 | Kuleto et al. 2022 | 0.880 | |
| | identification of learning difficulties | OE_4 | Kuleto et al. 2022 | | |
| | choice of subject | OR_4 | Heng et al. 2020 | | |
| | problem-solving (e.g. from review) | OR_10 | Vieno et al. 2022 | | |
| Implementation | colleagues' involvement | I_4 | Kuleto et al. 2022 | 0.721 | |
| | students' involvement | I_5 | Kuleto et al. 2022 | | |
| | artificial intelligence education | I_6 | Kuleto et al. 2022 | | |

The results of the exploratory factor analysis have also passed Bartlett's Test (<0.01) and the Goodness of fit Test (>0.00). Table 2 provides two important pieces of information to help interpret the factors. The communalities refer to the factor analysis as a whole and describe the weights of the sub-variables included in the analysis. The factor loadings, on the other hand, represent the weights of the sub-variables in the constructed factors so that the importance of the variables within the constructed factors (Opinion, Opportunity, Implementation) can be interpreted.

*Table 2: Factor weights and loadings of included sub-variables by factor*

| Sub-variables | | | Factor loadings | | |
|---|---|---|---|---|---|
| Variable code | Communalities | VIF | Opinion | Opportunity | Implementation |
| O_4 | 0.598 | 1.946 | 0.770 | | |
| O_6 | 0.764 | 2.779 | 0.853 | | |
| O_7 | 0.638 | 2.153 | 0.799 | | |
| O_8 | 0.654 | 2.341 | 0.785 | | |
| OE_3 | 0.262 | 1.342 | | 0.358 | |
| OE_4 | 0.397 | 1.394 | | 0.402 | |
| OR_4 | 0.802 | 1.719 | | 0.895 | |
| OR_10 | 0.486 | 1.637 | | 0.665 | |
| I_4 | 0.821 | 1.823 | | | 0.893 |
| I_5 | 0.552 | 1.980 | | | 0.733 |
| I_6 | 0.317 | 1.194 | | | 0.387 |

Cronbach's alpha (α) is widely used in the construction of questionnaire scales, indices and factors, where the composite indicators created should have an alpha value of at least 0.7 (Cronbach, 1951). Research on the methodology of factor analysis has emphasised the testing of normality (Fornell and Larcker, 1981), but in the case of the Likert Scale questions used in this analysis, it should be noted that these are not continuous interval scales and typically do not meet the criteria of traditional normality tests (e.g., Kolmogorov-Smirnov test, Shapiro-Wilk test). Determining the degree of normality violation (Rózsa et al., 2019), for which there is no generally accepted criterion, has been proposed for factor-based models (Dash and Paul, 2021). However, skewness of less than 2 and kurtosis of less than 7 are considered appropriate for normality tests in multivariate analysis (e.g., factor analysis) (e.g., Byrne, 2010). In this analysis, skewness was below 2 for all sub-variables, and only one sub-variable (I_4, kurtosis: 2.46) exceeded 2 for kurtosis. The values are acceptable in terms of normality, given the acceptance criteria described. The analysis of multicollinearity is also an important part of factor analysis, which is considered to be acceptable when the value of the variance inflation factor (VIF) is less than the threshold of 5 (Kushary, 2012). Thus, there is no collinearity manifested in the hypothetical model. Sub-variables' factor loadings below 0.3 were excluded (Field, 2013), and only those with higher values were included in exploratory factor analysis (Table 2). The factor weights (communalities>0.25) and factor loadings meet the requirements of factor analysis so that the separation of the factors (formative and reflective variables) by means of sub-variables can be considered feasible. The total variance explained by the three factors was higher than the preliminary expectation (33 %) and reached 57.20 %. On the basis of the results of this study, the presented exploratory factor analysis was found to be valid.

## 4. Conclusions

In conclusion, reflecting on the research question of the study, the adaptation of the model of Kuleto et al. (2022) has been successful. The successful model adaptation of the present study can contribute to the development of an acceptance model of AI for university lecturers/researchers in Hungary, which can be used as a theoretical framework in the future. The hypothetical model included a larger proportion of the original questions (6 variables) from Kuleto et al. (2022), while the other questions (5 variables) were involved based on the research of Kumar (2023) and Heng (2020). The last two papers, which also correspond to the research gap of the present study, specialise in university research and in the application of artificial intelligence in the university environment. The formative (opportunity with 4 sub-factors: problem detection (education), identification of learning difficulties (education), choice of subject (research), problem-solving (research) and opinion with 4 sub-factors: student performance, quality of research, the number of researches, time-saving) and reflective (implementation with 3 sub-factors: colleagues involvement, students involvement, artificial intelligence education) variables that have been developed through the exploratory factor analysis presented have been accepted. It is important to note that it is recommended that at least the questions (variables) related to implementation be redesigned in order to meet the correlation acceptance criterion more strictly. In order to better support communities through significant correlations, it is recommended that the questionnaire be redesigned (rephrased or new questions) to better meet this type of criteria in the final model. It is worth considering changing the implementation reflective variable to acceptance by lecturers, given that the concrete institutional implementation of artificial intelligence is still a very distant scenario. The results of the present study can be considered as a possible new research direction, thus providing researchers with the opportunity to conduct research using some of the variables identified in the present study, applying the methodology described and taking into account the experience of the present study, as a starting point for the construction of AI adoption models in higher education. For this reason, it is recommended that future researches take these findings into account and incorporate them into the creation of possible structural models, as this area of artificial intelligence research could have important social science and educational benefits.

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