Enhancing Quality Education at Scale through Generative AI and Adaptive Learning Systems

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ABSTRACT

In March 2024, Honoris United Universities is set to launch a pioneering course incorporating AI-generated learning materials and Adaptive Learning Systems (ALS) across its network. This contribution reports on an in-progress pilot study related to the conception, design, implementation, and assessment of an ALS, targeting a self-paced online short course about the United Nations Sustainable Development Goals (SDGs), Diversity, Equity, and Inclusion (DE&I), and Work Ethics, and tailored for the African context. The course includes two AI applications. The first one utilizes a Generative AI engine built on the top of a proprietary Large Language Model (LLM) to curate appropriate learning materials relevant to each nano-learning objective of the course. The second application lies in delivering the course to the learner in adaptive learning mode, leveraging a proprietary ALS that personalizes the learning pathway based on each learner's individual pace, progress, and comprehension. We first report on an empirical study that aimed to probe the initial student and faculty Knowledge, Attitude, and Perception (KAP) towards ALS before finalizing the design and implementation stages. Conducting this pre-intervention KAP survey offers several opportunities, such as providing baseline data of the current state of the KAP levels for benchmarking purposes, addressing potential misconceptions, biases, and concerns, enhancing end-users' adoption, and reinforcing a user-centric design approach. We then describe the process and the workflow adopted for the pilot course's design, creation, and implementation. In future, we plan to conduct a post-implementation empirical study, and assess outcomes from both students and teachers' perspectives. This includes evaluating students learning outcomes, engagement, and satisfaction, alongside the faculty perception and feedback on the effectiveness, relevance, and scalability of ALS. Our research aims to showcase in practical settings how to leverage the potential of ALS to expedite the curation of learning materials on a large scale and at reduced costs. Furthermore, it explores constructing adaptive learning courses designed to enhance access to quality education on a broad scale.

KEYWORDS

Adaptive Learning Systems, Personalized learning, AI-generated learning materials, Learner's satisfaction, Quality of education at scale, Sustainability.

INTRODUCTION

Over the past few years, there has been an increasing interest in integrating concepts and practices related to the United Nations SDGs in Engineering and Higher Education, including topics pertaining to DE&I, as well as social justice and work ethics. Version 3.0 of the CDIO syllabus (Malmqvist et al., 2022) recognized the pressing needs for engineering education to integrate the principles of environmental, social, and economic sustainability throughout the CDIO lifecycle. Topics pertaining to sustainability and sustainable development are already explicitly reflected in CDIO standards 2, 3, 7, 9, and 11 (CDIO, 2020).

Sustainable development has also been emphasized by accreditation bodies such as ABET that recognizes that graduates of accredited programs must have the ability to "design a system, component, or process to meet desired needs within realistic constraints such as economic, environmental, social, political, ethical, health and safety, manufacturability, and sustainability" (ABET, 2022).

Research motivation

Although various research studies (e.g. Ramirez-Mendoza et al., 2020; Desha et al., 2019; Wilson, 2019) have advocated the importance of embedding SDGs into engineering curricula and teaching practices, numerous other studies have highlighted the prevailing gaps in faculty competency when it comes to integrating SDGs concepts into their teaching practices. For instance, Barth & Rieckmann (2012) noted that many faculty members lack the proper expertise and professional development training to effectively integrate SDGs into curricula. Lozano et al. (2017) highlighted that the integration of SDGs into Higher Education requires system thinking, interdisciplinary approaches and pedagogical innovations that are not prevalent among faculty.

For the past years, there has been a growing interest in the application of Generative AI in the creation of intelligent tutoring systems, and personalized learning through ALS (Bond et al., 2023). An ALS is an AI-based intelligent learning platform designed to provide a personalized adaptive learning experience to students. Unlike traditional Learning Management Systems (LMS) which offer generic static content and assessment, ALS uses advanced AI algorithms to provide personalized learning paths, considering the individual needs, competencies, engagement level, performance data, feedback, responses, learning styles, and behavioral and error patterns that best match the individual student's profile. ALS aim to enhance engagement, facilitate learning, and improve student learning outcomes. Rooted in established theories and frameworks, this contribution aims to report on a real-world in-progress pilot study related to the design, implementation, and assessment of a Generative AI-based course delivered through ALS, centered on the SDGs and tailored for the African context. We position the adoption of these systems as an opportunity to further bridge the prevailing gap in SDGs competency among faculty, while leveraging the capabilities of ALS to deliver personalized learning experience to students at a large scale, within a specific African context.

Research questions

This study seeks to provide critical evaluation on three areas, answering the following questions:

1. Effectiveness of AI generated learning materials: How can AI-generated learning materials be used to construct robust and relevant teaching course content in a faster and cost-efficient manner, ensuring scalability?
2. Impact of ALS on Learning Outcomes: To what extent do the ALS improve students learning outcomes, engagement, and satisfaction?

3. Data-Driven Educator Empowerment: How data stemming from ALS can empower educators to enhance learning design and implementation, assessment and evaluation, to effectively monitor and support learners?

To address some of the above questions and to guide the analysis, design and implementation of the proposed ALS, we report on a pre-intervention empirical study that aimed to probe the initial student faculty Knowledge, Attitude, and Perception (KAP) towards ALS prior to the final design and implementation of the ALS. A post-intervention empirical study is also planned in future to assess the effectiveness and the impact of the proposed ALS.

Research contributions

The ensuing research distinguishes itself through three areas:

1. Contextual Uniqueness, discussing SDGs within an African lens: The learning materials discuss the specific challenges, opportunities, and nuances presented by the African continent. It adds a layer of complexity on the content creation.
2. Study Scope: Comprehensive pre- and post-implementation assessment of a real-world in-progress pilot: The methodology of this research is distinct in its comprehensive approach, encompassing both pre- and post-implementation assessments. Establishing the research in a real-world pilot not only enhances its practical relevance but also ensures that the findings are directly applicable and transferable to real-life. In addition, to the best of our knowledge, this is the first reported study that contributes to understanding the KAP of students and faculty towards ALS, albeit Kamoun et al. (2023) previously investigated the KAP among students and faculty towards ChatGPT in a broader context.
3. Scale of the surveys, incorporating both student and faculty perspectives: This approach ensures that conclusions and recommendations are grounded in a fuller understanding of the educational ecosystem.

LITTERATIVE REVIEW

Bond et al. (2023) conducted a thorough meta systematic review of the applications of AI in Higher Education. In their study, “personalized learning” through adaptive learning systems emerged as the top reported benefit of using AI in higher education. ALS enables the creation of personalized learning environments, and the customization of educational material to meet individual student needs, thus promoting student autonomy (Algabri et al., 2021; Buchanan et al., 2021; Alotaibi, 2023). Though many reviews reported in (Bond et al., (023) mentioned the potential of ALS to positively enhance learning outcomes, very few studies provided empirical evidence of the positive impact of ALS on students’ motivation, engagement, interests, and learning. In addition, some other studies have conveyed some skepticism considering the challenges associated with ALS in terms of potential technical and privacy issues (Li et al., 2021).

Table A1 (see Appendix A) summarizes the key reported merits of adaptive and personalized learning systems as reported in the literature.

Our research is rooted in and guided by the following established concepts, theories, and frameworks:

- Universal Design for Learning (UDL) framework (Meyer et al., 2014): It guided this research by providing a practical framework to effectively design and implement the ALS, based on UDL's key principles of (1) comprehending learners' diversity and needs (2) designing inclusive and personalized learning experiences and (3) personalizing the learning experience based on continuous feedback.

- Technological Pedagogical Content Knowledge (TPACK) framework (Mishra and Koehler 2016): TPACK provides a comprehensive model on how the success of the proposed ALS hinges on the synergetic and coherent alignment of technology (Generative AI system) with sound pedagogical strategies and course content / learning objectives.

UDL and TPACK provide a solid methodological base to effectively integrate ALS into students' learning experiences. Both frameworks contributed to informing our research design approach.

- Self-Determination (SD) theory (Ryan and Deci, 2017): This theory frames the idea of how ALS can empower student to have more control over their self-directed learning experiences.

- Technology Acceptance Model (TAM) (Venkatesh and Bala, 2008): TAM provides valuable insights on designing and implementing an AI-based adaptive and personalized LMS by considering the important factors of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) and their role in shaping the students and faculty attitudes and intentions to effectively adopt ALS. While the SD theory emphasizes the motivational factors for the successful implementation of the ALS, TAM focuses on the acceptance factors. Both SD and TAM provided a lens through which our research question #2 is formulated and examined. These two frameworks also guided the development of our perception survey instruments and will be revisited to inform the interpretation of our findings once this work-in-progress project is completed.

- Data-Based Decision Making (DBDM) in education (Lai and Schildkamp, 2013): DBDM provides a useful framework for collecting and analyzing data on student performance, learning style, engagement, and progression to personalize learning experiences. DBDM informed the development of our research question #3 and provided a methodological tool to effectively design the ALS.

- Human-machine Augmented Intelligence (Xue et al., 2022): This concept emphasizes how instructors and Generative AI can symbiotically collaborate to enhance cognitive performance through co-creation. It provided a sound contextualization for our research and will inform the interpretation of our findings once this study is completed.

METHODOLOGY

In this section, we start by outlining the research method adopted for our pre-intervention empirical study. This will be followed by an explanation of the methods and workflow utilized in the design, creation, and implementation of the pilot course.

Pre-intervention empirical study

Research Methods

The research methodology is based on an empirical quantitative approach, using surveys as data collection instruments. Following a similar approach as in (Kamoun et al., 2023), we developed a survey based on structured questionnaires, consisting of closed-ended questions, to generate insights about the knowledge, attitude, and perception (KAP) among faculty and students towards ALS.

Sample Selection and Data collection procedure

The student sample was selected via a combination of stratified sampling and convenience sampling methods. The faculty sample was selected via a census sampling approach. Student surveys were conducted via paper-based questionnaires that have been distributed during class time. Faculty surveys were conducted online, via Qualtrics.

Instruments and measures

The instrument employed covered three main domains: Knowledge (K), Attitude (A), and Perception (P) towards ALS.

The first (K) domain aimed to probe student and faculty knowledge about ALS. Each knowledge item response score was either 0 (false answer) or 10 (correct answer). The percentage of correct responses r_k was computed by dividing the score by 40 or 50 as applicable and multiplying by 100%, and this measure was used to group the knowledge scores on a 5-point Likert scale as follows: $r_k < 20 = 1$, $20 \leq r_k < 40 = 2$, $40 \leq r_k < 60 = 3$, $60 \leq r_k < 80 = 4$ and $r_k \geq 80 = 5$. Knowledge scores were interpreted as follows: 1 = very low, 2 = low, 3 = moderate, 4 = high and 5 = very high. Good knowledge was regarded when the overall average score, out of 5, and across all the items is greater than or equal to 4.

The second domain (A) probed student and faculty attitudes towards ALS and contained eight 5-point Likert items (A1-A8) and six 5-point Likert items (A1-A6) for students and faculty, respectively. The responses ranged from strongly agree, agree, neutral, disagree, and strongly disagree; each weighting 5, 4, 3, 2, and 1, respectively. High index scores reflect a more positive attitude towards ALS and vice-versa. To reduce bias, we have reverse-coded some items such that a response of "strongly agree" truly represents “strongly disagree”. For these reverse-coded items, scores were also reversed and recomputed accordingly. Attitude scores were interpreted as follows: 1 = very negative, 2 = negative, 3 = indifferent, 4 = positive, and 5 = very positive. A positive attitude was noted when the overall average score, out of 5, and across all the items is greater than or equal to 4.

The third domain (P) probed student and faculty perception towards ALS and contained fifteen 5-point Likert items (P1-P15) and twenty-nine 5-point Likert items (P1-P29) for students and faculty, respectively. To reduce bias, we have reverse-coded some items such that a response of "strongly agree" truly represents “strongly disagree”. For these reverse-coded items, scores were also reversed and recomputed accordingly. A positive perception was noted when the overall average score, out of 5, and across all the items is greater than or equal to 4.

Statistical analysis

This study used Statistical Package for Social Sciences SPSS (IBM Corporation, NY, USA, version 17) for data analysis. Demographic data was analyzed descriptively and depicted as frequencies as well as percentages. We applied the χ square test for goodness of fit to analyze a single categorical variable. We present general KAP levels descriptively in terms of means and standard deviations and we use an independent t-test for KAP score comparisons based on demographic variables which we illustrate in terms of means, standard deviations, and p values.

Real-World in-progress pilot implementation

To advance the development of the pilot course, we assembled a multidisciplinary team comprising academics, learning architects, learning engineers, and subject matter experts in Sustainability, Work Ethics, and Inclusion. Figure B1 (see Appendix B) illustrates the course construction and workflow process used for building the pilot course:

1. Macro-Curriculum Design by Academic Team: This foundational phase entails the academic cohort delineating the course structure and overarching learning objectives. The course, comprising 13 modules, each with a distinct macro-learning objective, follows a weekly-led format.
2. Prompt Script Creation by Learning Architects: Learning architects, utilizing a Large Learning Model, developed prompt scripts. These scripts encompass context, language style, and tone, tailored to the target audience and macro-learning objectives.
3. Material Generation Using a Proprietary Generative AI Engine: Employing a custom-built engine based on ChatGPT 4 LLM, this phase produces 65 to 80 nano-learning objectives per module, alongside preliminary learning materials, probes, and activities for the AIs experience.
4. Quality Assurance: Post-generation, the learning architects conduct a thorough quality assurance review, focusing on content clarity and relevance as per the initial scripting.
5. Review and enrichment by Subject Matter Experts (SMEs): SMEs scrutinize and refine the nano-learning objectives and materials for accuracy and depth, enriching them with factual data, additional sources, and references to augment the AI-generated content.
6. Exporting to the ALS: The SMEs’ reviewed course materials are integrated into the ALS.
7. Structuring Materials for ALS: Learning engineers structure the SMEs’ approved materials into an adaptive learning schema, leveraging the Generative AI module to tailor content to the ALS framework.
8. Materials Approval Decision Point: Following the final quality assurance by SMEs, the academic team conduct a review on the course directly on the ALS to ensure alignment with the initial curriculum design.
9. Engagement with the course on ALS: Learners engage with the course. The system dynamically adjusts content based on performance metrics. A dashboard, displaying student progress, alerts instructors about potential adjustments in face-to-face activities.

Post-intervention pilot survey

The initial phase of the post-implementation survey will prioritize the evaluation of key performance indicators related to students, aiming for a comprehensive understanding of the pilot's impact. Quantitative metrics, such as learning outcomes, usage satisfaction, engagement rates, and dropout rates, will be assessed to gauge the effectiveness of the pilot. Additionally, a qualitative survey will be employed to delve into the subjective experiences of students, unveiling potential challenges or barriers encountered during the learning journey.

Qualitative interviews with faculty members involved in the learning material development process, including learning architects, engineers, and SMEs, will facilitate the gathering of valuable insights to evaluate the efficiency and robustness of the learning materials creation process.

Simultaneously, we will administer the faculty members involved in the course implementation a survey to delve into their perceptions regarding the relevancy of the learning materials. An analysis will also be conducted to determine the extent to which faculty utilized learner analytics to improve learners' outcomes and tailor their intervention to provide personalized students' feedback and support.

PRELIMINARY RESULTS

Demographic characteristics

One Thousand one hundred sixty-one (1161) students participated in this study. Females constituted a slight majority with 53.7%. Most respondents were Tunisians (96.6%) and 63.8% of the surveyed students were aged between 18 and 22 years old. Further details are shown in Table C1 (see Appendix C).

Fifty-eight (58) faculty members participated in this study. Females constituted the majority with 79.3%, compared to 20.7% male participation. 50% of faculty have more than 2 years working experience at ESPRIT and 70.7% have more than 2 years' experience with Online Learning Platforms. Further details are shown in Table C2 (see Appendix C).

Reliability and validity of Student and faculty KAP

Internal consistency reliability (Cronbach's α) for student and faculty KAP emerged as high for all three domains ($\alpha > 0.7$). In addition, Principal Component Factor (PCF) analysis provided evidence on the construct validity of the student and faculty KAP instruments, with most of the items being highly loaded as expected ($r > 0.4$).

General KAP levels

The students' general KAP level towards ALS was in the moderate to neutral category (mean = 3.0 ± 1.213). Among the three KAP domains, Perception and Attitude emerged with the highest mean (3.2), followed by Knowledge (mean = 2.2 ± 1.42). Based on the mean scores, the sample of the student population demonstrated moderate positive attitudes and perceptions towards ALS and a level of knowledge that is below average. Refer to Table 1 for further details.

The faculty general KAP level was in the moderately positive category (mean = 3.3 ± 1.03). Refer to Table 2 for further details. We also note that students and faculty members had varied opinions about the KAP as reflected by the dispersion of the responses around the mean.

Table 1. Overall student Knowledge, Attitude, Perception, and total KAP level (1-5)

Domain	Mean	Standard Deviation	Median (Inter quantile range)	Interpretation
Knowledge	2.2	1.429	2	Low
Attitude	3.2	1.192	3.3	Moderately positive
Perception	3.2	1.020	3.4	Moderately positive
Total KAP	3.00	1.213	3.00	Moderate to neutral

Table 2. Overall faculty Knowledge, Attitude, Perception, and total KAP level (1-5)

Domain	Mean	Standard Deviation	Median (Inter quantile range)	Interpretation
Knowledge	3.2	1.345	3	Moderately positive
Attitude	3.3	0.845	4	Moderately positive
Perception	3.3	0.92	3.2	Moderately positive

Total KAP	3.3	1.03	3.4	Moderate to neutral

Knowledge results

The knowledge level of the student sample was relatively low. On the other hand, faculty knowledge of ALS was relatively higher, as some have been exposed to this concept through research seminars and upskilling acculturation online courses). Refer to tables 3 and 4 for details.

Table 3. Student Knowledge Regarding Adaptive Learning Systems (*N*=1161)

Question	**% of affirmative answers**
K1-Have you heard about Adaptive Learning Systems before today?	32.8%
K2- (Before Today) I knew the difference between adaptive learning systems and traditional LMS?	32.2%
K3- (Before Today) I Knew that adaptive learning systems use data and algorithms to adapt learning content to individual student needs and abilities.	39.8%
K4-Have you interacted with adaptive learning systems in the past?	26.9%

Table 4. Faculty Knowledge Regarding Adaptive Learning Systems (*n*=58)

Question	**% of affirmative answers**
K1-Have you heard about Adaptive Learning Systems before today?	84.5%
K2- (Before Today) I knew the difference between adaptive learning systems and traditional LMS?	84.5%
K3- (Before Today) I could provide a clear explanation of what adaptive learning systems entails	51.7%
K4-I have interacted with an adaptive learning system in the past	39.7%
K5-I have gained knowledge about adaptive learning systems from reliable sources such as workshops, conferences, or academic literature	50%

Attitude results

The mean student attitude score towards ALS was 3.2 ± 1.192 and the median was 3.3 out of 5, implying a moderately positive attitude. Refer to Table 5 for details.

Table 5. Student Attitude Towards Adaptive Learning Systems

Statement	**5. SA**	**4. A**	**3. N**	**2. D**	**1. SD**	**Mean***	**SDev***	**Median***
A1. I prefer using traditional platforms (e.g. Moodle) over Adaptive Learning Systems	166 14.3%	254 21.9%	412 35.5%	211 18.2%	118 10.2%	3.1	1.169	3
A2. I am excited about the possibilities that adaptive learning systems could offer for my learning	222 19.1%	402 34.6%	379 32.6%	95 8.2%	63 5.4%	3.5	1.059	4
A3. I do not trust the AI Algorithms behind adaptive learning systems	133 11.5%	299 25.8%	426 36.7%	220 18.9%	83 7.1%	3.1	1.081	3
A4. I would like to learn more about adaptive learning systems	291 25.1%	431 37.1%	344 29.6%	59 5.1%	36 3.1%	3.7	0.986	4

A5. I am open to trying adaptive learning systems	300 25.8%	425 36.6%	317 27.3%	74 6.4%	45 3.9%	3.7	1.034	4
A6. I feel confident in using adaptive learning systems	182 15.7%	368 31.7%	443 38.2%	125 10.8%	43 3.7%	3.4	1.000	4
A7. I do not feel comfortable asking questions to a virtual tutor	119 10.2%	184 15.8%	367 31.6%	301 25.9%	190 16.4%	2.7	1.197	3
A8. I am afraid that adaptive learning systems might be biased and discriminate me	141 12.1%	222 19.1%	427 36.8%	207 17.8%	164 14.1%	2.9	1.192	3

** *SA: Strongly Agree, A: Agree, N: Neutral, D: Disagree; SD: Strongly Disagree. SDev: Standard deviation*
** Greyed cells convey negative attitude statements*

For the case of faculty, the mean attitude score towards ALS was 3.3 ± 0.84 and the median was 4 out of 5 implying an overall moderate positive attitude. Refer to Table 6 for details.

Table 6. Faculty Attitude Towards Adaptive Learning Systems

Statement	5. SA	4. A	3. N	2. D	1. SD	Mean *	SDev*	Median*
A1. I am worried that adaptive learning systems might be biased especially on assessment part	2 3.4%	14 24.1%	24 41.4%	15 25.9%	3 5.2%	2.95	0.926	3
A2. I prefer using traditional LMS platforms over new AI driven approaches like adaptive learning systems	3 5.2%	10 17.2%	19 32.8%	17 29.3%	9 15.5 %	2.67	1.098	3
A3. I am excited about the possibilities that adaptive learning systems could offer to me and to my students	20 34.5%	29 50%	7 12.1%	2 3.4%	--	4.16	0.768	4
A4. I would like to learn more about adaptive learning systems	32 55.2%	21 36.2%	4 6.9%	1 1.7%	--	4.43	0.775	5
A5. I am open to exploring and integrating new technologies like adaptive learning systems into my teaching practices	35 60.3%	19 32.8%	3 5.2%	1 1.7%	--	4.5	0.755	5
A6. I feel confident in my ability to adapt and effectively use advanced learning platforms like adaptive learning systems	25 43.1%	27 46.6%	4 6.9%	2 3.4%	--	4.29	0.749	4

*** SA: Strongly Agree, A: Agree, N: Neutral, D: Disagree; SD: Strongly Disagree. SDev: Standard deviation*
** Greyed cells convey negative perception statements*

Perception results

Student perception level towards ALS was moderately positive (mean = 3.2 ±1.02) (see Table D1, Appendix D).

Faculty perception level towards ALS was also moderately positive (mean = 3.3 ±0.92) (see Table D2, Appendix D).

Comparison of KAP levels based on demographic characteristics.

Table E1 (see Appendix E) illustrates the associations between students' key categorical demographic variables and their knowledge, attitude, and perception towards ALS, based on an independent test. p <0.05 was considered statistically significant to infer that there is significant evidence that the demographic variable under consideration influences the mean

K, A, or P level. As may be seen, all demographical variables have some impact with varying degrees on student reported KAP towards ALS.

Table E2 (see Appendix E) illustrates the comparison of the reported KAP levels, for the case of faculty, based on demographic characteristics and using an independent t-test. As may be seen, gender had no significant impact on the reported KAP level, while working experience did not have any impact on the reported knowledge. University rank, on the other hand, had some impact with varying degrees on the reported KAP.

DISCUSSION

This paper is part of an in-progress pilot study. Future phases will provide more comprehensive answers to the research questions stated in the introduction. The following answers to the research questions are based on the findings gathered up to the current phase of the study:

Discussion related to the first question of the in-progress paper research: "How can AI-generated learning materials be used to construct robust and relevant teaching course content in a faster and cost-efficient manner, ensuring scalability?", the first finding pertains to time efficiency in the creation of learning materials. In the present phase of learning materials development, initial observations suggest that a learning architect employing an AI generative engine assistance achieves a speed enhancement of 3 times in an adaptive learning materials development ready to use on an ALS compared to manual creation without AI generative engine aid. Further research is under way to better quantify the time savings and cost efficiency gained from the adoption of the ALS.

The second key finding pertains to the quality of the learning materials produced by the AI generative engine. Despite undergoing numerous prompt adjustments, the output was deemed to partially meet the criteria for the diverse student profiles (undergraduate and postgraduate) of the course. Subject Matter Experts noted that the learning materials lacked depth and gravitas, particularly for the MBA student category. At this stage, a preliminary conclusion is that the solitary use of an AI generative engine is insufficient for producing unique, high-quality content on SDGs in Africa that is tailored to a diverse student profile. While an AI generative engine significantly surpasses the efficiency of a learning architect in generating a bulk of learning materials, SME intervention is essential for elevating the content to a higher standard. This involves not only proofreading and endorsing but also co-creating the learning materials. The post-implementation pilot phase of the research is expected to yield insights for calibrating the human-machine interactions in content creation.

Discussion related to the second question of the in-progress paper research "To what extent do adaptive learning systems improve learning outcomes, learner engagement, and satisfaction?": Initial results indicated that while surveyed faculty demonstrated a higher level of knowledge than students, many do not have a firm grasp of what ALS entail. Students and faculty showcased a moderate positive attitude and perception towards ALS, with a high degree of variability in the responses. While most surveyed students were enthusiastic about the opportunity to interact with ALS, many expressed some trust-related concerns. The majority of faculty surveyed expressed interest about the prospect of implementing ALS in their educational practices. Surveyed faculty and students reported a moderately positive attitude towards ALS. On the positive side, the majority perceived it as enabler for better learning experience, enhanced learning outcomes, and increased motivation. “Usefulness” and “ease of use” were also perceived among their expectations, in accordance with the TAM3 model (Venkatesh and Bala, 2008). On the negative side, there were few empirically validated reported concerns reported by both faculty and students regarding potential technical and privacy issues.

Discussion related to the third question of the in-progress paper research “How can data stemming from adaptive learning systems empower educators to enhance learning design and implementation, assessment & evaluation, to effectively monitor and support learners?”: Currently, only the pre-implementation survey has been conducted. The initial findings indicate that the majority of surveyed faculty expressed a positive perception towards the added value of ALS in their teaching and assessment. There were some concerns related to the potential of ALS to (1) make students overdependent on technologies, (2) require a significant investment of their time and effort, (3) reduce their direct interactions with students, and (4) make unreliable or incorrect decisions.

CONCLUSION

This research in-progress contribution offers some preliminary insights into the practical implementation of an ALS, tailored to a self-paced online short course on SDGs, and DE&I. It reports on the pre-intervention KAP towards the ALS among students and faculty. Our empirical findings revealed that faculty showcased a positive perception and attitude towards the potential of ALS in teaching and assessment, albeit with reservations about over-reliance on technology and possible impacts on faculty-student interactions. In future, we plan to conduct a post-implementation pilot survey including qualitative research to gain new insights and further qualitative and quantitative results assessing the relevancy and effectiveness of AI generated learning materials and ALS experience.

FINANCIAL SUPPORT ACKNOWLEDGEMENTS

The authors received no financial support for this work. The authors would like to acknowledge the contribution of Ibtissem Jabri and Amani Driss in the empirical study and statistical analysis.

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APPENDICES

Appendix A

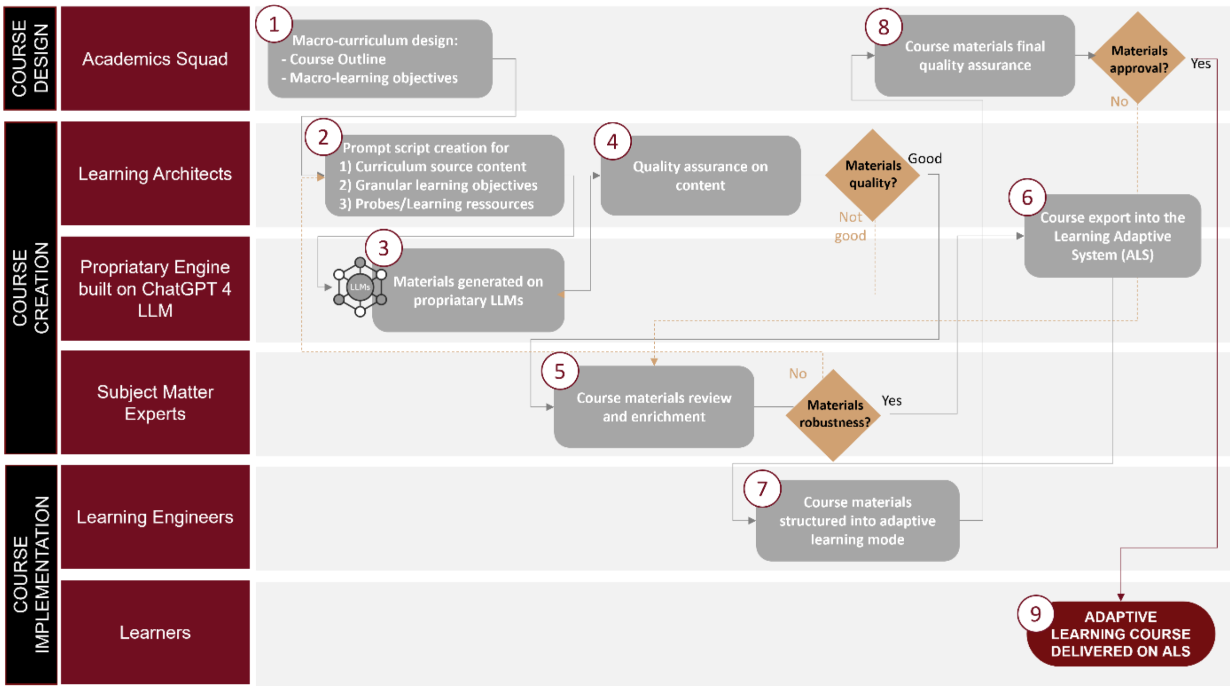
Table A1. Key Merits of ALS as Reported in the Literature

Sample Reference	ALS merit	Research method
(Yang et al., 2013)	Adaptation to individual student's learning style	Case-study
(Donevska-Todorova, et al., 2022)	Personalized learning paths	Design Research

Papadopoulos & Hossain, 2023	Data-driven insights for faculty	Conceptual study
(Ross, et al., 2018)	Increasing student motivation and engagement	Case-study
(Vesin et al., 2018)	Addressing diverse learning needs, including those with special learning needs	Conceptual/empirical study
(Feng et al., 2018)	Enhancing student learning outcomes	Quasi experiment
(Imhof et al., 2020)	Enhancing student autonomy and empowering learners	Conceptual
(Liu et al., 2022)	Alleviating stress and anxiety	Empirical study

Appendix B

Figure. B1. Workflow process for the pilot course building.



APPENDIX C

Demographic characteristics

Student demographic

Table C1. Demographic Characteristics of Sample Student Respondents (*n*=1161)

Demographic variable	Frequency (*n*)	Percentage (%)	p value*
Gender			0.000
Male	537	46.3	
Female	624	53.7	
Age			0.000
18-22	741	63.8	
23-25	345	29.7	
> 25	75	6.5	
Level of Study			0.000

Bachelor	861	74.1	
Master	300	25.8	
Nationality			0.000
Tunisian	1122	96.6	
Other	39	3.4	

* χ-*square test for goodness of fit. (Significance level p <0.05)*

Table C2. Demographic Characteristics of Sample Faculty Respondents (*n*=58)

Demographic variable	**Frequency (*n*)**	**Percentage (%)**	**p value***
Gender			0.000
Male	12	20.7	
Female	46	79.3	
University rank			0.000
Lecturer	15	25.9	
Assistant professor	37	63.8	
Associate professor	4	6.8	
Full professor	2	3.4	
Working experience at ESPRIT			0.000
< 2 years	29	50	
2-4 years	15	25.9	
> 4 years	14	24.1	
Experience with Online Learning Platforms			0.000
< 2 years	17	29.3	
2-4 years	23	39.7	
> 4 years	18	31	

* χ-*square test for goodness of fit. (Significance level p <0.05)*

APPENDIX D

Table D1. Student Perception towards Adaptive Learning Systems(*N*=1161)

Statement	**5. SA**	**4. A**	**3. N**	**2. D**	**1. SD**	**Mean***	**SDev***	**Median***
P1. Using Adaptive Learning Systems would enhance my learning outcomes more effectively than traditional LMS	277 23.9 %	454 39.1 %	306 26.4 %	81 7%	43 3.7%	3.7	1.020	4
P2. Using Adaptive Learning Systems would make it easier for me to understand complex topics	259 22.3 %	530 45.7 %	256 22%	90 7.8%	26 2.2%	3.7	0.956	4
P3. I believe Adaptive learning Systems would enhance my academic performance	217 18.7 %	455 39.2 %	367 31.6 %	90 7.8%	32 2.8%	3	0.903	4
P4. Adaptive learning systems would provide me more control of my own learning	149 12.8 %	482 41.5 %	392 33.8 %	99 8.5%	39 3.4%	3.5	0.938	4
P5. I fear that using adaptive learning systems might negatively impact my academic progress	113 9.7%	244 21%	368 31.7 %	312 26.9 %	124 10.7 %	2	1.136	3
P6. I believe Adaptive Learning Systems would be easy to navigate to use	171 14.7 %	483 41.6 %	382 32.9 %	91 7.8%	34 2.9%	3.5	0.934	4
P7. I expect Adaptive learning systems to provide reliable learning material	170 14.6 %	437 37.6 %	434 37.4 %	82 7.1%	38 3.3%	3.5	0.961	4
P8. I expect Adaptive Learning systems to provide me a wide range of learning materials tailored to my unique needs	173 14.9 %	459 39.5 %	391 33.7 %	98 8.4%	40 3.4%	3.5	0.980	4

P9. I am concerned about potential technical issues when using adaptive learning systems	158 13.6%	433 37.3%	421 36.3%	91 7.8%	58 5%	3.4	1.126	4
P10. I worry that my personal information might be at risk when interacting with adaptive learning systems	185 15.9%	312 26.9%	399 34.4%	182 15.7%	83 7.1%	3.2	1.087	3
P11. Using adaptive learning systems would be more challenging than using a traditional online LMS	194 16.7%	384 33.1%	375 32.3%	137 11.8%	71 6.1%	3.4	1.034	3
P12. The user interface of adaptive learning systems is important for me for an effective learning experience	228 19.6%	413 35.6%	368 31.7%	103 8.9%	49 4.2%	3.5	1.045	4
P13. Adaptive learning systems would increase my motivation for learning	204 17.6%	367 31.6%	433 37.3%	93 8%	64 5.5%	3.4	1.111	3
P14. I am afraid that adaptive learning systems would make me overdependent on technologies	135 11.6%	294 25.3%	433 37.3%	192 16.5%	107 9.2%	3.2	1.092	3
P15. I am concerned about the privacy issues due to the collection of personal data	190 16.4%	364 31.4%	380 32.7%	165 14.2%	62 5.3%	3.3	1.093	3

** Greyed cells convey negative perception statements*

TableD2. Faculty Perception Towards Adaptive Learning Systems(*N*=58)

Statement	5. SA	4. A	3. N	2. D	1. SD	Mean*	SDev*	Median*
P1. Using Adaptive Learning Systems would enhance students' learning outcomes more effectively than traditional LMS	17 29.3%	30 51.7%	9 15.5%	2 3.4%	--	4.03	0.878	4
P2. Using Generative AIcoupled to adaptive learning systems would help me create teaching material more effectively	26 44.8%	25 43.1%	6 10.3%	1 1.7%	--	4.31	0.730	4
P3. Using Adaptive learning systems would help me better tailor teaching material and assessment instruments to students 'need	17 29.3%	33 56.9%	7 12.1%	1 1.7%	--	4.14	0.687	4
P4. Adaptive learning systems would provide students more control of their own learning	13 22.4%	33 56.9%	8 13.8%	4 6.9%	--	3.95	0.804	4
P5. I anticipate that learning to use adaptive learning systems would be straightforward to me	9 15.5%	30 51.7%	15 25.9%	4 6.9%	--	3.76	0.802	4
P6. I expect that Adaptive Learning Systems would fit well with my current teaching and assessment educational practices	10 17.2%	32 55.2%	15 25.9%	1 1.7%	--	3.88	0.703	4
P7. The opinions of colleagues I respect would influence my decision to use adaptive learning systems	6 10.3%	15 25.9%	24 41.4%	8 13.8%	5 8.6%	3.16	1.073	3
P8. I worry that using adaptive learning systems might require significant changes in my teaching and assessment approaches	2 3.4%	20 34.5%	16 27.6%	18 31%	2 3.4%	3.03	0.973	3
P9. I am concerned about potential technical issues when implementing adaptive learning systems	5 8.6%	28 48.3%	16 27.6%	8 13.8%	1 1.7%	3.48	0.903	4
P10. I expect adaptive learning systems to provide robust and reliable tools for **teaching** purposes	7 12.1%	42 72.4%	7 12.1%	2 3.4%	--	3.93	0.617	4

P11. I expect the adaptive learning systems to provide robust and reliable tools for **assessment** purposes	9 15.5 %	36 62.1 %	10 17.2 %	3 5.2%	--	3.88	0.727	4
P12. I except the adaptive learning systems to help me better track individual student progress	15 25.9 %	32 55.2 %	7 12.1 %	3 5.2%	1 1.7%	3.98	0.868	4
P13. The user interface of adaptive learning systems is important for me than using a traditional LMS	15 25.9 %	31 53.4 %	10 17.2 %	1 1.7%	1 1.7%	4	0.816	4
P14. Using adaptive learning systems would be more challenging for me than using a traditional LMS	12 20.7 %	24 41.4 %	11 19%	11 19%	--	3.64	1.021	4
P15. Using adaptive learning systems would discourage contact between myself and the students	3 5.2%	9 15.5 %	21 36.2 %	20 34.5 %	5 8.6%	2.74	1.001	3
P16.Using Adaptive learning systems would diminish my role as an instructor	5 8.6%	10 17.2 %	15 25.9 %	18 31%	10 17.2 %	2.89	1.202	3
P17. I do not trust the AI Algorithms behind adaptive learning systems	2 3.4%	12 20.7 %	19 32.8 %	18 31%	7 12.1 %	2.72	1.039	3
P18. I am afraid that adaptive learning systems would make students overdependent on technologies	9 15.5 %	27 46.6 %	9 15.5 %	9 15.5 %	4 6.9%	3.48	1.143	4
P19. I worry that adaptive learning systems might require a significant investment of time and efforts	6 10.3 %	25 43.1 %	16 27.6 %	9 15.5 %	2 3.4%	3.41	0.992	4
P20. I am concerned about losing control over course content with the adoptive of adaptive learning systems	4 6.9%	14 24.1 %	14 24.1 %	17 29.3 %	9 15.5 %	2.78	1.185	3
P21. I am concerned that adaptive learning systems might discourage students from seeking help from their instructions	4 6.9%	22 37.9 %	11 19%	18 31%	3 5.2%	3.10	1.087	3
P22. I am concerned that adaptive learning systems might compromise the quality of student instructor interactions	1 1.7%	26 44.8 %	14 24.1 %	16 27.6 %	1 1.7%	3.17	0.920	3
P23. I worry that adaptive learning systems might not accommodate diverse learning styles and needs	1 1.7%	17 29.3 %	23 39.7 %	16 27.6 %	1 1.7%	3.02	0.848	3
P24. I am afraid that adaptive learning systems would substitute instructors in future	3 5.2%	18 31%	18 31%	13 22.4 %	6 10.3 %	2.98	1.084	3
P25. I am concerned about the potential privacy issues due to the collection of students' data	5 8.6%	20 34.5 %	24 41.4 %	5 8.6%	4 6.9%	3.29	0.991	3
P26. I am concerned that evaluating the effectiveness of adaptive systems might be challenging	4 6.9%	34 58.6 %	15 25.9 %	4 6.9%	1 1.7%	3.62	0.791	4
P27. I am concerned about the accuracy and reliability of adaptive learning systems assessments and recommendations	4 6.9%	26 44.8 %	19 32.8 %	8 13.8 %	1 1.7%	3.41	0.879	4
P28. I expect that Adaptive Learning Systems will save me time	11 19%	34 58.6 %	10 17.2 %	3 5.2%	--	3.91	0.756	4
P29. I consider the usage of adaptive learning systems for tracking and profiling students might be considered discriminatory and unethical	3 5.2%	12 20.7 %	24 41.4 %	15 25.9 %	4 6.9%	2.91	0.978	3

*** SA: Strongly Agree, A: Agree, N: Neutral, D: Disagree; SD: Strongly Disagree. SDev: Standard deviation*

APPENDIX E

Table E1. Association Between Students' Demographic Information and Their KAP Towards ALS (*n*=1161)

Demographic variable		Knowledge			Attitude			Perception		
		Mean	SD	p-value*	Mean	SD	p-value*	Mean	SD	p-value*
Gender	Male	2.2	1.423	0.004	3.1	1.190	0.001	3.2	1.020	0.004
	Female	2.1	1.421		3.2	1.188		3.1	1.015	
Age	18-22	2.9	1.328	0.000	3.3	1.189	0.000	3.1	1.011	0.000
	23-25	2.1	1.421		2.9	1.181		3.2	1.013	
	> 25	2.3	1.333		2.9	1.189		3.2	1.011	
Field of Study	**Level**	--	--		--	--	--	--	--	
	Bachelor	2.2	1.111	0.001	3.1	1.187	0.000	3.3	1.015	0.002
	Master	2.1	1.567		3.2	1.190		3.2	1.011	
Year of Study	1	2.3	1.421	0.000	3.3	1.191	0.000	3.1	1.010	0.001
	2	2.1	1.324		3.2	1.193		3.2	1.007	
	3	2.4	1.322		3.1	1.889		3.1	1.015	
Nationality	Tunisian	2.5	1.420	0.001	3.1	1.187	0.000	3.1	1.016	0.000
	Other	2.1	1.399		3.2	1.886		3.2	1.011	

** Independent **t-test** (p<0.05 is considered statistically significant to confirm the impact of the demographic variable on the domain)*

Table E2. Association Between Faculty Demographic Information and Their KAP towards ALS (*n*=58)

Demographic variable		Knowledge			Attitude			Perception		
		Mean	SD	p-value* intergroup	Mean	SD	p-value* intergroup	Mean	SD	p-value* intergroup
Gender	Male	3.3	1.980	0.477	3.8	0.845	0.322	3.3	0.920	0.330
	Female	3.2	0.982		3.9	0.843		3.2	0.910	
University rank	Lecturer	3.1	1.322	0.002	3.8	0.856	0.003	3.4	0.899	0.000
	Assistant professor	3.2	1.298		3.9	0.801		3.2	0.911	
	Associate professor	3.1	0.988		4	0.837		3.3	0.889	
	Full professor	3	0.989		3.8	0.867		3	0.910	
Working experience at ESB	< 2 years	3	0.988	0.132	3.8	0.846	0.040	3.2	0.990	0.000
	2-4 years	3.1	0.979		3.9	0.843		3.1	0.991	
	> 4 years	3	1.287		4	0.844		3.00	0.899	

** Independent **t-test** (p<0.05 is considered statistically significant to confirm the impact of the demographic variable on the domain)*