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Measuring sustainable use of artificial intelligence in higher education: A novel explainable AI model

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Abstract

The rapid use of artificial intelligence (AI) in higher education offers opportunities for improved learning and operational efficiency, but raise questions about how its use can be sustained and its impacts assessed. Unchecked AI deployment can create ethical, equity and quality challenges. It is posited a new explainable AI (XAI) derived measurement model to examine sustainable use of AI in higher education. We developed a multifaceted measure to evaluate AI use, in terms of institutional support, user attitudes, ethical practices, educational outcomes and environmental issues. A combined sustainability artificial intelligence (SAUI) utilization index was developed through Analytic Hierarchy Process (AHP) weighting and statistical validation. Then, we constructed a machine learning model (XGBoost model) to infer the SAUI with SHapley Additive exPlanations (SHAP) for interpretable predictions. Factor analysis, structural equation modelling, clustering and predictive modelling were implemented. The study results show that faculty training and positive attitude toward AI have a more powerful contribution in influencing sustainable use of AI, compared to institutional facilitating conditions. Ethical and risk considerations were of moderate importance, whereas demographics had no predictive power. The explainability factor is especially important to stakeholders wanting actionable insights in education. Future research should include broader applications for this framework in other areas, and incorporate longitudinal data for analysis, in support of sustainability over time, supported in the knowledge that the presence of AI in academia promotes positively to sustainability goals.

Keywords: Sustainable development, Education, ChatGPT, Explainable artificial intelligence, Ethics, Artificial intelligence.

1. Introduction

The growth of Artificial Intelligence (AI) in the area of higher education, is enabling AI to improve all the areas of higher education including administration, as well as teaching and learning [1,2]. The AI allow intelligent tutoring systems and learning analytics to operate more efficiently and effectively with respect to administrative functions, using automated grading, chatbots, and AI to assist in improving the personalization and efficiency of teaching [2]. AI has potential benefits to include greater student engagement and satisfaction through assisting students in a more personalized way, improving academic support services, and enhancing research capabilities [3-5]. There are examples emerging where generative AI models, such as ChatGPT, are already being utilized by students as a means to assist them in writing and generating ideas [2,6]. This demonstrates how educational tasks are being performed differently. Although there are many reasons why educators are embracing AI at a rapid pace, the increasing concern of whether the use of AI in higher education is sustainable in the future and how to evaluate the sustainability of AI in higher education is growing.

Sustainable AI use in education refers to the incorporation of AI into educational settings, in a manner that is ethically acceptable, morally justifiable, and continues to enhance the quality of education. AI use must continue to improve the quality of education; maintain ethical standards; serve the interests of equity and justice; and cause no lasting damage to students or institutions [7-9]. Sustainable AI use contributes to achieving the UN's sustainable development goal 4 on Quality Education through responsible use of technology [10]. Past studies have concluded that AI can contribute significantly to the accomplishment of multiple other SDGs, through promoting innovation and efficiency and developing digital literacy [10,11]. However, past studies also warn of potential risks such as data privacy issues and widening of the existing inequities in society resulting from the misuse of AI. Therefore, ensuring the sustainability of AI in education represents a balancing of the benefits of the positive and negative impacts. It should effectively advance the high-level goals setting up our educational systems towards greater equity and inclusion without compromising ethical educational practice.

While these challenges are acknowledged, no holistic framework exists to quantify how sustainably AI is being employed in academia. There are already numerous studies which build on technology acceptance that explore [12-14], for example, perceived usefulness and ease of use as factors impacting the first use stage. Although these models contribute knowledge on the question of whether educators and students take AI up, many fail to address how AI is implemented and actually used over time, and whether such use continues to be beneficial and ethical [3,15-17]. But they can only be used to directly or indirectly infer. User's behavior intention or self-reported use in short term, and it is difficult to set up long-term sustainable index over time [18-20]. Furthermore, the focus has been on adoption characteristics and adoption barriers while ethical use, pedagogic impact and continuous development are less quantified in previous research into sustainability. Yet another chasm is the interpretability of AI in educational implementations [21-23]. A major reason why institutions have used AI applications such as predictive models of student success, and decision-making systems, is because they did so without establishing a process for communication of the results to those who will be impacted by those results, as a result, there may be a loss of trust in the assertions made about the impact of AI on decision-making. The use of Explainable AI (XAI), is an option for holding stakeholders accountable for their actions with regard to AI, while at the same time providing the necessary support for building trust in the assertion that AI decision-making is appreciated and necessary for the long-term use of AI [9,24,25]. However, very few works have combined the explainability concept with assessing the sustainable integration of AI.

Recent events underscore the importance of these factors. Generative AI’s 2023-24 eruption has prompted discussion of academic integrity, cognitive offloading and policy responses at universities [26-28]. If the use of AI tools is too extensive, students’ critical thinking and autonomy would be repressed, thus posing a risk to the continuity of learning results [6,29-31]. This is again a testament that “sustainable use” not only refers to prolonging the use, but also the responsible use that sustains educational quality [32,33]. Moreover, environmental sustainability of AI e.g., energy use of AI infrastructure is a new factor that universities for trying to cut carbon footprints consider [34-36]. Yet, in academic literature relatively less is known about any measurable metrics or models that would include the environmental dimension in educational AI use.

To address these gaps, this study attempted the following objectives:

1) Develop a novel measurement Sustainable AI Utilization Index (SAUI) model for higher education that captures multiple dimensions of sustainable AI use including technological, pedagogical, ethical, and environmental.

2) To utilize XAI to clearly explain which factors are contributing to the sustainability scores for education. The purpose of this objective is to prevent the model from being a "black box" while developing an education leader's ability to understand and rely on the model for decision making.

3) Identify patterns and determinants of the use of sustainable AI in education.

This research contributes to both theory and practice by providing, first, some of the initial efforts to develop a quantifiable index for the use of AI in education that addresses sustainability; second, in doing so, as well as through its use of multiple scientific disciplines to form a multi-faceted model that draws upon the principles of sustainable development and technology adoption. Second, the addition of explainability to the assessment itself is new; in particular, the ability to provide a reason for the numerical score, and thus allow for targeted improvement and accountability of the institution being assessed. This reflects a larger trend toward what we refer to as "human-centered XAI", which is concerned with making assessments mediated by AI understandable and actionable to human decision-makers. Third, the paper adds to the scant global research in AI in higher education in developing countries by providing empirical evidence from an Indian setting. In such a world, where AI-enabled learning is more likely to be an optional enhancement rather than the default standard of educational provision, it will be paramount for education sectors worldwide to increase their adaptive capacity in order to accommodate new technologies. Indeed, while much AI-in-education research and development tends to focus on Northern blocs (e.g. North America; Europe; East Asia), this paper illuminates challenges and opportunities that typify a region with extreme diversity in institutions' capacities and social conditions. It therefore contributes to an understanding of the impact of context-specific factors on sustainable AI deployment, which is relevant from a local policy perspective as well from a more global comparative standpoint. Last, but not least, our interpretable model has implications for future research. It can be further extended and referenced by other researchers who attempt to assess AI interventions in education or any other domain from a sustainability perspective. By proposing a method that can be replicated or extended by other researchers, we open up a new line of investigation between AI, education and sustainable development.

2. Methodology

The study's methodology contained five main stages: (1) determining the dimensions for evaluating the sustainable use of artificial intelligence (AI) and creating a measuring tool; (2) collecting information on the higher education institutions of Maharashtra; (3) developing a Sustainable AI Utilization Index (SAUI) using a weighted model; (4) developing an Explainable Artificial Intelligence (XAI) model to forecast and explain the SAUI; and (5) conducting statistical analysis and validating the findings.

Research design and sample

We developed a case study research design focused on the higher education sector of the state of Maharashtra. The target population included the higher education institutions that have incorporated AI tools or systems into some part of their operation. The study was cross-sectional, providing a snapshot of the current status of AI integration into the higher education system of Maharashtra in 2025, however the survey was designed to assess continuing practices and attitudes contributing to long term sustainability. As the survey provided assurance of anonymity, institutional data was kept confidential and only reported in aggregate form.

Sustainable AI utilization measurement: Dimensions and instrument

In order to evaluate the sustainable use of AI, it was necessary to establish and operationalize the key dimensions that contribute to sustainability in the specific context of this study. [16,37-40] Literature and expert input were consulted to develop the instrument, assuring content validity [41-43]. Prior studies on AI in education and sustainability were reviewed along with factors utilized in technology adoption models and ethical AI frameworks [44,45]. Based upon these reviews, five major dimensions were established to guide the measurement model:

Dimension 1 (D1): Institutional support and infrastructure

The degree to which the institution provides support for integrating AI. This dimension considers facilitating conditions such as the availability of AI tools, IT infrastructure, funding, and administrative support for AI initiatives [22,30,46-48]. Additionally, this dimension assesses whether the institution has formal policies or strategies concerning AI.

Dimension 2 (D2): Human capacity and attitude

Preparedness and mindset of individuals towards AI. This dimension considers the attitudes towards AI, prejudices/misconceptions, and the level of training/skills required to utilize AI effectively. This dimension also considers the presence of a culture of continuous learning.

Dimension 3 (D3): AI integration into teaching/learning

Extent and method in which AI is integrated into curriculum and pedagogy. This dimension assesses not only whether AI tools are being used, but how they are being used, and whether those uses are enhancing educational outcomes in a sustainable manner. This dimension considers the incorporation of AI into curriculum design, improvements to the teaching process, and the engagement of students with AI.

Dimension 4 (D4): Ethical and equitable use

Responsible use of AI covering ethics, equity, and policy compliance. This dimension considers whether the use of AI is monitored for bias/fairness, whether data privacy is preserved, and whether there are mechanisms to ensure that all students will benefit.

Dimension 5 (D5): Outcomes and continuous improvement

Ultimately, sustainable use should result in positive outcomes and an institution's capacity to learn and improve with AI over time. This dimension considers indicators of educational outcomes that can be partially attributed to the use of AI, as well as mechanisms for receiving and utilizing feedback to improve.

For each item under these dimensions, the respondents evaluated them based on a 5-point Likert Scale (1 = Strongly Disagree to 5 = Strongly Agree) for opinion-based statements, or yes/no or numeric responses for factual questions. To create the composite Sustainable AI Utilization Index (SAUI) for each institution, the researchers combined the responses. In addition to the institutional scores, the researchers also analyzed the perceived sustainable use scores for each respondent. The primary objective of the study was to develop an institutional score. The researchers calculated the mean response for each item within an institution, and then combined them according to dimension weights. Prior to aggregating the items, the researchers tested the reliability of the instrument. The overall survey had a Cronbach's alpha of 0.91, which indicated very high internal consistency. Similarly, the reliabilities of the sub-scales for each dimension were good (alpha values ranged from 0.78 for D5 to 0.85 for D2). The researchers conducted an exploratory factor analysis (EFA) to determine if the items fit together as expected. The EFA supported the existence of the five factors corresponding to the researcher-defined dimensions (all eigenvalues > 1), accounting for 68% of the total variance.

Index construction and statistical modeling

We next calculated the Sustainable AI Utilization Index (SAUI) for each university after collecting the data. The SAUI is viewed as an equally-weighted composite of the five dimensions (D1-D5) that reflect their contribution to sustainable AI in higher education. The AHP was used instead of assuming all dimensions were equally-weighted in order to determine the weightings in a systematic way. Each dimension was compared to every other dimension using pairwise comparisons with the question "Is this dimension more important to sustain the use of AI in higher education than that one?" Using the 1-9 Saaty Scale, each comparison was made. Their answers were then used to create a single pairwise comparison matrix where their judgments were averaged together via geometric means. The CR for the matrix was 0.08 or less than 0.10, therefore it was deemed a reasonable set of judgments. The normalized principal eigenvector of this matrix gave the weights: $w_1 = 0.25$ (Institutional Support), $w_2 = 0.20$ (Human Capacity & Attitude), $w_3 = 0.20$ (AI Integration in Teaching/Learning), $w_4 = 0.15$ (Ethical & Equitable Use), $w_5 = 0.20$ (Outcomes & Improvement). These weights suggest that our experts viewed institutional backing as slightly the most influential single factor (25% of the index), while ethical considerations were slightly lesser (15%), perhaps reflecting that without infrastructure, even ethics can't be implemented – but all factors had substantial weight, reinforcing the multi-dimensional nature of sustainability.

We validated the structure of this index by performing a confirmatory factor analysis (CFA) treating each dimension as a latent factor and then a second-order factor representing SAUI. The CFA showed acceptable fit (CFI = 0.93, TLI = 0.91, RMSEA = 0.052), supporting the idea that a higher-order "sustainability" factor can be inferred from the five sub-dimensions. All factor loadings were significant ($p<0.001$), and in the second-order model, loadings of each dimension onto the overall SAUI factor were: 0.88 for D1, 0.81 for D2, 0.84 for D3, 0.73 for D4, 0.79 for D5, broadly in line with the weight importance (D4 indeed had the lowest loading consistent with lowest weight). This exercise gives additional confidence that the weighted sum formulation in Equation (1) is capturing a cohesive construct.

We formulated a Structural Equation Modeling (SEM) to test hypothesized relationships among factors, inspired by prior research findings. Specifically, we modeled how D2 (Human Attitude) and D1 (Support) influence D3 (Integration) and D5 (Outcomes) which in turn could influence D4 (Ethical practices) or vice versa.

Explainable AI model development

While the SAUI provides a quantitative gauge of sustainable AI use, one of our primary objectives was to make the analysis explainable and actionable. In order to accomplish this, we created a predictive model that is capable of learning from data which factors contribute to a higher or lower level of sustainability, and which will provide an explanation for each of the institutions in a way that humans can understand. The method is useful for two reasons: (a) it provides validation for the Index, as it allows us to test whether machine learning models are able to consistently differentiate between high and low levels of sustainability based on the same set of input variables; and (b) it utilizes advanced XAI methods to determine and prioritize the factors contributing to sustainability, potentially revealing non-linear patterns or factor interactions that may be missed by a basic regression analysis.

We selected a Random Forest (RF) ensemble as the base predictive model due to its strong performance with smaller sample size datasets and the fact that RFs can be used to model both continuous and categorical data [49-51]. Additionally, one of the most significant advantages of RF models is their internal estimates of the importance of the input features. Finally, RF models generally do not require extensive tuning. Our model's target variable was the SAUI score. We considered two modeling setups: a regression approach to predict the exact SAUI value, and a classification approach to predict categories e.g., "High", "Medium", "Low" sustainability class. Given the small number of institutions, model training had to be done carefully to avoid overfitting. For the RF regression, we used leave-one-out cross-validation to evaluate performance. For the XGBoost classification, we used a stratified 5-fold cross-validation. To find the best combination of parameters in our Random Forest (RF), and Extreme Gradient Boosting (XGB), we used a basic Grid Search to find the best hyper-parameters for each algorithm that would result in the highest cross validation R^2 and cross-validation accuracy respectively.

Next, we ran SHAP (Shapley Additive Explanations) to understand the output of our models [52-55]. SHAP explains the model's output by assigning each variable an amount that it contributes to the model's output for each prediction using Shapley values from Cooperative Game Theory to fairly allocate the difference between the model's output and the average output over all variables. In short, for each institution, we can now state the following factors contributed x to your predicted SAUI compared to the baseline. Additionally, we viewed global SHAP Summary Plots to see which factors are most influential overall, as well as to view how each factor relates to each outcome. In terms of equations, SHAP creates an additive explanation model:

$$f(x) = \phi_0 + \sum_{j=1}^{M} \phi_j(x) \tag{2}$$

This ensures global consistency and local accuracy. We used the Tree SHAP implementation which is optimized for tree models. Additionally, for a couple of specific institutions, we used Local Interpretable Model-agnostic Explanations (LIME) as a complementary method, to see if it provides similar interpretations. LIME fits a simple interpretable model locally around the instance to be explained. While our main focus was on the index and predictive model, we also performed an exploratory cluster analysis on the institutions based on their dimension scores (D1–D5). Using k-means and hierarchical clustering, we found an elbow in inertia and a silhouette analysis supporting 3 clusters, which corresponded well to intuitive groupings of high, medium, low sustainability institutions.

Data analysis and validation procedures

We examined Pearson correlations among the five-dimension scores and with the overall SAUI. As expected, all dimensions were positively correlated (r ranging 0.4–0.7, all $p<0.05$), with the strongest correlation between D1 support and overall SAUI (r = 0.72) and the weakest between D4 ethical use and SAUI (r = 0.42). This gave a preliminary indication that institutions strong in infrastructure tend to score well, whereas having ethical policies alone doesn't guarantee a high SAUI unless accompanied by other strengths. We also checked correlations of SAUI with external factors like institution size (found a mild positive correlation r =0.3, not significant at 0.05 level) and with urban vs rural location.

For the RF regression predicting SAUI, the leave-one-out cross-validation yielded a Mean Absolute Error (MAE) of 4.5 (on a 0–100 scale) and an R^2 of 0.82, indicating the model explains about 82% of variance in SAUI, quite high given only a few features. This indicates our chosen variables are able to capture the main elements of the Index with minimal random noise. Our XGBoost classifier was able to achieve an overall classification accuracy of 90% (27/30), while achieving perfect precision and recall for the High and Low classes with the only error being two instances where it incorrectly classified Medium/High classes. In addition to these we ran some additional tests including running the model with all other dimensions removed at once to check whether the removal of any single variable would have had a dramatic effect upon the model's accuracy. We were also able to run a Multiple Linear Regression to estimate SAUI which resulted in an acceptable adjusted R^2 of 0.75 with statistically significant coefficients for infrastructure, faculty training, and curriculum integration. Thus, the consistencies between both the linear and nonlinear model estimates add further confidence to the results.

3. Results and discussions

Level of Sustainable AI Use

The average SAUI, out of a total of 100, across all institutions was 58.3. While this indicates that many institutions have some degree of sustainable AI use, it also suggests that many will need to make considerable progress before we can say that they are using AI in a truly sustainable way. The scores, which ranged from 34.7 (the lowest) to 84.5 (the highest), indicated that about 20% of institutions fall within the "High Sustainability" category (SAUI > 70); about 50% fall in the "Medium" category (50-70); and about 30% fall in the "Low" (< 50) category. Therefore, while a relatively small number of institutions are at the forefront of developing sustainable AI practices, a large number of other institutions are just beginning to adopt these practices and face their own sustainability challenges. A further observation has been made. Institutions that are well established tend to cluster around the medium levels of sustainability. They have many initiatives, but do not have either sufficient agility or policy specifics to enable them to become top performers. On the other hand, small private institutions have had a more varied experience of sustainable AI adoption. While a couple of small private institutions were top performers in terms of sustainability, a number of other small private colleges have low levels of sustainable AI adoption. Figure 1 illustrates the SAUI, Predicted SAUI and Residual.

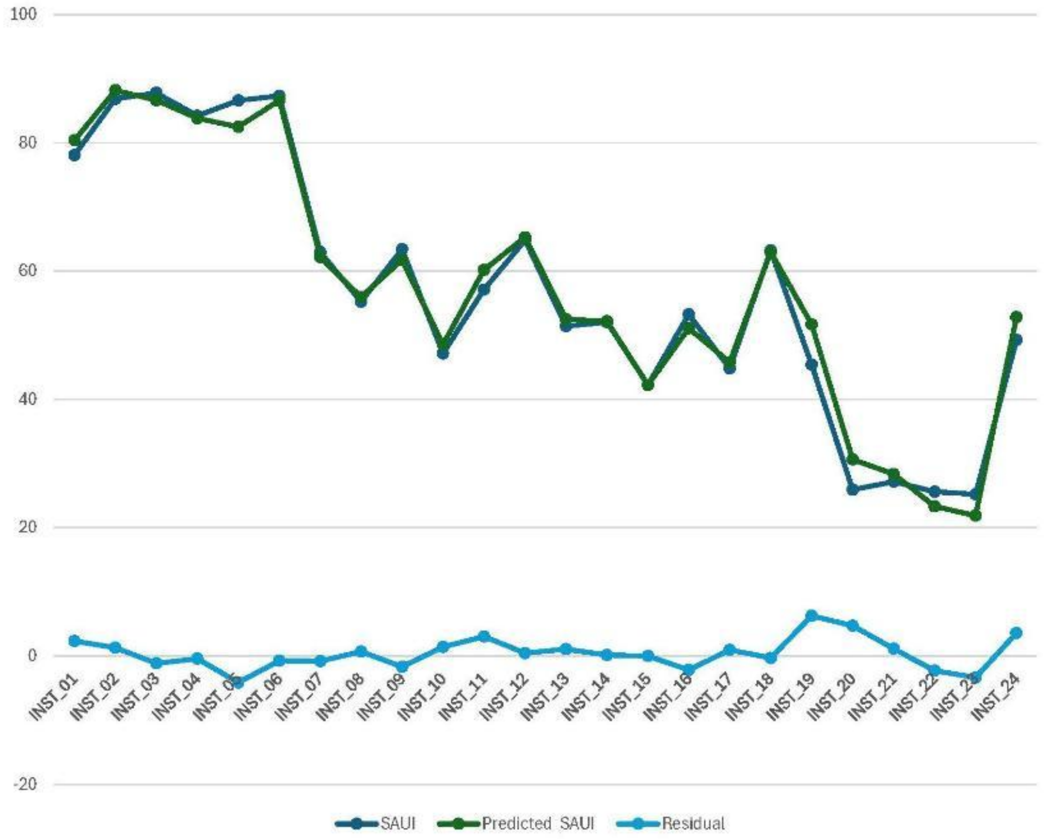

Fig. 1 SAUI, Predicted SAUI and residual

This finding demonstrates why measuring and steering sustainable use is important. The case study probably represents the case in many regions of the world where there are some leading players and others still struggling to catch up in responsible AI implementation. It echoes the findings in worldwide surveys that AI is now starting to aid many of the SDGs in higher education but also gives rise to challenges in terms of quality and equity. The presence of medium scores indicates partial progress. AI may for example be used to help in operation to and for example react to the imposition of yet more needs like training or oversight in ethics, all of which would be required for sustainability. Institutions scoring high in our studies will give a context and it is pleasing to know that as a mid to high score of mid-80s could be achieved even within the constraints of a caveman context if the right intent is there. All-inclusive could inspire other institutions that such turns can be achieved with planning. The detail is found amongst that in Table 1 with the cluster profile summary.

Table 1 Cluster profile summary

Cluster	Count	SAUI mean
Leaders	6	85.14
Emerging	9	58.18
Nascent	9	36.99

Our novel contribution was to add the dimension of explainability to a measurement model. We cannot empirically compare this to past research, however, conceptually we agree with many of the calls in the literature to provide transparency into educational AI. For example, a commentary from educators could argue that institutions need to be accountable regarding their deployment of AI; therefore, the institutions need to understand what they are doing. Our models' explanation of why one institution is lagging behind others provides the exact same accountability and transparency. Our model is also aligned with human-centered XAI principles, i.e., we place the human decision makers at the center of the decision-making process by providing them with explanations about the reasons behind those decisions, which can guide their actions. For example, saying "your score is low" will give a university administrator much less information than saying "your score is low primarily because your faculty do not have AI training and you do not have an AI policy," where these two factors contribute to approximately 60% of the difference between you and the highest scoring institutions. This type of explanation-based approach may increase the level of trust that decision makers have in the evaluation process and thus increase the likelihood that the decision makers will consider the findings serious enough to warrant changes rather than viewing the findings as arbitrary. The positive reaction that several of our participants showed when we explained to them why the model's scores were lower indicated that XAI-based feedback can empower decision-makers and help them identify and fix problems that they had previously been unaware of or unwilling to acknowledge. Table 2 presents the top features based upon global importance.

Table 2 Top features by global importance

Feature	Mean_abs_shap	Mean_shap	Direction
Training Hours	6.536	−2.280	negative
Ethics Policy	6.370	0.019	positive
Outcomes Improved	5.877	2.494	positive
Student Computer Ratio	2.805	1.054	positive
Infra Adequacy	2.435	0.282	positive
Attitude Score	2.123	−0.673	negative
Teaching Integration Score	1.910	−0.254	negative
AI Curriculum Score	1.675	0.208	positive

Factors Influencing Sustainable AI Use

Faculty AI training and skills: This feature, representing how well faculty are trained and comfortable with AI tools, had the highest average SHAP value magnitude. In nearly all high-scoring institutions, faculty training initiatives or high self-rated AI proficiency were present, boosting the SAUI. SHAP values for this feature were strongly positive for institutions that had regular AI workshops or a high percentage of faculty using AI in teaching. For example, at the top-scoring institution, this factor alone contributed about +8 points to their SAUI prediction relative to baseline. Conversely, institutions that lacked faculty development in AI saw this feature drag their predicted score down.

Infrastructure and policy: This was effectively captured by features like Infra Score and Policy Exist [23,56,57]. SHAP analysis showed that having adequate infrastructure e.g., computing power, internet bandwidth, technical support staff and a formal AI policy or strategy significantly contribute to higher SAUI. The SHAP contributions in the range of +5 to +10 on this aspect were enjoyed by institutions with above-average budgets and infrastructure in place for AI implementation.

Degree of AI incorporation in curriculum and teaching: This aspect, measured by items such as Teaching Integration Score (TIS) and Curriculum AI Score (CAIS), was shown to be another strong determinant by use of the SHAP values. Institutions that integrated AI into their teaching instruments were reflected in their greater sustainability. An institution that had AI tutoring elements in large introductory classes and an AI across the Curriculum program would have a good Teaching Integration Score, which might add some +6, according to SHAP, to their predicted score SAUI.

Ethics and Policy Measures: Interestingly, the existence of ethical guidelines or governance procedures in AI was a moderately strong factor. The SHAP result for institutions with either an ethics policy AI or a program for training faculty in this area was a favorable one, but not as great as the above-mentioned factors. This suggests that although ethics are extremely important, in the data a number of institutions had apparently similar mediocre disciplines inv involved here. Therefore, the variations in ethical practice were less contributing to the differing scores. This was the same for several institutions which has little or no discourse regarding ethics or policies about AI and its use. Although this was a statistically reliable explanation for their lower scores, it became apparent that the institutions in this category had many other discrepancies.

Perceptions of Outcomes and Evaluations: Institutions where respondents believed that unique positive outcomes were had from AI and that there was an internal body responsible for evaluation of AI influence had a somewhat more pronounced SAUI above institutions where this was not the case. This factor had a noticeable, but smaller influence in SHAP rankings. This factor would be reflected in, say, the college which had operated AI-driven analytics and had shown that those students in danger of heading for failure were identified and aided greatly in such a way that there was a recorded 10% increase in the pass rate of students in certain subjects. This sort of success story added to the confidence in AI. Hence the support those institutions had also reflected high on their scores.

Implications for Practice and Policy

Some of the significant results from this research can be generalized to apply to many other educational systems. As such, there are several important takeaways for universities, colleges, policymakers and educational leaders across a variety of contexts:

Institutional AI strategies and investments: To maximize the value of AI, universities/colleges will need to develop a comprehensive and integrated AI strategy [58-61]. We found that piecemeal or ad-hoc approaches to integrating AI in education resulted in poor sustainability of those efforts. An effective strategy would include investing in the technical infrastructure, professional development of faculty, curriculum development and pedagogical models that incorporate AI, and creating supportive policy frameworks for these efforts to occur simultaneously.

Faculty development and culture: Human factors were identified by us as the most critical success factor [62-64]. Consequently, we believe that higher education institutions must create a culture of AI awareness and appreciation among educators. Institutions should provide regular opportunities for educator professional development related to AI in education. These opportunities could range from providing educators with an introduction to using AI-based tools in their teaching to providing educators with an opportunity to engage in seminars focused on developing their own AI-based applications for education.

Development of ethical and inclusive frameworks: Although ethics was not the top predictor based upon numeric values alone, its importance in ensuring that AI is used in education and administrative processes in a sustainable and responsible manner cannot be overstated. Institutions should either develop their own or adopt existing guidelines for using AI in education and administration [1,65,66]. Examples of guidelines that should be developed or adopted include policies regarding data privacy, algorithmic transparency, and academic integrity. Institutions should also involve students in discussions related to ethics in AI, and foster a collective understanding of how to responsibly use AI.

Policy development at higher levels: For policy makers at the state and/or federal levels, this research provides evidence that can be utilized to advocate for and design programs of support. Based upon our research, the two most important factors related to the successful adoption of AI in education are infrastructure (technology) and training (faculty). Policy makers may consider programs that fund upgrades to technology infrastructure in colleges and universities in underserved regions, and programs that fund large scale faculty training initiatives related to the use of AI in education.

Preparing students and changing curricula: While the sustainable use of AI in higher education is primarily concerned with how institutions utilize technology to improve the delivery of instruction and learning, it also includes preparation of students to live and work in a world where AI is ubiquitous. Our research indicates that institutions are just starting to integrate AI-related content into their curricula. We recommend that institutions expand their efforts in this area, and that every student, regardless of major, graduates with an understanding of AI and its benefits and limitations.

Ongoing monitoring and evaluation: Sustainability requires continuous evaluation. Institutions should develop processes for ongoing monitoring and evaluation of the use of AI and its impact. Some examples of ways that institutions might monitor and evaluate AI include annual surveys of faculty and students about the effectiveness and problems with AI-based tools; audits of AI algorithms to determine whether they contain biases; tracking of the amount of time spent utilizing AI-based tools; etc.

Although our study is localized, the model and findings have global relevance. AI in higher education is a worldwide phenomenon, and many of the same questions arise, how to integrate effectively, avoid harm, involve humans, and persist over time. The explainable AI measurement model can be adapted to other contexts. It provides a structured way to think about and assess progress. As AI technologies evolve, institutions will need to adapt this model, possibly adding new criteria. But the core idea remains that balanced development across infrastructure, people, practice, and ethics yields sustainable benefits.

4. Conclusions

This research aimed to address the timely and complex problem of measuring and promoting sustainable use of AI in higher education, through a new XAI model. We demonstrated that sustainable embedding of AI in higher education is a multi-dimensional phenomenon, which can be measured and explained. The Sustainable AI Utilization Index (SAUI) we developed was a good point of measure to assess the degree an institution is embedding AI that is effective, ethical and enduring. We found a relatively moderate average level of sustainability in AI use in our case study and significant variation among institutions indicating leaders and laggards. Our multiple case studies showed the dominant drivers of this variability: strong institutional support, both infrastructure and policy support; sustained human capacity building, especially around training and positive attitudes; deep curricular integration of AI into a program or curricular unit, and practice-guided adherence to ethical use were emergent themes as some of the many criteria for sustainable AI use. These factors relate and complement prior research, but provide a coherent system placing long-term and responsible use above initial take-up of more or less accidental type. With other XAI approaches, SHAP has enabled not only to reach the predictive performance for sustainability outcomes but also to generate human-interpretable explanations as explanation genies for institution's performances. This new contribution is the ability to make visible the reasons why institutions do well or badly in their AI project. The analysis expands the theoretical debate by providing and validating a comprehensive measurement model of AI sustainability in education. The use of explainable AI in the assessment is a new methodological contribution; it shows how XAI can be applied outside of the conventional interpretation of models as a decision-making support tool for educational management. We have developed an interdisciplinarity framework connecting ideas from technology adoption, sustainable development and ML interpretability. These results represent a useful diagnostic instrument and provide evidence-based suggestions. Our findings show that tangible investment in faculty or in infrastructures may have a positive effect on the sustainable integration of AI. For institutions such as colleges and universities that want to leverage AI as a game-changer, we demonstrate that there is need to take a holistic and accountable approach. To consider AI adoption as simply a straightforward plug-and-play or as a single project will clearly be insufficient. Rather, it will require the whole ecosystem of support, learning and oversight. The rewards are great for doing so. In addition to improved efficiency and learning experience that aligns with social needs and contributes to broader SDG, the institutions that achieved the highest levels of sustainable AI use reported numerous benefits, including the ability to modify their own programming based on explainable AI feedback, and to create life-long, adaptive learning and understanding as AI technologies evolve. On the policy side of the dimension, our study suggests that supporting services at the state or national level could focus on developing capacities and ethical guidelines for the use of AI in academia, and facilitating collaboration and knowledge exchange between institutions, as the effects of knowledge sharing were evident in our results.

This body of research holds several promising avenues for future research. One direction is to develop an automated, AI-powered advising system for higher education. In essence, transform the explainable model into a software product that any institution can input its own data to receive a report on their institutional sustainable AI use and personalized recommendations. This could be accompanied by a benchmarking figure so that institutions could compare themselves to their peer group. Another route would be to explore micro-level effects on instruction and learning. By examining whether sustainable use of AI (as captured by SAUI scores) predicts students' learning, retention decisions or skill levels at a macro level. Is there a statistically significant difference in student outcomes between high SAUI institutions and low ones? Our impression is that the answer could be yes, and if so, such evidence would add to the case of why we should invest in AI for sustainability. Furthermore, other qualitative study might complement our quantitative approach. Detailed case studies of a handful of these entities would give narrative insight into the change management and obstacles and human stories behind the numbers.

Author Contributions

AM: Conceptualization, methodology, software, writing original draft, and writing review and editing. DRP: Data collection, methodology, software, visualization, writing review and editing. NLR: Data collection, methodology, visualization, writing original draft, writing review and editing, and supervision.

Conflict of interest

The authors declare no conflicts of interest.

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