UNDERSTANDING AI ADOPTION IN EDUCATION: A TAM PERSPECTIVE ON STUDENTS' AND TEACHERS' PERCEPTIONS

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Abstract: Over the past 30 years, we have experienced exponential growth. The advent of the Internet marked a significant shift in how we work and access information. We are now in a new phase, where the speed of information processing and storage capacity have prompted another exponential change. The arrival of new technologies such as mobile applications, Big Data, and artificial intelligence (AI) is transforming the university environment. These innovations aim to enhance the educational experience, optimize administrative processes, and support academic research. The effectiveness of these technologies depends on their acceptance by students and faculty, making it crucial to evaluate user adaptation. Despite extensive research on technology development, there is a lack of studies validating their impact and acceptance in academic settings. This research addresses this deficiency by presenting a new model based on the Technology Acceptance Model (TAM) tailored for university students and faculty. The study introduces an assessment system for digital maturity levels using a fuzzy 2-tuple linguistic model and the analytic hierarchy process (AHP). The results demonstrate a significant correlation between the use of AI and the enhancement of the academic experience in universities.

Technology adoption; Artificial intelligence; University environment; TAM model; Digital maturity; Educational processes.

1. INTRODUCTION

In recent years, the world has witnessed constant and rapid changes in an increasingly volatile, uncertain, complex, and ambiguous environment. This fact, combined with economic growth and the emergence of new technologies, is creating new opportunities in various fields, including university education.

Digital technologies have evolved to connect people and things globally, helping to address personal and global challenges. According to a UNESCO report, digital innovation has the potential to complement, enrich, and transform education, accelerating progress towards the Sustainable Development Goals (SDG 4) for education and enhancing the quality and relevance of learning (UNESCO, 2023).

The Technology Acceptance Model (TAM) has been extended to assess the acceptance of digital academic reading tools in higher education. Studies indicate that factors such as perceived ease of use and perceived usefulness are critical determinants for the acceptance of technology by students (Lin & Yu, 2023)this study contributes to the following findings: (1.

Additionally, research on artificial intelligence in higher education highlights the trends and applications of AI in various educational contexts. A systematic review of studies shows how AI is being utilized to enhance teaching and learning in universities (Crompton & Burke, 2023).

The Technology Acceptance Model (TAM) was proposed by Fred Davis in 1989 as an extension of the Theory of Reasoned Action (TRA) by Ajzen and Fishbein (Davis, 1989). TAM was designed to predict and explain the acceptance of technology by end-users, focusing on two main constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEU). PU refers to the degree to which a person believes that using a particular system would enhance their job performance, while PEU refers to the degree to which a person believes that using a particular system would be free of effort.

Since its introduction, TAM has been extensively validated and expanded to include various contextual and technological use factors. Venkatesh and Davis (2000) extended the original model to TAM2, incorporating social and cognitive factors such as experience and voluntariness. Later, Venkatesh and Bala proposed TAM3, integrating even more variables to explain the intention to use technology (Venkatesh & Bala, 2008). This model has been fundamental in understanding how and why individuals accept and use new technologies across different disciplines.

The university environment is a unique context where students and faculty interact with various technologies to enhance learning, teaching, and academic administration. Adapting TAM in this context is crucial to understanding the factors influencing technological adoption among students and academic staff. Recent studies have applied TAM to evaluate the acceptance of digital tools and learning platforms in higher education, demonstrating that PU and PEU are significant determinants of the intention to use (Cheung & Vogel, 2013; Lin & Yu, 2023).

Technology acceptance in the university environment is vital for the successful implementation of innovations such as artificial intelligence (AI), Big Data, and mobile applications. Evaluating the digital maturity of students and faculty using TAM can provide valuable insights into adaptation levels and potential barriers to technological adoption. A study by (Wang et al., 2022) integrated additional factors such as perceived security and personal investment into TAM, showing a moderate level of explanatory power for the use of online learning applications.

Research indicates that the Technology Acceptance Model (TAM) effectively explains social media influence, highlighting factors like perceived ease of use, critical mass, and connectedness (Al-Qaysi et al., 2020)and the Technology Acceptance Model (TAM. Studies reveal that factors such as perceived enjoyment, self-efficacy, and perceived security extend the TAM (Ikhsan, 2020), while age significantly impacts the adoption of social media and artificial intelligence (Marín Díaz et al., 2023).

2. METHODOLOGY

2.1. Criteria for Measuring AI Technology Acceptance

The selected criteria for our model to measure the technological adoption of AI in the university environment focus on the following aspects:

1. Perceived Usefulness (PU): This criterion measures the degree to which students and faculty believe that using AI will enhance their academic and professional performance.
2. Perceived Ease of Use (PEU): This criterion assesses the degree to which users believe that using AI will be free of effort.
3. Perceived Security (PS): This criterion evaluates the degree to which users feel secure using AI, including their confidence in the protection of personal data.
4. Personal Investment (PI): This measures the level of commitment and resources (time, effort) that users are willing to invest in learning and using AI.
5. Social Influence (SI): This criterion considers the impact of peers, colleagues, and superiors on an individual's decision to adopt AI.
6. Digital Maturity Assessment AI Adoption (DMAI): It is a compendium of the other criteria , reflecting the overall measurement formed by these factors.

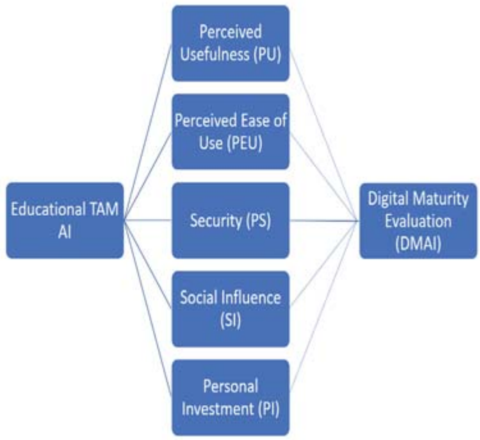

Figure 1. University AI Adoption Framework TAM-AHP. Source: Own elaboration.

2.2. AI Adoption Evaluation Framework Using TAM and AHP

The objective is to measure the selected criteria: perceived usefulness (PU), perceived ease of use (PEU), perceived security (PS), social influence (SI), and personal investment (PI). Information will be collected from university students and faculty through a survey. Using the AHP model integrated with the 2-tuple linguistic model, we can establish a classification of digital maturity regarding the use of AI and, additionally, perform clustering to group individuals based on their digital maturity levels.

The fuzzy linguistic model, LD2T, is essential for handling heterogeneous data in the university context due to inherent uncertainties in decision-making processes. LD2T allows decision-makers to use linguistic terms, capturing imprecision and uncertainty effectively (Herrera & Martínez, 2000).

Combining AHP and LD2T enhances decision-making by providing a structured framework for analyzing criteria and alternatives, while LD2T captures heterogeneous data through linguistic variables (Marín Díaz et al., 2023). In practical applications, AHP and LD2T can help prioritize university projects that align with student preferences. For example, AHP can evaluate criteria like technological accessibility, sustainability, and safety, while LD2T captures students' linguistic preferences regarding these criteria, enabling personalized interactions and services.

The complete process involves gathering survey data from university students and faculty to measure their perceived usefulness, perceived ease of use, perceived security, social influence, and personal investment. This data is then analyzed using the AHP model integrated with the 2-tuple linguistic model to classify digital maturity levels in relation to AI usage. Additionally, clustering techniques are applied to group individuals based on their digital maturity levels, as illustrated in the corresponding figure.

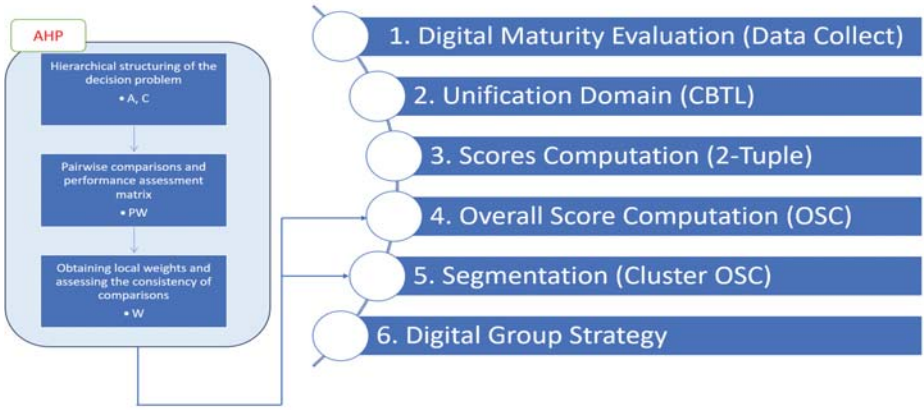

Figure 2. AI Adoption Evaluation Framework Using TAM and AHP in Universities. Source: Own elaboration.

1. Data Collection: This phase involves gathering essential data and information relevant to the variables or criteria under investigation. Each variable included in the model is quantified within a scale ranging from 0 to 4.
2. Determine the CBTL Domain of Expression for Each Criterion: This step involves establishing linguistic terms or categories to represent the various levels or degrees of each criterion. In this study, given the specific context, a five-point scale will be utilized, consisting of the values will be employed. Since this scale involves linguistic expressions, it will be modeled using the set
3. The 2-tuple model, based on fuzzy logic, is utilized to manage linguistic uncertainty and quantify the degree of membership for each linguistic term. For each evaluation, the variables are calculated as . This data range is then transformed into 2-tuple linguistic variables.
4. Calculate the Global Score for Each Interaction Using the AHP Model: The AHP model is employed to determine a global score for each student based on the weighted criteria.
5. Designate the Clusters That Identify Different Levels of Digital Development: Interactions can be grouped into clusters based on their similarities and differences in terms of the identified levels of digital development.

6. Develop a Digital Group Strategy for Each Cluster: This step involves creating tailored experiences, strategies, or interventions that address the specific characteristics, preferences, and needs of each cluster. Doing so can optimize digital development and enhance the overall satisfaction of individuals within each group.

3. DIGITAL MATURITY AI MODEL (DMAI), PRACTICAL APPLICATION

3.1. Data Collection

In this study, we establish a methodological framework to assess digital maturity levels using AHP (Analytic Hierarchy Process), 2-tuple linguistic model, and k-means clustering. A total of 422 records were selected for the study. Of these, 138 records pertain to individuals aged 18-20 years, representing students in the early years of their university education. The age range of 21-23 years corresponds to intermediate years, where students have acquired sufficient motivation to understand their future career aspirations. The age group of 24-25 years includes students who are either completing or have completed their studies and are seeking to specialize in their professional careers.

Figure 3 presents a bivariate diagram, where the X-axis represents the Age Range and the Y-axis represents the number of students for each of the TAM model evaluations. It is evident that with the increase in age, the students' valuation towards personal investment in developing digital maturity in AI is higher. A similar trend is observed with the influence of the environment, particularly from the faculty.

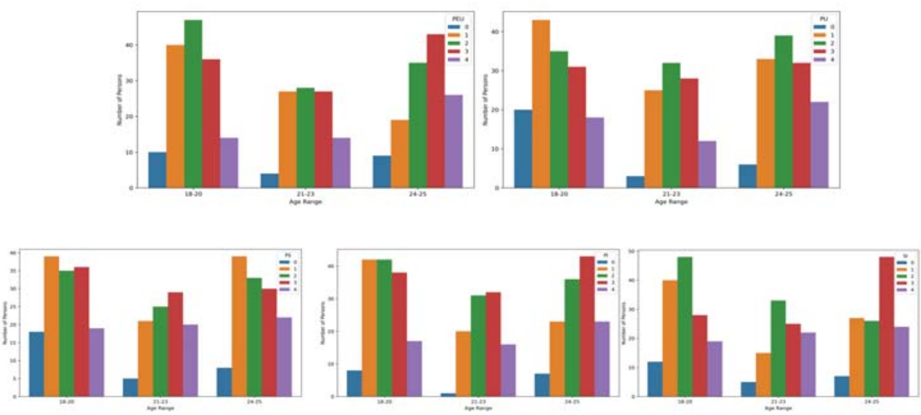

Figure 3. Histograms for AGE, PU, PEU, PS, PI, SI. Source: Own elaboration.

3.2. Unification Domain (CBTL)

The variables were categorized into a linguistic domain, and the results are displayed in Table 1. A sample set of data comprising 15 records has been selected. ID indicates the identifier of each individual included in the data sample.

Table 1. *Unfication Domain CBTL (2-tuple)*

ID	AGE	PU	PEU	PS	PI	SI
1	20	VL	M	L	L	L
8	18	L	H	L	L	M
16	20	VL	VL	M	VH	M
22	18	VL	M	L	M	M
118	18	M	M	M	M	M
143	20	L	M	H	VH	M
147	21	M	L	H	H	L
198	23	VH	M	L	H	H
219	22	L	VL	M	M	VH
284	23	VH	M	L	H	VH
404	22	VL	VH	L	L	H
407	24	VH	VH	H	H	M
408	25	L	H	M	VH	H
415	25	M	L	L	H	VH
418	24	H	H	VL	L	H

3.3. Individual Score Computation

At this stage of the study, it is vital to determine the relative importance of each feature in the DMT model before computing the overall interaction score. For this, the AHP model will be applied.

We will construct the following pairwise comparison matrix using the Saaty scale, as shown in Table 2.

Table 2. *AHP comparison matrix*

$$W = \begin{array}{cc} & \begin{array}{ccccc} PU & PEU & PS & PI & SI \end{array} \\ \begin{array}{c} PU \\ PEU \\ PS \\ PI \\ SI \end{array} & \begin{bmatrix} 1 & 1/3 & 1/3 & 1/5 & 3 \\ 3 & 1 & 1 & 1/3 & 3 \\ 3 & 1 & 1 & 1/3 & 3 \\ 5 & 3 & 3 & 1 & 5 \\ 1/3 & 1/3 & 1/3 & 1/5 & 1 \end{bmatrix} \end{array}$$

The individual hierarchical results yielded satisfactory outcomes, and consistency was confirmed when CR ≤ 0.10. In this case, CR is 0.057, validating the accuracy of the model's results.

The final weightings obtained are as follows: }.

As we can observe, the weight matrix assigns the highest value to personal investment in time to familiarize oneself with the study of AI applied to the university environment. This indicates that personal dedication and effort are considered the most significant factors in the digital maturity evaluation for AI adoption among university students.

Following personal investment, both perceived ease of use and perceived security hold equal importance, emphasizing that students' perceptions of how easy and secure it is to use AI are crucial in their acceptance and effective utilization of these technologies.

Perceived usefulness is ranked next, highlighting its moderate importance in the overall evaluation. This suggests that while students need to see the practical benefits of AI, this criterion is not as critical as personal investment or perceived ease of use and security.

Lastly, social influence has the smallest weight, indicating that the impact of social networks and peer opinions is considered the least significant factor in this context. Although it plays a role, it does not weigh as heavily as the other criteria in evaluating digital maturity for AI adoption.

This prioritization of criteria helps us understand where efforts should be focused to enhance the digital maturity of university students, ensuring they are well-prepared to integrate and utilize AI effectively in their academic and professional pursuits.

Table 3 displays the overall score of the DMAI (DME) model, as established in the preceding steps.

Table 3. *DMAI, Overall score*

ID	AGE	PU	PEU	PS	PI	SI	DMAI
1	20	VL	M	L	L	L	(L,0.025)
8	18	L	H	L	L	M	(L,0.101)
16	20	VL	VL	M	VH	M	(M,0.123)
22	18	VL	M	L	M	M	(M,-0.088)
118	18	M	M	M	M	M	(M,0.000)
143	20	L	M	H	VH	M	(H,0.028)
147	21	M	L	H	H	L	(M,0.116)
198	23	VH	M	L	H	H	(M,0.120)
219	22	L	VL	M	M	VH	(M,-0.070)
284	23	VH	M	L	H	VH	(H,-0.113)
404	22	VL	VH	L	L	H	(M,-0.108)
407	24	VH	VH	H	H	M	(H,0.043)
408	25	L	H	M	VH	H	(H,0.034)
415	25	M	L	L	H	VH	(M,0.059)
418	24	H	H	VL	L	H	(L,0.100)

The procedure described allows individual scores to be obtained for each person based on the designated criteria. This establishes a recommendation, prioritization and personalization model that assesses the potential of university students to use AI technology. Importantly, the methodology is not limited only to the selected criteria, but can be extended to cover a wider range of criteria, sub-criteria and various areas of numerical and linguistic representation.

3.4. Clustering

The correlation matrix between the DMAI score and the previously determined parameters, after applying the AHP model, underscores the significance of the identified characteristics. Notably, digital maturity levels increase with age, reflecting a greater commitment as students grow older.

Specifically, the matrix indicates a 28% correlation between age and digital maturity level. This moderate positive relationship suggests that as students age, their digital maturity in using AI tends to rise. This finding highlights the importance of considering age as a significant factor in assessing digital maturity and AI readiness in the academic environment.

Applying a clustering process using k-means, we obtain the following results:

Table 4. *Cluster represented in 2-tuple*

Cluster c	AGE	DMAI	Students
0	(VH,-0.065)	(M, 0.085)	185
1	(L, −0.079)	(M, -0.045)	115
2	(M, 0.100)	(M, 0.101)	122

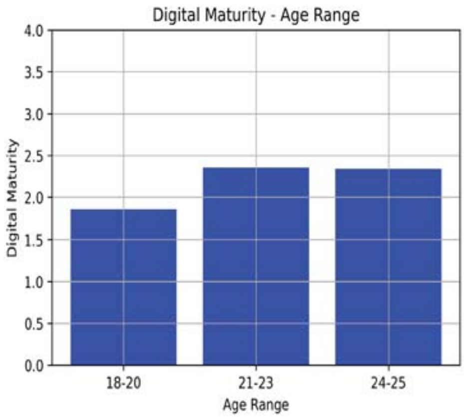

Figure 4. DMAI Range by Age. Source: Own elaboration.

3.5. Conclusions

The analysis of the clusters reveals significant insights into the digital maturity levels of university students regarding their readiness to use AI technology. The final weightings obtained and the clustering results suggest that different age groups exhibit varying degrees of digital maturity, influenced by several factors such as personal investment, perceived ease of use, perceived security, perceived usefulness, and social influence.

Cluster 0:

- Age Group: Senior students.
- Digital Maturity: Moderate with a positive inclination.
- Conclusion: Senior students tend to have a higher digital maturity level, likely due to greater exposure and experience with technology. This group, being the largest, indicates a substantial portion of the student population is well-prepared for AI integration.

- Recommendation: Focus on further enhancing their digital skills and leveraging their positive disposition towards technology for advanced AI applications.

Cluster 1:

- Age Group: Younger students.
- Digital Maturity: Moderate but slightly below the average.
- Conclusion: Younger students show a lower digital maturity level, possibly due to less experience and exposure. This is the smallest group, suggesting a need for targeted interventions.
- Recommendation: Implement specialized programs to boost their digital maturity, providing additional support and resources to bridge the experience gap.

Cluster 2:

- Age Group: Middle-aged students.
- Digital Maturity: Moderate with a positive trend.
- Conclusion: Students in the middle age range display a balanced level of digital maturity with potential for growth. This group's size is intermediate, indicating a significant portion of the student body is on an upward trajectory in digital competence.
- Recommendation: Maintain and enhance their digital maturity through continuous learning opportunities and tailored educational strategies.

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