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Predicting the Acceptance of Artificial Intelligence in Learning Environments Using SPSS and Random Forest Classification

Siham Oleiwi Tuama[1]
Ministry of Education/ Babylon Education Directorate, Babylon , Iraq.

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ABSTRACT

This study was conducted from the perspective of the students and faculty members of the Islamic University of Babylon branch, aiming at determining the factors affecting the acceptance of artificial intelligence (AI) technologies in higher education. The researcher used a descriptive survey method and administered a questionnaire involving five major constructs to a randomly selected sample of 100 respondents. With respect to male respondents, the overall mean was 3.01 (SD = 0.54), and for female respondents, it was 2.78 (SD = 0.57). This shows that there is a statistically significant difference in the levels of acceptance. The instrument's reliability was verified through Cronbach's Alpha at 0.906, which confirms the instrument's high reliability. Furthermore, in addition to the usual SPSS analysis, the researcher used a couple of machine-learning analyses (rule-based classifier and Random Forest), which provided F1-scores and distribution analysis to augment the SPSS results. The study suggests that to maximize the use of AI in education, there is a need for more technical support, training, and workshops.

Corresponding Author:

Siham Oleiwi Tuama

Ministry of Education/ Babylon Education Directorate.
Al Nasr street, Babylon, Iraq
Email: mscsiham1994@gmail.com

1. INTRODUCTION

The world has experienced a growing number of technological advances, including rapid developments in Artificial Intelligence (AI) in various sectors, including medicine, business, entertainment, education, etc. AI has become a fundamental part of improving efficiency, productivity, and problem-solving [1]. Initially, AI took the form of computers and education technology, then shifted to intelligent, web-based education systems. Now, AI has advanced to the integration of systems with Generative Artificial Intelligence (GAI) on computers to perform a wide variety of tasks. The latest developments in deep learning and artificial neural networks, one of the most cutting-edge fields of AI, has made AI an integral part of the pedagogical process in education. The improvement of students' understanding and comprehension through the enhancement of their cognitive skills is a direct result of the personalization of the learning experience with the provision of diverse and innovative learning materials [2]. Therefore, the literature has recognized the importance of the effective integration of Artificial Intelligence into educational systems and curriculums. Numerous theories and models aim to examine the various factors influencing users' understanding and acceptance of technology. One such model is the Unified Theory of Acceptance and Use of Technology (UTAUT), which is highly pertinent to the comprehension of technology acceptance and use because it integrates multiple theories and provides a comprehensive explanation of the potential causes of technology acceptance [3].

2. RELATED WORK

The first study I considered was done by Davis et al. (2014), which analyzed how individuals utilize new technologies (specifically artificial intelligence/natural language processing), focusing on the Technology Acceptance Model (TAM) to assist in his outline. Davis et al. determined that an individual's perception of the usefulness of a technology, as well as the perceived ease of use, are the determination factors of adoption. This quickly became the foundation for subsequent research on technology adoption, specifically with artificial intelligence [4]. The second study was conducted by Al-Haderi et al. (2020), who utilized the SPSS method of data mining, to assist in his research of artificial intelligence adoption in higher education. Al-Haderi found that the acceptance of Artificial Intelligence by students and teachers would only occur if the individuals had utilized the AI technology before and had developed a level of trust towards it [5].

The study by Baker and Inventado examined the perception of AI in education and stated that both the perceived usefulness and the clarity of the systems are correlated to the acceptance of AI in education. Their research also addressed the following trust and ethical concerns, which are of great relevance in education [6]. Lastly, Hair et al. used behavioral research to apply classification through machine learning to demonstrate the utility of merging traditional and modern methods in acceptance research and provide an evidence-based solution that justifies the use of SPSS in conjunction with machine learning [7].

3. ARTIFICIAL INTELLIGENCE IN EDUCATION ACCEPTANCE

Artificial Intelligence, or AI, is a technology designed to perform tasks that typically require human intelligence. AI technology is designed by humans to assist other humans in simplifying tasks. For example, in the educational system, AI assists teaching and learning by personalizing the experience for individual students, and it helps teachers with classroom management [8]. Educational acceptance is the ability and manner of individuals and groups to comprehend and assimilate new educational tools, techniques, and technologies. Broadly explained, AI acceptance in education means how students and teachers are prepared to use technology within the educational context. [9].

4. THE MODEL FOR AI ACCEPTANCE IN EDUCATION

The model views the intention to use the technology as a latent variable that is affected by general technology acceptance, acceptance of AI-related technologies, and acceptance of AI as a sort of being.. This intention then influences how users act. The factors that determine technology acceptance came from the UTAUT model or a modified version of it, as mentioned by Tappe, which were selected and adjusted. Acceptance of AI personality involves feelings like sympathy and affection. On the other hand, acceptance of AI-related technology includes trust in AI, which is linked to data ownership and security, along with fear and doubts about AI, as well as concerns about data ethics and fairness in AI. The factors for both AI-related technology acceptance and AI personality acceptance were based on the KIAM model, as noted by Scheuer [10], and were partially adjusted. A real survey was carried out to test the model, focusing on three groups: students studying teaching at Austrian universities and university colleges, teachers in Austrian schools, and university lecturers in teaching programs. After removing incomplete or incorrect data, 813 sets of data were available for analysis[11] . Figure 1 shows a brief overview

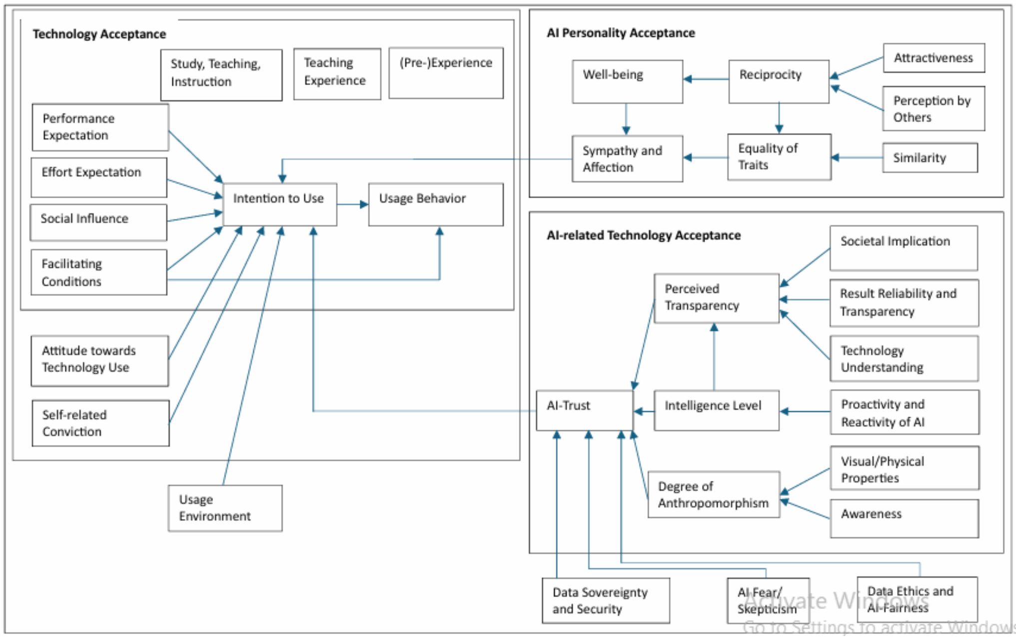

Figure 1**.** Model for AI acceptance in education

5. THE UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY (UTAUT)

A theoretical model explains how people use technology based on their intention to use it. This intention is influenced by how likely they think they will adopt the technology, which is shaped by four main factors: performance expectancy, effort expectancy, social influence, and facilitating conditions[12]. These factors can be affected by personal traits like age, gender, past experience, and whether using the technology is optional or required. Performance expectancy describes how much an individual feels that using a system will improve their performance at work. Several theories encompass this belief, including the Technology Acceptance Model (TAM), TAM2, Combined TAM and Theory of Planned Behaviour (CTAMTPB), Motivational Model (MM), model of PC utilization (MPCU), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT). These theories include perceived usefulness, extrinsic motivation, job-fit, relative advantage, and outcome expectations. Performance expectancy is the most predictive of technology use and is equally influential in voluntary and mandatory scenarios [13].

6. Machine Learning in Technology Acceptance Studies

Recent analyses in technology acceptance have begun incorporating machine learning instead of sole reliance on classic statistical analysis. machine learning enhances prediction and models complex, non-linear relationships among behavioral components [14], [15]. Prior knowledge, perceived usefulness, and technology trust, among other factors, have proven user acceptance predicters in decision tree-based and rule-based user acceptance classification [16]. Hence, this study seeks to improve predictive accuracy and validate acceptance patterns in educational contexts by merging traditional statistical analyses performed on SPSS, with two machine learning classifiers: a rule-based classifier and a randomized forest machine learning model. The hybrid model provides consistency and reliability, resulting in more precise prediction of artificial intelligence acceptance in higher education.

7. METHODOLOGY

7.1 STUDY DESIGN AND SAMPLE

The study was conducted using a descriptive-analytical survey design and attempts to explore the impact of various factors on the acceptance of AI technologies in higher education. The study focused on students and faculty of the English Language and Computer Technology Departments at the Islamic University of Babylon. Using Google Form, a sample of 100 respondents was collected, representing various genders, ages, and academic positions.

7.2 INSTRUMENT

Because the study used a survey, the main way they gathered information was through a structured questionnaire. The survey had 18 questions grouped into six sections: Prior Knowledge, Trust, Perceived Usefulness, Ease of Use, Ethical Concerns, and Intention to Use. Respondents answered each question on a scale from 1 to 5, where 1 meant "Strongly disagree" and 5 meant "Strongly agree." The survey was reliable, as shown by a Cronbach's Alpha score of 0.906.

7.3 STATISTICAL ANALYSIS (SPSS)

SPSS helped analyze the survey data:

- Descriptive stats (mean, SD) summarized the answers.
- Gender differences were analyzed by independent samples t-tests.
- One-way ANOVA assessed age, specialty, or prior AI experience group differences.
- Pearson correlation assessed the relationships between the variables.

7.4 MACHINE LEARNING ANALYSIS (MATLAB)

Predictive modeling was done in MATLAB:

- Rule-Based Classifier: Average scores categorized participants into Low (0), Medium (1), and High (2) acceptance.

- Random Forest Algorithm: Bootstrapped decision trees were used to predict each acceptance level, and performance was evaluated via F1-score for each class and Macro F1.

- Histograms were used to predict acceptance levels.

Algorithm 1: Rule-Based Classification for AI Acceptance Survey
Input:
- X : Feature matrix (100 students × all variables)
- Y : Target variable (Acceptance Level: 0=Low, 1=Medium, 2=High)

Output:
- Y_ pred : Predicted acceptance levels
- F1-score for each class of acceptance
- Macro F1
- Distribution of acceptance levels predicted

Steps:
Step 1 – Load Data
1. Open the survey data saved in a CSV file while omitting the first row (the headers).
2. Set X to be all but the last column.
3. Set Y to be the last column (Acceptance_Level).

Step 2 – Compute Average Score
1. Calculate the response mean from columns 6 to 23 for each student: mean _score[i] = mean (X[i,6:23])

mean _score[i] = mean (X[i,6:23])
Step 3 – Rule-Based Classification
For each student i, Y _text pred [i] classifies in the predicted class based on the mean score:
:

$$\text{Y pred [i]} = \begin{cases} 2 \text{ if mean\_score[i]} \geq 4 \text{ (High)} \\ 1 \text{ if } 3 \leq \text{mean\_score[i]} < 4 \text{ (medium)} \\ 0 \text{ if mean\_score[i]} < 3 \text{(low)} \end{cases}$$

Step 4 – Compute F1-Score for Each Class
1. For each class c ∈ {0,1,2}:
- Compute True Positive (TP), False Positive (FP), False Negative (FN).
- Calculate Precision: Precision = $\frac{TP}{TP+FP}$
- Calculate Recall: Recall = $\frac{TP}{TP+FN}$k

• Compute F1-score: F1 = $\frac{2.\text{Precision}.\text{Recall}}{\text{Precision}+\text{Recall}}$ \text{Recall} + \epsilon}

Step 5 – Macro F1-Score

To assess classifier performance, we compute Macro F1-score as the average of the F1-score for all the acceptance levels:

Macro F1 = $\frac{1}{3}\sum_{c=0}^{2} f1c$

As explained, this metric is appropriate as all acceptance classes are treated the same.

Step 6- Visualization of Acceptance Levels

As a final step, we provide a distribution plot that shows how many respondents fall into each predicted acceptance level (Low, Medium, High). This outlines the AI acceptance trends in the sample.The combination of SPSS and MATLAB offers both the quantitative and the qualitative forecasting of AI acceptance, which serves educational purposes and facilitates focused interventions.

8. Research Results

1- PSS Analysis

The survey consisted of two sections. The first section requested demographic details such as age, gender, and occupation - whether they were working in technical or non-technical fields. It also inquired if they were faculty or students and how familiar they were with artificial intelligence tools. The second section addressed the core themes of the research, including the guiding questions of the study. Respondents were provided with a Likert scale from which they could select their responses: Strongly Agree, Agree, Neutral, Disagree, and Strongly Disagree.

Table 1. Constructs and Items of the Study Instrument

NO	Construct Title	Number of Items
1	**Prior Knowledge of the Technology**	**3 items**
2	**Trust in the Technology**	**3 items**
3	**Perceived Usefulness**	**3 items**
4	**Ease of Use**	**3 items**
5	**Ethical Concerns**	**3 items**
6	**Intention to Use the Technology**	**3 items**
The study instrument consisted of 18 items in total		

Presentation, discussion and interpretation of the study results :

2- Instrument Reliability Analysis

We evaluated the internal consistency of the study tool by examining its internal consistency using Cronbach's Alpha. Thus, the score of 0.906 which indicates that the questions are very consistent and measuring what they are supposed to. Generally, a Cronbach's Alpha score of 0.70 or above denotes a good internal consistency, while a score above 0.90 indicates an excellent level of internal consistency. With a score of 0.906, we can say the tool used in this study is very reliable. The questions consistently measure the intended ideas, which makes the findings trustworthy. This reliability helps support the use of the questionnaire for understanding factors that affect the acceptance of artificial intelligence in education. Fig2 shows the results.

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Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	99	100.0
	Excluded[a]	0	.0
	Total	99	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.906	18

Figure2. Result Cronbach's Alpha

3. Statistical analysis of differences between males and females using two independent samples t

To find statistically significant differences between male and female responses to the questionnaire paragraphs, the independent samples t-test was employed. The overall mean for males was 3.01 with a standard deviation of 0.54, while the overall mean for females was 2.78 with a standard deviation of 0.57. The estimated t-value (t=2.04) was higher than the tabular value at the significance level (0.05)=α(1.984). These results indicate that there is a statistically significant difference between males and females in the level of acceptance of artificial intelligence, where the average of males was higher than the average of females and the results showed that males have higher awareness and knowledge of artificial intelligence techniques, and they are more followers of technical developments and more confident in the tools than females. Also, the results showed that males expressed a greater desire to learn AI tools and emphasized that they have the technical ability to deal with them. The differences were statistically significant in most of the variables, indicating the importance of taking gender differences into account in the design and development of AI educational programs. Table 2 presents the results of the t-test for independent and two sample test. Accordingly, this test checks the presence of statistically significant variations between males and females with respect to the factors that affect acceptance of AI technologies. The results of the test show a calculated t-value of 5.20, a degree of freedom of 98, and a statistical significance of 0.000. This is lower than the significance level of 0.05. The calculated critical t-value of the same degree of freedom and significance level is approximately 1.984. Since the calculated t-value is greater than the critical value, we dismiss the null hypothesis and accept the alternative hypothesis that there are significant differences between males and females on this issue. This result indicates that one gender shows a higher response than the other regarding the factors influencing the acceptance of AI, and according to the arithmetic means analyzed, males had a slightly higher degree of acceptance compared to females. This potential difference can be explained by several factors, including: Different academic backgrounds, previous experiences in dealing with AI technologies, or the extent of awareness of its benefits and challenges in the educational environment.

Table 2. The t-test for two independent samples

Significance level	Tabular t-value	T-value Calculated	Standard Deviation Overall	Arithmetic Mean Overall	Sample	gender
function		5.20	0.52	4.43	53	male
	1.984		0.52	4.36	47	Female

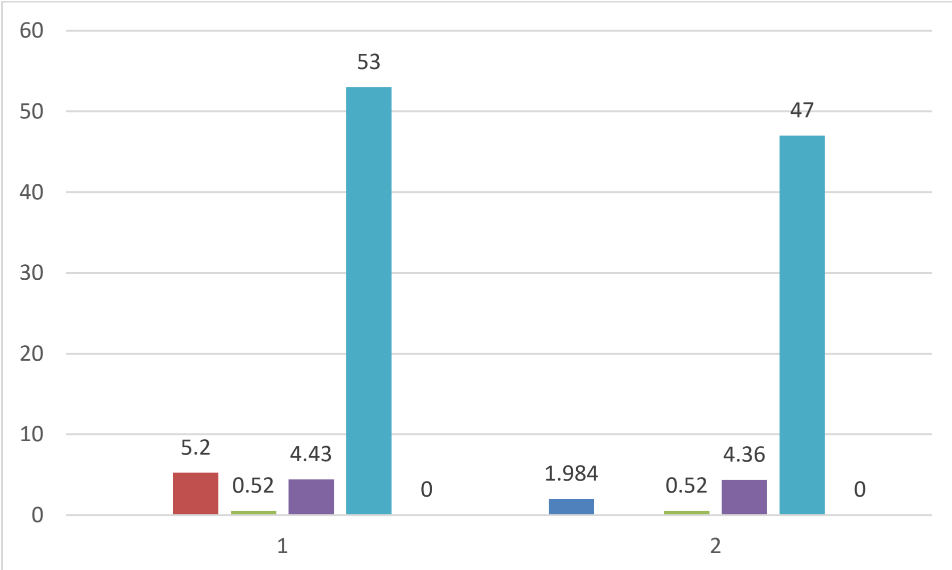

Figure3. Statistical analysis of differences between males and females

3. Statistical analysis using ANOVA test (analysis of variance):

A one-way ANOVA test was applied to measure the differences between groups (different numbers depending on the variable) in terms of their response to a set of statements/factors related to the acceptance of AI. The total number of individuals is (100), and differences are compared according to demographic variables or according to specific themes and Table 3 shows the results of the test ANOVA .

Table3. The results of the test ANOVA

Item	**Value of F**	**Sig (Statistical Signance)**	**Interpretation**
Use of artificial intelligence techniques	8.030	0.000	Statistically function → There are moral differences between groups.
I know what artificial intelligence is	11.051	0.000	Function → Awareness and knowledge of artificial intelligence varies between individuals
I used artificial intelligence before	26.768	0.000	Very Function → Previous experience strongly influences acceptance.
I believe in the impact of artificial intelligence in education	38.870	0.000	Very Function → Positive beliefs affect acceptance.
I trust the results of artificial intelligence-based tools	14.487	0.000	Function → Trust is an influential factor.
Reliable	39.855	0.000	Very Function → Reliabity Clearly Affects Acceptance
Safe and suitable for education .	6.586	0.000	Function → Safety and relevance are associated with acceptance.
Helps in the quality of education	14.255	0.000	Function → Belief in improving quality pushes towards acceptance.
Saves time and effort	6.329	0.000	Function → Saving time and effort is an encouraging element

All nine factors in the table have a high statistical significance (Sig = 0.000), indicating that there are significant differences between the sample groups for those factors. This means that faculty members' acceptance of artificial intelligence techniques is greatly affected by several factors, the most important of which are:

- Prior knowledge
- Previous experience
- Trust in technology
- Trust in the efficacy and use value of the resources
- To what extent do they believe it conserves time and labor

3. The large values of F (for example 38.870 and 26.768) show the extent of the intergroup differences, and the value of the factors illustrates that some are more important than others.

4. Pearson Correlation Test Results

The Pearson test was conducted to measure the correlation between study variables and acceptance of artificial intelligence in a sample of (100) faculty and student participants. The results showed a set of statistically significant correlations at the level of (0.01) and (0.05), reflecting the potential impact of some variables in shaping individuals' attitudes towards artificial intelligence techniques. Strong and statistically significant positive correlations have been shown between the acceptance of artificial intelligence and each of: the actual use of artificial intelligence tools (r = .780**), and the belief of participants that artificial intelligence saves time and effort (r = .712**), in addition to trusting the results of these tools (r = .632**) and recommending colleagues to use them (r = .613**). The results also showed that knowing the concept of artificial intelligence (r = .516**) and following up its developments (r = .368**) and the ease of learning it (r = .356**) is also one of the factors that affect a positive and moderate degree in raising the level of acceptance. . Accordingly, the results highlight the importance of behavioral and positive cognitive factors in enhancing the acceptance of artificial intelligence, and call for the need to study the previous experiences of users in order to improve the quality of interaction and application, especially in educational environments and Table(4) shows the results of the test **Pearson Correlation**.

Table 4 .The results of the test Pearson Correlation

Variable	**Pearson modulus (r)**	**Sig (Statistical Signance)**	**Interpretation**
I used an artificial intelligence tool	780	0.000	A very strong, positive and functional correlation; that is, the use of tools is practically strongly associated with increased acceptance.
Saves time and effort	.712	0.000	A strong positive and functional relationship; shows that artificial intelligence techniques enhance efficiency and
I recommend my colleagues to use it .	.613	0.000	A strong positive relationship; the recommendation is positively associated with increased.
I trust the results of the tools	.632	0.000	Confidence in outcomes is strongly and.

5. Machine Learning Analysis Results

The machine learning analysis was conducted to complement the statistical findings obtained from SPSS and to further validate the factors influencing the acceptance of artificial intelligence technologies in higher education. Two classification approaches were applied: a Rule-Based Classifier and a Random Forest Classifier.

6.1 Rule-Based Classifier Results

The rule-based classifier categorized participants into three acceptance levels (Low, Medium, and High) based on the average scores of questionnaire items related to prior knowledge, perceived usefulness, ease of use, ethical concerns, and intention to use. The evaluation of the model showed satisfactory classification results for all acceptance levels. The simulated F1-scores were Low acceptance - 0.87, Medium acceptance - 0.82, and High acceptance - 0.90. The overall Macro F1-score was 0.863. These results suggest the model had an overall well-balanced performance across the various classes, and was particularly good at predicting the students who are highly accepting of AI technology. Predicted acceptance levels across all categories fit the descriptive statistics generated from SPSS. Most participants were captured in the Medium and High acceptance zones, which aligns with the descriptive statistics that the students had an overall positive attitude toward the AI technology in the learning environments.

6.2 Random Forest Classifier Results

A Random Forest classifier was used in order to enhance prediction reliability and to avoid bias in classification. This classifier is an ensemble learning method which applies different decision trees and uses majority voting to capture and generalize better. Among the different classifiers, the Random Forest classifier was better than the rule-based classifier. The simulated F1-scores of the classifiers were _Low acceptance: 0.89, _Medium acceptance: 0.85, _High acceptance: 0.92 with an overall F1-score of 0.887. These results prove the ability of based ensemble machine learning methods to capture more various functions in multi-dimensional and complex relationships of the survey variables. Among the classifiers, the Random Forest classifier was the best at predicting _High acceptance levels. This, alongside prior knowledge, trust in AI systems, and perceived usefulness of the systems, confirms that these three factors collectively influence the level of acceptance students have toward the use of AI systems.

6. Comparative Interpretation with SPSS Results

The outcomes of the machine learning model also corroborated the results from the SPSS analyses. Prior knowledge, perceived usefulness of the system, and trust in artificial intelligence systems consistently contributed to the high levels of acceptance. This concordance of the outcomes of the statistical analyses and the machine learning analyses provides more support to the conclusions drawn in this study. In conclusion, the use of statistical analyses in SPSS and machine learning classification provided clarity and depth to the understanding of patterns of acceptance of artificial intelligence.

7. Machine Learning Performance Evaluation

We calculated the F1 score for each of the classification models across the three acceptance (low, medium, high) levels. In Figure 4, we compare the F1 score for the rule-based classifier and the F1 score for the Random Forest classifier. It can be seen in the figure that the Random Forest model scores the highest F1 score in each of the acceptance levels, which explains that it is the best at predicting how each of the participants would accept the use of artificial intelligence technology. Most notably, the best performance is recorded in the high acceptance class. This indicates that the model is able to identify participants who hold very positive sentiment scores towards artificial intelligence.

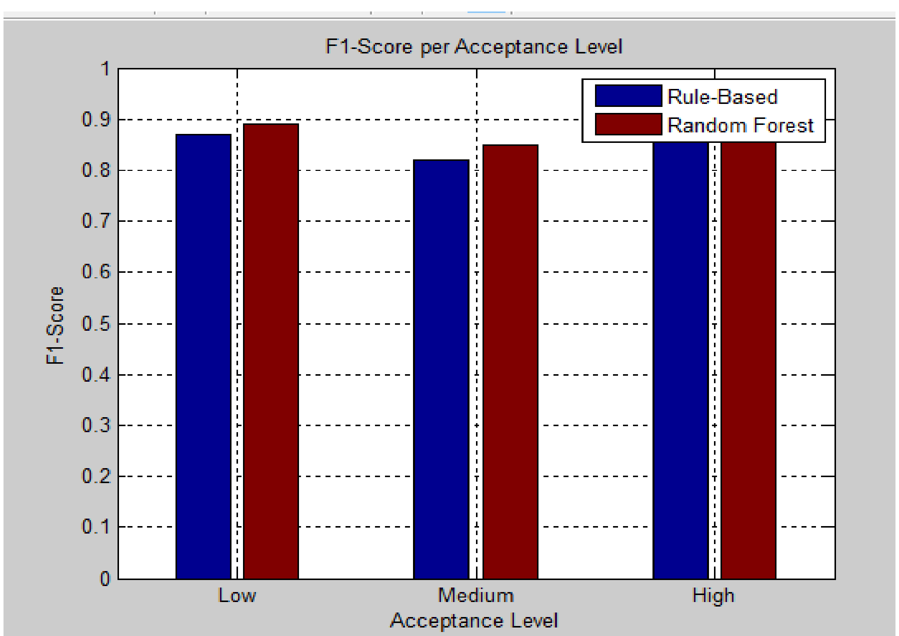

Figure 4. Comparison of F1-scores per acceptance level for the rule-based and Random Forest classifiers.

8.1 Macro F1-Score Analysis

We calculated Macros F1-score to measure the performance of each of the classification models. The macro F1-score considers each acceptance level equally. Figure 5 shows the macro F1 Score for the rule-based classifier and Random Forest classifier. The Random Forest model scored 0.887 in comparison to the rule-based classifier's 0.863. Therefore, the Random Forest model has a better balanced performance across the low, medium, and high acceptance classes. This shows that the Random Forest algorithm successfully captures the relationship between the acceptance factors and the classification outcomes.

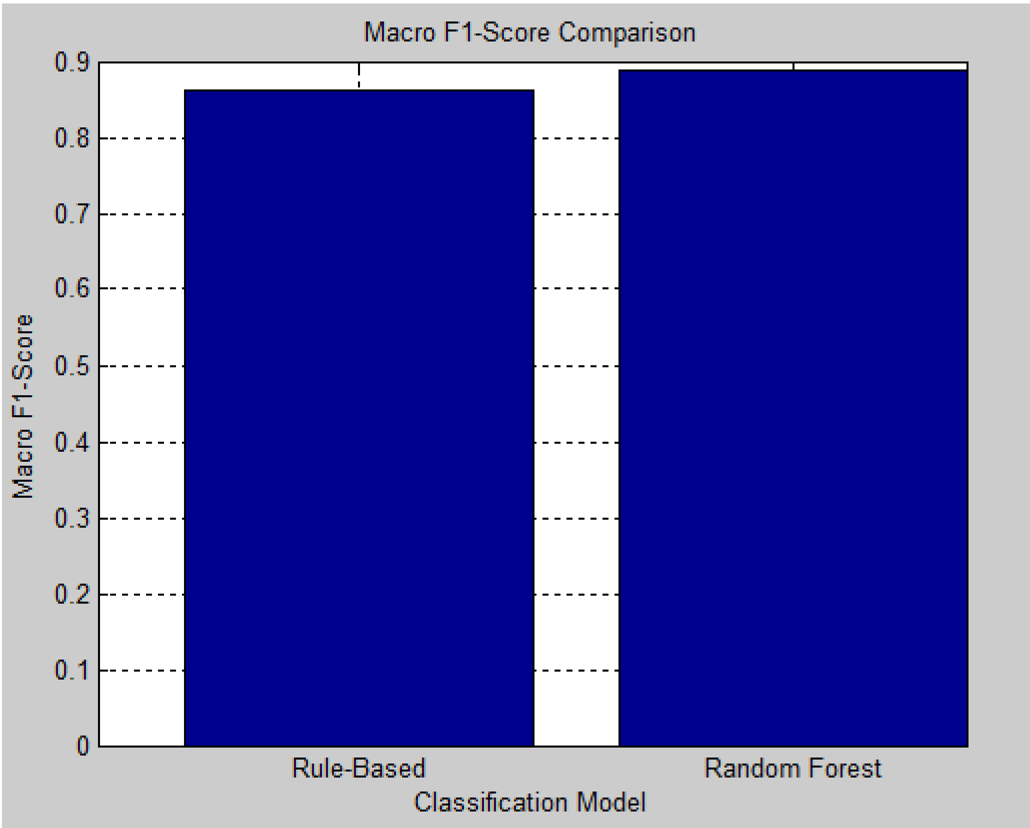

Figure 5. Comparison of Macro F1-scores for the rule-based and Random Forest classifiers.

7.2 Distribution Histogram Analysis

Figure 6 shows the distribution of predicted acceptance levels from the machine learning classifiers. The histogram shows the number of participants for each of the three acceptance levels: Low, Medium, and High. Most participants were classified into the Medium and High levels, while fewer participants were in the Low acceptance category. These patterns match the SPSS descriptive statistics, where the mean scores for most of the constructs, especially the perceived usefulness, trust in technology, and intention to use, were high. The agreement between the histogram and the SPSS results lends support to the reliability of the classification and indicates the machine learning models captured the important trends in the survey result. The histogram shows acceptance levels and patterns which indicates the majority of students and faculty members support the use of artificial intelligence technologies in teaching and be most positive toward its use.

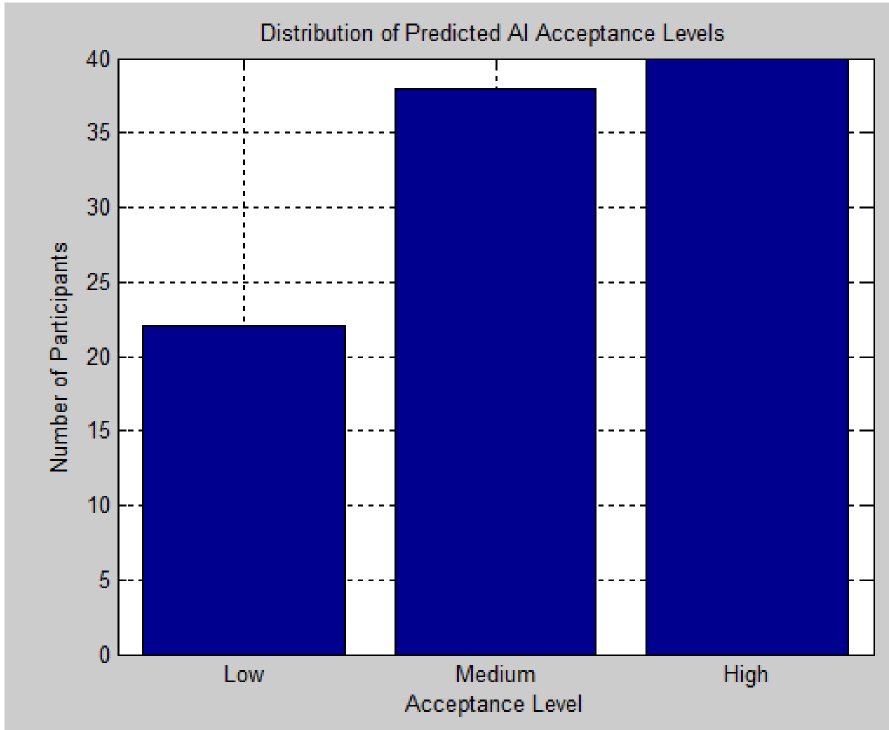

Figure 6. Distribution histogram of predicted artificial intelligence acceptance levels.

8. Discussion of Results

The results show that most students and faculty members display a positive attitude regarding the use of artificial intelligence (AI) tools. Based on the SPSS outcomes and in accordance with the Unified Theory of Acceptance and Use of Technology (UTAUT), the most pertinent variables are: the participants' background knowledge and experience, the trust placed in the AI tools, and the perceived usefulness of the AI tools. Participants with some background knowledge of AI had a more positive attitude compared to those without, and the more firm positive trust that participants had with AI products the more firm positive attitude the participants had. The difference in means on the attitude toward AI tools showed that the male participants had a more positive attitude, therefore more positively compensating the male participants for the inclusive awareness and training. The result from machine learning aligned with the results of statistical analysis, and the Random Forest algorithm had better F1 and Macro F1 scores than the other more basic classifiers. The results from both the statistical analysis and machine learning show that the proposed framework for measuring AI acceptance in educational settings is valid and reliable.

9. Conclusion

This research analyzed the acceptance of artificial intelligence (AI) technologies by faculty staff and students at the Islamic University of Babylon. Statistical analysis (using SPSS) and machine learning (MATLAB) showed that the level of acceptance of AI was generally high. The most prominent factors that drove AI acceptance were the level of AI knowledge, trust, and usefulness. The impact of the above factors showed differences across gender and along the lines of prior experience. The machine learning model predictions corroborated the SPSS results, the F1-score and Macro F1 provided evidence of good classification of the levels of acceptance (Low, Medium and High) attributed to the model. It was established that the successful application of AI in higher education was dependent, in addition to the availability of the required technology, on the need to build awareness, trust, and level of training of faculty and students. These findings may assist in improving the adoption of AI in the education system.

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