Unveiling Student Satisfaction in Online Learning: Leveraging Artificial Neural Networks for Predictive Insights

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***Abstract*— Amidst the surge in online learning, understanding factors contributing to student satisfaction becomes paramount. This study utilizes an Artificial Neural Network to predict satisfaction levels in online courses, considering variables like Online self-efficacy, Instructional design, Perceived Usefulness, Perceived System Quality, Assessment, and Learner Content Interaction, which impact attitude and behavioral intention. Primary data collected via a survey of 382 postgraduate management students from Tamil Nadu, India, was used to train the ANN model, enhancing its accuracy through techniques like data preprocessing, feature selection, and model optimization. Leveraging ANN capabilities, the study aims to identify key factors influencing student satisfaction in online learning, offering insights into their intricate relationship. The ANN demonstrated strong predictive performance. Behavioral Intention achieved 97.00% during training and 92.17% during testing, while Attitude reached 99.25% in training and 96.52% in testing. The Satisfaction model showed 98.13% in training and 97.39% in testing. Confusion matrices and key metrics like True Positive Rates (TPR) and True Negative Rates (TNR) highlighted the model's reliability, with TPR above 88% and TNR over 96% for all outcomes. These findings underscore the potential of ANN-based models for assessing student satisfaction in online learning environments and highlight the significant role of Attitude and Behavioral Intention in satisfaction forecasting. Moreover, the predictive prowess of the ANN model provides educators and institutions with a practical tool to assess and improve student satisfaction in online learning environments.**

***Keywords*—Online Learning, Artificial Neural Network (ANN), Predictive modeling, Predictive analytics, Students' Satisfaction, online platforms.**

***ICTIEE* Track*:* Curriculum Design**
ICTIEE Sub-Track: Leveraging AI in Curriculum Design

I. INTRODUCTION

In the fast-paced ecosystem of higher education, driven by technological progress and system shocks such as the COVID-19 pandemic, the quality indicators of e-learning like effectiveness and satisfaction have drawn increasing attention. Alnagar (2020) highlights the significance of understanding the factors behind e-learning satisfaction in enhancing learning experiences. Online learning, facilitated by digital technology, has emerged as a pivotal educational mode, offering flexibility and accessibility through the Internet. Online learning caters to diverse needs, enabling learners to access educational resources and engage in coursework at their convenience. This flexibility appeals to individuals with busy schedules, professionals, and those with limited access to traditional institutions. It provides a wide array of educational opportunities, empowering learners to tailor their educational journey to their interests and aspirations. Additionally, online learning supports a personalized, self-driven approach, allowing learners to control both the pace and order of concepts. This individualized learning experience enhances comprehension and retention. Through statistical techniques such as regression analyses and structural equation modeling, researchers have explored various antecedents that influence student satisfaction in e-learning education. These investigations, including those by Alnagar (2020), shed light on both the opportunities and challenges in online education. Emerging methodologies like Artificial Neural Networks (ANN), as demonstrated by Alnagar (2020), hold promise for accurately predicting student satisfaction. Several studies have been done to predict students' performance in e-learning using Neural Network Analysis (Qiu et al. et al., 2022; Wan et al. et al., 2022; Brahim, G.B., 2022; Aydoğdu, Ş., 2020). However, Dalia Kamal Fathi Alnagar (2020) created an ANN model that explores how instructor attitudes and responses, course flexibility and types, virtual interactions, assessments, internet quality, and technology quality influence.

Although studies have investigated factors impacting

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satisfaction in online learning, using interactions as proxies: learner-instructor, learner-content and self-efficacy, the literature review does not address MOOCs' unique characteristics and challenges. In contrast to traditional learning, MOOCs differ in scale, diversity of participants, and instructional design, which may influence student satisfaction differently. By leveraging ANN methodology, the study aims to fill this research gap by providing predictive insights into factors affecting student satisfaction in MOOCs through the mediating effect of attitude and behavioral intention. The authors envision that the study offers a nuanced glimpse into the dynamics of MOOCs and informs strategies for improving student experiences and outcomes in these increasingly popular online learning platforms.

II. Literature Review

In as early as 1985, Davis predicted the acceptance and usage of technological applications using two variables: perceived usefulness and perceived ease of use in the Technology Acceptance Model (TAM). These variables are crucial as they influence users' decisions to adopt and engage with Technology. Perceived usefulness focuses on how much a technology user trusts that using a Technology boosts performance. Perceived ease of use measures how much the Technology is free from effort. TAM also includes “behavioral intention” and “actual use of the Technology” as dependent variables, offering a framework to forecast and explain user engagement with technological tools. Several studies have applied TAM to various domains, including recent work by Alshammari (2020), which reinforced the model's relevance in understanding technology adoption.

Alongside TAM, Self-Determination Theory (SDT) explores behavioral intentions in online learning contexts. Raman et al. (2022) applied SDT to develop frameworks that address how intrinsic and extrinsic motivations influence online learning behaviors. This approach focuses on how fulfilling psychological in online learning platforms impacts users' engagement and satisfaction.

The Theory of Planned Behavior explains how attitudes toward specific behaviors influence intentions and actions. In online learning, positive attitudes toward the educational process are linked to increased motivation, engagement, and persistence. This theory helps clarify how learners' attitudes shape their intentions to engage in and persist with online learning (Ajzen, 1991).

Moore proposed a framework in 1994 that identifies how a learner's interaction with other learners, instructors, and content affects satisfaction in a distance learning environment. Hillman, Willis, and Gunawardena (1994) expanded on this by including another learner interaction, i.e., with the technology interface, as it facilitates engagement with content, instructors, and peers. Interactions play a critical role in distance education due to the physical separation between learners and instructors (Moore & Kearsley, 1996). To the existing set of interactions by Moore’s model, Anderson, and Garrison (1995) added the following interactions: between instructors, users, and content to content, offering a comprehensive view of how various interactions affect the learning experience.

Research by Bray et al. (2008), Burnett (2001), Moore and Kearsley (1996), Northrup, Lee, and Burgess (2002), and Thurmond and Wambach (2004) consistently underscore the positive impact of interaction on student satisfaction in distance education. These studies emphasize how effective interactions contribute to a more satisfying and engaging online learning experience.

A broad array of research has investigated online learning, revealing challenges and opportunities for enhancing student satisfaction. Studies by Ulum (2022), Mihail and Carmen (2022), Aljawarneh and Alharbi (2021), Chae and Shin (2016), Hwang, Wu, and Chen (2012), and Goldenberg, Andrusyszyn, and Iwasiw (2005) have explored various factors impacting online learning satisfaction. Key factors influencing student satisfaction include learner-instructor interaction (Alqurashi, 2019; Kuo et al., 2013), learner-content interaction (Alqurashi, 2019; Kuo et al., 2013), and Internet or online self-efficacy (Aldhahi & Baattaiah, 2021; Alqurashi, 2019; Kuo et al., 2013; Chu and Chu, 2010; Eastin and LaRose, 2000). Among these, learner-learner and learner-instructor interactions are often found to be more strongly correlated with student satisfaction than learner-content interaction (Bolliger & Martindale, 2004; Jung et al., 2002; Rodriguez Robles, 2006; Thurmond, 2003). Battalio (2007) concluded that learner-instructor interaction was particularly crucial. However, Rodriguez Robles (2006), in a web-based distance education context demonstrated that student satisfaction was not dependent on Internet self-efficacy.

Shen and Marra (2013) emphasized the role of self-efficacy in online learning, identifying dimensions such as course completion, social interaction with peers, handling course management tools, instructor interaction, and academic collaboration. Zaheer and Babar (2015) highlighted student satisfaction across dimensions, including assessment, course content, instructor quality, and learning resources. Puska and Puska (2020) identified metacognitive strategies, self-efficacy, goal setting, and social dimensions as influential factors. Chang and Tung (2008) proposed a hybrid model for technology acceptance that integrates innovation diffusion theory and TAM, emphasizing perceived system quality and computer self-efficacy, leading to user acceptance of e-learning tools. Further, research has examined how course elements like structure, quality, and support systems factors, peer networks affect the e-learning experience (Arbaugh, 2000; Areti, 2006).

Online self-efficacy (Prior et al., 2016; Keshavarz et al., 2023), instructional design (Elkilany, 2015; Watson et al., 2016), perceived usefulness (Azman et al., 2020), perceived system quality (Um, 2021), assessment methods (Williams, 1992; Bahar & Asil, 2018), and learner-content interaction (Sun & Hsu, 2013) are just a few of the factors that influence a student's attitude towards learning. These factors play a role for assessing the way students interact with and perceive their learning experience. In the same vein, a student's behavioural intention regarding learning is influenced by several of factors, including online self-efficacy (De Vries, 1988; Mallya, 2019), instructional design (Alshammari, 2020), perceived usefulness (Hwa et al., 2015), and perceived system quality (Jameel et al., 2021; Chang & Tung, 2008). Still, there remains a gap in the literature that needs to be addressed by additional investigations on the relationship between behavioural intention and other variables including assessment and learner-content interaction.

Also, a positive attitude has been strongly associated with online learning satisfaction (Santosa, 2009; Mei Yuan, 2021), and behavioural intention additionally indicates a strong link with satisfaction (Liaw, 2008; Meštrović, 2017). In order to boost student outcomes, it is crucial to create well-designed, captivating, and efficient online learning environments. These findings emphasise the interconnection of attitude, behavioural intention, and satisfaction.

Further research indicates that other factors affect student attitudes and satisfaction in online learning environments, which include compatibility and computer self-efficacy along with the TAM factors (Su-Chao et al., 2007; Mallya et al., 2019). Online self-efficacy is particularly significant, as higher levels are associated with more favorable attitudes and increased satisfaction (Joo et al., 2000; Shen et al., 2013; Bütüner et al., 2023). Research has indicated that self-efficacy affects the aim to enroll in online courses by influencing the perception of its utility and ease of use. (Su-Chao et al., 2007; Yajuan Cui, 2021; Thuy Thanh Thi Doan, 2021).

Instructional design is another critical factor; Artino (2008) and Bolliger and Martindale (2004) emphasized that well-structured, interactive courses enhance students' attitudes and motivation. Technological factors like technical support, LMS design, and self-related factors like efficacy impede LMS utilization, particularly in contexts like Saudi Arabia (Alshammari et al., 2016). Instructor quality impacts attitudes and satisfaction through effective interactions. The Community of Inquiry (CoI) framework by Garrison, Anderson, and Archer (2000) is widely used to assess and improve this aspect. Research by Kuo et al. (2014) and Eom, Wen, and Ashill (2006) highlights that instructor interaction and quality, including timely feedback and clear instruction, are critical determinants of student satisfaction and behavioral intentions.

The perceived quality of online learning systems is also crucial. Studies by Al-Fraihat, Joy, and Sinclair (2020), Mohammadi (2015), and Lee, Yoon, and Lee (2009) show that high-quality, user-friendly systems promote positive attitudes and greater satisfaction. Mailizar et al. (2021) integrated perceived system quality into an extended TAM, including most of its factors. Assessment methods also affect attitudes; Boud and Falchikov (2006) like formative valuations and just-in-time feedback (Hattie & Timperley, 2007).

Learner-content interaction remains crucial, as interactive content impacts learners' attitudes and engagement. Liaw (2008) and Al-Fraihat et al. (2020) demonstrate that content interactivity, such as multimedia elements and interactive exercises, significantly influences learners' attitudes and intent to engage with the learning platform. Finally, satisfaction with online learning significantly impacts behavioral intentions. Eom, Wen, and Ashill (2006) found that satisfaction with course structure, interaction, and technology positively influenced students' intentions to continue using online learning systems. Positive attitudes strongly correlate with increased satisfaction, as highlighted by Kuo et al. (2014), Al-Fraihat, Joy, and Sinclair (2020), and Sun, Tsai, Finger, Chen, and Yeh (2008).

The application of deep learning (DL), machine learning (ML), and artificial neural networks (ANN) in education research is supported by a number of studies. Mutawa et al. (2023) applied ML models to predict student satisfaction and emotions in online education, integrating ANN and Random Forest (RF) to increase tailored learning and engagement. Recent research investigations that use data from MOOCs and Learning Management Systems (LMS) to predict student performance, including Bayan et al. (2024), highlight the crucial role of DL. Learning behaviour has been discovered as an important attribute in the exceptionally high precision of techniques such as Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory networks (LSTMs). Al-Azazi and Ghurab (2023) put forward an ANN-LSTM hybrid model, a day-wise multi-class prediction framework, that substantially improved performance prediction across educational environments.

After conducting an extensive literature review, we identified a gap in utilizing ANN models for predicting student satisfaction in online learning environments, particularly considering the mediating effects of students' attitudes and behavioral intentions. In this study, we aim to develop an ANN model to predict student satisfaction, with online self-efficacy, instructional design, perceived system quality, assessment methods, and learner-content interaction as the independent variables, as illustrated in Figure 1.

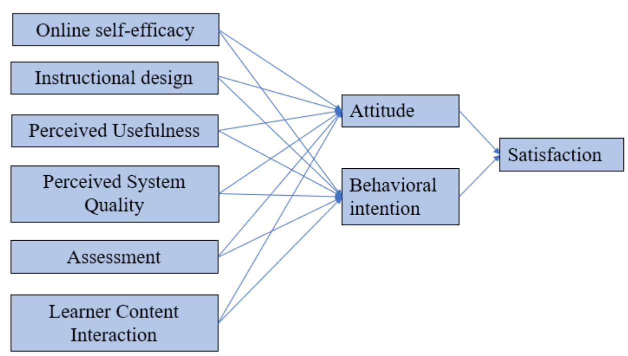

Fig. 1. Conceptual framework, (Source: Based on own work)

These independent variables, well-supported in the literature, will be tested for their associations with the dependent variable, student satisfaction. Furthermore, behavioral intention and attitude will be employed as mediating variables to explore their influence on the relationship between the independent variables and student satisfaction. By incorporating these mediators, our ANN model will comprehensively predict student satisfaction from the students' perspective, addressing a significant gap in existing research.

III. Materials and Methods

A. Participants and Data Collection

During the second semester of the 2022-2023 academic year, data was collected from colleges and universities in Tamil Nadu, India, with 382 students who had undergone the MOOC from various postgraduate programs randomly selected to participate in the research. The survey questions employed in this investigation were adapted from prior studies. A 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree), was utilized to assign weights to the variables including Online self-efficacy (Resnick & Jenkins, 2000), Instructional/Course design (Hung and Chou (2015), Perceived Usefulness (Davis et al., 1989; Bhattacherjee, 2001), Perceived System Quality (Al-Fraihat et al. (2020), Assessment, and Learner Content Interaction (Alqurashi (2019). These variables were then utilized to forecast student satisfaction (Kuo, Walker, et al., 2014), with '0' representing dissatisfaction and '1' indicating satisfaction.

B. Data modeling

In the world of Artificial Intelligence, ANNs have become a key player, driving innovation in countless industries and applications. Inspired by the interconnected neurons in the human brain, ANN are complex algorithms designed to process information in a similar way (Dongare et al., 2012). This study makes use of supervised learning, in which respondent data on a 1-to-5 scale across several items is used to collect data on factors, including students' satisfaction with learning. By modifying weights to reduce prediction errors, the ANN is trained to predict outputs (Walczak, 2019; Dike, 2018). The application of ANNs in predicting student satisfaction in online learning environments is driven by their ability to handle complex, multi-dimensional data, learn from and adapt to new information, and provide accurate predictions despite potential data limitations. This makes them a powerful tool for understanding and improving the factors that contribute to student satisfaction.

Like its biological counterpart, an ANN is made up of layers containing interconnected processing units called artificial neurons. Information flows through these neurons via weighted connections, where each connection's weight represents the strength of influence between neurons. Through a process of training, ANNs can learn to recognize patterns, make predictions, and perform tasks by adjusting these connection weights based on provided data (Wu & Feng, 2018)

The first step is the input layer, where raw data arrives. Each node in this layer handles a specific aspect of the data. The number of nodes matches the number of features in the data, ensuring everything gets attention. Hidden layers are the real workhorses (Shahmansouri et.al 2021). Through a training process called backpropagation, these hidden layers learn to identify complex patterns within the data. Finally, the output layer is the finishing line. Here, the network delivers its final product, a prediction or answer based on what it's learned from the data.

In ANN, the calculation process involves updating weights based on input data and propagating these inputs through the network to compute outputs. This step is essential for training the network to ensure precise predictions or classifications. The first step in the calculation process is to compute the input to each neuron in the hidden layers and output layer.

The input Z_i to neuron i is calculated as

$$Z_i = \sum_{j=1}^{n} X_i * W_{ij} + B_i \quad (1)$$

Finally, the output Z_i of neuron i in the output layer is computed by applying an appropriate activation function called sigmoid.

$$O_i = \frac{1}{1+e^{Z_i}} \quad (2)$$

After calculating the output, we need to calculate the error for the network. It is calculated as:

$$E_i = O_i(1-O_i)\sum_j (O_i - T_i)W_{ij} \quad (3)$$

The weight update procedure includes calculating the gradient of a loss function concerning the network's weights and modifying the weights to diminish the loss. The specific formula for weight updates depends on the chosen optimization algorithm and loss function. The weights are updated using the following formula

$$W_{ij}^{t+1} = W_{ij}^{t} + \eta E_i O_i \quad (4)$$

For binary classification, Binary Cross Entropy (BCE) can be used as a loss function. The formula for binary cross entropy is

$$BCE = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)] \quad (5)$$

N: is the number of samples
y_i: is the true label for sample i (0 or 1).
$\hat{y}_i$: is the predicted probability for sample i.
Finally, the bias gets updated using the following equation

$$B_i^{t+1} = B_i^{t} + \eta E_i \quad (6)$$

The neural network model was constructed using a feed-forward neural network in Python 3.10.11 on a Windows 10 system with 8GB of RAM. The model was trained using the backpropagation learning algorithm employing the ADAM approach with a learning rate 0.05. For our binary classification problem, binary cross-entropy was used as a loss function. It measures the discrepancy between the predicted probabilities and the actual binary labels, providing a way to quantify the model's performance during training. Minimizing this loss helps the model make more accurate predictions. To monitor the model's performance during training, we included the metrics as Accuracy. By tracking accuracy, we can understand how well the model distinguishes between the two classes. The data was randomly divided into a training subset of 70% and a test subset of 30%. Table I shows the number of train and test data.

C. Data Preparation

The data preprocessing involved several crucial steps to ensure the dataset's integrity and readiness for analysis. Initially, normalization was performed using the Min-Max procedure, which scales the data to a fixed range, typically between 0 and 1. This process ensures that all features contribute proportionally, preventing those with larger scales from dominating the analysis. Hence in this investigation chose to employ Min-Max normalization among other normalization techniques since it has been shown in several studies (Chepino et al., 2023; Manogaran & Louzazni, 2022; Gokhan et al., 2019) to be effective in generating improved results. Next, all missing values were identified and removed, resulting in a complete and robust dataset devoid of gaps that could lead to inaccuracies. Various methods were considered for handling missing values, such as imputation or predictive modeling, but removal was chosen for this context. Finally, the dataset was thoroughly examined for outliers using statistical techniques like the Interquartile Range (IQR) and Z-score and visual methods like box plots. It was confirmed that no outliers were present, ensuring that extreme values would not distort the analysis or model performance. These preprocessing steps collectively ensure that the dataset is clean, normalized, and free of inconsistencies, providing a solid foundation for accurate and reliable results in subsequent analyses or model building. Basically, activation function is selected based on the output required. Different transfer functions were selected in the neural network like linear, sigmoid, ReLu, Linear sigmoid, tanh, etc., (Guo, W. W. 2010, Aydoğdu, Ş. 2020). Gaudart, J., Giusiano, B., and Huiart, L. (2004) revealed that in a multi-layer perceptron environment, consistency is achieved when using a sigmoid transfer function. So we utilize the Sigmoid as the transfer function in both the hidden layers and the output layer.

TABLE I
TRAIN TEST DATA SPLIT-UP

Sample	Number	Percentage
Train	267	70%
Test	115	30%

IV. RESULTS

This section describes the model's results designed to forecast student satisfaction, featuring two hidden layers comprising 5 and 3 neurons, respectively. Given the binary classification nature of the output, a single-neuron output layer is employed. Initially, we predict attitude and behavioral intention through six independent variables: Online self-efficacy (OS), Instructional design (ID), Perceived Usefulness (PU), Perceived System Quality (PSQ), Assessment, and Learner Content Interaction (LCI). Subsequently, using behavioral intention and attitude, the study forecasts student satisfaction with online learning.

Figure 2 and Figure 3 illustrate the Neural Network model that predicts Behavioural intention and Attitude. We construct the model to predict the Behavioural intention and attitude using the six features given to the input layer. Two hidden layers consist of five and three neurons, and transfer the inputs to the output with one neuron. The model was trained using the training data set that fit the model to predict the Behavioural intention and Attitude. We tested the model using the test data to find its accuracy.

Tables II and III show the input and output samples from the neural network. The ANN gets Online self-efficacy (OS), Instructional design (ID), Perceived Usefulness (PU), Perceived System Quality (PSQ), Assessment, and Learner Content Interaction (LCI) as the input and the model predicts the attitude and Behavioral intention, respectively.

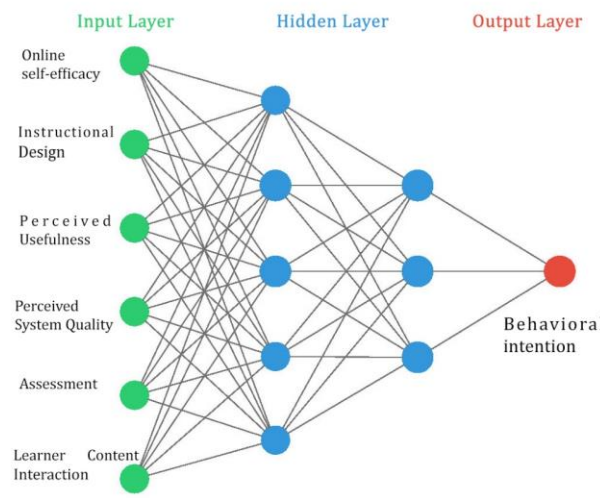

Fig. 2. Model to predict Behavioural Intention, *(Source: Based on own work)*

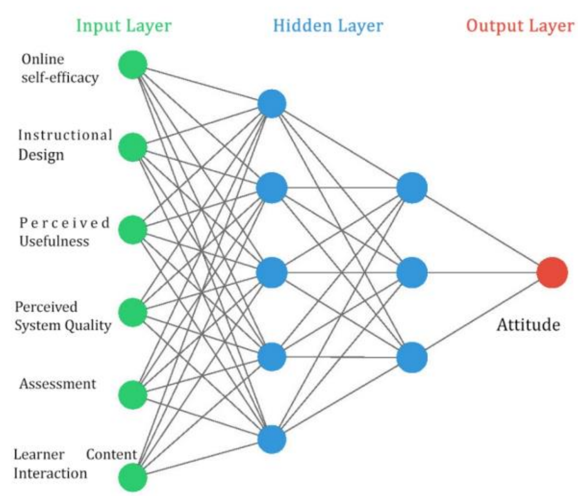

Fig. 3. Model to predict Attitude, *(Source: Based on own work)*

TABLE II
SAMPLE OUTPUT FROM THE MODEL THAT PREDICTS BEHAVIOURAL INTENTION

	Input						Behavioral Intention	
#	Online Self Efficacy	Instructional Design	Perceived Usefulness	Perceived System Quality	Assessment	Learner Content Interaction	Actual	Predicted
0	5	4	4	3	4	4	1	0.99
1	3	5	4	4	4	4	1	1.00
2	5	5	3	3	3	4	1	0.98
3	2	4	1	1	1	1	0	0.01
4	2	2	2	4	2	3	0	0.08
5	1	3	5	4	3	4	1	0.99
6	2	5	4	4	4	5	1	1.00
7	1	3	2	2	2	2	0	0.02
8	5	4	4	4	5	4	1	1.00
9	1	4	1	1	1	1	0	0.01

TABLE III
SAMPLE OUTPUT FROM THE MODEL THAT PREDICTS ATTITUDE

	Input						Attitude	
#	Online Self Efficacy	Instructional Design	Perceived Usefulness	Perceived System Quality	Assessment	Learner Content Interaction	Actual	Predicted
0	5	4	4	3	4	4	1	0.97
1	3	5	4	4	4	4	1	0.97
2	5	5	3	3	3	4	1	0.96
3	2	4	1	1	1	1	0	0.03
4	2	2	2	4	2	3	0	0.58
5	1	3	5	4	3	4	1	0.78
6	2	5	4	4	4	5	1	0.97
7	1	3	2	2	2	2	0	0.08
8	5	4	4	4	5	4	1	0.98
9	1	4	1	1	1	1	0	0.03

Looking at the sample outputs, we conclude that the predicted values are mostly close to the actual values (Rounded to the nearest highest integer). Figure 4 predicts satisfaction using Behavioural intention and Attitude. It has two neurons in the input and two hidden layers with five and three neurons each. Output has a single neuron that predicts the

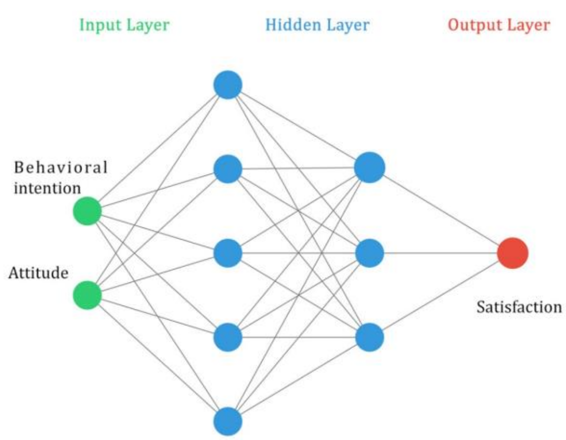

Fig. 4. Model to Predict Satisfaction, (Source: Based on own work)

satisfaction of the student. Table IV shows the sample output from the model that predicts Satisfaction using Behavioural intention and Attitude.

TABLE IV
SAMPLE OUTPUT FROM THE MODEL USING BEHAVIOURAL INTENTION AND ATTITUDE

#	Attitude Predicted	Behavioral Intention Predicted	Satisfaction Actual	Satisfaction Predicted
0	0.97	0.99	1	0.99
1	0.97	1.00	1	0.99
2	0.96	0.98	1	0.99
3	0.03	0.01	0	0.02
4	0.58	0.08	0	0.93
5	0.78	0.99	1	0.99
6	0.97	1.00	1	0.99
7	0.08	0.02	0	0.02
8	0.98	1.00	1	0.99
9	0.03	0.01	0	0.02

The model summary in Table V shows the confusion matrix for the Training and test data for all three models. The statistics for training and testing of data are shown in Table VI. Figures 5, 6 and 7 show the Receiver Operating Characteristics Curve for all the models.

TABLE V
CONFUSION MATRIX OF THE MODEL

Model	Event	Count	Predicted Class (Training)		AUC	Count	Predicted Class (Testing)		AUC
			0	1			0	1	
Behavioral Intention	0	115	109	6	97.00%	63	56	7	92.17%
	1	152	2	150		52	2	50	
Attitude	0	117	116	1	99.25%	62	59	3	96.52%
	1	150	1	149		53	1	52	
Satisfaction	0	114	111	3	98.13%	59	58	1	97.39%
	1	153	2	151		56	2	54	

TABLE V
STATISTICS OF THE TRAINING AND TESTING OF DATA FOR ALL THE MODEL

Particulars	Model	Training %	Test %
TPR	**Behavioural Intention**	94.8%	88.9%
FPR		5.2%	11.1%
FNR		1.3%	3.8%
TNR		98.7%	96.2%
TPR	**Attitude**	99.1%	95.2%
FPR		0.9%	4.8%
FNR		0.7%	1.9%
TNR		99.3%	98.1%
TPR	**Satisfaction**	97.4%	98.3%
FPR		2.6%	1.7%
FNR		1.3%	3.6%
TNR		98.7%	96.4%

The provided data evaluates a classification model's performance on three outcomes: Behavioural Intention, Attitude, and Satisfaction, using confusion matrices and AUC scores for training and testing datasets. For Behavioural Intention, the model achieved an AUC of 97.00% in training and 0.92.17% in testing, with slightly higher misclassifications: only 6 out of 115 instances for Class 0 and 2 out of 152 for Class 1 in training, and similar misclassification rates in testing.

For Attitude, the model's AUC was 99.25% in training and 96.52% in testing, with minimal misclassifications: 1 out of 117 instances for Class 0 and 1 out of 150 for Class 1 in training. The Satisfaction outcome showed an AUC of 98.13% in training and 97.39% in testing, with very few misclassifications: 3 out of 114 instances for Class 0 and 2 out of 153 for Class 1 in training. Overall, the model exhibits high accuracy and robustness, especially in predicting behavioral intention and satisfaction, as indicated by AUC scores close to 1.0 and low misclassification rates across both datasets.

The statistical performance of the classification model across three outcomes—Behavioural Intention, Attitude, and Satisfaction was evaluated using metrics for both training and testing datasets. For Behavioural Intention, the model achieved a True Positive Rate (TPR) of 94.8% during training and 88.9% during testing, a False Positive Rate (FPR) of 5.2% in training

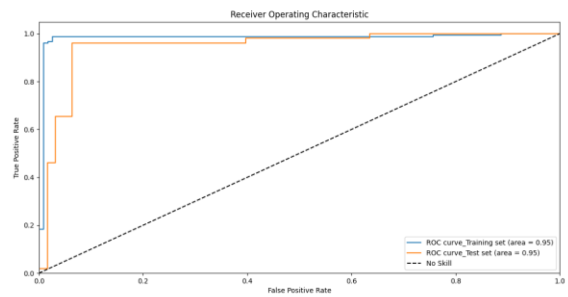

Fig. 5. Receiver Operating Characteristics Curve for Attitude, (Source: Based on own work)

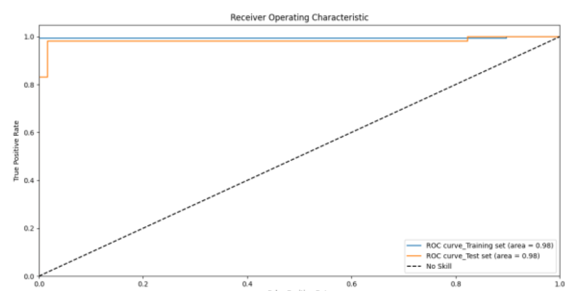

Fig. 6. Receiver Operating Characteristics Curve for Intention, (Source: Based on own work)

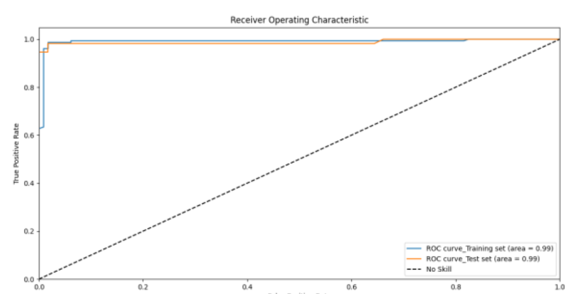

Fig. 7. Receiver Operating Characteristics Curve for Satisfaction, (Source: Based on own work)

and 11.1% in testing, a False Negative Rate (FNR) of 1.3% in training and 3.8% in testing, and a True Negative Rate (TNR) of 98.7% in training and 96.2% in testing. For Attitude, the TPR was 99.1% in training and 95.2% in testing, the FPR was 0.9% in training and 4.8% in testing, the FNR was 0.7% for training and 1.9% for testing, and the TNR was 99.3% for training and 98.1% for testing. For Satisfaction, the TPR was 97.4% in training and 98.3% in testing, the FPR was 2.6% in training and 1.7% in testing, the FNR was 1.3% in training and 3.6% in testing, and the TNR was 98.7% in training and 96.4% in testing. These statistics indicate that the model generally performs well, especially in predicting Behavioural Intention and Satisfaction, with high TPRs and TNRs, though there is a noticeable decrease in performance for Attitude in the testing phase.

The Figures 8, 9 and 10 show the growing accuracy with epochs for Attitude, Intention and Satisfaction.

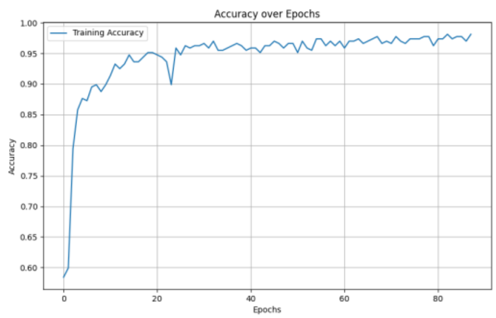

Fig. 8. Growing accuracy with epochs for Attitude, (Source: Based on own work)

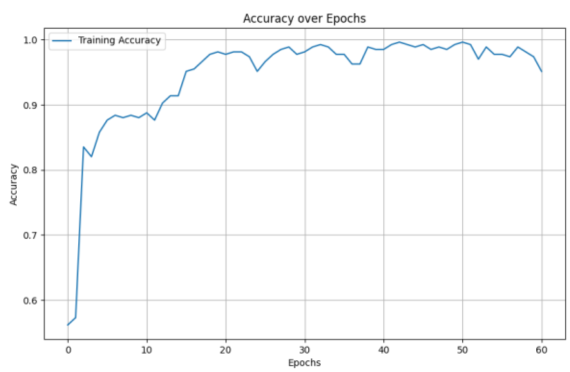

Fig. 9. Growing accuracy with epochs for Intention, (Source: Based on own work)

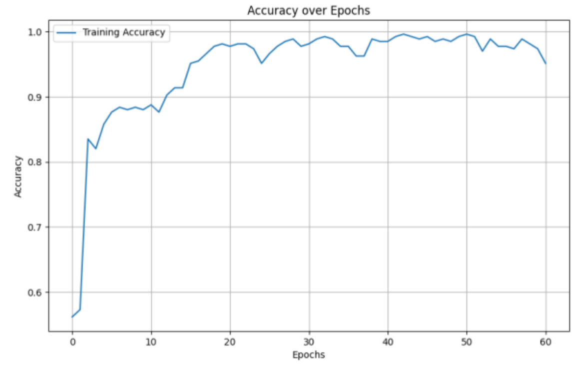

Fig. 10. Growing accuracy with epochs for Satisfaction, (Source: Based on own work)

V. IMPLICATIONS

The research on the satisfaction levels of postgraduate management students with online MOOC courses using ANN has several significant implications for the future of E-learning. ANN enhances personalized learning by analyzing student interactions, performance, and feedback data to predict satisfaction with online courses. Once trained, these models tailor course content, pacing, and instructional methods to individual needs, increasing engagement and improving outcomes. By generating real-time predictions, ANNs enable adaptive learning paths and targeted interventions, such as custom feedback and support. They also allow for dynamic adjustments based on ongoing data, ensuring that personalization remains effective. This technology scales efficiently, automating personalization across large student populations and optimizing resource use while enhancing the educational experience.

The high accuracy rate of the ANN model in predicting student satisfaction highlights the importance of considering various factors such as course flexibility, instructor attitudes, and technology quality in course design. Institutions and regulating bodies can use these insights to refine online course offerings, ensuring they meet students' diverse needs and preferences. The ability of ANNs to accurately forecast student satisfaction provides educators and administrators with valuable data-driven insights. These insights can inform strategic decisions regarding resource allocation, curriculum development, and instructor training, ultimately leading to improved educational experiences. The research demonstrates the feasibility of using advanced machine learning techniques like ANNs in scalable online learning environments like MOOCs. This can help MOOC providers optimize their platforms to accommodate many students while maintaining high satisfaction levels. Policymakers and educational planners can use the insights from this research to develop policies and frameworks that support the effective implementation of E-learning initiatives. By addressing these practical aspects, educational institutions can significantly enhance the effectiveness and satisfaction of online learning, ultimately leading to better educational outcomes and more positive learning experiences for students.

Conclusion, Limitations & Future Work

This research developed a model to analyze postgraduate management students' satisfaction with online MOOC courses using ANN. Building on previous studies that highlight the superior accuracy of ANNs, we employed a multilayer perceptron neural network with a back-propagation algorithm to forecast student satisfaction based on their engagement in e-learning activities. The model achieved a remarkable classification accuracy rate of over 92%, successfully categorizing students into satisfied and unsatisfied groups.

Empirical evidence supports that e-learning significantly enhances student performance and facilitates effective knowledge acquisition by offering flexibility and ease of use. Students value the convenience of accessing materials anytime and appreciate intuitive, user-friendly interfaces that reduce cognitive load (Al-Fraihat et al., 2020). Interactive features and adaptive learning technologies further boost engagement and comprehension, leading to a more effective learning experience (Artino, 2007; Chang & Tung, 2008). The study also revealed an impressive AUC, demonstrating excellent discrimination ability of the ANN model.

While the study focused on postgraduate management students, its methodology and findings can be adapted to other disciplines. Expanding this research to include a broader range of educational contexts will deepen our understanding of factors influencing student satisfaction and help develop more effective e-learning strategies. Future research should explore additional predictors and different educational settings to enhance the overall quality of education and personalized learning experiences.

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