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Emotion Analysis of Art Class Students Based on Machine Learning

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A R T I C L E I N F O

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A B S T R A C T

Purpose The study's primary objective is to investigate the association between self-efficacy, convenience, perceived usefulness, attitude, and emotions. This paper also sought to comprehend the mediating function of attitude. **Methodology / Approach** This study utilized a quantitative, cross-sectional design. Using a self-administered questionnaire adapted from previous studies, the data was obtained. 70% of the responses were usable. The study was analyzed using the PLS-SEM and PLS-3.3.9 software packages. **Findings** The study's findings indicate that attitude has a significant influence on shaping emotions. Furthermore, convenience and perceived utility influence student attitudes toward technology use. Conversely, self-efficacy does not significantly influence students' attitudes. **Practical Implications** These findings are essential for academicians' future research. These findings are also helpful for the formulation of technology adoption policies for students. **Originality** This study is one of the very few that examine machine learning in the context of the education industry.

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1.0 Introduction

Numerous institutions, including art colleges and universities, have produced countless international and domestic instructors and artists for decades. These institutes also contain specialist skills in the sphere of arts who have significantly contributed to the growth of the country's culture and arts sector; with the advancement of local culture and the development of the skills, people's interest in the arts increases over time. Therefore, the number of students electing to enroll in universities and colleges for a degree in the arts increases annually (Joseph, 2020).

In this sense, one of the essential tools is machine learning, which employs statistical and mathematical models to enable accurate prediction. Consequently, various types of learning are feasible with machine learning. Thus, machine learning facilitates a more precise interpretation of the data. Data-driven machine learning is the primary foundation of contemporary technology. Machine learning can aid in identifying things that cannot be observed without using current technology (Hua, Li, & Yang, 2022).

In the past two decades, machine learning has gained popularity. It is regarded as one of the pillars of contemporary IT. Every field is experiencing a daily increase in data, which is readily accessible to all stakeholders. Therefore, intelligent data analysis combined with technological advancement is required. Machine learning is currently integrated into various facets of our daily life. However, the comprehension of technology still lags. Therefore, it is necessary to comprehend the aspects that can aid in advancing machine learning (Alsharif et al., 2020).

Emotional state refers to the recognition of feelings within a person and the dynamic environment of that person when dealing with others. In contrast, emotions are temporary shifts in an individual's disposition. The passage of time transforms this into a person's negative or positive emotional state. Emotions impact a person's quality of life (Çetin, Mustafa, & Doğanay, 2021).

The setting in which pupils learn and interact with their friends and families directly impacts their moods. According to researchers, emotions are the individual's feelings toward a person, thing, or circumstance that distinguish them as either unreal or genuine. There are a variety of pleasant experiences the pupils can have. These experiences include liveliness, happiness, pleasure, zeal, and amusement (Acosta-Gonzaga & Ruiz-Ledesma, 2022). On the other side, negative emotions include anger, despair, anxiety, annoyance, and boredom. Emotions play a crucial role in the learning process in motivating the student. Later, it also impairs performance and learning. During the learning process, intellectual emotions have a vital influence. They are related to the educational accomplishments and learning of students. Providing emotional support to children during the learning process is difficult. Therefore, it is essential to identify the things that can drive kids to learn so that their attitudes can be molded (Mirahmadizadeh et al., 2020).

A person's attitude has a substantial effect on their actions. When utilizing a social network, the individual's disposition changes drastically. The individual's personality is affected by the personalization, credibility, amusement, and informativeness of machine learning, a form of contemporary technology. Students' attitudes must be evaluated to design instruments that can enhance students' learning. The daily mood of the pupils influences the students' decision-making. With machine learning, students can get more significant results than with traditional computer simulation. The development of such technologies has a favorable impact on the educational sector. A significant difficulty is evaluating students' attitudes toward machine learning (Kuleto et al., 2021).

On the other side, self-efficacy also influences kids' academic success. Additionally, it tends to affect family relationships, accomplishments, and learning. Consequently, a lot of research has focused on enhancing individuals' self-efficacy. Learners with a high level of self-efficacy are more successful than those with a lower level of self-efficacy. Additionally, it affects the capacity of the individuals (Rafiola et al., 2020). Thus, self-efficacy also influences the choices of students. Students with a high self-efficacy level exert more effort to meet their obligations and manage the determinants of failure. These kids can recover quickly from failures and ultimately achieve their objectives.

On the other hand, students with poor self-efficacy believe they cannot achieve their goals. Therefore, it is improbable that they will accept challenges and exert substantial effort. Students with poor self-efficacy have modest aspirations, which leads to disappointment and negatively impacts their performance. Consequently, self-efficacy is regarded as one of the most crucial tools for developing a success mindset in pupils (Bartimote-Aufflick et al., 2016).

Because of space and time constraints, the learning and teaching method has been modified. This modification is essential for convenience and efficacy. As IT aims to simplify students' lives, convenience is tied to the student's use of space and time. Additionally, IT simplifies the daily tasks of individuals. The success of the IT industry is dependent on the IT factor. One of the most significant aspects of machine learning is convenience.

Regarding its uses in the education sector, machine learning has facilitated student and professional convenience (Kvavik, 2018). A variety of machine-learning techniques have facilitated student learning. Machine learning has made additional tasks, such as summarizing key points, highlighting teachings, and separating distinct liquids, simple and quick for students. In several studies, researchers have also noted that self-learning by students facilitates the development of personal abilities through individualized learning, as it is one of the most effective strategies for improving various skills. M-learning explicitly promotes convenient learning by allowing the learning process to occur anytime, anywhere, and on any device, such as mobile phones and laptops (Temdee, 2020). Students fulfill their academic objectives effectively and efficiently due to convenience.

The literature about students and their use of technology is becoming increasingly intricate over time. Several earlier studies have examined how students use technology for their academic pursuits. These kids utilize digital technology due to its apparent utility. The factor of perceived usefulness measures the extent to which technology must be employed while evaluating the technology that an individual must use (Elkaseh, Wong, & Fung, 2016). It also facilitates the evaluation and implementation of technology for the individual. Researchers have stated that users will accept a technology if they perceive it as beneficial. Therefore, user perception is highly critical to technological uptake. It is considered that users will adopt technology if their attitude toward technology is positive.

Consequently, pupils use technology for their academic pursuits due to its helpfulness and utility (Henderson et al., 2015); as evident from the preceding explanation, the adoption and application of machine learning are advantageous for students. E-learning can be utilized to teach students with both short-term and long-term information. In this sense, perceived usefulness is a significant predictor of the students' adoption of M-learning (Lu et al., 2017).

The study's primary objective is to investigate the association between self-efficacy, convenience, perceived usefulness, attitude, and emotions. This paper also sought to comprehend the mediating function of attitude.

2.0 Literature Review

Machine Learning

Machine learning is training a model with data to increase the generalization of data and the quality of decisions. In terms of learning style, machine learning algorithms fall into distinct groups (Janiesch, Zschech, & Heinrich, 2021). The technique is derived using many data sets, including the required outputs and inputs and a mathematical model in supervised learning. Regression algorithms and classification algorithms are crucial in supervised learning kinds. In semi-supervised learning, multiple unlabeled and labeled data combinations are utilized to produce predictions. In supervised learning, the mathematical models' created data set does not contain labels of desired outputs. Therefore, it comprises just input data sets. The unsupervised learning algorithm builds data patterns and structures in clusters and categorization. In the present dynamic environment, the algorithm of learning reinforcement provides feedback in the form of negative or positive reinforcement (von Wangenheim, Marques, & Hauck, 2020).

Positive Emotion

Researchers employ various methods to examine emotions and their impact on various elements. There is no definitive agreement in the literature regarding the definition and explanation of emotions. Personal objectives are the primary motivation for studying emotions within management sciences. On the other side, emotions also influence the individual's psyche. Nonetheless, emotions also affect the functional aspects of individuals. Two fundamental variables modify emotional states (Leisterer & Jekauc, 2019). A factor is the cognitive part of the individual's objective. In addition, the classical conditional is another component that influences an individual's emotions. Emotions affect an individual's cognition, but they also tend to be influenced by the cognitive process.

Additionally, emotions influence the behaviors and recollections of persons. Additionally, kids need to be conscious of their feelings. Additionally, they must learn to control their emotions (Tyng et al., 2017).

Researchers have identified six distinct emotions that an individual may exhibit. These include astonishment, grief, delight, fear, disgust, and rage. These emotions emit signals that carry information that is also useful to others. Everyone has unique methods of expressing feelings (El Hammoumi et al., 2018).

Attitude towards Adoption of Machine Learning

A person's attitude toward technology is based on their beliefs about a topic that has the potential to impact that person's conduct. Researchers have defined attitude as an individual's appraisal of many phenomena. Summers and Abd-El-Khalick (2018) describe attitude as "a state of readiness or disposition to respond in a particular manner." There are definite grounds for these judgments based on data from the environment and surrounding area. An individual's attitude toward technology is defined as "a certain feeling concerning technology, based on a certain concept of technology, and that carries with it an intention to behave in favor of or against technology" (Autio et al., 2017).

Individual attitude plays a significant part in the formation of intentions to accept online learning since attitude is a crucial factor in adopting technology. The desire of students to study a particular subject indicates that they have an agenda toward that subject, such as an agenda toward science. Regarding technology, it is assumed that pupils have the disposition to study social networks and technology. There are a few obstacles that students may encounter when adopting Web 2.0. Technology also contributes to the enhancement of the students' learning process. Therefore, it is crucial to comprehend the pupils' perspective on technology. Researchers have explored the impact of students' attitudes toward technology on their academic achievement. These studies indicate that the use of technology for educational purposes has favorably affected the academic performance of students and motivated them to use technology (Nketiah-Amponsah et al., 2017).

Self-efficacy

Academic self-efficacy influences the pupils' academic success. Academic self-efficacy refers to the ideas and attitudes of students regarding their ability to attain academic success. It also encompasses a student's confidence to complete and achieve academic work. Self-efficacy beliefs contribute to an individual's exceptional performance by enhancing persistence, effort, and dedication. Students with high self-efficacy can regulate their failures in fewer attempts than those with low abilities.

Consequently, self-efficacy can influence persistence and task performance. In other words, students with poor self-efficacy avoid task adoption and choose to delay task completion (Roebianto, 2020). Regarding the academic application of technology, self-efficacy demonstrates the utilization of technology for the students' proficiency. Based on practice and experience, it can be enhanced and modified as time passes. Students' performance is affected by their level of self-efficacy and is improved as a result (Hayat et al., 2020).

Convenience

Individuals' preferences for services and products are considered convenience in evaluating services. Efforts and time savings are two crucial variables that determine the convenience of a service or product. Convenience is a critical factor influencing an individual's perception of behavioral control. Convenience is proportional to the amount of time and effort required by consumers to complete tasks. Additionally, scholars reported that the most significant aspect of studying technology in the context of students is convenience. Literature mentions five characteristics of convenience, including execution, use, acquisition, and location and time. Thus, convenience is regarded as a significant component in the acceptability of IT among individuals (Pakurár et al., 2019).

Researchers contend that online computing provides pupils with greater convenience. Therefore, the adoption of IT is influenced by factors such as perceived convenience. In addition, researchers noted that convenience is the extent to which students assume that technology is user-friendly and efficient (Li et al., 2021). Students' use of various forms of technology makes it easier for them to complete academic tasks. Regarding electronic textbooks and various applications, it is simple for students to utilize these programs due to their convenience. Students' acceptance of m-learning is also influenced by technological factors (Mokhtar, Katan, & Hidayat-ur-Rehman, 2018).

Perceived Usefulness

Scholars have defined perceived usefulness as "the extent to which individuals believe that using a particular system will enhance their performance." Past research on innovation and exploration has demonstrated that technology's perceived usefulness influences humans' attitudes. Past research has shown a correlation between performance and a high level of perceived usefulness. Moreover, perceived utility is an essential aspect influencing system adoption. Shah and Attiq (2016) also showed a favorable correlation between user pleasure and perceived utility. Studies on the antecedents of the adoption of online courses among higher education students identified perceived usefulness as one of the critical factors.

If students believe online learning can enhance their performance, they are more inclined to adopt such a system. This will have a favorable effect on their performance. Researchers have also observed that perceived usefulness positively influences intentions to adopt online learning, suggesting that students are more inclined to accept perceived use if they find it important and valuable. Consequently, perceived usefulness is crucial in the education industry (Keržič et al., 2019). Therefore, this study aims to examine the relationship between perceived usefulness, attitude, convenience, self-efficacy, and emotions among Malaysian art students.

Hypotheses building

Attitude and Positive Emotion

Attitude represents a person's favorable or unfavorable impression of technology usage. Indicated by the user's level of action toward technology usage, behavioral intention factors reveal the user's activity level. Several earlier research has found a positive correlation between behavior and attitude, indicating that attitude influences behavior. Scholars conclude that the explanation of an individual's attitude determines the acceptance of new services or technologies. Along with perceived behavioral control and subjective standards, TRA and TPB frameworks also hypothesize that attitude significantly influences the adoption of new technologies. In the context of e-learning, a number of previous research have found that attitude substantially impacts intentions. Therefore, researchers also anticipated that user attitudes would favorably influence intentions to use online learning (Nassr, Aldossary, & Nasir, 2021).

The individual's attitude has a substantial impact on the individual's willingness. This truth is widely acknowledged within the area of online education. During the epidemic, several kids selected home-based education. They shifted their offline traditional learning style to online learning. Thus, from a psychological standpoint, attitude plays a crucial role in molding students' desire to adopt online learning in higher education. Several research studies have also proven that a positive attitude influences students' propensity to utilize online learning. Perceived behavioral control, which forecasts the individual's resources and capacity to influence behavior, is one of the elements affecting behavioral intention. According to scholars, learning attitude and perceived behavioral control significantly influence the propensity to utilize online courses. Thus, attitude is one of the most significant predictors of the user or student participation in online learning (Zhao et al., 2022).

Self-efficacy and Attitude towards Adoption

Self-efficacy evaluates an individual's capability to do a specific task. This notion stems from social cognitive theory, which asserts that self-efficacy is essential to human behavior. At the same time, acceptance of new technologies is contingent on a better level of self-efficacy. A higher level of self-efficacy demonstrates the individual's ability and confidence that they possess the skills necessary for adopting technology. A person's success rate will increase if they have more confidence in themselves (Cserdi & Kenesei, 2021).

Self-efficacy is a significant external component that influences the individual's multiple behavioral and purposeful factors. In adopting new technology, self-efficacy demonstrates an individual's confidence in determining their conduct. Self-efficacy plays a crucial role in adopting technology at the advanced level. It also affects a person's attitude toward using technology. It is one of the best methods for investigating the individual's attitude regarding its influence on behavior and its correlation with intentions and readiness to pay (Kulviwat, Bruner II, & Neelankavil, 2014).

Convenience and attitude toward adoption

Researchers found that a person's willingness to use Moodle is highly influenced by their perception of its convenience. In addition, experts have noted that mobile payment applications are user-friendly and convenient for both genders. Additionally, all genders are willing to use mobile phones due to their convenience. Further, scholars argued that it is necessary to consider aspects that can help shape the attitudes of consumers. These elements include utility and convenience. In addition, they noted that convenience is a significant element in e-payment system acceptance. However, convenience is also one of the elements that can encourage banks to adopt innovative technology such as e-payment systems. Consequently, it tends to shape the attitudes of individuals (Putit et al., 2021).

Convenience is one of the reasons why customers utilize the internet for extended periods. Thus, there exists a positive association between intentions and product usability convenience. Customers sense a different type of convenience when purchasing on the internet. These advantages include comparability, time, and effort savings. Users' perceptions of convenience directly impact their online shopping behavior. Youths worldwide prefer to utilize online services due to their convenience, demonstrating that convenience is one of the most influential factors in the intentions and attitudes of consumers. Customers are mostly encouraged to purchase things from online businesses because of their convenience, but communication is one of the most crucial components in providing value to customers. Consumers must give information regarding the cost and time savings associated with purchasing tickets online.

Regarding students' and other segments of society's propensity to purchase tickets online, convenience is the most influential aspect. Some of the researchers also indicated that convenience does not favorably influence attitudes. While few authors have observed attitude change due to the convenience of online adoption of services and products (Koundinya, 2019).

Perceived usefulness and attitude toward adoption

Scholars have identified a variety of factors that influence the acceptability of technology. It is often recognized that an individual's attitude affects their purpose in accepting new technology. The user's attitude is influenced by two factors: usability and utility. According to experts, the most significant expectation procedure is convenience. It is considered that the perceived usefulness and simplicity of the technology influence attitudes regarding the acceptance of technology. When a person realizes that a technology item or software benefits them, they will incorporate it into everyday activities (Wijaya & Budiman, 2019).

Scholars have defined perceived usefulness as believing technological utilization can significantly enhance performance. In the context of students, applications facilitate comprehension of the learning process. In addition, applications have made studying anywhere convenient for pupils. There are several methods for measuring perceived utility. The apparent utility will favor the users' attitude, and pupils will be motivated to utilize the system. Numerous research studies have been undertaken on perceived utility's influence on attitudes toward technological usage. According to surveys, Internet banking is favourably adopted by users due to its perceived usefulness. These studies demonstrate a positive correlation between these variables (Islami, Asdar, & Baumassepe, 2021).

The objective of machine learning is to reduce errors. Another essential objective is to give users necessary and valuable information. According to scholars, technological improvements have facilitated the detection of faults in the general procedures of banks and insurance organizations. Consequently, machine learning has a substantial impact on the efficiency of companies. People will use machine learning in their daily lives if they have a favorable attitude toward machine learning and view it as applicable (Zhang, Wang, & Li, 2021).

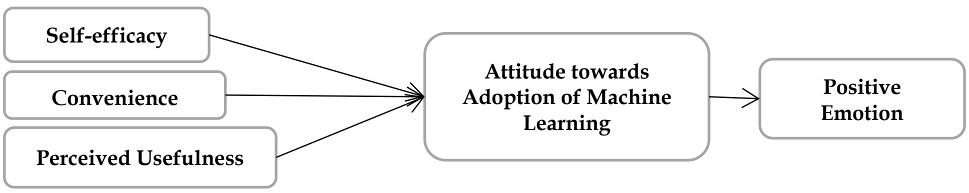

Figure 1: *Theoretical Framework*

The hypotheses from the above review of literature are proposed as follows:

H1: *Attitude has a positive effect on positive emotions.*
H2: *Convenience has a positive impact on attitude.*
H3: *Perceived usefulness has a positive effect on attitude.*
H4: *Self-efficacy has a positive impact on attitude.*
H5: *Attitude mediates between convenience and emotions.*
H6: *Attitude mediates between PU and emotions.*
H7: *Attitude mediates between Self-efficacy and emotions.*

3.0 Methodology

This study used a quantitative research strategy in conjunction with other approaches to achieve the research aims. A cross-sectional approach was utilized to identify the time horizon of the investigation. Primary data was the study's primary source of information. To acquire primary data, a survey questionnaire was created. To create the study's questionnaire, a comprehensive literature review was undertaken. This survey was constructed using a seven-point Likert scale. On this scale, 1 corresponds to "strongly disagree," 4 to "neutral," and 7 to "strongly agree." The data was collected from students in the arts. This questionnaire was obtained using Convenience Sampling by the respondents themselves. As stated, the study's components were modified from the pats studies. Items of emotions were adapted from Sanchez and Vazquez (2014); items of self-efficacy were adapted from Yau and Leung (2018); items of convenience were adapted from Nuryyev et al. (2020); items of attitude were adapted from Zhang et al. (2021); and items of perceived usefulness were adapted from Akour et al. (2021).

400 eligible respondents were recruited from among Malaysian arts students in this survey. After questionnaire distribution, 281 usable questionnaires were returned. Thus, 70.25 percent of replies in the present study were useable. These responses were initially screened for out-of-the-ordinary responses. Validity checks were performed on 381 responses later. In addition, the reliability of these responses was evaluated using composite reliability and Cronbach's Alpha. Earlier proposed hypotheses were tested against the proposed study variables. The study's data were evaluated using Smart PLS 3.0 and SEM. The Sem approach in this work consists of various statistical tools that help researchers validate and enhance theories and models (Anderson & Gerbing, 1982). This method is favored for testing evaluations and hypotheses (Hair, Ringle, & Sarstedt, 2011). Under SEM, there are two theory-based methods: covariance-based SEM (CB-SEM) and variance-based SEM (VB-SEM). According to academics, CB-SEM has a set of model parameters and is sensitive to errors.

PLS-SEM, on the other hand, authorizes researchers to evaluate the causal association between study variables using questionnaire-specific items (Rezaei, 2015). In addition, PLS-SEM is favored by researchers over CB-SEM for expanding structural theory (Hair et al., 2011). It is also suggested that the PLS-SEM method should be utilized when the objective is to obtain accurate findings for a model with many variables and relationships (Henseler et al., 2014). PLS-SEM is appropriate for this investigation since the suggested model is complex, with four direct and three indirect interactions. In addition, this model contains one dependent variable, one mediating variable, and three independent variables (Ringle, Sarstedt, & Straub, 2012). To conduct PLS-SEM analysis, Smart PLS-3.3.9 was utilized in this study. The PLS analysis is based on two processes: the measurement model (used to evaluate the inner model) and the structural model (used to assess the outer model). The measurement model analysis evaluates the links between the constructs' validators and indicators.

In contrast, the structural model is utilized to evaluate the presented hypothesis (testing the relationship between constructs) (Anderson & Gerbing, 1982). These outcomes were assessed using path coefficient, standard deviation, and P-values. In contrast, the structural model is also used to evaluate the R square.

4.0 Results

This study began its examination by evaluating the demographic characteristics of the respondents. 64% of the respondents were female, and 36% were male. In addition, 42% of respondents were married, while the remaining 58% were unmarried.

The measurement model is the initial step in analyzing Smart PLS or PLS-SEM. In this phase, factor loading is computed to determine whether or not the variables of the study measure the same idea throughout their items. Regarding this, Hair Jr et al. (2014) proposed that the value of factor loading should exceed 0.40. Researchers recommend eliminating the item if the factor loading value goes below this threshold. This study's factor loadings are listed in table 1 of the study. It is obvious from the numbers that all factor loading values exceed the 0.40 criterion. Thus, factor loading is allowed in this investigation.

Table 1

Factor loading

	ATD	CNV	PE	PU	SE
ATT1	0.706				
ATT2	0.824				
ATT3	0.888				
CNV1		0.748			
CNV2		0.717			
CNV3		0.806			
CNV4		0.754			
PE1			0.661		
PE2			0.753		
PE3			0.820		
PE4			0.657		
PU1				0.854	
PU2				0.796	
PU3				0.819	
SE1					0.714
SE2					0.840
SE3					0.770
SE4					0.664

Note: SE= self-efficacy, PU=perceived usefulness, CNV= convenience, ATT= attitude, PE= positive emotions

Additionally, this study evaluated the data's convergent validity and reliability (Sekaran, 2003). Two tests, namely Cronbach Alpha and Composite reliability, were conducted to confirm the dependability of the data. Researchers suggested that acceptable CR and Cronbach alpha values should be more than 0.70. As seen in table 2, all Cronbach Alpha and CR values are more significant than 0.70. Therefore, they are acceptable.

Additionally, analyze the AVE values for confirmation of convergent validity. Regarding this, Fornell and Larcker (1981) proposed that the value of AVE should exceed 0.50. The collected data indicates that AVE values exceed the benchmark value of 0.50. Consequently, convergent validity is also attained in the present investigation.

Table 2

Composite Reliability

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
ATD	0.734	0.762	0.850	0.655
CNV	0.752	0.758	0.843	0.573
PE	0.702	0.715	0.816	0.527
PU	0.764	0.777	0.863	0.678
SE	0.740	0.766	0.836	0.563

Note: SE= self-efficacy, PU=perceived usefulness, CNV= convenience, ATT= attitude, PE= positive emotions

This study also analyzed the VIF test to confirm no multicollinearity issue with the data. Regarding this, studies proposed that the value of VIF be smaller than 5.0. (Ramayah et al., 2018). The VIF values are listed in table 3, demonstrating no multicollinearity issue with the data.

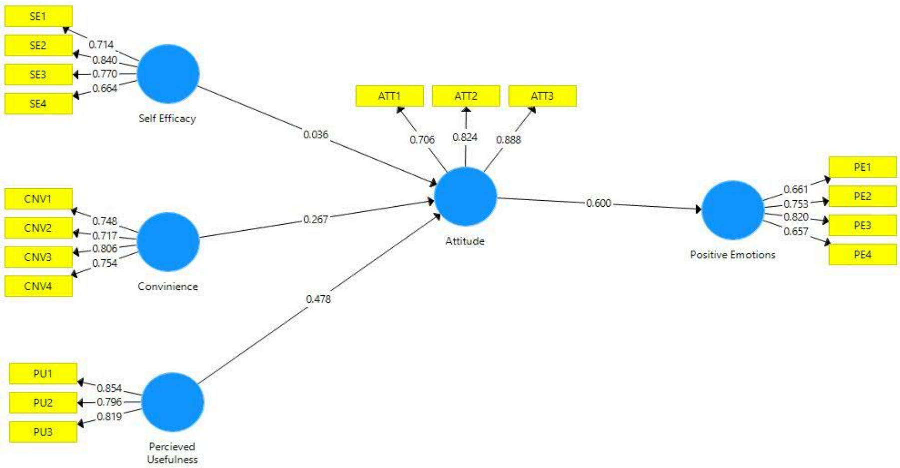

Figure 2: *Measurement Model*

Note: SE= self-efficacy, PU=perceived usefulness, CNV= convenience, ATT= attitude, PE= positive emotions

Table 3

VIF

	ATD	PE
ATD		1.000
CNV	1.829	
PU	1.506	
SE	1.425	

Note: SE= self efficacy, PU=perceived usefulness, CNV= convenience, ATT= attitude, PE= positive emotions

Using Fornell and Larcker's (1981) and the HTMT approach, the discriminant validity of the final measurement model was assessed. Using the technique of Fornell and Larcker (1981), discriminant validity is established if the values of the square root of the AVE placed on the matrix diagonal are more significant than the remaining matrix values. Table 4's numbers demonstrate discriminant validity using the Fornell and Larcker (1981) technique.

To identify discriminant validity, Henseler, Ringle, and Sarstedt (2015) found few errors using Fornell and Larcker's (1981) approach. For the evaluation of discriminant validity, this study also utilized the HTMT ratio, also known as the Monotrait heterotrait of correlations, as proposed by Henseler et al. (2015). Researchers assert that discriminant validity in the data is maintained when the HTMT confidence interval does not contain values greater than 0.90. The data in table 5 clearly demonstrate that all values are within the acceptable range for HTMT criteria and meet the discriminant validity requirements for HTMT (Hair Jr et al., 2016). In this phase, the measurement model is also established.

Table 4

Fornell and Larker

	ATD	CNV	PE	PU	SE
ATD	0.809				
CNV	0.560	0.757			
PE	0.600	0.605	0.726		
PU	0.644	0.575	0.591	0.823	
SE	0.359	0.541	0.480	0.375	0.750

Note: SE= self efficacy, PU=perceived usefulness, CNV= convenience, ATT= attitude, PE= positive emotions

Table 5

HTMT

	ATD	CNV	PE	PU	SE
ATD					
CNV	0.738				
PE	0.808	0.823			
PU	0.840	0.755	0.783		
SE	0.475	0.727	0.664	0.491	

Note: SE= self efficacy, PU=perceived usefulness, CNV= convenience, ATT= attitude, PE= positive emotions

Later this study examined the structural model for the assessment of the hypothesis of the study. The significance of the hypothesis was established based on t-values. The direct relationships of the study are mentioned in table 6 of the study. These statistical results show that the H1 of the study is accepted, indicating ATT has a significant positive effect on PE (Beta=0.600, t=14.367). Moreover, H2 of the study is also accepted, showing CNV positively affects ATT (Beta=0.267, t=3,940). Also, a positively significant relationship exists between PU and ATT (Beta= 0.478, t=6.840), accepting H3. On the other hand, H4 of the study is rejected as the t-value of the relationship between SE and ATT is less than 1.967.

Table 6

Direct relationships

		Beta	SD	T value	P Values	Decision
H1	**ATT -> PE**	0.600	0.042	14.307	**0.000**	Accepted
H2	**CNV -> ATT**	0.267	0.068	3.940	**0.000**	Accepted
H3	**PU -> ATT**	0.478	0.070	6.840	**0.000**	Accepted
H4	**SE -> ATT**	0.036	0.060	0.590	**0.278**	Accepted

Note: SE= self-efficacy, PU=perceived usefulness, CNV= convenience, ATT= attitude, PE= positive emotions

This study also investigated the indirect or mediating interactions between the variables. As shown in Table 6, these results demonstrate that ATT mediates the link between CNV and PE and that PU and ATT simultaneously accept H5 and H6. While H7 of the study is not supported, indicating that attitudes do not mediate between SE and PE.

Table 7

Indirect Results

		Beta	SD	T Statistics (|O/STDEV|)	P Values
H5	**CNV -> ATD -> PE**	0.160	0.043	3.700	**0.000**
H6	**PU -> ATD -> PE**	0.286	0.052	5.533	**0.000**
H7	**SE -> ATD -> PE**	0.021	0.036	0.587	**0.279**

Note: SE= self efficacy, PU=perceived usefulness, CNV= convenience, ATT= attitude, PE= positive emotions

After the structural model, Hair Jr (2020) proposed calculating the model's prediction capability using R square. The value of the R square is included in Table 7 and Figure 3, indicating that it is satisfactory, as Cohen (1980) stated that the value of the R square should be greater than 0.10. The R square values in this study meet this criterion.

Table 8

R square

	Original Sample (O)
ATD	0.470
PE	0.360

Note: SE= self-efficacy, PU=perceived usefulness, CNV= convenience, ATT= attitude, PE= positive emotions

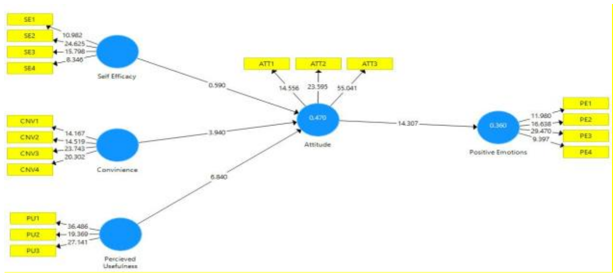

Figure 3: *Structural Model*

Note: SE= self-efficacy, PU=perceived usefulness, CNV= convenience, ATT= attitude, PE= positive emotions

5.0 Discussion and Conclusion

This article aimed to determine the effect of self-efficacy, convenience, perceived utility, and attitude toward technology adoption on students' emotions. The study's outcomes indicate that comfort is one of the most influential factors in shaping students' attitudes toward technology adoption. These findings are consistent with another study (Putit et al., 2021). In addition, perceived usefulness plays a significant role in shaping the mindset of the students. According to the study's findings, if students believe that adopting a certain technology will benefit them, they will develop a positive attitude regarding its adaptability. This result is comparable to those presented by Islami et al. (2021).

Furthermore, according to the findings, the students' willingness to use technology has a favorable impact on their attitudes (Nassr et al., 2021). On the other side, the data indicate that students' self-efficacy has little effect on their attitudes regarding technology adoption. In conclusion, the mediating effect of attitude between convenience, perceived utility, and happy feelings is proven.

6.0 Limitations and Implications

This study addresses the dearth of research on machine learning in the education industry. Nevertheless, there are a few drawbacks to the present study. This study investigated the role of attitude as a mediator. Future research could also examine the moderating effect of student trust in adopting technology. In addition, this study can be used in the telecom industry, as technology is constantly transforming and evolving in this sector. In conclusion, the R square values of the present study are 47% for attitude and 36% for emotions, indicating that additional elements can increase the variables' output level. The study's findings are useful for policymakers in the education sector tasked with developing technology adoption policies for pupils.

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