Date of publication MAR-31, 2025, date of current version AUG-18, 2024.
www.computingonline.net / computing@computingonline.net

Print ISSN 1727-6209
Online ISSN 2312-5381
DOI 10.47839/ijc.24.1.3881

Learners' Adoption of Course Recommendation Systems by Integrating External Factors and Technology Acceptance Model

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ABSTRACT The use of the course recommendation systems is an important focus of research in the field of educational technology. Understanding how students interact with them and accept these systems is essential as the learning environment is changing due to the integration of digital platforms. The Recommendation systems (RSs) are useful tools for narrowing down the course options and exposing students to the courses that suit their needs. The majority of the research related to recommendation systems focuses on effectiveness rather than factors influencing its acceptability, and in practice, user satisfaction cannot be explained by accuracy alone. This study considers the course recommendation systems and examines whether the courses proposed by our recommender systems (RS) are accepted by learners, particularly research students, based on their learning requirements. This can help researchers understand why some users embrace new technology while others resist it. Therefore, research scholars (n=150) willingly engaged in this study were asked to use the RS and complete a questionnaire based on their experience as part of a self-administrated longitudinal survey. This study evaluates the effect of external variables that the Technology Acceptance Model (TAM) does not account for, such as perceived availability, relevance, and experience. It also evaluates the recommendation system's capacity for making accurate recommendations. When compared to our keyword (75.11% accuracy) and N-gram (89.85%) based approaches, the accuracy of our hybrid recommendation was calculated to be 95.25 percent. The findings further support the extended TAM's role as a useful theoretical framework for explaining academics' acceptance of RS and other elements that have a positive bearing on the TAM's core variables. Consequently, a new modified TAM that includes three outside elements is proposed. The results' validity and dependability are confirmed by the significant value calculated for Cronbach's alpha. Because the ramifications of this study effort are crucial for faculties, scholars, and institutions, the observed results can help developers of the recommendation systems in maximizing the user experience.

KEYWORDS Recommendation System; Technology Acceptance Model; Information Retrieval; Course.

I. INTRODUCTION

THE popularity and advancement of web technologies has resulted in a plethora of advanced applications that can recommend alternative things to users based on their requirements. Various possibilities arise which stress the need for the usage of the Recommender system (RS) and the way it can be integrated into education. As a result, it became indispensable to assess the use of the Recommender system in a different way. Therefore, RS has been seen as a valuable tool, where it has been used to make recommendations for news, movies, music, and online connections, among other things.

A recommendation system is a tool that uses different information retrieval techniques to filter the Items or learning resources and then present them to the user [1]. The recommendation systems have been developed across different domains such as News, Music, Movies, and e-commerce [2], e-tourism, e-governance [3], where it has achieved a huge success rate. The Recommender systems are very popular areas of research that provides need-based suggestions [4], but the algorithms underlying traditional Recommendation systems such as News, Music, Movies, and e-commerce, cannot be redeemed in educational systems, as recommendations in the educational scenario may change over a while due to change in the students need or the context [5].

The main chore of the Recommender system in e-learning systems is to recommend the appropriate courses or the learning material that is relevant concerning student's needs and helps them in making decisions [6]. It is logical that applications of the Recommender system should be available for learners and should encourage effectual acceptance of recommendations based on relationship, preferences, and attributes among students [7]. A lot of research is focused on the use and acceptance of information technology. In literature, recommendation systems have a significant impact on emerging information system techniques, and they are usually centered on individual experience and skills for assessing the potentially large quantity of items that are available [8]**.** Many researchers are currently investigating the elements having a direct impression on acceptance of recommendation systems by their users for maximizing their recognition. Malaysian research group [9] investigated the impact of new technology by studied factors like its usefulness, intention to use, ease of use, understanding user's preferences, the intent of reuse the system, accuracy in recommending items, and interaction with the system.

Kang et al., [10] using a learner-centered approach tried to observe the significance of meeting online student's needs. Hughes [11], on the other hand, recommended creating communities of online learners to provide online support services to meet the needs of online students and enhance the interaction among students. Zhu Z [12] found out that in this age of information technology the concept of smart education is to portray a kind of new learning process and believes that the latest developed technologies can help in seamless personalization and assist learners to study in a more flexible, effective, and comfortable way. There are high chances that the outcome of this progressive shift in technology will bring more prevailing and interactive modes of communication and ensure the delivery of learning content of high quality.

The efficiency of the recommendation systems, mainly, dependent on the factors that are ahead of the prominence of the recommendation algorithms. To address the difficulties of forecasting and describing system, many descriptive models in information systems have been investigated. The Technology Acceptance Model (TAM), on the other hand, stands out and has widespread acceptance in the information systems field [14, 15]. The idea of reasoned action provided by [17] was used to develop this model. TAM model is based on the user beliefs, attitudes, and intentions in technological adoptions**.** There are two more criteria that constitute the construct of belief: perceived usefulness and perceived ease of use. Both determinants, as well as intention and attitude, constitute a sequence that illustrates the user's system adoption. Hsiu-Mei [18] showed that perceived interaction and perceived self-efficacy are two essential factors, which affect learning motivation, perceived usefulness, and perceived ease of use. Authors also claimed that motivation towards learning is also an interpreter to affect perceived usefulness.

This study is conducted keeping course recommendations as a testbed and a questionnaire appropriate for an educational domain. In the form of the TAM model, three new external variables will be introduced to the baseline: lack of RS availability, experience, and relevance. The goal of this study is to see how well university students especially research scholar's embrace recommender systems, and to learn more about the factors and underlying acceptance and behavioral intention to use the recommendation system for course selection. To our knowledge, there are no technology acceptance studies connected to the recommendation approaches used in educational domain or in e-learning. To fill this research gap, this study investigates the perceived availability, relevance, and experience of the recommender approach, as well as the actual deployment of recommendation approach in such models. The remainder of the document is organized as follows. The aspects of the Technology Acceptance Model employed in this study are briefly explained in the next section. In Section 3 the associated work concerning TAM applications of recommendation system will be discussed. In Section 4, a research model is proposed and in Section 5 the chosen methodology is described. Section 6 discusses the results analyzed with the proposed model, and Section 7, 8 present the discussion and conclusion respectively.

II. RELATED WORK

In recent years, higher educational institutions have integrated e-learning systems and educational technologies into their educational frameworks [19]. The imperative for higher education institutions to remain at the forefront of technological advancements in teaching and learning is undeniable [20]. The rapid development of learning technologies underscores their potential to revitalize higher education facilities. [21] emphasized the pivotal role of course selection in the advancement of technology-based education. This allows students to select courses with greater precision and professionalism, aligning more closely with their needs and interests. [22] introduced a framework based on the Sparse Linear Method (SLIM) for generating top-N course recommendations tailored to students. This approach incorporates both sparse regularization and expert knowledge, enhancing the precision of course recommendations.

The proliferation of information within e-learning environments has imposed a significant burden on students, complicating the process of selecting courses of interest. Recommender systems, widely employed in e-commerce [23], online libraries, e-health, sports, and, to a lesser extent, education, have emerged as a solution. These systems customize and filter information to meet students' specific needs [24]. Personalization, often in the form of recommendations, has gained traction and is being implemented across various domains, including social, business, and health [25]. Recommender systems simplify decision-making by offering tailored suggestions, minimizing the user effort. Nevertheless, the adoption of any new technological concept, regardless of its complexity, is subject to acceptance testing. Various models have been developed to characterize the relationship between technology and its users.

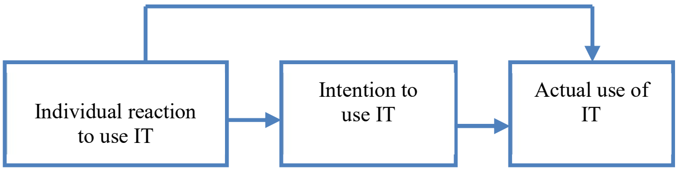

Figure. 1. Basic concepts of User Acceptance Models UAM

The study of user acceptance of technology is a well-explored field, with the Technology Acceptance Model (TAM) being one of the most prominent and widely accepted models due to its simplicity, robustness, and applicability in explaining and predicting the factors influencing the user adoption of new technologies [26]. Several researchers have employed TAM to evaluate the acceptance of recommendation systems for various purposes. For instance, [27] applied TAM to mobile shopping, while [28] focused on the retail and banking industry to assess the adoption of recommender systems.

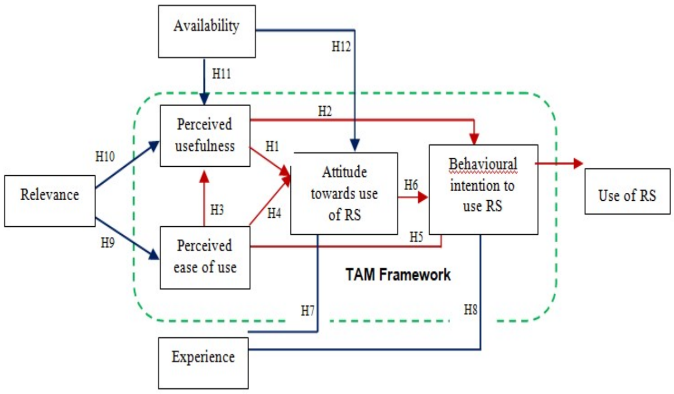

Figure 2. Conceptual Research Model

Similarly, [29] evaluated a recommendation system based on personality using TAM, with a primary aim to propose music based on users' personality, emotions, and mood. In line with TAM's behavioral parameters, [30] designed a system for recommending virtual communities to active users, integrating filtering functions based on the user needs. They employed a customized version of TAM to assess individual acceptance of the recommender system for an online trading experience [31].

A key focus in these studies is the adoption of technology by intention and the exploration of independent factors affecting it. Consequently, several variables contribute to the acceptability of recommendation technology, particularly considering users' experience with the system. This process, a complex one preceding the achievement of a visually appealing and user-friendly interface, highlights that even similar interface systems can yield different user perceptions when underlying algorithms are modified [32]. Davis [33] sought to address questions regarding the factors influencing users' acceptance or rejection of newly discovered information technology. Initially, it was found that users would adopt an application if they believed it would be useful and enhance task performance compared to performing the task without it. Furthermore, the perceived benefits of using an application outweighed the effort required, even if it was perceived as challenging to use. These two findings were later conceptualized as "perceived usefulness" and "perceived ease of use" in the renowned Technology Acceptance Model (TAM).

While TAM and its extension, TAM2, have proven valuable in research, several studies have criticized and addressed the limitations of these models. The following research studies provide insight into these challenges [34]. TAM-2 introduced by [35], which focuses on technology in the workplace, proposed an external variable output that influences perceived usefulness. However, this output is only high if users perceive job relevance, indicating that users are unlikely to accept new technology without perceived relevance. In our proposed model, we consider relevance as an external factor to understand its impact on technology acceptance. Similarly, Senior Technology Acceptance (STAM) [36] aimed to examine individual factors contributing to the acceptance of technology usage but did not account for the availability feature, essential for understanding individual differences. The role of experience was emphasized in numerous studies [37] in facilitating technology adoption. These studies revealed that the influence of experience on perceived usefulness can be complex. However, they did not explore the role of experience in relation to the user behavioral intentions and attitudes toward adopting new technology, which is the focus of our study. Hye Lee and Stoel [38] found that as users gain experience with technology, their perceptions of technology become more positive. Therefore, a clear relationship exists between the relevance of technology, its availability, and the user experience, which warrants further investigation.

III. PROPOSED CONCEPTUAL MODEL

In this research, we aim to comprehend the acceptance of Recommender systems by Indian research scholars by establishing a model that integrates the original TAM with external constructs. To this end, we developed a questionnaire which recognized the advantages of this research methodology and suggested adapting an existing questionnaire. We followed established guidelines and criteria to develop our questionnaire, drawing on prior research and theoretical concepts. This study extends the TAM in the context of recommender systems by introducing three external variables: relevance, availability, and experience. Behavioral intention serves as the dependent variable in our study, while the remaining constructs are considered independent variables.

Our new theoretical model is built upon existing research models, incorporating the core TAM constructs: perceived ease of use, perceived usefulness, behavioral intention to use, and actual system use. Additionally, we introduce three external variables: availability, relevance, and experience. The research model primarily targets research scholars, considering their expertise in choosing courses and the availability of technology for such tasks. It is important to note that, as suggested by [40], the behavioral intention to use technology is similar across both inexperienced and experienced users, allowing the application of TAM even before technology adoption. This research is significant because it considers a range of factors. Firstly, no prior research has delved into the availability, experience, and relevance of Recommender systems concerning behavioral intention to use them, validated by TAM. Secondly, this discovery sets the stage for future research aimed at enhancing E-learning systems. As a result, the questionnaire employed in this study may be utilized in future investigations.

A. RESEARCH HYPOTHESES

a) Hypotheses related to TAM variables

Numerous studies and the usage of Recommender systems have affirmed the relationship between various TAM constructs [41]. According to [42], Perceived Ease of Use (PEU) is linked to an individual's perception of how easy a new technology is to use, which students often consider as a factor in adopting advanced technology. Perceived Usefulness is believed to be the primary variable driving usage behavior. Legris [43] found in their research that 80% of studies based on TAM showed the impact of Perceived Ease of Use on Perceived Usefulness and Perceived Usefulness on Behavioral Intention.

Therefore, we hypothesize the following relationships between perceived ease of use, perceived usefulness, attitude toward using, and intention to use Recommender systems:

H-1: There is a positive effect of Perceived Usefulness on attitudes toward using Recommender systems.

H-2: There is a positive effect of Perceived Usefulness on the behavioral intention of using Recommender systems.

H-3: There is a positive effect of Perceived Ease of Use on Perceived Usefulness of Recommender systems.

H-4: There is a positive effect of Perceived Ease of Use on attitudes toward using Recommender systems.

H-5: There is a positive effect of Perceived Ease of Use on the intention to use Recommender systems.

H-6: There is a positive effect of attitude toward using on the user's intention to use Recommender systems.

b) Hypotheses regarding TAM variables and external factors

After reviewing the literature, it is clear that the TAM constructs, while useful, may not be sufficient, and additional external variables may influence them [44]. Experience has been found to have a positive effect on Perceived Usefulness [45]. In this study, we introduce external variables, including RS availability, RS relevance, and RS experience, which we believe will impact the original TAM constructs, as they have not been studied extensively in previous research.

H-7: RS Experience can have a positive and significant effect on attitudes toward using Recommender systems.

H-8: RS Experience can have a negative effect on the behavioral intention of using Recommender systems.

H-9: RS Relevance can have a negative effect on the perceived ease of use of Recommender systems.

H-10: RS Relevance can have a positive and significant effect on perceived usefulness of Recommender systems.

H-11: RS Availability can have a positive and significant effect on attitudes toward using Recommender systems.

H-12: RS Availability can have a positive and significant effect on perceived usefulness of Recommender systems.

IV. METHOD

A. PARTICIPANTS

This research work used the convenience-sampling technique for data collection in which 150 PhD scholars of computer science were given a trial of the system where they have provided the research title as queries as shown in Table 1 to our system and in return the system has recommended some courses to them as shown in Figure 3 and Figure 4.

Table 1. Research Queries given by Scholars to our Recommendation System

Scholars Research Title as Query	Relevant Courses by our Keyword based system	Most Relevant Courses by Our Hybrid Recommendation System
Knowledge discovery from databases using AI	2	4
Data Analytics in Healthcare System	2	4
Software Requirements Elicitation Techniques	2	5
Knowledge discovery in E-learning Systems	2	5
Malware Detection and Protection Against Web Attacks	3	5
Opinion Mining and Social Interaction Using Clustering Algorithms.	2	6
Opinion Mining in Online Customers Reviews Using Supervised Method	2	5
Energy efficient resource management in cloud computing	2	5
Network Security Analysis and Detection of Ports Scans	3	5
An Effective Hybrid Gateway Discovery Scheme in Integration of Internet & MANET	2	5
Biometrics Security & Forensics in digital passport system	3	5
CBIR Using Image Mining Techniques	1	4
Location Based Web Targeted Advertisement on Cloud	2	5
Knowledge Extraction from Social Web Source for Online Recommendation System	3	5
Study on the effectiveness of Agile methods on Communication product software engineering	3	6
Average Relevant Courses	**2.2 %**	**4.93 %**

The accuracy and course relevancy are shown in Figure 5 (a,b), along with the ontology and inference-based diagram in Figure 6 and Figure 7 to make them understand the hierarchy of the subject in a particular area. Then they were asked to give their feedback with the help of a questionnaire. The online survey would have been an appropriate tool because the demonstration was an important task to be carried out to receive genuine feedback from scholars. The scholars who participated in the experiment were from the computer science engineering, information technology, computer applications, and mathematics department.

There were 69 Male, 81 Females in the age group from 24 to 46 years and they were generally aware of the traditional way of choosing the course work for their PhD program which could guarantee their evaluations of using the Recommender system in a much better way. To ensure the content's validity, a questionnaire was created in this study based on the fundamental TAM assessment scales and other literature [46], with slight modifications to meet the context of the Recommender system. The survey was established to investigate the relationship between constructs in the suggested research model, and the experiment was largely conducted with research scholars (PhD) and faculty (perusing PhD) from institutes of Tamil Nadu, where we introduced our course Recommender system to them. We evaluated our research model for another reason: learners investigated traditional course selection methods: thus, this study allowed us to compare previous outcomes.

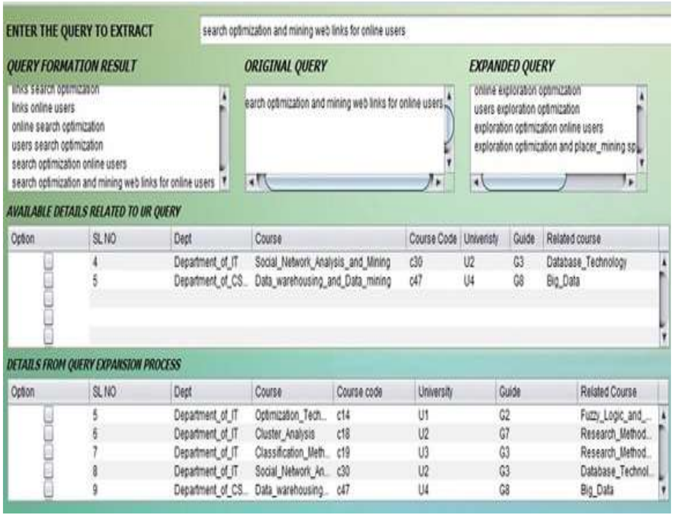

Figure 3. Course Recommendation by our Keyword-Based System

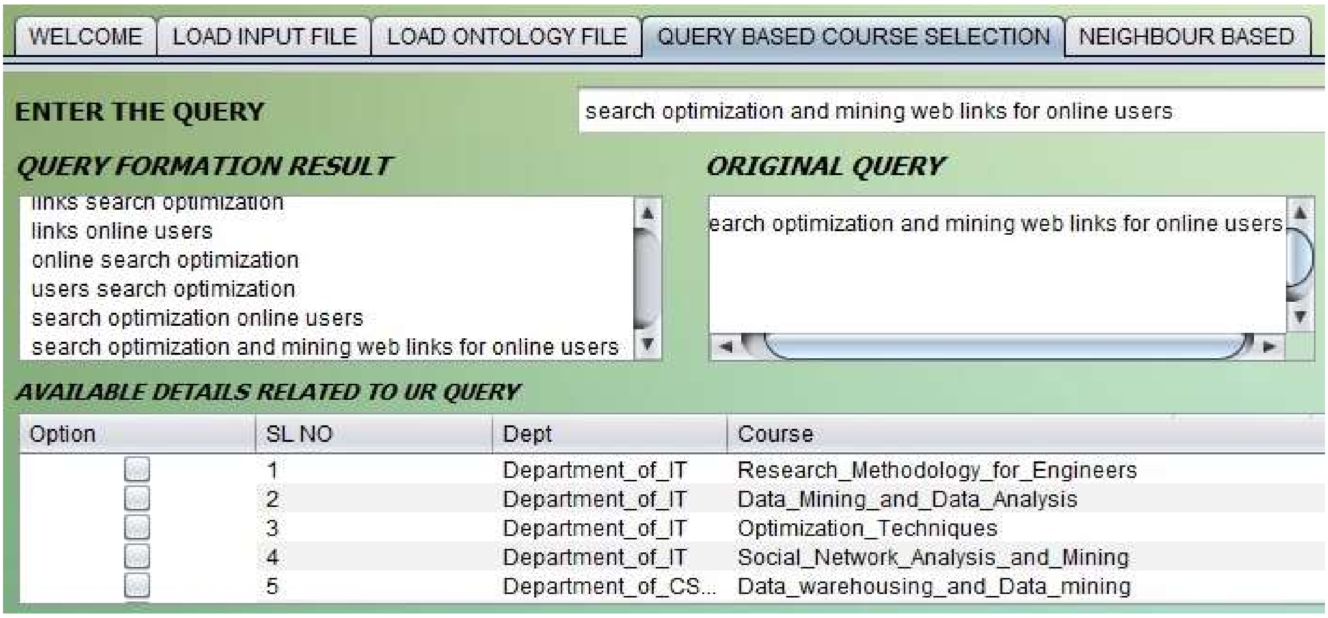

Figure 4. Course Recommendation by our Hybrid System

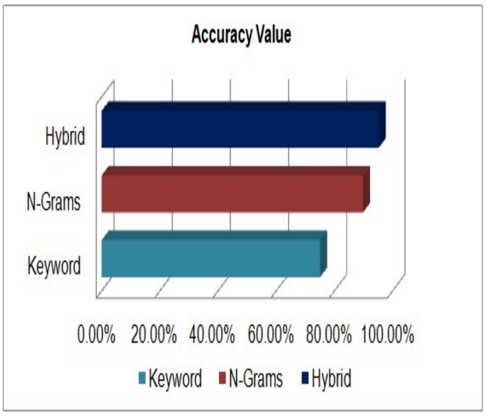

Figure 5a. Course Relevancy Comparison

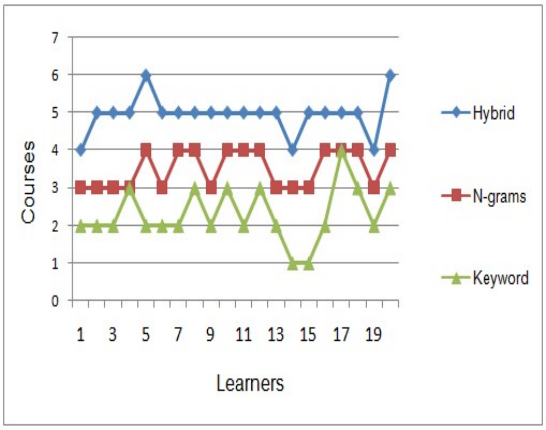

Figure 5b. Accuracy for Three Different Methods

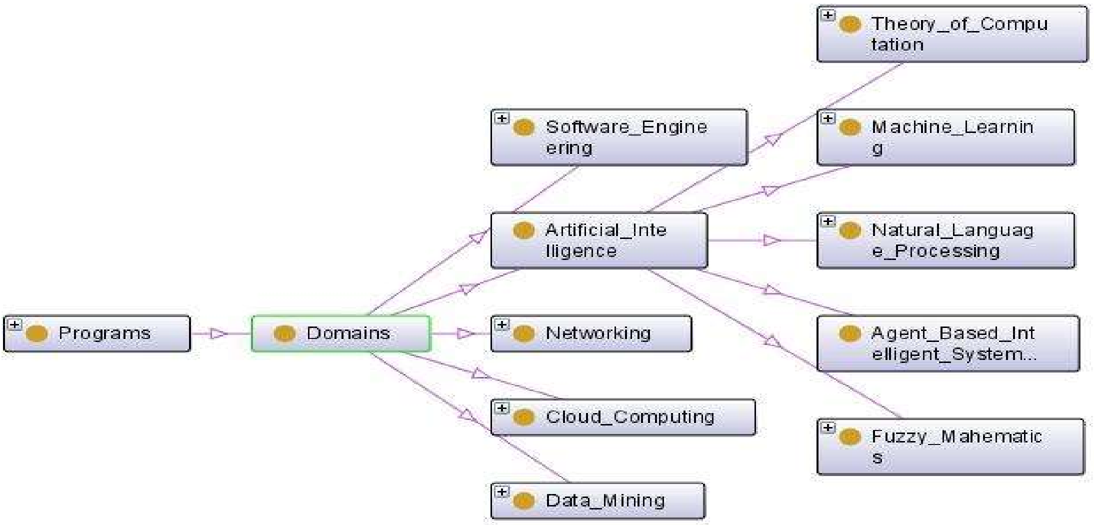

Figure 6. An Onto-Graph of Major Areas

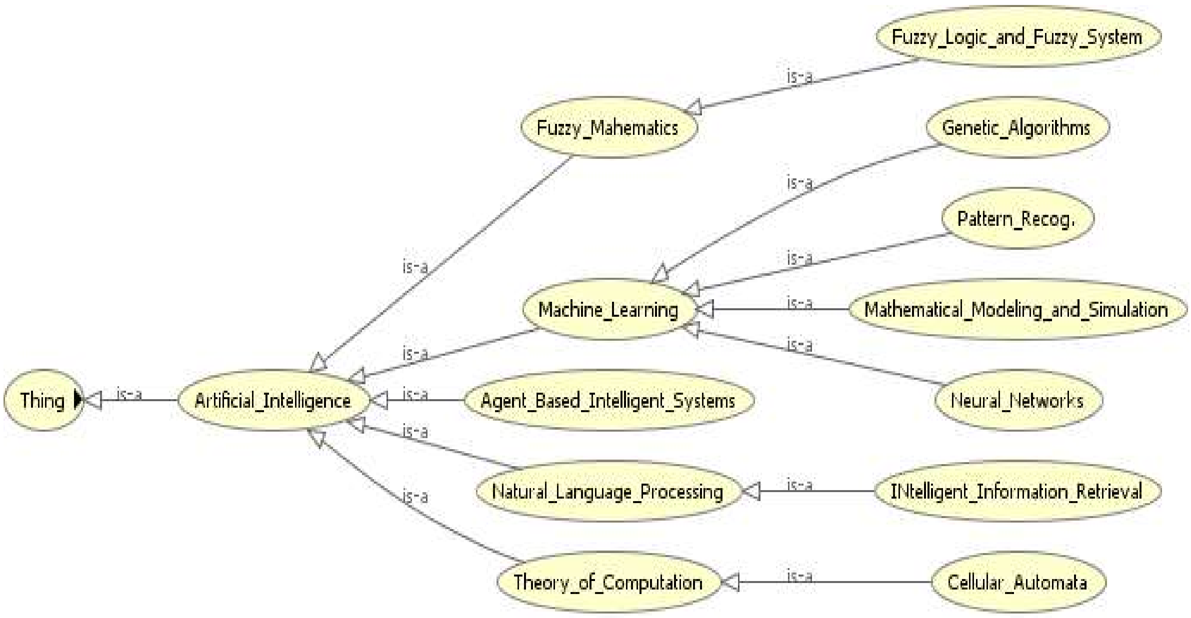

Figure 7. An Inference Diagram of Major Areas

B. INSTRUMENTATION

It is difficult to get a response from the complete population; sampling is the only way to draw conclusions from a limited sample size in a particular community [47]**.** The survey sample consists of researchers and research faculty members from three different universities, and convenience sampling (non-probability) was utilized because it has been used in many studies on technological acceptability due to its shorter time period and higher response rate. As a result, convenience sampling proved to be the most effective strategy for this study. Section 1 of the research instrumentation deals with the demographic information, experience, availability, and relevance of the participants.

Table 2. Participants' Characteristics

Attribute	Variable	Frequency	Rate
Gender	Male	37--- 69	46.%
	Female	43 ---81	54%
Age	23-30	96	63%
	31-40	51	34%
	> 40	3	3%
Time Spend on Course Selection	1-2 weeks	12	8%
	3-4	84	56%
	5-8	45	30%
	> 8	9	6%
Course Satisfaction & Relevancy	Fully	12	8%
	Partial	108	72%
	Irrelevant	30	20%
Designation	Scholars	115	76.%
	Faculty	35	24.%
Course Selection Methodology	Manual	150	100%
	Tech. Assisted	Nil	0.0%

Sections 2-5, on the other hand, employ a five-point -Likert response scale. For our new external variable, ten (10) questions were multiple choices, while the rest were developed using the Likert-5 scale with matching options: strongly Agree (1), Agree (2), cannot say (3), Disagree (4), Strongly Disagree (5). The questions posed, as well as the TAM variable linked with them, are detailed below. To ensure lucidity, unambiguousness, and comprehensiveness, three teachers with experience of handling research scholars were consulted for doing the pilot test & seven scholars who were in the stage of completing their PhDs to check the readability of the content present in the survey tool. The final version consisted of 30 items (excluding Name and Gender) that were presented to the 150 participants.

C. DATA COLLECTION

Over 175 people had access to the questionnaire that had been produced. The response percentage reported was 85.71 percent, with 150 valid responses afterwards used for analysis. External variables are measured in the first section of the study, while TAM components are measured in the second section, as mentioned in the questionnaire design above. As per the thumb rule, we should have a 5:1 ratio of participation concerning the total number of valid items [48]. While the minimum sample size for the estimation of likelihood should be 100 as per the recommendations given by [49]**.** In this study, the questionnaire comprises 30 items which give a suitable sample size of 150. Similar sample size results were obtained by previous studies [50], therefore collective size of sample (n=150) of this study is adequately effective and the details are provided in Table 2.

V. RESULTS

A. STATISTICAL ANALYSIS

In Table 3, Mean, Standard deviation, Skewness, and Kurtosis (as data normality) have been provided for PEOU, PU, ATU, Availability, Relevance, and Experience. The internal constructs are given a value range from 1-5, with 3 being the midpoint and the external constructs are given range from 1 to 4 with 2 being the middle point, as the number of items in external constructs is less compared to internal constructs. The range of mean is 4.44-4.53 for the first three constructs, which indicates that the overall response of scholars towards the recommender system is positive. The mean value further implies that the scholars have perceived more ease of use (PEOU=4.53) than the perceived usefulness (PU=4.45) and attitude towards using (ATU=4.44) the recommender system. The range for standard deviation is between 0.354 to 0.75, suggesting that the feedback of the scholars is barely stretched. For checking the normality of the data skewness, the bounded likelihood estimation value**,** should be within ± 3 as per [47] and for Kurtosis, the range should be under$\pm$ 10. Table 3 shows the desired value range for data normality for all the items in both Skewness and Kurtosis.

B. VALIDITY AND RELIABILITY ANALYSIS

The two-step approach suggested by [49] analyzed the model by assessing validating the reliability of the variables and SEM was used to check the variable significance. To evaluate the constructs' validity and reliability, the Average Variance Extracted (AVE) and composite reliability were computed and initially discriminant validity, reliability and convergent validity of the constructs were also tested. Within a single factor, reliability is used to assess the consistency of item-level mistakes.

Table 3. Convergent Validity and Reliability of the Constructs.

Constructs	Items	Cronbach's alpha	Factor loadings	CR	AVE
Perceived Ease of Use (PEOU)	PEOU1 PEOU2 PEOU3	0.765	0.894 0.845 0.848	0.920	0.75
Perceived Usefulness (PU)	PU1 PU2	0.863	0.838 0.877	0.765	0.53
Attitude towards use (ATU)	ATU1	0.755	0.857	0.923	0.75
Behavioral Intention to Use (BIU)	BIU1	0.890	0.894	0.923	0.750
Availability	A1, A2	0.764	0.787 0.787	0.76	0.61
Experience	E1, E2	0.763	0.794 0.778	0.76	0.76
Relevance	R1, R2	0.863	0.887 0.857	0.86	0.61

Additional tests were conducted utilizing Cronbach's alpha reliability assessment in addition to the previously described reliability and validity tests to examine instrument stages. Cronbach's alpha is internal consistency metric or a scale reliability that indicates how consistently a set of dependable variables loads on the same factor. Cronbach's alpha is a function of the number of test items and the inter-correlation (average) between them. This reliability metric will assess how closely a bunch of objects are linked. When the value of Cronbach's alpha reaches 0.07, constructs are regarded to have internal consistency dependability, according to studies [47]**.**

Using SPSS 21.0, we reacquired coefficients of Cronbach's alpha to evaluate the relationships in the structural model. All the metrics in this study have a good level of reliability, ranging from 0.755 to 0.863, with 0.863 being a satisfactory result for both PU and Relevance. The average scale was greater than 0.70, indicating that the survey was reliable. Table 3 shows the Cronbach's alpha coefficient for several criteria. Cronbach's-alpha is greater than 0.7 for all five components, indicating that the data is reliable. This value can be deemed adequate or sufficient in this study. By using the FL > 0.5, (factor loading in Eq.1) convergent validity was tested, for CR > 0.7 (Composite Reliability in Eq.2) and AVE > 0.5 (Average Variance Extracted in Eq.3) (Cheung, R., & Vogel, D., 2013) similar tests were done. The results in Table 4 suggested that the value of FL is above 0.5 ranged from 0.778- 0.894. It also shows all-composite reliability measures ranged from 0.76 to 0.923.

$$e_i = 1 - \lambda_i{}^2 \text{ Eq.} \quad (1)$$

The standardized factor loading for item i is (Lambda), while ε is the respective error variance for item i. As illustrated in Eq. 2, the error variance (ε) is calculated using the value of the standardized loading ((λ), while as Average variance is given in Eq.3.

$$(CR) = \frac{\sum_{i=1}^{k} \lambda_{i2}}{\sum_{i=1}^{k} \lambda_{i2} + \sum_{i=1}^{k} \lambda_{i2} Var(e_i)} \quad (2)$$

$$(AVE) = \frac{\sum_{i=1}^{k} \lambda_{i2}}{n} \quad (3)$$

As a result, the suggested model has met the item reliability recommendation. Convergent validity is established when different items are utilized to assess the same construct and the findings from the different items are mainly the result, the suggested model has met the item reliability recommendations. Convergent validity is established when different items are utilized to assess the same construct and the findings from the different items are substantially related. Table 4 further demonstrates that each item's factor loadings are highly significant (p<0.001) and greater than 0.5. If the constructs can be separated sufficiently from one another, discriminant validity is assessed, and if the square root of the AVE for a construct is greater than its correlations with other constructs, the same validity is established [54].

The value of CR > 0.7 is above the satisfactory measures and the values of AVE greater than 0.5 are also above the acceptable criteria.

The overall results indicated that convergent validity for all the constructs was satisfactory. Table 5 shows that the model meets the requirement for discriminant validity efficiently. We have seen that all appropriate reliability measures and fit indexes come within the suggested ranges; signifying the fact that the measurement model fulfilled all criteria for the model fit, construct validity, and reliability. As a result, the model might be used to evaluate the hypotheses in Section 3 about causal relationships.

To ascertain a bi-variate relationship between the variables or constructs, the analysis for finding the correlation is conducted. Cohen [55] suggested that the relation effect could be estimated in terms of strong, medium and small if and only if the range falls between 0.5 < r < 1.0, 0.3 < r < 0.5, 0.1 < r < 0.3, respectively. In Table 4, except for the correlation between Experience and Perceived Ease of Use, all other correlations are statistically significant positive. A strong positive association is found between Perceived Usefulness and Perceived Ease of Use, Attitude Towards Using and Perceived Ease of Use PEOU - Perceived Usefulness. The medium type of association is found between Availability and Perceived Usefulness - Attitude towards Using, Experience and Availability - Attitude towards Using, Relevance and Experience –Availability, Attitude Towards Using and Perceived Usefulness. The higher and medium values of correlation coefficients among external variables suggest that for path analysis these external variables can be considered [56], and that is the reason they were carefully in the part of path analysis.

For discriminant validation the values of square root of Average Variance Extracted (AVE) are tested to check co-relationship between constructs and the relations lower than Sqrt of AVE will be easily confirmed for discriminant validity [57]. The diagonal values of co-relation, i.e., the square roots of AVE in Table 5, show that they are greater than correlations values between the constructs and thus can be considered discriminant validity for all constructs. This in-turn suggests that all the variables discussed in the model exhibit higher discriminant validity, validity of convergence along with adequate reliability.

Table 4. Correlations as Discriminant Validity (Square Root of AVE in Diagonals).

Constructs	PEOU	PU	ATU	Availability	Experience	Relevance
PEOU	0.866	-	-	-	-	-
PU	0.687**	0.729	-	-	-	-
ATU	.812**	.835**	0.867	-	-	-
Availability	0.298*	0.332*	0.427*	0.786	-	-
Experience	-0.198	0.278*	0.324*	0.331*	0.786	-
Relevance	0.212*	0.298.*	.321*	0.327*	0.363*	0.872

Note: ***P ≤0.001, **p ≤ 0.01, *p ≤0.05, square roots of AVEs values are presented diagonally

Constructs	PEOU	PU	ATU	Availability	Experience	Relevance
PEOU	0.866	-	-	-	-	-
PU	0.687**	0.729	-	-	-	-
ATU	.812**	.835**	0.867	-	-	-
Availability	0.298*	0.332*	0.427*	0.786	-	-
Experience	-0.198	0.278*	0.324*	0.331*	0.786	-
Relevance	0.212*	0.298.*	.321*	0.327*	0.363*	0.872

Note: ***P ≤0.001, **p ≤ 0.01, *p ≤0.05, square roots of AVEs values are presented diagonally

C. STRUCTURAL MODEL

The proposed modified models fit indices final summarization is shown in Table 5. When the entire indices fall in the literature-recommended value ranges, the constructs are said to be well-fit. The data include the Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), Comparative Fit Index (CFI), Root Mean Squared Residual (RMSR), and Root Mean Square Error of Approximation (RMSEA). After determining the measurement model's reliability and validity, we performed analysis of the path to investigate the association between the latent variables. AMOS 23.0 was used to test the structural model. The constructs are well-fit because entire indices fall in the range of literature-recommended values.

Table 5. Summary of structural model fit indices

Fit Index	Critical Value	Measurement Model	Explanation
X^{2}/df	<3 [51]	1.35	Good
Goodness of Fit Index (GFI)	> 0.90 [51]	0.934	Good
Comparative Fit Index (CFI)	> 0.95 [51]	0.967	Good
Adjusted Goodness-of-Fit Index (AGFI)	> 0.90 [51]	0.916	Good
Root Mean Squared Residual (RMSR),	< 0.10 [51]	0.058	Good
Root Mean Square Error of Approximation (RMSEA)	< 0.08 [51]	0.03	Good
Normed Fit Index (NFI)	> 0.90 [51]	0.901	Good

Table 6 depicts the outcomes of the created path analysis and except for H10 and H7, the paths from Experience to Attitude toward Using and Relevance to Perceived Usefulness. All the path coefficients in Table 6 were determined to be statistically significant. After considering the correlations, estimated pathways, and modification indices, the inconsequential paths were eliminated, and the paths which are significant were considered.

Table 6. Parameter Estimate of path analysis

Path	Standard Coefficients	Standard Error	Supported
H1 : ATU ⟵ PU	0.41***	0.18	YES
H2 : BIU ⟵ PU	0.47***	0.17	Yes
H3 : PU ⟵ PEOU	0.35***	0.15	Yes
H4 :ATU ⟵ PEOU	0.42***	0.17	Yes
H5 : BIU ⟵ PEOU	0.48***	0.14	Yes
H6 : BIU ⟵ ATU	0.45***	0.16	Yes
H7 : ATU ⟵ EXP	0.08	0.10	No
H8 : BIU ⟵ EXP	0.57***	0.06	Yes
H9: PEOU ⟵ REL	0.32**	0.04	Yes
H10: PU ⟵ REL	0.09	0.13	No
H11: ATU ⟵ AVAIL	0.29*	0.13	Yes
H12: PU ⟵ AVAIL	0.49***	0.13	Yes
Note: ***p < 0.001,**p < 0.01, *p < 0.05			

VI. DISCUSSION & IMPLICATIONS

A. DISCUSSION

The growing popularity of RS in educational institutions has increased awareness of its use in the classroom, which is centered on the concept of personalization. Additionally, the recommender systems are offered to maximize a learner's learning experience because course selection has a direct impact on the learner's performance. In this connection, one of the first measures has been to investigate students' adoption of RS. Current research, on the other hand, fails to uncover qualities that may influence students' adoption of RS, as well as factors that may be influenced by their usage of RS. Therefore, the proposed comprehensive model was enhanced to bridge the gap. This study investigated the elements that influenced students' acceptance of and use of a course recommendation system in higher education as shown in Figure 8.

The proposed study methodology was built around the TAM characteristics of perceived utility, perceived ease-of-use, and behavioral intention. External elements were added to TAM to forecast the fundamental TAM constructs of Availability, Experience, and Relevance. Structural equation modelling was used to investigate the interactions between these constructs. Perceived Usefulness and Perceived Ease of Use are both significant predictors of Attitude towards Using and Behavioral Intention, according to the findings.

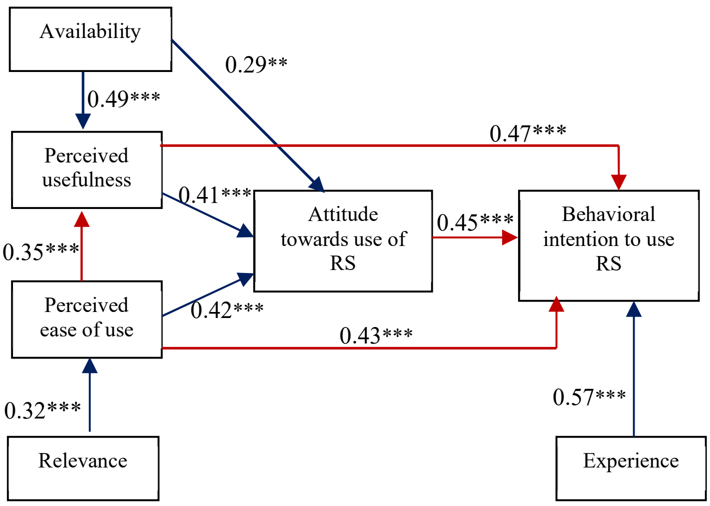

Figure 8. Verified model for acceptance and use of the recommender system

The findings are consistent with those of prior TAM research [59, 60]. Furthermore, perceived usefulness is found to be a stronger interpreter of behavioral intent than perceived ease of use, which is in line with earlier studies [61]. When it comes to the intention to utilize RS in course selection, learners are less hesitant to use it and are more likely to focus on its use and benefits. When it comes to the intention to use RS in course selection, learners who feel free to utilize RS are more likely to focus on the utility and benefits of doing so. It may be deduced that, even though a vast majority of students still lack access to RS, students' trust in the system remains a concern. Another evidence to understand student varied impressions of using RS could be the surprisingly unsupported hypothesized association between Experience with Attitude towards utilizing Relevance with Perceived Usefulness.

In addition to the core TAM elements, external factors such as availability, experience, and relevance are introduced to improve the model's explanatory power. Experience has been shown to be a key predictor of Behavioral Intention to Use, and its expansion proves more beneficial perceptiveness, and this outcome is consistent with the previous study [62]**.** Learners who have more familiarity with RS may be more familiar with the types of courses offered by the system. By detecting appropriate courses based on the learner inquiries, RS benefits can be maximized, as it is fully semantic and ideal for the learners' future development. As a result, as the learner's experience with RS grows, so does his or her productivity and quality of learning. This conclusion supports [63] assertion that "Once learners have experience of what RS can and cannot do, learners can reflect on the function of such systems in the recommendation process in a more realistic and less defensive way". Another piece of evidence that could help explain learner perceptions of utilizing RS is the surprisingly projected link between relevance and perceived ease of use. Even though the uncorroborated hypothesis contradicts [35] Technology acceptance model, it is consistent amid previous research [37]**.**

One probable elucidation is that RS is deemed simple to use, which does not necessarily imply that learners find it useful. As a result, greater effort should be put into understanding the antecedents of the learner's perceptions of usefulness. In addition to the analysis of unique TAM structures, RS availability is integrated as an external component to increase the model's instructional power. The availability of a RS is seen to be a major predictor of perceived usefulness and attitude towards using it. Increasing experience, availability, and relevance could lead to higher judgments of usefulness for all three factors. Besides, the subsequent result of using RS is confirmed. Learners' attitudes towards utilizing RS can be influenced by perceived usefulness, perceived ease of use, availability, and relevance. Because RS is primarily connected with the ease of use, easy accessibility and quick reaction are not difficult to comprehend. If a learner finds RS to be simple to use, they will be driven to use it to improve their subject knowledge and will strongly encourage others to use RS while selecting courses and performing other learning tasks. Furthermore, experience is discovered to be a strong predictor of RS behavioral intention. The outcomes of this study revealed important elements that influence the adoption of RS and the advantages of doing so.

B. IMPLICATIONS

Despite learners' increased attention to tools that propose courses for their study, studies investigating the other external elements for RS's adoption behaviors in suggesting courses at the educational level, particularly at the research and master's level, are still lacking. The current research could help with both theoretical and practical applications of the RS research. The expanded quasi-circular model with Availability, Experience, and Relevance, in theory, aids in identifying the variables that influence RS adoption and those that are influenced by employing RS. Furthermore, being a novel recommendation technology in education, RS's adoption research demands a robust and thorough model. As a result, this research could help enhance TAM theory in RS research. In practice, the findings of this study may offer recommendations to faculties, researchers, policymakers, and RS developers. Even though TAM has been widely used in e-learning studies, more information about content-specific and contextual usage is required [64]. By giving enormous and overwhelming influence of learners perceived utility about their intent to use RS, the RS developers must be conscious of technological limits that affect recommendation quality, and for faculties to be aware of the non-technological antecedents of the Perceived Usefulness, Attitude towards using and behavioral intention. Instructing learners to increase their use of the RS and documenting their views, for example, could be a beneficial strategy to improve recommendation algorithms, given that experience has been shown to be a substantial predictor of behavioral intention. Furthermore, Perceived Usefulness and Perceived Ease of Use are shown to have a significant impact on students' attitudes toward RS, whereas Experience may have an impact on their behavioral intentions. This research suggests that the conceptions have a cyclical influence relationship, which could lead to pedagogical recommendations for faculty. Using RS as an instance, faculties might use it as an assisting tool for improving learner's outcomes. Moreover, faults and inconsistencies in the RS outputs might be exploited to improve systems to make them more competent. Finally, the outcomes of this study may help policymakers better comprehend the RS and become more conscious of how to incorporate it into educational sites and portals.

C. LIMITATIONS

However, there are certain limitations to this study that should be addressed in upcoming research studies. Primarily, the studied sample sizes are smaller that may restrict the findings to be generalized. In future, the size of the sample taken should be bigger so that it will be examined to improve expounding power of the models. Second, the majority of the study's participants are beginner researcher scholars. According to [64], situation-based and population external constructs may contribute to various TAM outcomes. Learners with various domains and knowledge backgrounds about the RS will be involved in subsequent study to further validate the findings. Finally, this study's conclusions are based on self-reported and cross-sectional data. Students' attitudes towards using RS may evolve over time. To capture the desire to utilize the RS, a long-term study with a different source of data (e.g., Qualitative data: interviews and observations) would be examined.

VII. CONCLUSION

The incorporation of the recommender systems into the educational space is a crucial step in improving the standard and customization of the educational experiences. These systems provide an effective tool for scholars as technology continues to transform education. Recommender systems offer personalized content recommendations that consider different learning styles and preferences by leveraging the power of the user behavior analysis. The goal of this research is to figure out whether scholars will accept the recommendations suggested by the RS and what are the factors that influence a student or scholar to embrace new technologies. Making well-informed decisions based on reliable advice promotes engagement, lessens information overload, and opens the door for more profound learning experiences. However, effective integration necessitates constant improvement to guarantee the highest level of accuracy and efficiency, as well as careful consideration of ethical issues. As educational institutions continue to adopt new technologies, the addition of thoughtfully created and morally upstanding recommender systems demonstrates their dedication to providing students with a comprehensive and individualized educational experience. In this study it was seen that the scholars found the RS very useful in terms of choosing a course suggestion as they are very much relevant and would be helpful for their learning needs. One more thing was observed by the scholars who have already completed their course work, that the courses they have chosen manually was less relevant, time consuming and not appropriate as per their learning needs. The study, which includes a customized original TAM, aims to assess research experts' and students' willingness to use a recommender system. The TAM's basic constructs were modified to validate the relationship between perceived usefulness, perceived ease of use, attitude toward usage, and the impact on behavioral intention to use in general. No unexpected findings were reported in earlier constructs; hence the current study verifies past findings and empirical evidence based on the technological acceptance paradigm. It also successfully proves TAM's applicability to recommender systems. The findings of this study indicated that TAM is a reliable model for acceptance that may be used to predict behavioral intentions towards RS use before it is implemented. Furthermore, the study model has been validated in the setting of higher education with the highest level of the group. Furthermore, this research may aid institutions and E-learning software manufacturers in their efforts to implement such features in their educational domain.

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