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Students' Behavioral Intention towards Adoption of Peer Recommender Systems in Tanzania

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Abstract

This work investigates factors influencing students' behavioral intention to use peer recommender systems for collaborative learning in Tanzanian secondary schools. Peer-assisted learning (PAL) is a longstanding educational approach, and recommender systems (RS) offer a technological means to enhance PAL by matching students with suitable peers beyond their immediate classrooms. However, the successful adoption of such systems depends on user acceptance, especially in developing contexts where technological and cultural factors play a significant role. Drawing upon the Unified Theory of Acceptance and Use of Technology (UTAUT), we developed a research model with four core determinants: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. These factors were hypothesized to predict students' intention to adopt a peer recommender system. A survey of 1,029 secondary students from 8 schools in Tanzania was conducted. Results indicate that all four factors significantly affect behavioral intention. Performance expectancy, social influence, and facilitating conditions showed positive effects, while effort expectancy demonstrated a significant negative effect. The UTAUT model explained approximately 74% of the variance in students' behavioral intention, demonstrating its strong explanatory power in this context. Key recommendations include investing in necessary ICT infrastructure, ensuring the system is easy to use, leveraging social support from teachers and peers, and clearly communicating learning benefits to students. With the proper supportive conditions and user-centric design, peer recommender systems can be a viable tool to foster online peer learning among secondary school students in Tanzania.

1. Introduction

Peer-assisted learning (PAL) is a pedagogical approach grounded in collaborative engagement, wherein students provide mutual support and tutoring to facilitate learning. This model has been implemented across educational levels for several decades and remains pertinent in contemporary educational settings due to its capacity to foster active learning and peer engagement [1]. In recent years, PAL has been increasingly employed in diverse domains, such as medical education, to enhance educational outcomes and clarify conceptual frameworks surrounding collaborative learning [2], [3].

The integration of digital technologies has amplified the potential of PAL, extending its reach beyond individual classrooms or institutions. The theory of connectivism posits that learning occurs through dynamic networks comprising both human and non-human nodes, with technology serving as a crucial enabler of these connections [4]. In this digital era, secondary school students can form virtual learning communities that transcend geographical boundaries, provided that appropriate technological platforms are accessible and effectively utilized [5].

Recommender systems (RS) have emerged as a promising technological innovation to facilitate such peer connections. These systems are algorithm-driven tools designed to suggest items, such as products, services, or content, based on users' preferences or behavioural patterns [6]. While RS are extensively used in commercial settings to personalise user experiences, their educational applications have expanded to include the recommendation of learning resources, courses, and collaborative activities tailored to individual learner profiles [7].

Of particular relevance is the use of RS to recommend peer learners or study groups. This form of application, referred to as peer recommender systems, enables the formation of learning networks based on complementary academic needs, shared interests, or behavioural traits. Studies such as those by Bouchet et al. [8] and Potts et al. [9] have demonstrated the efficacy of such systems in Massive Open Online Courses (MOOCs), where learners were matched with suitable discussion or study partners. These studies illustrated the feasibility of leveraging RS to foster meaningful peer interactions, contributing to improved learner engagement, performance, and motivation, as well as reduced dropout rates.

Notably, Ma et al. [10] conducted a study in a high school context and found that a peer tutor recommender system substantially improved students' practical skills in computer science classes. Their findings underscore the practical value of integrating such systems into formal educational settings, particularly for promoting personalised and collaborative learning.

Despite their potential, the successful implementation of peer recommender systems in education is contingent upon user acceptance. The mere availability of technological tools does not guarantee their effective use; adoption is influenced by a constellation of contextual and cultural factors. In sub-Saharan African educational contexts, persistent challenges, such as inadequate infrastructure, limited technical support, and insufficient teacher training continue to hinder effective ICT integration[11]. Tanzania exemplifies this reality, especially in rural areas where schools frequently lack adequate computer facilities and reliable internet connectivity [12]. These barriers can significantly constrain access to digital learning innovations, including RS-based platforms.

However, local studies have shown that when ICT infrastructure is available and properly implemented, it can enhance both teaching and learning experiences. Schools in Tanzania that have invested in ICT resources report higher levels of student engagement and more enriching educational experiences, particularly in online or blended learning environments [13]. These findings affirm the importance of contextual readiness in fostering the adoption of new educational technologies.

Further insights are provided by Mtebe and Kondoro [14], who analyzed usage patterns of the Halostudy eLearning system in Tanzanian secondary schools. Utilizing data mining tools on 68,827 individual records, they discovered that system usage was moderate and on the decline. Notably, there was significant variability in the use of multimedia elements across subjects, with Biology exhibiting the highest engagement and Mathematics the lowest. Additionally, students from urban regions, such as Dar es Salaam, Mwanza, and Arusha demonstrated higher system usage compared with those from peripheral regions. These findings highlight the challenges in sustaining student engagement with eLearning platforms and underscore the need for strategies to enhance usage, particularly in underrepresented regions.

Complementing these findings, Mwakisole et al. [15] proposed a cloud-based computing architecture for eLearning systems in Tanzanian secondary schools. Their study revealed that cloud-hosted systems outperform traditional school-based servers in terms of scalability, maintainability, and access reliability. These performance advantages are particularly significant for supporting data-driven educational innovations, such as recommender systems, which require dependable backend infrastructure to function efficiently. By offering centralized access and ease of content updates, cloud-based platforms present a practical foundation for deploying peer recommender systems at scale in diverse educational contexts.

Despite the growing global interest in educational RS, there is a notable research gap concerning their use in secondary education within sub-Saharan Africa. Specifically, there is limited empirical evidence on how students in this region perceive and intend to use peer recommender systems for collaborative learning. Much of the existing literature on educational RS has focused on system design and effectiveness, predominantly within higher education contexts in the Global North [16]. The socio-educational environment in Tanzanian secondary schools, characterised by communal learning traditions, limited resources, and evolving digital infrastructures, warrants a focused investigation into student perceptions and behavioural intentions toward such technologies.

This study aims to address this gap by exploring Tanzanian secondary school students' intention to adopt and use a peer recommender system for collaborative learning. To this end, the research applies an extended version of the Unified Theory of Acceptance and Use of Technology (UTAUT), a well-established model for analysing technology adoption behaviour [17]. The model has been contextualised to reflect the unique characteristics of the Tanzanian secondary school environment, and hypotheses have been developed to investigate the determinants of students' intention to use peer recommender systems. By doing so, this study contributes to both theoretical and practical understandings of how such systems can be effectively deployed to enhance peer-assisted learning in secondary education settings across sub-Saharan Africa.

2. Literature Review

Peer-assisted learning (PAL) has a long-standing history as a pedagogical strategy. It significantly enhances student learning outcomes by enabling learners to support one another through sharing knowledge collaboratively. Traditionally implemented through one-on-one tutoring sessions or structured group study arrangements, PAL has been shown to improve both conceptual understanding and practical skills for learners and peer tutors alike. These benefits have been widely documented across both secondary and tertiary education systems, affirming PAL as an effective approach to deepen learning through peer interaction [1].

In recent years, the evolution of digital technologies has revitalised the application of PAL by extending peer learning opportunities beyond the physical boundaries of traditional classrooms. Online platforms now facilitate synchronous and asynchronous peer interaction among students, thereby widening access to PAL practices. The theoretical underpinning of this transformation is grounded in the theory of connectivism, which argues that knowledge resides in distributed networks and that meaningful learning is achieved by forming connections with various “nodes,” including individuals and digital content [4]. In this context, digital technologies serve as key enablers that connect learners with resources and peers across spatial and temporal divides.

The increasing penetration of the internet, particularly via mobile devices, has further facilitated the feasibility of virtual peer learning among secondary school students, even in geographically remote areas. Nevertheless, one of the major challenges within online PAL environments lies in the selection of appropriate peer collaborators from an extensive array of potential participants[18], [19]. Traditionally, the process of identifying suitable peer partners has relied heavily on the judgment of teachers or the initiative of students themselves. This manual approach is inherently time-consuming and often constrained by existing social networks or limited exposure to diverse peer groups. Consequently, the educational technology community has shown growing interest in developing intelligent systems that can automate and optimise the peer-matching process [20].

Recommender systems (RS) have emerged as a promising technological solution to address this challenge. RS are algorithmic tools that suggest the most relevant items based on users’ profiles, preferences, or historical behaviours. Initially developed for commercial domains, such as e-commerce and media streaming, RS technologies have been successfully adapted for educational purposes. In the education sector, early applications focused primarily on recommending personalised learning materials, such as articles, videos, and digital courses, using learners’ interaction data or academic performance records as input criteria [6], [21].

Over the past decade, a growing body of scholarly literature has explored the integration of RS within educational contexts. Empirical studies have shown that RS not only help students navigate learning resources more effectively but also improve their engagement with course content. For example, Bouchet et al. [8] implemented a peer recommender system within a Massive Open Online Course (MOOC) and observed that learners were generally receptive to discussion partners suggested by the systems. Potts et al. [9] evaluated a reciprocal peer recommendation algorithm in a large-scale online class and demonstrated that the system could efficiently form learning pairs, facilitating collaborative academic support.

Further advancements have been noted in the work of Shou et al. [22], who introduced a peer recommendation model using network representation learning to identify peer learners in university settings. Their findings indicated high matching accuracy and positive learner feedback, underscoring the system’s potential for broader educational use. Despite these promising results, the focus of most of these studies has been on adult learners in higher education or participants in global open courses. As such, there remains a paucity of research concerning the applicability of peer RS to secondary school contexts.

Moreover, the existing literature primarily evaluates technical performance indicators, such as algorithm accuracy, system scalability, and usage statistics, without adequately addressing the motivational and cultural factors that influence user acceptance. This is especially relevant for younger students in developing countries, who may encounter unique challenges related to digital literacy, learning autonomy, and cultural norms surrounding education and technology use.

Introducing any educational technology, including recommender systems, into sub-Saharan African secondary schools necessitates careful consideration of the region’s distinctive contextual factors. Governments and educational institutions across Africa have increasingly recognised the transformative potential of ICT in bridging educational disparities and improving teaching and learning processes [23]. However, practical impediments continue to obstruct widespread adoption. These include inadequate ICT infrastructure, frequent power outages, poor internet connectivity, and a lack of skilled personnel to support and maintain technological systems [24].

In Tanzania, both qualitative and quantitative studies have provided comprehensive analyses of the barriers and opportunities related to ICT integration in secondary education. Ndibalema [24], [25], for example, identified a range of structural limitations, including insufficient computer laboratories, limited technical support for teachers, and a general lack of teacher readiness to integrate ICT into pedagogical practice. Similarly, Mwila [25] conducted a comprehensive survey in the Kilimanjaro region and found that schools with well-established ICT infrastructure and consistent training programmes were more likely to report enhanced learning outcomes. Conversely, schools lacking these resources experienced stagnant or declining academic performance.

These empirical findings point to the critical importance of facilitating conditions in the successful deployment of educational technologies. Facilitating conditions encompass the availability of supportive infrastructure, access to technical expertise, and administrative endorsement, all of which significantly influence the adoption and sustained use of technological innovations [17]. In the Tanzanian context, cultural norms and social dynamics further complicate technology integration. For instance, students often depend on guidance and approval from key figures, such as teachers, parents, and school leaders. These authority figures can either encourage or discourage the use of new technologies, thereby serving as powerful mediators of social influence [24].

In summary, existing literature affirms the potential of recommender systems to augment peer-assisted learning by automating the process of peer selection, thereby enhancing the efficiency and quality of collaborative educational experiences. However, numerous factors, ranging from system usability and infrastructural readiness to social and cultural acceptance, affect the actual uptake of such systems, particularly among secondary school students in sub-Saharan Africa. Notably, there is a significant gap in empirical research focused on understanding the behavioural intentions of African secondary students to adopt peer recommender systems for learning.

This study seeks to address that research gap by investigating the determinants of behavioural intention to use peer recommender systems among Tanzanian secondary school students. Drawing from UTAUT, the research model incorporates contextual variables such as perceived ease of use, facilitating conditions, and social influence, to better understand the complex interplay of factors that shape students' acceptance of educational technology in this setting. Through this analysis, the study aims to contribute to both theoretical advancement and practical implementation strategies for peer recommender systems in Tanzanian and comparable educational environments.

2.1 Theoretical Framework

To explore the determinants of technology acceptance among Tanzanian secondary school students in relation to a peer recommender system, this study adopts UTAUT as its theoretical framework. The UTAUT model, developed by Venkatesh et al. [17], integrates elements from eight previously established models of technology acceptance, providing a comprehensive framework for explaining users' behavioural intentions and subsequent technology usage. UTAUT was selected due to its comprehensive nature and its established predictive power in educational technology adoption studies. Thus, this work as well extended the UTAUT model to investigate the behaviour intention of adopting and using peer recommender systems in online learning environments.

The model extension was based on the four constructs of the UTAUT model, which includes performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) [17]. These constructs are recognised as critical drivers of behavioural intention to adopt new technologies, with each representing a distinct domain of user perception. The original UTAUT also includes moderating variables, such as age, gender, experience, and voluntariness of use. However, given the homogeneous nature of the current sample (adolescent students) and the hypothetical deployment status of the system, these moderating variables were not applicable and thus excluded. Thus, this research focuses exclusively on the direct effects of the four core constructs (Figure 1).

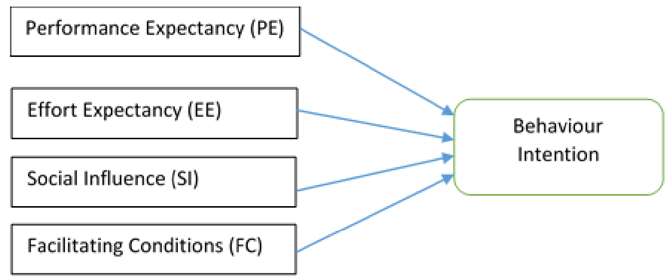

Figure 1. UTAUT research model.

Each construct was operationalised and contextualised for the secondary school learning environment.

2.2 Performance Expectancy

Performance Expectancy refers to the degree to which an individual believes that using a particular technology will yield performance gains. In the educational setting, it represents the student's belief that a peer recommender system will enhance their academic performance. For Tanzanian secondary school students, this may involve expectations that the system can assist in identifying suitable learning partners, provide access to better peer support, or increase the efficiency of collaborative learning sessions. Prior research confirms that perceived usefulness strongly influences technology acceptance in education [17].

Hypothesis 1 (H1): Performance Expectations positively influence students' behaviour intention to use peer recommender system.

2.3 Effort Expectancy

Effort Expectancy captures the perceived ease of using the system. It reflects the extent to which students believe that the peer recommender system will be simple, intuitive, and require minimal technical effort. In contexts where digital literacy varies significantly, especially in rural Tanzanian schools, systems that are user-friendly and accessible across devices (e.g., smartphones) are more likely to be adopted. Previous studies have consistently found that ease of use plays a significant role in predicting intention to use educational technology [17], [26].

Hypothesis 2 (H2): Ease of use (Effort Expectancy) positively influences students' Behavioural Intention to use peer recommender system.

2.4 Social Influence

Social Influence measures the extent to which students perceive that influential people, such as teachers, parents, or peers, think they should use the technology. In the Tanzanian school context, where teacher endorsement is highly valued and peer relationships are critical to learning motivation, social influence can play a pivotal role. If the system is promoted by teachers or if it becomes popular among classmates, students may be more inclined to adopt it to align with peer expectations or gain social approval. Social influence has been identified as a strong predictor of technology adoption in collectivist cultures, such as those in sub-Saharan Africa [17], [26], [27].

Hypothesis 3 (H3): Social influence positively influences students' behaviour intention to use peer recommender systems.

2.5 Facilitating Conditions

Facilitating Conditions refer to the individual's perception of the availability of the technical and organisational infrastructure required to use the system. This includes access to digital devices (computers or smartphones), internet connectivity, and technical support within the school environment. In many Tanzanian secondary schools, particularly those in underserved regions, inadequate facilities and poor connectivity can limit students' ability to benefit from digital innovations. The influence of facilitating conditions on behavioural intention has been demonstrated in numerous studies, especially in settings with limited ICT infrastructure [16, 27] .

Hypothesis 4 (H4): Facilitating Conditions positively influence students' behavioural intention to use peer recommender systems.

2.6 Behavioural Intention and Hypotheses

All hypotheses were framed in the affirmative, reflecting the theoretical assumptions of UTAUT and the positive findings from prior research on technology acceptance in educational contexts. Although the peer recommender system had not yet been deployed at the time of data collection, behavioural intention was used as a proxy indicator of future usage, in line with UTAUT studies which demonstrate that intention is a reliable predictor of actual behaviour [17]. This approach enabled us to anticipate the key drivers and potential barriers to system adoption in secondary school's once implementation occurs.

3. Methodology

3.1 Research design and sampling

This research employed a quantitative, cross-sectional survey design to investigate the factors influencing secondary school students' behavioral intention to use a peer recommender system in Tanzania. The target population comprised O-level secondary school students (Forms 1 to 4), generally aged between 13 and 20 years. Eight schools from Njombe and Mbeya regions were selected using a convenience sampling technique. The schools represented a mix of urban and semi-urban settings and included one all-girls school to ensure diversity in the student sample. Data collection was conducted using paper-based questionnaires administered in school assembly halls or similar venues. Participation was voluntary, and confidentiality was assured. Out of the 1,600 distributed questionnaires, 1,029 valid responses were collected.

3.2 Survey Instrument Development

The data collection instrument was a structured questionnaire divided into three main sections. Section A introduced the purpose of the survey and included an informed consent prompt. Section B contained items measuring the core constructs of the UTAUT model: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Behavioral Intention. These items were adapted from Venkatesh et al. [17] and contextualized to refer specifically to a peer recommender system for finding compatible partners. Responses were recorded on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Table 1 shows the content of section B of the tool that included the construct items of the UTAUT model.

Section C gathered demographic information, such as age, gender, school, and class year. The questionnaire was piloted with ten recent O-level graduates to ensure clarity, and minor revisions were made based on their feedback. Section C, was reserved for collecting demographic data. This section was purposely placed in the last part of the tool to minimize chances of the questions which would be skipped if they were placed instead. The demographic data that were collected includes birthdate, grade, gender, and school name.

3.3 Survey Administration Procedure

The survey was administered in person by researchers and trained assistants, who provided instructions and ensured that students completed the questionnaires individually within approximately 15-20 minutes. Ethical considerations were observed, including obtaining permission from school authorities and assuring students of anonymity and voluntary participation.

3.4 Data Analysis Techniques

Data analysis was conducted using open-source statistical packages, including Jamovi and JASP. The process included descriptive statistics to summarise participant demographics and response patterns. The internal consistency of each construct was assessed using Cronbach's alpha, with all constructs exceeding the 0.70 reliability threshold. The suitability of the data for factor analysis was evaluated through the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity. Exploratory factor analysis was performed using principal components extraction with Promax rotation to confirm the construct validity of the instrument. Subsequently, multiple linear regression analysis was used to test the research hypotheses, with Behavioral Intention as the dependent variable and the four UTAUT constructs as independent variables.

3.5 Model Estimation Procedures

Among the objectives of analysing survey data included the need to examine the relationship between independent variables (PE, SI, FC, and EE) and an independent variable, BI. Multiple linear regression analysis was performed to assess the predictive power of the four UTAUT constructs on behavioral intention. The general regression model was specified as shown in equation (1):

$$BI = \beta_0 + \beta_1 xPE + \beta_2 xSI + \beta_3 xFC + \beta_4 xEE \quad (1)$$

where β_0 is a mean value of the dependent variable (BI), and the other β coefficients (β_1, β_2, β_3, and β_4) represent the strength and direction of the effect of each predictor on behavioral intention.

4. Results

4.1 Sample Characteristics

Data were collected from 1,029 valid responses obtained from secondary school students in Tanzania. The sample comprised students from eight secondary schools located in Njombe and Mbeya regions, selected through convenience sampling.

Table 1. UTAUT based constructs items.

Core Constructors	Variable code	Construct Item
Performance Expectancy (PE)	PE1	I would find peer recommender systems useful in finding peers for collaborative learning.
	PE2	Using peer recommender systems will enable me getting the matching peers for collaborative learning more quickly
	PE3	Using peer recommender systems increases the chance of collaborating with peers from other schools
	PE4	Using peer recommender systems will increase the success of my studies through the ease of getting peers for collaborative learning
Effort Expectancy (EE)	EE1	It would be easy for me to become skilful at using the peer recommender systems
	EE2	I would find peer recommender system easy to use
	EE3	Learning to operate peer recommender system is going to be easy for me
	EE4	My interaction with the peer recommender system would be clear and understandable.
Social Influence (SI)	SI1	If I see my fellow students using peer recommender system, I would also try to use it
	SI2	If the people who have been giving me advice on my studies recommend me to use the peer recommendation system, it will affect my intention to use the peer recommender system.
Facilitating Conditions (FC)	FC1	I will get guidance and support on proper use of peer recommender system from the system and user's guide
	FC2	There will be help when I get problem in using peer recommender system
	FC3	The peer recommender system is going to be more similar other application I have once used
	FC4	I have the necessary resource to access peer recommender system
	FC5	My school have necessary resources to support me accessing the peer recommender system
Behaviour Intention (BI)	BI1	I intend to use peer recommender system once it becomes ready for use
	BI2	I would use peer recommender system once it becomes ready for use
	BI3	I plan to use peer recommender system once it becomes ready for use

Students from all four forms (Form 1 to Form 4) participated. The overall response rate was approximately 64.31%, (1029 respondents), out of the 1,600 questionnaires distributed. Of the respondents, approximately 58.89% were female (606) and approximately 41.11% were male (423), with ages ranging from 13 to 25 years, though the majority were between 15 and 19 years old.

4.2 Instrument Validation

The reliability and validity are the key aspects of research methodology appropriate for evaluating the accuracy and consistency of the tool used to collect data [28, 29] . For this purpose, various studies often use Cronbach's Alpha coefficient [31]. Likewise, the internal consistency of each construct was assessed using Cronbach's alpha. Based on the results following the analysis of the survey data using Jamovi statistical software, the overall Cronbach's alpha coefficient was 0.966. The resulting Cronbach's alpha coefficient aligns with the requirement that Cronbach's alpha coefficient should be greater than 0.70 [32]. The Cronbach's alpha coefficients for each construct are as shown in Table 2.

Table 2. Cronbach's alpha coefficient.

	Core Constructs	Cronbach's Alpha Coefficient
1	Performance Expectancy (PE)	0.902
2	Effort Expectancy (EE)	0.869
3	Social Influence (SI)	0.903
4	Facilitating Conditions (FC)	0.839
5	Behaviour Intention (BI)	1.00

As shown in Table 2, all constructs met or exceeded the 0.70 threshold, with values at least 0.839, indicating high reliability.

4.3 Sampling Adequacy

The measure of the sampling adequacy was evaluated using Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy technique [33]. Based on the KMO measure, the KMO value should be at least 0.50 for the need of performing factor analysis [33]. For this purpose, the Jamovi version 2.3.26 statistical software was used. The results from performing the KMO Measure of Sampling Adequacy (MSA), as shown in Table 3.

Table 3. KMO Measure of Sampling Adequacy (MSA).

	Core Constructs	KMO MSA
	Overall	0.803
1	Performance Expectancy (PE)	0.772
2	Effort Expectancy (EE)	0.800
3	Social Influence (SI)	0.805
4	Facilitating Conditions (FC)	0.795
5	Behaviour Intention (BI)	0.843

Based on the KMO MSA in Table 3, the overall KMO value for 18-items from the four constructs was evaluated to 0.803. From this value, KMO_MSA = 0.803, it was confirmed that the minimum required sampling adequacy of the collected data was satisfied. The evaluation setup was performed with Bartlett's test of sphericity $p < 0.001$, indicating that the minimum required correlation between items is satisfied for performing principal component analysis.

4.4 Principal Component Analysis

The principal components analysis extraction method on 18 construct-items was used for performing factor analysis. All items from each construct loaded successfully. The loading for each construct-item is as shown in Table 4. During the factor analysis, the default Jamovi (version 2.3.26) minimum loading factor of 0.3 was used.

Moreover, the default Promax was used as the Kaiser Normalization rotation method. The resulting loadings for each of the 18 construct-items was as shown in Table 4.

Based on the information shown in Table 4, all survey items loaded strongly on their intended constructs (factor loadings > 0.3), confirming construct validity.

4.5 Regression Analysis

A multiple linear regression analysis was conducted to assess the predictive power of the four UTAUT constructs on behavioral intention. The model was statistically significant (F-test, $p < 0.001$), with an R value of 0.861 and an R-squared value of 0.742.

Table 4. Component Loadings for UTAUT based Construct Items.

	Performance Expectancy	Effort Expectancy	Social Influence	Facilitating Conditions	Behaviour Intention
PE1	0.750				
PE2	0.843				
PE3	0.909				
PE4	0.863				
PE5	0.877				
E1		0.888			
E2		0.929			
E3		0.808			
E4		0.762			
S1			0.956		
S2			0.956		
FC1				0.909	
FC2				0.926	
FC3				0.781	
FC4				0.720	
FC5				0.510	
BI1					0.973
BI2					0.973
BI3					0.844

This indicates that the four predictors collectively explained 74.2% of the variance in behavioral intention. The adjusted R-squared was 0.741, and variance inflation factors (VIFs) were all below 2, confirming no multicollinearity.

Other information to assess the predictive power of the four UTAUT constructs on Behavioral Intention are shown in Table 5. Table 5 shows the intercept, the beta values, and the standard errors for all the four constructs. Based on the results presented in Table 5, three constructs have significance positive effect and one construct has negative effect on students' behavioural intention to adopt and use peer recommender system at $p<0.001$. Each construct can be interpreted as follows:

H_1 (PE → BI) is supported: PE positively and significantly predicts BI ($\beta = 0.488$, $p < 0.01$).

H_2 (SI → BI) is supported: SI also has a positive and significant effect ($\beta = 0.586$, $p < 0.01$).

H_3 (FC → BI) is supported: FC is the strongest positive predictor ($\beta = 0.924$, $p < 0.01$).

H_4 (EE → BI) is not supported: EE had a negative but non-significant effect on BI ($\beta = -1.012$, $p < 0.01$).

The PE variable has positive beta coefficient, therefore for every 1-unit increase in the perceived usefulness, the behaviour intention will increase by 0.488 coefficient value. The SI variable has positive beta coefficient; therefore, for every 1-unit increase in the influence of people perceived important, the behaviour intention will increase by 0.586 coefficient value. The fourth construct is as well having a positive effect on the dependent BI variable. That is, for every 1-unit increase in the facilitating infrastructure, the behaviour intention will increase by 0.924 coefficient value. The EE variable has negative beta coefficient; therefore, for every 1-unit decrease in the required effort to use the system, the behaviour intention will increase by 1.012 coefficient value. The other information from the Table of results is the intercept. This value represents the mean value of the dependent variable (BI) when all independent variables are not considered. In our case, the mean value of the dependent variable is 0.566. Thus, based on these regression coefficients, the estimated regression equation is as shown in equation (2):

$$BI = 0.566 + 0.488PE + 0.586SI + 0.924FC - 1.012EE \quad (2)$$

The statistically significant regression coefficients for all four UTAUT constructs affirm the applicability of the UTAUT model in this context.

Table 5. Research Model Coefficients.

	Core Constructs	Coefficient	Std. Error	p-value
	Model intercept	0.566		
H_1	Performance Expectancy (PE)	0.488	0.902	<.001
H_2	Social Influence (SI)	0.586	0.903	<.001
H_3	Facilitating Conditions (FC)	0.924	0.839	<.001
H_4	Effort Expectancy (EE)	-1.012	0.869	<.001

4.6 Descriptive Statistics

The mean scores for each construct are shown in Table 6.

Table 6. Means of constructs

Core Constructs	PE	EE	SI	FC	BI
Mean	4.522	3.650	3.616	3.407	4.346

5. Discussions

This study sought to identify the determinants of Tanzanian secondary school students' behavioural intention to adopt a peer recommender system. It used UTAUT as a guiding framework. The findings broadly align with theoretical expectations and are consistent with patterns observed in both global and local technology adoption research. Each UTAUT construct was found to significantly influence intention, reflecting the multifaceted nature of technology acceptance in the Tanzanian secondary school context.

Facilitating conditions emerged as the strongest predictor of behavioural intention. It underscores the importance of infrastructure and support in shaping students' readiness to adopt a peer recommender system. This finding is consistent with that obtained by Yuan et al. [34], which identified facilitating conditions as the most influential factor in elementary teachers' adoption of educational technologies in China. Similarly, Mtebe and Raisamo [12] emphasized that access to ICT infrastructure and technical support is essential for e-learning adoption in Tanzanian universities. In secondary schools, facilitating conditions include access to computers or smartphones, internet connectivity, reliable electricity, and support from teachers or IT personnel. The strong influence of this construct suggests that, even when students are willing to adopt new technology, the absence of enabling resources remains a major barrier. The finding echoes the conclusions of Ndibalema [28], who found that poor infrastructure hinders ICT use in Tanzanian secondary schools. Comparable insights are observed in Kweka and Ndibalema [24], who reported that teachers in Tanzanian public secondary schools struggle to integrate ICT due to persistent infrastructural deficits. Another relevant work by Kafyulilo et al. [35] indicated that the lack of digital content, hardware, and teacher training limited the effective implementation of technology-supported pedagogy in science subjects. These studies reinforce that, for peer recommender systems to succeed in Tanzanian schools, significant investment in foundational ICT infrastructure and training is imperative.

Effort expectancy was also significant, but with an inverse relationship: higher perceived ease of use was associated with greater intention to adopt the peer recommender system. Although the regression coefficient was negative, this reflects scale coding and reaffirms the widely accepted notion that ease of use promotes technology adoption [36]. This result is supported by studies such as Zuiderwijk et al. [37], who found that technological complexity hindered adoption of open data platforms. In the Tanzanian context, Mtebe et al. [38] identified that secondary school students prefer digital learning platforms that are simple, familiar, and easy to navigate. Mwalongo [39] similarly reported that when secondary school teachers found ICT tools too complex or time-consuming, they were less likely to adopt them. These findings underscore the importance of designing systems that align with user expectations and competencies. Developers must prioritise intuitive interfaces, minimal steps to get started, and integration with familiar user experiences (e.g., WhatsApp-like messaging or social media interfaces) to lower the cognitive load of use.

Performance expectancy was also a strong and significant predictor of intention, with a mean score of 4.52 indicating high perceived usefulness. Students believed that the peer recommender system would improve their learning efficiency and outcomes. This perception is aligned with findings from Pal et al. [40], who reported that educational recommender systems enhance learning performance and engagement. The UTAUT literature consistently identifies performance expectancy as a key determinant of technology acceptance [17], [41]. In Tanzania, Mtebe and Raphael [42] found that mobile-supported learning applications positively impacted students' academic engagement and were regarded as beneficial for exam preparation and coursework. Additionally, Minga and Ghosh [43] found that students in digitally enhanced secondary schools believed technology improves access to learning materials and enhances peer engagement, leading to better learning outcomes.

Social influence also had a positive and significant effect on students' behavioural intention. This reflects the role of teachers, peers, and possibly parents in shaping perceptions and acceptance of new technologies. This is especially true in collectivist cultures like Tanzania, where social norms and the approval of others are pivotal in forming individual behavior, an observation that is also supported by the research Sife, Lwoga and Sanga [27]. The positive effect of social influence aligns with the UTAUT proposition that peer and authority endorsement is particularly influential in voluntary adoption contexts [17]. In Tanzanian secondary schools, Mwalongo [39] and Ndibalema [28] both found that teacher attitudes and support were central to successful ICT integration. Moreover, Komba and Nkumbi [44] observed that students are often highly responsive to encouragement from school authorities when adopting new learning practices. This finding suggests that teachers and student leaders should be actively engaged in any rollout of the peer recommender system. School-wide communication and endorsement strategies can serve to normalise and promote the platform's use.

Collectively, the results validate the applicability of the UTAUT model to a sub-Saharan African secondary education setting. The high explanatory power (R^2 = 0.742) of the model affirms its robustness, even outside its traditional corporate or higher education domains. While most prior studies applying UTAUT have focused on university students or professionals in developed countries, this research contributes to an emerging body of literature demonstrating the model's relevance in under-resourced school environments. Moreover, this work represents, to our best knowledge, the first empirical application of UTAUT to the case of a peer recommender system for peer-assisted learning in secondary education. In doing so, it bridges a critical gap between recommender system design and the user-centered realities of their implementation in low-resource contexts. The results also highlight the necessity of a balanced approach to technology implementation, one that addresses not only user perceptions of utility and ease but also infrastructure readiness and community engagement. These findings serve as a practical guide for educators, developers, and policymakers aiming to foster digital transformation in Tanzanian schools and comparable contexts.

Building on these findings, the research offers implications for both theory and practice. Theoretically, the research offers a validated conceptual model extending UTAUT to the domain of peer-assisted learning and educational recommender systems in Tanzanian secondary schools. The high explanatory power of the model (R^2 = 0.742) confirms the relevance of the four core UTAUT constructs in predicting students' behavioural intention to adopt a peer recommender system. Notably, the strong influence of facilitating conditions suggests that, in contexts where ICT infrastructure is limited, access and support may serve as foundational elements for shaping users' perceptions and intentions. The findings contribute to theoretical literature by reaffirming the universality of UTAUT while highlighting the need for adaptation in resource-constrained educational settings.

Practically, the findings underscore several actionable priorities for implementation. Facilitating conditions should be a primary focus; without reliable infrastructure, device access, and technical support, the likelihood of student adoption remains low regardless of perceived benefits. Schools must invest in appropriate ICT tools and human support structures to ensure readiness. Equally critical is the need for simplicity in system design. Given that effort expectancy negatively affect intention, designers should develop user-friendly interfaces tailored to the digital competencies of secondary school students. Additionally, social influence emerged as a key driver of intention, pointing to the importance of cultivating a supportive environment through teacher advocacy and peer ambassadors. These practical insights can inform stakeholders aiming to integrate similar technologies in Tanzanian and comparable contexts.

The study also offers a roadmap for sustainable integration of peer recommender systems into secondary education. Emphasising the perceived usefulness of such systems, particularly in improving learning outcomes, will be vital for encouraging student adoption of the system. Training programs, orientation sessions, and public endorsements of the system's benefits should be incorporated into school culture. Future implementation efforts should also focus on providing continuous training and feedback mechanisms to adapt the system to evolving needs. By grounding these practices in the determinants identified in this study, educators and policymakers can increase the likelihood of successful adoption and long-term usage of peer learning technologies in resource-constrained environments.

Limitation and Future Research

There are certain limitations that should be acknowledged when interpreting the findings. First, although the sample size was relatively large (1,029 students), it was drawn from only eight schools across two regions of Tanzania using convenience sampling. As a result, the generalisability of the findings may be limited, especially when considering the diversity of socio-economic, regional, and school-level differences across the country. Future research should aim to include a broader and more representative sample from various regions and school types, including private and rural institutions, to validate the findings. Moreover, the reliance on self-reported behavioural intention, rather than observed usage, presents another limitation. While intention is a strong predictor of actual use, it cannot fully account for the gap between intent and action that may arise due to unanticipated contextual barriers.

A second limitation relates to the scope of the research model and design. While the UTAUT framework explained a substantial proportion of the variance in behavioural intention, approximately 26% remained unexplained, suggesting the presence of other influential factors not included in the model. Future studies could consider additional constructs, such as trust, perceived enjoyment, ICT literacy, and privacy concerns, which may play important roles in technology adoption among adolescents. Furthermore, the cross-sectional design limits the ability to capture changes in perception over time. Longitudinal studies could better capture the evolving nature of students' technology acceptance, especially as they gain experience with such systems. Differences among student subgroups, such as age, gender, or ICT proficiency, were not explored in this work but warrant further investigation to inform more tailored intervention strategies. Ultimately, addressing these limitations through expanded, longitudinal, and in-situ research will enhance our understanding of how to support the successful integration of peer recommender systems in secondary education.

6. Conclusion

In the digital age, peer-assisted learning is no longer confined to physical classrooms, offering new opportunities for collaboration through technology. Tanzanian secondary school students' willingness to adopt a peer recommender system, a digital tool designed to match them with complementary peers for academic collaboration, was examined. Using UTAUT as a guiding framework, we identified four key determinants of behavioural intention: performance expectancy, effort expectancy, social influence, and facilitating conditions. Empirical analysis confirmed the significance of all four factors, with facilitating conditions such as access to infrastructure and support emerging as the most critical factor. Students were also more likely to adopt the system when they believed it would enhance their learning (performance expectancy), when they felt encouraged by peers and teachers (social influence), and when the system was perceived as easy to use (low effort expectancy). These findings highlight the practical and psychological prerequisites for successful technology adoption in resource-constrained secondary school settings.

By extending UTAUT to a younger population in a developing country context, we contribute a validated model for understanding student intentions regarding peer learning technologies. The results suggest that thoughtful system design, institutional readiness, and community support are essential to ensure uptake. For practitioners, the study provides clear directions: invest in ICT infrastructure, prioritize user-friendly design, secure endorsements from educators, and demonstrate tangible academic benefits. Successfully implemented, peer recommender systems can broaden learning networks, foster collaboration, and improve academic outcomes. As Tanzanian secondary schools increasingly integrate digital solutions, understanding user acceptance becomes critical. This study offers foundational insights for future research and implementation strategies aimed at leveraging technology to enhance collaborative learning across diverse educational environments.

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