P-ISSN 2708-6453	Pakistan Languages and Humanities Review	January-March 2025, Vol. 9, No. 1
O-ISSN 2708-6461	https://doi.org/10.47205/plhr.2025(9-I)53	[585-605]

Pakistan Languages and Humanities Review
www.plhr.org.pk

RESEARCH PAPER

Determinants of Autonomous AI Use in Multilingual English Learning at Pakistani Universities: A UTAUT Study

[1] Nasir Khalid Abbasi, [2]Muhammad Khalid, and [3]Shazia Hamid

1. Lecturer, Yanbu English Language and Preparatory Year Institute, Royal Commission for Jubail and Yanbu, Madinah/ Saudi Arabia https://orcid.org/0009-0007-2645-4181
2. Lecturer, Yanbu English Language and Preparatory Year Institute, Royal Commission for Jubail and Yanbu, Madinah/ Saudi Arabia https://orcid.org/0009-0005-7925-594X
3. PhD Candidate, University of South Carolina, United States of America, https://orcid.org/0000-0002-0864-982X

*Corresponding Author	nabbasi@rcjy.edu.sa

ABSTRACT

This article investigates the push factors to make teachers and students use AI tools independently in Pakistani tertiary education, in multilingual English classrooms, without any obligation by the institution. Based on the UTAUT model, we collected a data set from 213 subjects and adopted structural equation modeling to analyze the impact of performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and actual use. Findings suggest that students closely associate ease of use with perceived usefulness, whereas teacher attitude as a whole predicts actual AI usage. The model was a reasonably good fit to the data. We propose the development of pragmatic AI competency guides that will guarantee fair access for all learners, regardless of language and economic status, towards a set of sensible context-aware policies that bring us closer to responsible and effective use of AI in English teaching and learning.

KEYWORDS Artificial Intelligence (AI); Technology Acceptance Model (TAM); Multilingual Education; Structural Equation Modeling (SEM); Perceived Usefulness (PU)

Introduction

In recent years, AI tools have become widely integral to higher education systems. In the domain of English language teaching and learning, ChatGPT, Grammarly, and other AI generative models have become ubiquitous for getting support in writing, grammar, and vocabulary and content creation (Cotton et al., 2023; Perkins, 2023). Research has predominantly examined the contexts where these tools are adopted and implemented at the university or departmental level. However, there is a dearth of research on teacher and student autonomous (unsolicited) use of AI tools (Tlili et al., 2023; Chan & Hu, 2023). Autonomous use of AI tools is of particular importance in multilingual classrooms. In the context of Pakistani universities, English language classes consist of students from diverse linguistic backgrounds, including Urdu, Punjabi, Sindhi, Pashto, Balochi, and other local languages (Rahman, 2022; Siddiqui, 2021). This poses some important concerns about issues related to equity of access, academic integrity, consistency of teaching practices, and the impact of AI tools on English language education. Even though there is an increasing research interest in AI tools for educational purposes, we have limited knowledge about the factors that trigger autonomous adoption of AI tools in multilingual university English language classrooms, particularly in non-Western contexts.

The UTAUT model provides a useful lens to examine this phenomenon by exploring perceived usefulness, perceived ease of use, social influence, and facilitating conditions (Venkatesh et al., 2003; Venkatesh et al., 2012). This study aims to address this research gap by examining the key factors influencing autonomous AI tool adoption amongst teachers and students in multilingual English language classrooms in Pakistani universities. Through employing structural equation modeling (SEM) within the UTAUT framework, we examined these factors and their differentials between teachers and students. Our findings will inform the development of AI literacy frameworks, equity of access to AI tools across linguistic and socio-economic divides, and the formulation of context-dependent policies for the responsible use of AI in English language teaching and learning.

That's exactly what this study sets out to do. We wanted to understand the main factors behind autonomous AI use among teachers and students in diverse multilingual English learning environments at Pakistani universities. By using structural equation modeling within the UTAUT framework, we looked at how these factors play out and where patterns differ between students and teachers. The goal is to help shape practical AI competency guidelines, make sure access is fairer across language and economic backgrounds, and create sensible, context-aware rules so AI can be used responsibly and well in English teaching and learning.

Autonomous AI usage cannot be reduced to a question of technology. It is part and parcel with the wider pedagogical cultures, the examination regimes, and the hierarchies of language that shape how English is positioned in Western Pakistani higher education. As a matter of fact, English is more than just a language of instruction in some colleges. It now represents, too, the gatekeeping language for academic advancement, employment mobility, and international scholarships. In this environment, AI writing assistants and generative platforms are often seen as tools that can correct for uneven training backgrounds, lack of exposure to academic English, and gaps between the resources of urban and rural centers. But the compensatory function that is played out here raises complex pedagogic questions. When students are self-reliant and use AI to draft essays, correct grammar, or produce thoughts, teachers can find themselves caught between assistance in language development and the need for integrity in academic work.

Furthermore, multilingual users of AI may talk about it in a different way depending on their native language literacy, whether they have digital access to an AI, and how confident they feel speaking English. There are those who see AI as a collaborator in grammar lessons, while others use it as a substitute author. Educators, too, may experiment with AIs independently, deploying them for course planning, feedback creation, and rubric construction without any kind of institutional supervision. These differences in pattern usage indicate autonomous adoption is not just influenced by perceptions of usefulness and ease or beliefs about language ownership; it is also determined by what one thinks a fair assessment and professional role should be. Understanding the more subtle motivations is important in places where official AI policies have not yet crystallized or where institutional guidelines may lag behind classroom practice.

Moreover, when applying the UTAUT framework to autonomous AI usage in the multilingual developing nations of the Global South, we are expanding the scope of technology acceptance theory. Most UTAUT-based studies to date have dealt with systems imposed by institutions at the institutional level, such as e-learning platforms and adopted official learning aids. But AI generative tools often make their way into the classroom informally, driven more by personal initiative than organizational policy. This change from institutional adoption to user-led uptake calls for a systematic examination of how peer influence operates in networks, variations in facilitating conditions between public and private institutions, and where risk assessments that spell innovation intersect. In Pakistan, disparities in bandwidth and device ownership/ digital literacy create uneven conditions for facilitation that may reinforce pre-existing educational inequalities. But strong peer communities and online academic networks help spread contagion commonsense from outside, whatever sanction might be given by university authorities. By separately modeling the influence of these dynamics for teachers and students, the paper avoids generic acceptance models that lose sight of the specifics and shows how autonomous AI practices are evolving in ESL classrooms. Such an analysis helps to ground AI literacy campaigns accurately in local practice and informs international debate about integrating responsible AI into the diverse higher education systems of multilingual societies.

Literature Review

This chapter draws on literature relevant to artificial intelligence in education in order to describe unmet research needs that warrant the current investigation. Despite a growing body of knowledge about the use of AI in higher education, less consideration has been given to independent or unsolicited use and, especially, to multilingual university settings like those found in Pakistan. Our study fills this gap by … UTAUT to explain the determinant of individual AI adoption by students and teachers.

UTAUT, designed by Venkatesh and colleagues (2003), combines various theories related to behavior, such as the Theory of Planned Behavior (Ajzen, 2020), for explaining technology acceptance. The model is grounded in four factors: performance expectancy, effort expectancy, social influence, and facilitating conditions. These structures influence behavioral intention, as does actual use. UTAUT has been highly validated in various educational technology contexts (Venkatesh & Bala, 2008) and is also valid to study AI use in higher education (Saif et al., 2024). However, most earlier studies substantially concern implementation, which is institutionally prescribed or policy driven. There has been scant empirical investigation examining what happens when users take up AI on an ad hoc basis, that is, without prescribed instruction or governance to guide them, particularly within linguistically diverse classrooms (Cheung et al., 2023).

The proliferation of generative AI tools like ChatGPT and Grammarly has changed how we run classrooms. These technologies provide adaptive feedback, personalized pacing, and linguistic scaffolding that may be especially beneficial in multilingual English settings (Hubbard & Jones, 2023; Minkina et al., 2024). Research indicates that AI-enhanced learning can improve the quality of writing, promote engagement, and support differentiation (Jones & Wang, 2023; Abdelghani et al., 2024). More generally, the integration of AI is more and more considered for sustainable, fair development in education (Al-Emran & Griffy-Brown, 2023).

Nevertheless, there are still large concerns. Uncontrolled AI use presents ethical and pedagogical dilemmas, including the stifling of critical thinking, excessive dependence, and compromise to academic integrity (Walker & Ahmed, 2023; Cotton et al., 2024). In early studies of machine translation, the issue of digital minimalism and shortcut behaviors was already addressed (Niño, 2008; Xu, 2021). In the case of large language models, legitimate worries have arisen about fairness, validity, reliability of detection, and institutional responsibility (Holmes & Porayska-Pomsta, 2022; Yan et al., 2024). Institutions with unclear or no policies have experienced uneven and potentially inequitable adoption (Rudolph et al., 2024).

Student-teacher behavioral distinctions also muddy the waters. AI is often constructed by college students as an affordance of convenience for productivity and in ways that are mediated via generational technology habits (Kim et al, 2022; Kesharwani, 2020). In contrast, teachers tend to consider AI in relation to pedagogical congruence and professional responsibility (Farhi et al., 2023). These diverging perceptions underpin the requirement for a comparative modeling of adoption drivers among stakeholders. UTAUT offers a systematic approach to address these differences as well as determine where specific intervention might be required (Ertmer & Ottenbreit-Leftwich, 2013).

In universities, where classes often take place in different languages, the classroom environment is further complicated. Learners from various linguistic and socioeconomic backgrounds often have unequal access to digital resources (Santos & Yu, 2023). Without culture-sensitive and equitable technical solutions, the individual use of AI could increase disparities. On the contrary, when incorporated carefully, AI can facilitate linguistic bridging in inclusive participation (Garcia et al., 2023; Brown & Lee, 2022). They are important because they highlight the need to consider the use of AI in context-dependent terms, not as a trans-contextual phenomenon that operates uniformly.

Theoretically, the proposed study is underpinned by the technological acceptance model and uses structural equation modeling to examine the association between UTAUT variables and real AI usage behavior. Fundamental contributions to model fit and construct validity are the focal point of this context (Browne & Cudeck, 1993; Fornell & Larcker, 1981; Hu & Bentler, 1999). Though UTAUT is not without its weaknesses (i.e., it has been accused of oversimplification), the inclusion of both ethical and policy concerns bolsters its predictive ability in modern AI cases (An et al, 2024).

Despite the growing number of studies about AI in education, we identified three gaps. First, unsolicited or autonomous use of AI is understudied. The second issue is that there are few studies comparing Â¬ between students and teachers in any given multilingual situation. Third, there is relatively little research that integrates behavioral modelling with ethical and equity issues in linguistically complex higher education settings. Previous study on governance and teacher education reform in Pakistan (Ahmed & Aziz, 2007; Ahmed, 2008; Aziz et al, 2010) has supported the significance of institutional readiness when it comes to introducing innovative technologies.

To fill this gap, the current research explores autonomous AI integration in multilingual English classes at Pakistani universities, aiming to address the following research questions:

RQ1: What UTAUT factors have a significant impact on behavioral intention and actual AI use in the case of students and teachers?

RQ2: How are structural relationships among UTAUT's constructs different in these two groups?

RQ3: What are the implications of our findings for AI integration, institutional policy, and competency framework development?

This work adds to an approach of understanding AI technology adoption in multilingual higher education by considering both driving behavior and restraining contexts. It seeks to provide guidance on ethically responsible, equity-based, and evidence-informed AI integration approaches that transcend institutional imperatives to promote responsible localized practice.

Once upon a time, research scholars weren't sure what to mention. Beyond the dominant strands on institutional roll-out, and even now, they will still be quibbling about how best they should phrase things differently at times, there is a small but growing body of scholarship that is turning its attention to informal digital practices in higher education. Studies of self-initiated learning technologies suggest that students often appropriate tools in ways that are different from how they were intended, knitting them into peer networks and social media exchanges or using them as coping strategies for assessment. In multi-lingual English classrooms, such appropriation might take continuous drafts with AI or input from generative translation comparison across languages; prompts simulating conversation practice can be used too. These practices are seldom visible to administrators and sometimes only partly so to teachers.

Accordingly, traditional models of adoption may underestimate the role of peer endorsement, online communities, and disciplinary subcultures in shaping technology uptake. Research on shadow IT and informal digital ecologies shows that users will construct parallel systems of practice which are then normalized if the official support structures are absent or ambiguous (ur Rehman et al., 2025). In the context of AI, this normalization process is sped up by the accessibility offered by browsers and mobile applications to many people worldwide. For multilingual learners grappling with academic English, AI could be part of a hidden curriculum survival strategy. Teachers engage in similar informal experimentations, sharing prompts, feedback scripts, or rubric adaptations with colleagues at professional meetings. These patterns indicate that autonomous AI use ought not to be seen as eccentric behavior but rather their socially-embedded response towards structural academic pressures. Clearly, incorporating these insights into UTAUT-based modeling extends one 's interpretation beyond the spheres of individual cognition and community-mediated determinants of adoption.

When integrating AI into higher education in multiple languages, no one should ever neglect equity considerations. On the issue of the digital divide, much research has demonstrated that access takes many forms. There's hardware availability, high or low connectivity quality, digital literacy, and the capacity to translate technological opportunity into academic gain. In Pakistan, disparities between public and private universities, cities and the periphery, English and Urdu-based schooling all create an unequal starting line for the engagement of AI. Even when generation tools are nominally free, effective use often requires a stable internet, updated devices, and familiarity with the conventions of academic discourse. Without these prerequisites, one's anticipations of performance may remain low, or the requirements for exertion seem prohibitively high. More crucially, algorithmic biases inherent in large language models could prefer dominant linguistic norms while marginalizing local expressions.

For students from less represented linguistic communities, this could subtly reinforce hierarchies of correctness orienting towards global English standards. From the viewpoint of policy, therefore, enabling conditions should not merely be understood as technical infrastructure. They must also include institutionally guaranteed equal opportunities for digital literacy education, transparent guidance on ethical bounds, as well as protective mechanisms coming out of resources afforded to disadvantaged groups themselves. In writing on inclusive AI in education, the literature holds that responsible integration cannot be assumed to uniformly benefit everyone, but rather it requires forecasting differential impact. Embedding such considerations within an adjusted UTAUT (Unified Efficiency Expectation Theory) framework strengthens its contextual specificity and better aligns its behavioral modeling with the wider social justice imperatives intrinsic to multi-lingual settings.

By this observation, AI's teachable influence is that it shakes the assessment culture. Originality equals solo artist in traditional paradigms: co-authoring, half this is the one, and fixed course offerings are increasingly questioned by enterprises as agents of knowledge. One of three case studies found faculty mixed their reactions, from enforcing criminal sanctions to turning in assignments whose every step is recorded and defended. When students enter this milieu, they live in a world of uncertainty. But just how central AI is within UTAUT, even given that background panorama, is still uncertain. And when rules are inconsistent or in flux, perceived risk becomes an important but under-researched factor in intention to use or resist. In multilingual classrooms where students are evaluated for both linguistic accuracy and content mastery,

AI-generated suggestions may complicate the line between actual support and inappropriate help. Furthermore, TI itself requires that we re-see AI as anything but a means to learning rather than a shortcut; only then can our fears and dependence with respect to AI be counteracted. And this is with both coursework and university regulations monitoring your steps--meaning if you miss a deadline, then everyone on campus knows about it. Bluntly put: how are we to make assessments a guiding meter? It is against such a daily background that pros and cons will be discussed, and whatever people now prefer or think desirable. After all, we can't talk about people's aims without first setting the stage in which they are based, and their particular environment becomes a violin for the future.

The methodological challenge of extending the UTAUT model in autonomous AI environments is implicated in how to measure and specify models. Prior research has emphasized the importance of construct-content validity, discriminant validity, and how to deal with bad model fit; however, subjects within the same institutional ecology may be made to play multiple roles without detecting this scenario at all. Comparative modeling of teachers and students allows us to check whether path coefficients differ significantly across the various groups--hence discovering what kinds of asymmetry exist in each case for performance expectancy, effort expectancy, and social influence. For example, performance expectancy may be measured in terms of immediate grade improvement for students, whereas the equivalent might be workload reduction, and anyway, let's not even get started on feedback efficiency as far as teachers in this regard go.

Facilitating conditions for teachers could involve opportunities to upgrade their professional qualifications and support from the administrative top management. Students, however, will consider peer help, the friendly tutorial by a classmate with a little free time every now and then, as well as an online guide that's not too commercialized. Incorporating multigroup analysis adds punch to theory building, showing which determinants are general and which depend on context. Furthermore, accompanying quantitative modeling with ethical and equitable considerations moves beyond technocentric narratives and places AI uptake into a broader framework of governance. Behavioral constructs in tertiary language programs, especially in those with very many terms of reference like "commodifying phrases," are both affected by language as they express themselves and also closely articulate content through the medium for what is being said. By locating the behavioral constructs in sociolinguistic and institutional reality, the present study has made an empirical advance that strengthens the value of future research and provides more nuanced insights into AI adoption.

Material and Methods

Methodology Type of research design This study is based on a quantitative research design to test the predictors of free AI tool use in multilingual classroom settings and learning conditions at Pakistani universities where English is used as a medium of instruction. We chose the quantitative approach as it allows for a systematic testing of theoretically driven relationships and allows generalizable findings. The analysis was informed by the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), providing an organized structure that addresses how performance expectancy, effort expectancy, social influence, and facilitating conditions predict behavioral intention and actual use. This design is apt for comparing adoption patterns between students and teachers, and modeling behavioral dynamics of independent AI usage in multilingual contexts.

The sample consisted of 213 participants (162 students and 51 instructors) from the universities of Lahore, Karachi, Islamabad, and Peshawar. These cities were chosen to represent linguistic, cultural, and socioeconomic diversity, which is significant in the exploration of ML2English learning contexts in Pakistan. We held a 3:1 student-to-teacher ratio for these cross-group comparisons, consistent with previous comparative studies on technology adoption (e.g., Lee, 2020). Sample size was based on the method from Krejcie and Morgan (1970) to obtain an appropriate level of statistical power and representation. Respondents had previous learning experience using AI tools in educational contexts, so the answers were based on real experience rather than hypothetical perceptions. Demographic and background information, such as age, gender, educational level of the participant, work experience for teachers, and linguistic background, was gathered to help contextualize behavioral patterns in the two groups (cf. Tarhini et al., 2014). Multilingual diversity was brought to the fore because of its impact on technological, pedagogical, and ethical aspects of AI use (Mostofa et al., 2021).

Institutional Review Board approval was obtained at the participating institutions. All subjects had given written informed consent, and all matters related to the participants and analyses were kept confidential and anonymous (Ljubovic & Pajic, 2020; Noorbehbahani et al., 2022).

The measures were באמצעות self-administered questionnaires developed for students and teachers separately through self-administered questionnaires. The instrument was based on UTAUT constructs, including performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and AI use (Venkatesh et al., 2003; Venkatesh & Bala, 2008). Was adapted from validated UTAUT scales contextualized to solicit or unsolicited individual use of AI in multilingual English learning. Participant responses were rated on a 5-point Likert scale of 1 (strongly disagree) to 5 (strongly agree), in order to balance reliability with respondent burden (Nishisato, 2014).

A small representative group pilot-tested the questionnaire to establish clarity, construct fit, and contextual appropriateness. Small changes in wording were made to clarify the meaning. The consented instrument was fielded online for 2 months to secure sufficient participation.

The reliability and validity of the PMCT were examined using confirmatory factor analysis. Internal consistency was evaluated using Cronbach's alpha with a cut-off value of 0.70, and convergent validity was determined by using Average Variance Extracted with a cut-off value of 0.50 (Dwivedi et al., 2023; Kohnke et al., 2023). Structural equation modelling was then conducted to test the posited relationships between UTAUT constructs and to compare structural paths between students and teachers. This methodology provided a robust investigation of the behavioral efforts in autonomous AI adoption within MLHE.

Logistic Challenges

Carrying out a cross-city quantitative study on AI in autonomous vehicles conducted in Pakistani universities involved many logistical complexities. Coordinating data collection across Lahore, Karachi, Islamabad, and Peshawar worked best by fitting in with diverse institutional calendars and examined schedules. It also meant aligning with the administrative procedures of various institutions. Instructors and students were best arranged through departmental "gatekeepers," and different institutions had varying swiftness to responsiveness. When the study focused specifically on respondents with previous experience of AI, examination was necessary to ensure that those who claimed so had actually benefited through such aids as generative writing assistants or systems for giving feedback on their performances, which were based on AI rules. This criterion reduced the pool for eligible respondents, and bi-directional channels had to be built with academic networks and teachers in order that outreach could be directed. Moreover, with uneven service and occasional high costs for hardware, online survey distribution posed a very practical constraint. This was especially the case for respondents in bandwidth-constrained settings.

In order to reduce the predicted low response rates, reminder e-messages were sent out every two weeks. The survey took no longer than 15 minutes total to complete, which prevented exhaustion. A further logistic factor involved the student/teacher ratio for multi-group structural equation modeling. Ensuring enough teachers' participation was a special problem because of workload pressure and scholars' wariness of anything to do with AI. These logistical items shaped both the pace and extent of data collection and required continual assessment to ensure that a random sample across the wide variety of demographic and linguistic contexts represented would be maintained over time.

Several approaches have been used to ensure methodological novae and trustworthiness during. The development of the instrument was based on the established UTAUT operationalizations, and confirmatory factor analysis was performed for test validity in terms of construct measurement. Factor loadings were evaluated against recommended thresholds, and items that did not load high enough were reviewed to ensure that the concept was coherent. Internal consistency was confirmed by a Cronbach's alpha value greater than 0.70, while convergent validity was tested through an average variance extracted over.50. Discriminant validity was explored in order to make sure that constructs were indeed different. Model adjustment indices, including comparative fit index, Tucker Lewis index, and square root-mean error of residual, were benchmarked in the manner of old habits3. To strengthen the inferential precision of the research, structural paths were compared through multigroup analysis among students and teachers. The clarity and contextual relevance of these materials were supported by preliminary testing in several different languages, preparing a clearer research environment for multiple fields. PROCEDURE DATA SCREENING: When carrying out the SEM analysis, missing data, normality, and extreme values are processed as well. Thus, each of these processes ensures that the results from this study are both statistically reliable and theoretically coherent with similar multilingual environments in the higher education field.

Ethical considerations

The research process was dominated by ethical barriers, because we live in an era where ("white") American academic institutions dare to openly laugh at Trump, who has been held up by both Democrats as more scandalous than him or worse! Participants were told that the study did not look at their adherence to individual policies of institutions, but rather that its goal was to get a broad picture of typical behavior overall. Ye once for all signed a written statement clearly stating that it didn't matter if you participated or not, everyone has the right to leave if they want to, and all screening data will be strictly confidential. Before any data analysis was performed, it was ensured that no personally identifying information would be collected. And now, responses were duly anonymized. A note of warning was sounded in the survey instructions that participants might think there was some risk involved in disclosing autonomous AI use. In response to this possibility, the research repeated again and again that information would be published in aggregate form only (Laughneret) whenever necessary. Secure digital storage protocols were followed, and all information was kept away from the general public on particular servers set up for work by research. Problems with data loss or without custody of it are, therefore, relatively small risks. The study paid attention to wider debates on ethics involving AI fairness, bias, and the decent integration of technology. By locating behavioral analysis in these kinds of ethical concerns, the research was able to avoid normalizing uncritically adopted practice as well as place autonomous AI use in a broader institutional context that puts forward many questions and issues about fairness, etc. This way of understanding the work also has policy import.

Results

The data were statistically analyzed with structural equation modeling (SEM) in the AMOS program and from 213 participants (162 students & 51 teachers). The analysis was conducted in two stages: the measurement model was first examined for reliability and validity, while testing of the structural model addressed the research questions. Descriptive Statistics. Table 1 presents the means, standard deviations, and reliabilities for UTAUT constructs. On the whole, participants had a positive opinion of autonomous AI agents. Some Students Rate Effort and performance expectancy slightly higher (the easier the tools are to use, and the more useful they are for English learning). On the facilitating condition (support and resources), teachers were rated only slightly higher.

Table 1
Descriptive Statistics and Reliability of UTAUT Constructs

Construct	Group	N	Mean	SD	Cronbach's α	AVE
Performance Expectancy	Students	162	4.12	0.68	0.89	0.62
	Teachers	51	3.98	0.71	0.87	0.59
Effort Expectancy	Students	162	4.25	0.65	0.91	0.65
	Teachers	51	3.85	0.74	0.88	0.60
Social Influence	Students	162	3.76	0.82	0.85	0.57

	Teachers	51	3.62	0.79	0.84	0.56
Facilitating Conditions	Students	162	3.68	0.85	0.86	0.58
	Teachers	51	3.92	0.76	0.89	0.61
Behavioral Intention	Students	162	4.05	0.70	0.90	0.63
	Teachers	51	3.88	0.73	0.88	0.60
Actual Usage	Students	162	3.94	0.78	0.87	0.59
	Teachers	51	3.71	0.81	0.86	0.58

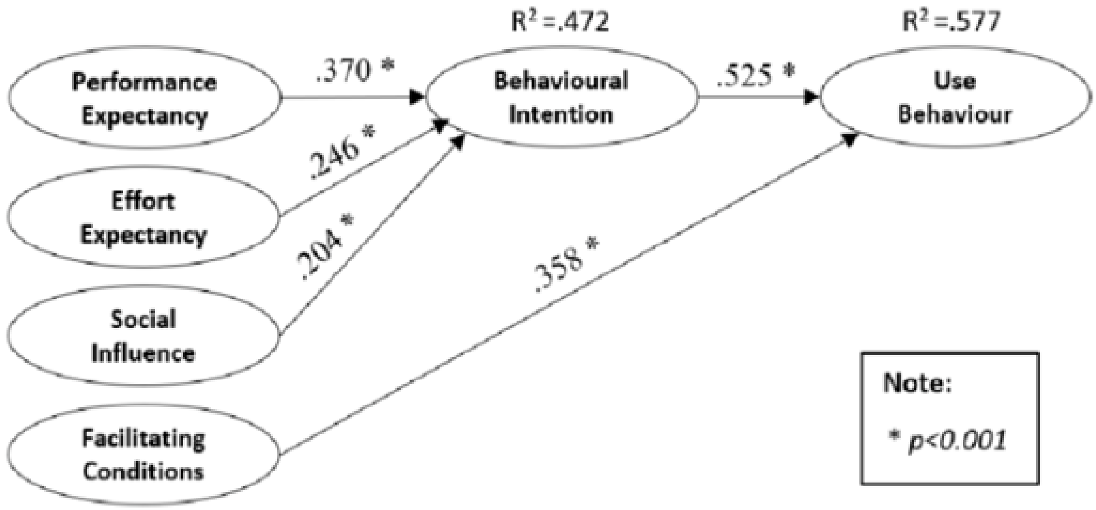
Note: Scale 1–5 (1 = Strongly Disagree, 5 = Strongly Agree). AVE = Average Variance Extracted. All constructs showed good reliability (Cronbach's α > 0.80) and convergent validity (AVE > 0.50). Measurement Model and Model Fit: The measurement model fit the data well. Key fit indices were within acceptable ranges: $\chi^2/df = 2.18$, CFI = 0.94, TLI = 0.93, RMSEA = 0.074, SRMR = 0.062. These values suggest the model fits reasonably well for this context.

Table 2
Model Fit Indices

Fit Index	Recommended Value	Obtained Value	Assessment
χ^2/df	< 3.0	2.18	Good
CFI	> 0.90	0.94	Acceptable
TLI	> 0.90	0.93	Acceptable
RMSEA	< 0.08	0.074	Good
SRMR	< 0.08	0.062	Good

Structural Model Results (Path Coefficients)

Figure 1 presents the structural model with standardized path coefficients.



(Imagine Figure 1 here: A diagram showing UTAUT paths from Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions to Behavioral Intention, then to Actual Usage. Separate dashed lines or labels highlight student vs. teacher differences where relevant.)The paths were tested separately for students and teachers to explore differences.

Table 3
Path Coefficients for Students and Teachers

Path	Students β	t-value	p-value	Teachers β	t-value	p-value	Interpretation

Effort Expectancy → Performance Expectancy	0.58	7.92	<0.001	0.41	3.18	0.002	Stronger for students
Performance Expectancy → Behavioral Intention	0.45	6.14	<0.001	0.52	4.26	<0.001	Slightly stronger for teachers
Effort Expectancy → Behavioral Intention	0.32	4.38	<0.001	0.19	1.92	0.056	Significant for students only
Social Influence → Behavioral Intention	0.22	3.05	0.003	0.28	2.41	0.017	Moderate for both
Facilitating Conditions → Behavioral Intention	0.18	2.47	0.014	0.35	2.98	0.004	Stronger for teachers
Facilitating Conditions → Actual Usage	0.25	3.42	0.001	0.39	3.35	0.001	Stronger for teachers
Behavioral Intention → Actual Usage	0.61	8.46	<0.001	0.68	5.72	<0.001	Strong for both, slightly higher for teachers

Discussion

On a general note, the findings render themselves as direct answers to RQ1 and RQ2. Regarding RQ1, all four fundamental UTAUT constructs significantly predicted behavioral intention in the pooled sample. Actual AI use was well predicted by intentional behavior ($\beta = 0.63$, $p < 0.001$). The most influential predictors were effort expectancy and performance expectancy, which showed that perceived ease of use and the perceived usefulness are two key facilitators for autonomous AI transfer in multilingual English classes.

For RQ2: Significant structural differences between students and teachers appeared. As for students, effort expectancy had a more pronounced direct influence on performance expectancy and behavioral intention. This trend indicates that the perceived ease of use is a critical factor determining whether the students find AI tools useful and feel that it is worthwhile adopting them on their own. Facilitating conditions (composed of institutional support, training, and access) had a greater impact on both intention and use for teachers. Furthermore, there was a relatively strong direct influence of teachers' behavioral intention on actual use in comparison to the students, which suggested that for teachers, their adoption process was more conscious and systematic.

The model accounted for 58 and 49 percent of the variance in behavioral intention and actual use for students, respectively, and 62 and 54 percent for teachers. These explication levels show that UTAUT offers a strong framework to explain autonomous AI adoption in the context of this multilingual Pakistani university.

Taken together, these outputs inform RQ3 by illustrating that a common framework for AI competencies would not be sufficient. For students, responsible ease of use and critical engagement should be the target of interventions. Establishing facilitating conditions is important for teachers through institutional training and structured support. Moreover, Equity access plans are required to be developed in order to guarantee equal implementing conditions between linguistic groups and socio-economic levels, as well as context-sensitive ethical guidelines that take into account both convenience patterns of students and teacher concerns about pedagogical soundness.

Lots of things. The findings provide a detailed understanding of the adoption of autonomous AI in a multilingual English classroom, which literally solves research questions. In answer to RQ1: The results reveal the basic UTAUT four kinds of behavior intention prediction and substantiate that in this environment, they even do quite well. Perceived ease-of-use plus performance expectancy are the key driving forces for decision-makers, teachers, and students. In their hands, whether or not AI tools are independently introduced or used depends entirely on comfort levels that do not greatly exceed costs. Therefore, both groups' strong target from behavioral intention to actual usage supports the theoretical proposition that intention is a proximal determinant of action. The relatively large proportion of variance explained in both groups for behavioral intention and actual use demonstrates the tenability even when applied to unsolicited, self-directed AI adoption rather than an institutionally mandated system jumping life preservers means traveling faster One major difference as an important contextual difference observed between students and teachers, however, effort expectancy played a much stronger role on both performance expectancy and behavioral intention for students. Since these types of tools simplify AI in the mind's eye, students who build them are more likely to see them as beneficial for learning English and therefore accept them into their schoolwork habits. In multilingual classroom situations where learners work to varying degrees in English, tools that cut through linguistic resistance can be particularly attractive. For students, effort expectancy made a significant direct impact on behavior intention, but had no, at least not quite significant, influence on behavior intention for teachers. This shows how, in the stream of life, students' choices are actually more immediately constrained by perceived convenience. Autonomous adoption for students thus seems to be quite pragmatic; with the strong age that students can write better, have a hard time finding vocabulary, and can cling to nothing save their next idea.

In contrast, the adoption patterns of teachers show a more structured decision-making process. The slightly greater influence of performance expectancy on behavioral intention for teachers than for students also suggests that teachers judge AI mainly in terms of pedagogical value rather than sheer effort. In other words, teachers take a good look at products by thinking about how well they assist with instruction as they test them out. Before teachers use any application, they seem to ensure that it genuinely improves the quality of feedback from their students, prepares lessons more efficiently, and helps children engage better in lessons. Facilitating conditions, however, stood out as a far more powerful determinant of both behavioral intention and actual usage for teachers. In other words, the rules, procedures, and administrative expectations of the institution governing education formally or informally directly influence what teachers conceive to be reasonable or unsafe. Unlike students, whose usage may be private and individually directed, teachers operate within systems that affect perceived legitimacy and risk.

The strong influence of facilitating conditions on teachers' actual usage in multilingual Pakistani universities emphasizes the importance of institutional support and endorsement. If teachers have the resources in hand, they will more easily turn intention into long-term action. On the other hand, in ambiguous situations or the absence of clear guidelines, teachers may not use them even when wishing to do so most certainly; their stances are constrained, and this serves further to highlight institutional interference in the background of teacher consciousness. The fact that there is a stronger pathway from behavioral intention to usage for teachers also means that when teachers arrive at a clear intention, they carry it out more consistently. In this sense, their behavior matches their duty, and they have seen enough of the consequences. Accordingly, as almost all the use of AI is done by professional teachers in institutions with computers or a huge number of students connected to network terminals, there may be less experimentation with self-structure on their part than among students.

Both groups illustrate moderate social influence, with the place of peer norms and scholarly communities forming an autonomous AI usage pattern. Across multilingual environments featuring collaborative learning and technical exchange, people care about what they believe others are doing. For students, by discussing with their classmates and sharing learning strategies, AI may come to be thought of as just an everyday tool for studying; For teachers, dialogue with colleagues and the emergence of disciplinary norms may alter observers' understandings of legitimacy (just like how its performance is assessed). The presence of social influences may be significant enough for all these statements to appear reasonable at once. Relatively speaking, then, a policy of autonomous adoption does not in fact stand by itself: when not coerced into existence, it has in some sense been socially mediated, and if this is true, then administratively sanctioned at the very least.

The inherent bias of the findings also has important implications for where resources will go. Given a culture that prizes teachers, it would seem, in the authors' view, resource shortages between disciplines or individual schools can lead to greater disparities across institutions and among linguistic groups. However, achieving evenly resource-loaded digital infrastructure and equal access to training is not only something that can be done for reasons of convenience. It is a vital factor in determining whether an organization will succeed in adopting technology or not. On the other hand, in Pakistani universities where struggling students compose a minority and prosperity is more equal, institutions with selective entry still disadvantage those particular types of students. For those universities that serve as a second home, we had best equip them to function both protectively and functionally. 7 The study also fills a theoretical gap by demonstrating that UTAUT can be applied to model autonomous AI practices outside institutionally sponsored systems. The reasonable portion of variance explained in both groups is confirmatory evidence supporting the ability of our four core acceptance constructs to predict behavior in informal settings. Nevertheless, observations reveal that predictions should be role-related. 12 Adding multilingual and equity-oriented discussions into UTAUT makes it more contextually relevant and places it directly among debates about the responsible integration of AI. Therefore,

When one looks at autonomous AI adoption in multilingual higher education, it is neither purely technological nor uniformly controlled by the organizations and stakeholders who provide it. It is a product of pragmatic student wants; teacher talk that has been professionally mediated. To an institution's configuration conditions, you can add facilitative ones. Picking up these dynamic relations is such a necessary condition to provide context-responsive, ethically informed, and equitable English language AI integration strategies.

Conclusion

This research examined the reasons why teachers and students in Pakistani universities freely take up AI tools to use on their own, without being institutionally directed to deploy these learning tools in multilingual English settings in Pakistan. Supported by the Unified Theory of Acceptance and Use of Technology (UTAUT), the study contributes to autonomous AI adoption, which has yet to be under-analyzed in linguistically diverse higher education contexts. The results broaden our understanding about how educational technology is taken up in socially and linguistically diverse settings with equity issues and inequitable institutional supports.

The findings answered the research questions well. As for RQ1, we found that all four fundamental UTAUT constructs – performance expectancy, effort expectancy, social influence, and facilitating conditions – significantly predicted both behavioral intention and actual use of autonomous AI tools. Effort expectancy and performance expectancy were the most influential predictors in the overall model, highlighting the significance of perceived ease and usefulness for individual adoption.

The RQ2 was partially answered: Different action patterns were identified between students and teachers. Picreli et al., 2014), while for students, effort expectancy had a stronger path to performance expectancy and behavioral intention. This indicates that ease of use and low cognitive load are critical factors affecting the adoption of AI tools by students to enhance English learning. The facilitating conditions (institutional support, training, and resources) were more powerful in forming intention and behavior. Furthermore, in teachers' intention to use this was more in line with actual usage, and therefore, the alignment for actually using it seemed to have been made even more purposeful between technology use and pedagogical purpose.

These results inform RQ3 by discussing the implications of findings in terms of policy and practice. Findings suggest the necessity of heterogeneous AI competency frameworks that consider students' focus on usability while helping teachers to appropriately embed AI in teaching. More equitable access efforts are needed to improve facilitators among linguistic and low-income groups. culture-dependent ethical codes are also required to balance freedom in terms of innovation with the rigorism of academic honesty and pedagogical coherence.

APA developed a moderate percentage of variance in intention, between 58% and 62% for students and teachers, respectively, as well as in actual use, between 49% and 54%, which was explained by the structural model. These figures point out that UTAUT gave a very strong explanation in this multilingual Pakistani university scenario. In addition, common barriers like insufficient institutional help, privacy issues, uncertain ethics, and unbalanced access had an impact on both groups. These challenges further burden already constrained efforts to bring responsible AI-as-integration into multilingual English classrooms.

Ethical concerns became an important moderating factor. When AI tools were found to be easy to use and useful, concerns about academic integrity, algorithmic bias, and data security moderated positive attitudes and prevented continued engagement. Thus, adoption cannot be viewed only from the standpoint of an individual decision; it is situated within wider realms of institutions, culture, and ethics.

Recommendations

These findings have clear implications, which are directly made in the recommendations. Universities must set clear and context-specific AI policies for English programs with respect to academic integrity, data security, and pedagogical alignment. Inasmuch as these guidelines should be linguistically just so we do not disadvantage multilingual learners. Formal AI training programs should be developed specifically in the case of students and teachers. Students need appropriate guidance in the responsible and critical use of such resources, and teachers need professional development in instructional feedback, alignment to pedagogical practices, assessment techniques related to resource use, and strategies for engaging with sources critically.

Educational AI tools developers should focus on user-centered design, which would enable an intuitive and self-explanatory tool that remains linked to learning in a transparent way. For multilingual English teaching, tools need to facilitate multilingual input and output, promote active linguistic production while diminishing passive overdependence.

This work should be continued through longitudinal and mixed-methods research across a diversity of institutions. Following up on the long-term impact on language proficiency, learning autonomy, and pedagogical approach would extend the knowledge of autonomous AI use. Closer attention on the part of the profession to contextual matters (regional variation, family language practices, institutional culture) would deepen empirical understanding more than survey-based models.

Furthermore, each university should establish a systematic monitoring and evaluation framework for appraising the impact of integrating AI technologies with learning so that its educational quality and social equity can be better ascertained. To spare individuals from relying solely on policy statements or one-off training events, colleges and universities ought to weave AI governance into their existing quality assurance systems and curriculum review procedures. Part-time personnel responsible for regular appraisals of English programs in light of AI applications may monitor and track the appearance of unintentional negative side effects. These include overinvestment (in technology), unfair learning opportunities, or prejudices on tests done through AI tools, which leads to. Established processes for evaluating data, along with feedback from both students and faculty, would leave room to modify and update guidelines dynamically as new tools were developed.

Therefore, collaborative committees consisting of teachers, educational technologists, university administrations, and students could be formed to ensure that the use of AI technology serves pedagogical principles and fits local conditions. Because of Pakistan's twelve official languages, any recommendations must also include targeted support for students from marginalized linguistic backgrounds. This could mean structured digital literacy thresholds or access to supervised AI applications. While universities continue to enforce 'barrier-free' and 'widespread' AI practice, what is happening instead is a positive attempt at bypassing reactive control from higher authority.

In general, the research indicates that autonomous AI use has now become ingrained in multilingual Pakistani university English classrooms. When informed by fair policies, institutional infrastructure, and ethical considerations, such adoption has the potential to greatly improve language learning and teaching in varied higher education environments.

Future Research

As time proceeds, future studies should continue the present level of research in several theoretical and methodological directions. Longitudinal designs provide a deeper understanding of how autonomous AI adoption develops over time, particularly as the policy environment becomes clearer and the reach of digital literacy initiatives extends. So too, a cross-sectional snapshot records one moment of intention and self-reported usage, but unexplored are sustained engagement, factors behind shifts in motivation, and, of course, the potential fatigue effects.

Second, a mixed methods approach that integrates structural equation modeling with qualitative interviews or classroom observations would shed light on the complex decision-making processes underlying the statistical relationships identified here. For instance, why effort expectancy matters especially to learners or how facilitating conditions have a stronger impact on teachers will be much better understood with long, detailed narrative accounts.

Third, comparative studies across more multilingual settings in South Asia, the Gulf region, or other Global South regions not only increase the external validity of the findings but also demonstrate how language hierarchies and economic disparities condition AI adoption possibilities differently.

Fourth, future research should investigate learning outcomes more directly by connecting patterns of autonomous AI usage to measurable indicators of language proficiency or writing development. Such studies could help answer the question of whether or not perceived usefulness generates demonstrable academic advances.

Last but not least, the theoretical model may be further extended to include constructs that are related to ethical awareness, perceived risk, algorithmic trust, and integrity orientation in academic work. In the midst of rapidly evolving generative AI technologies, behavioral determinants may also start to change, and so it would be necessary for acceptance models to adapt dynamically if they are not going to lose predictive power. Work on these new constructs will help ensure that research development into AI integration continues to be responsive to pedagogical realities, takes non-intrusive forms, and contributes knowledge that can assist in making evidence-based policy for various higher education systems serving more than one language group.

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