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RESEARCH PAPER

Drivers of AI Tool Adoption in Multilingual English Classrooms: A TAM-Based Structural Equation Model

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ABSTRACT

This study examines the drivers of unsolicited artificial intelligence use and the factors shaping its adoption in multilingual English classrooms without institutional direction. Grounded in the Technology Acceptance Model, it addresses a gap in existing research that has focused on policy driven AI integration while overlooking independent use by teachers and students and its implications for equity, academic integrity, and pedagogical alignment. Using a quantitative design, survey data from 321 participants were analyzed through structural equation modeling with perceived ease of use, perceived usefulness, attitude, behavioral intention, and actual usage. Findings show that students exhibit stronger links between perceived ease of use and usefulness, whereas teachers emphasize the relationship between attitude and actual usage. Model fit indices indicate a reasonable explanatory fit for AI adoption behavior. The study recommends developing AI competency frameworks, ensuring equitable access, and adopting context sensitive guidelines for ethical and effective AI use in English education.

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

Introduction

Consider AI in classrooms where students automatically adjust their essays and do other activities related to languages. This situation can have practical and pedagogical problems, namely in the case of multilingualism, even though it would be possible to be transformative. Students are not required to do something, and they appear to play with AI language models, tech, and technology adoption in unsolicited use in Smith et al. 2023 and Brown and Lee 2022. While UAI can have a positive impact on teaching and learning in some contexts, it presents unique and unparalleled challenges in a number of linguistically and culturally diverse situations (Chen et al., 2023). The adoption of AI tools in multilingual classrooms is especially complicated because of different skill levels and rates of digital literacy, AI tools that are restricted to certain languages, and the potential for culturally biased or insensitive AI responses. AI tools, including ChatGPT and Grammarly, are changing the way learners engage with languages as they provide a wide range of solutions that are customized, easy, and responsive (Abdelghani et al., 2024). Amjad et al. (2024) demonstrate that purposefully designed AI-driven technologies can reduce learner anxiety and enhance communicative competence, reinforcing the importance of guided and pedagogically aligned AI use in English language classrooms.

Still, most of the literature concerning AI in Education regards solicited usage, where agencies or educators intentionally teach with the help of these apps (Chan & Colloton, 2024). On the other hand, where stretch AI usage is defined, this is the adoption of AI technologies by students and teachers alone, without any institution's support in the education space. This makes the issues very difficult and makes them meet the requirements, cutting across doing so ethically, advancing skills, and achieving specified goals (Almeida & Johnson, 2023).

Figure 1 below (a radar chart) summarizes the patterns of AI application by students and teachers from 2018 to 2023, suggesting that adoption and application patterns have increased throughout the duration.

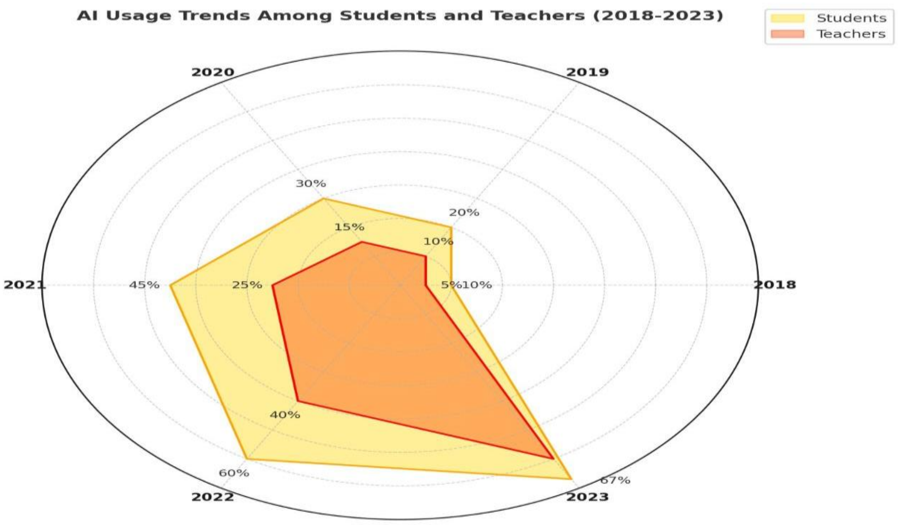


FIGURE 1. AI usage trend among students and teachers

Sources: collected by the research through multiple sources (US Department of Education, AIPRM, Business Solutions)

Unsolicited AI use refers to the independent adoption of AI tools by users—students or teachers—without institutional directives or formal inclusion in curricula. For instance, a student using ChatGPT for essay drafting without explicit teacher guidance exemplifies this concept. This study focuses on assessing the factors that promote unsolicited AI use within multilingual English language classrooms using the technology acceptance model (TAM) as a guide. These constructs are required to interpret these relationships, and they are PEEU, PU, ATT, BI, and, not to mention, AU (Davis, 1989; Venkatesh & Bala, 2008). SEM provides an analysis of relationships that helps us to better understand how students and teachers apply AI in their various linguistic and cultural situations (Nguyen et al., 2023). Marissa and Hamid (2022) mentioned that the teachers should create an environment that will foster bilingual students' agency. Ahmed and Aziz (2007) argue that college-level teacher education needs a major shift to meet new educational, social, and professional challenges. They point out that unless there are broad changes in curriculum, governance, and professional development, efforts to improve teacher education will stay scattered and ineffective. The requirement of English as a lingua franca increases and offers various risks and advantages in the infusion of AI. Diversity of language background calls for culturally relevant pedagogy and equal technological options (Santos & Yu, 2023). On the other hand, in many cases, the unsolicited use of AI by students or teachers is similar to what has been referred to in plagiarism studies, where technology is employed for self-interest and not purposeful endorsement by a particular institution (Abdelhamid et al., 2022). Exploring those dynamics may allow seeing how AI technologies mentor learning, ethics, and broader English language teaching objectives (Greenfield, 2023).

This paper seeks to fill these gaps by offering three main objectives. First, it intends to establish the underlying cognitive-behavioral factors on the list of instruments in multilingual English classes. Second, it contrasts the views of students and teachers, with particular emphasis on the differences in the adoption and acceptance of AI between the two groups. Last, the research provides strategies for responsible, efficient, and just AI use in English language education and acquisition and multilingual education. Ahmed (2008) underscores that effective governance is essential for quality enhancement in higher education, a principle that directly applies to the need for clear institutional frameworks guiding technology use in multilingual English classrooms.

The outcomes of the research study will be used to support teachers, policymakers, AI developers, and those using AI unsolicitedly. This study encourages the creation of AI literacy, models of cultural relevance, and dispensed access models by interconnecting gaps in policy and practice within the institutions (Jiang et al., 2024). Aziz et al. (2010) show that systematic institutional analysis and strategic planning are essential for improving the effectiveness of English language institutions, a view that supports the need for structured frameworks when integrating AI tools in multilingual English classrooms. Such ideas can also be applied to newly developed scholarship concerning linguistic justice that aims at describing the developments in multilingual education and the outcomes of multilingualism-related results of its elements (Garcia et al., 2023).

Literature review

The chapter has provided an elaborate overview of the literature on the use of the educational potential of artificial intelligence tools and the identified gap therein. The discovery of these gaps aids in setting up the thesis of this study, which is based on the Technology Acceptance Model (TAM) by Aderinto, and is intended to conduct a more organized study of the trends and the implications that may act as facilitators and restraints of AI usage and integration in higher education.

TAM and AI in Education

The Technology Acceptance Model (TAM), formulated by Davis (1989), is perceived as an attempt to provide an explanation of the adoption of technology within the pedagogical process in most representative parts of the developing world. It postulates that the drivers of the Attitude (ATT), behavioral intent (BI), and actual use (AU) of users in the education context are Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). TAM has been extensively studied in educational settings in relation to various technologies such as automated marking systems, educational websites, and artificial intelligence (AI) applications (Venkatesh & Bala, 2008).

Other recent literature emphasizes that TAM is also relevant in the context of higher education, for example, in the study of AI use (Saif et al., 2024). Nonetheless, where such a framework might come from in the first place for some barely literate AI users or AI users outside the academic context, as far as the unsolicited application of AI is concerned, TAM, particularly in multilingual classrooms, still needs to be explored (Cheung et al., 2023). This research seeks to expand the horizons of the TAM in a setting where AI is adopted in a manner that is 'unruly.' It has specific implications on policy, teaching, and learning, and the ethics of it all.

Figure 2 (a history line) represents the chronological history and the various substages of the Technology Acceptance Model (TAM) from 1989, when its starting phase of Perceived Ease of Use (PEOU) was developed, to the Final developing stage of Actual Use (AU), which is aimed to be accomplished by 2024.

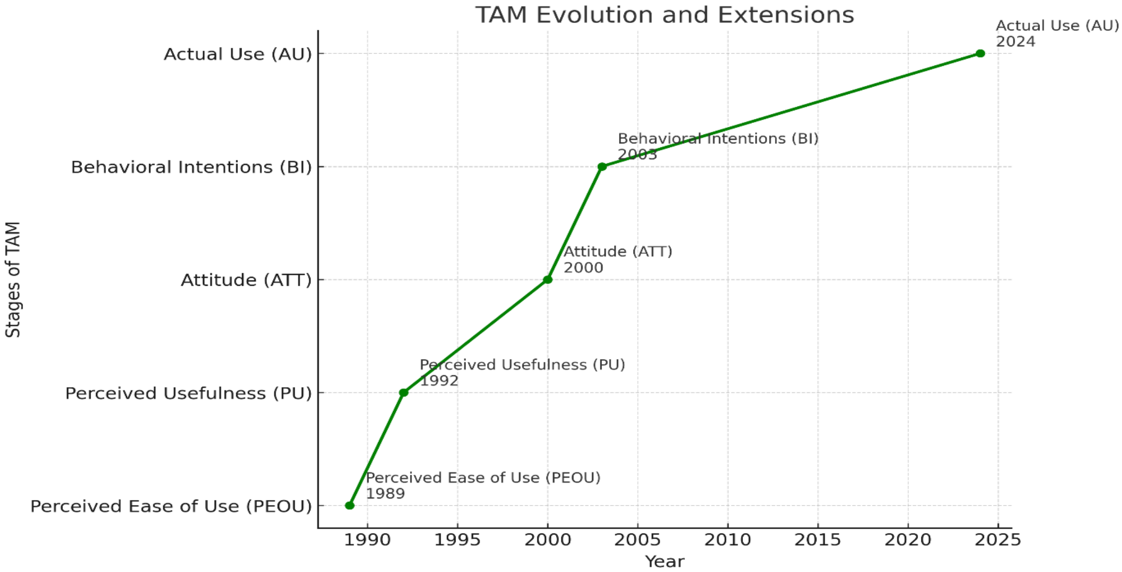


FIGURE 2. Technology Acceptance Model Evolution and Extensions

The prospects of AI and the Risks it Brings

Tools such as ChatGPT and Grammarly are becoming integral to education, allowing students to engage in self-paced guided learning (Ariyaratne et al., 2024). These tools solve issues in multilingual English classrooms where students face language and cultural difficulties (Chen et al., 2023). AI language technologies have shown sufficient evidence to improve language learning, educate different types of learners, and enhance teaching methods (Jones & Wang, 2023). Other studies have only examined requesting use and adding AI into system policies without asking how the users started to adopt those technologies independently. The analysis in question is likely to clarify possible violations of guidelines and what educational value there is in unregulated uses.

Unsolicited AI Use: Ethical and Pedagogical Implications

Digital technologies have opened the door to unregulated use of AI tools like ChatGPT for students and educators without any institutional parameters (Almogren et al., 2023). This raises ethical and educational concerns, especially in multilingual contexts. The use of AI tools to complete learning tasks is, in part, a result of students' avoidance of critical thinking, language learning, and other higher-order processes (Walker & Ahmed, 2023; Comas-Forgas et al., 2021). This does not serve well with real learning and can decrease the involvement of students in the subject matter.

Similarly, the problem of evaluating the products created by students using AI and upholding academic honesty exists (Cotton et al., 2024; Garib & Coffelt, 2024). The excessive use of AI by students leads to less involvement in classroom sessions and a rise in academic dishonesty (Almeida & Johnson, 2023; Golden & Kohlbeck, 2020). This shows the necessity to work out ethical principles regarding the application of AI to sustain core academic values and practices.

This paper will fill these gaps. It also brings to mind certain problems and concerns of AI getting out of hand in the process of making policies, particularly in multilingual classes.

Behavioral Differences: Students Vs. Teachers

The studies indicate that students and teachers have great dichotomies in terms of their attitudes and application of AI applications. It is noted that AI applications are perceived as simplified and, consequently, easy and accessible learning by the learners (Kim et al., 2022; Chan & Lee, 2023). Teachers consider it valuable only if it improves their work in doing AI and is consistent with their teaching objectives (Farhi et al., 2023). These opposing views emphasize the need for comparative analysis to explain the behavioral aspects behind the usage of AI in multilingual situations. The definition of the AOT in that case, however, allows for a better organization of this analysis and the determination of the places where changes should be made.

Multilingual Classrooms: Challenges and Opportunities

Examining AI changes in classroom settings can also be done against the background of multilingual English classrooms. These situations have ethnic diversity of population; they have different degrees of exposure to technology and different cultures, which affect the perception and utilization of the AI tools (Santos & Yu, 2023). It is clear from the evidence that an unjustified application may lead to the exploitation of culture and the deviation of a class from pedagogical purposes. It has been established that using culturally relevant models and models of fair distribution of resources enables AI to positively contribute to achieving educational goals in the context of multi-language classrooms (Garcia et al., 2023).

Theoretical and Methodological Framework

Of the three types of theory recognized by McCoy et al. (2007), the Technological Acceptance Model (TAM) emerges as the most favorable technical framework for the study. Models that include constructs such as Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitudes (ATT), Behavioral Intentions (BI), and Actual Usage (AU) might provide a strong foundation to address how and why technology adoption behaviors are exhibited (Davis, 1989). Then, it will explain how key aspects of TAM are important and should be fleshed out in applied contexts. It will further demonstrate how the importance of TAM is more evident in different fields outside education, too; this is especially so when applied AI is used. Recognizing the shortcomings of this framework and its critique, one should consider remedial explanations and strategies, especially concerning Ajzen–Fischer's policy framework, which concerns the motivators and ethics of the unregulated.

Such an approach combines theoretical and empirical dimensions, the user's behavioral and policy framework, and the ethics of pedagogy and education concerning the relevant outstanding issues (An et al, 2024). The adoption of a mixed-methods framework encompasses and integrates all dimensions of user behavior from the reasons for AI utilization to the consequences it entails.

Current Evidence and Research Trends

Perceptions of AI Use in Conflict with Academic Efforts

Research provides a unified perspective regarding AI tools and conflicting academic efforts, which in itself is compounded by the fact that AI tools can enhance the academic efforts of a student (Camilleri, 2024). Students consider writing, problem-solving, and research tools powered by AI to be invaluable resources, while teachers, on the contrary, provide mixed signals. They all point out that AI can enhance collaborations, and while some are almost wholly dependent on the AI tools to provide interactions, most are concerned about the negative consequences that can be derived from the use of these tools (Farhi et al, 2023).

The Need for Institutional Readiness and Policy Gaps

The lack of seamless integration of AI technologies into learning institutions has been noted in the literature as one of the possible problematic areas. There are still a lot of learning institutions that do not have formal policies governing the use of AI technologies. As a result, at present, numerous educational establishments stray towards the implementation of AI tools and technologies in a haphazard way (Rudolph et al., 2024). Avoidable consequences of the absence of institutional approval are caused by the unregulated educational use of AI, where students and educators both employ AI models like ChatGPT.

The Need for Ethical and Equitable AI Integration

Due to the imbalance in the degree of AI structural incorporation, the necessity to consider some ethical aspects and equity of access plays a vital role (Abulibdeh et al., 2024). The possibility of the abuse of AI tools or academic fraud is a legitimate cause of concern among academic institutions. It is necessary to have the institution of tailored policies and institutional structures, considering the peculiarity of the various education systems.

Challenges in AI Integration

The use of AI tools in education zones is mainly challenged by issues of ethics, academic integrity, and the gaps that exist in institutional frameworks.

In terms of self-directed learning, self-regulating practices, and self-monitoring, the author stresses the importance of academic honesty. Learning environments that do not have regulations around the use of AI, such as ChatGPT, create environments where students resort to using these tools to complete assignments. (Cingillioglu, 2023). It is even difficult to assess student learning when there is the possibility of a student submitting AI-generated writing. The ability to perform deep critiques of complex documents through high-level writing is no longer necessary. Further Discourse Analysis provides context for the use of AI. It critiques student autonomy, self-directed learning, and tech responsibility as regressive in the loss of ability to think critically, creatively, problem solve, and even control the loss of knowledge (Almeida & Johnson, 2023). It is within such constraints that the use of AI in education creates numerous issues, as the education system operates within a framework of great limitations.

These functions need further analysis of ethics and fairness related to the reliability of communication and the content generated by the AI tools and the tools available to identify such content (Huang & Tan, 2023). For AI to be used ethically in education, comprehensive policies, teacher training, and detection systems will need to be established.

Despite the significant advancements in AI literacy in education, there are still areas that need attention, especially in the areas of uninvited AI usage and multilingual education. As AI becomes increasingly prevalent, there are significant ethical, status, and pedagogy concerns that will need to be addressed in a multilingual classroom. The breadth of such a research area needs to be expanded to specifically include a socio-metric consideration of the unequal student-teacher dynamic and how it relates to multilingualism. This paper addresses these issues based on the Technology Acceptance Model (TAM) and structural equation modeling (SEM) regarding the study of uninvited AI use. The suggested actions will certainly start to solve these issues related to the reasonable application of AI in an attempt to positively influence learning performance and create social equity in a multilingual environment.

These notes shed light on the multifaceted interplay of forces that affect the adoption, in particular, the ease of use and usefulness of the systems perceived, and the perceived ethical and pedagogical issues. The research questions that underlie this study are based on these factors.

With these goals in view, this study is the foundation of the research questions and hypothesis to be used in the study below:

Hypotheses

H1: Perceived ease of use (PEOU) positively influences perceived usefulness (PU) for students and teachers in multilingual English classrooms.

H2: Perceived ease of use (PEOU) positively influences attitudes (ATT) toward unsolicited AI use in multilingual English classrooms.

H3: Perceived usefulness (PU) positively influences attitudes (ATT) toward unsolicited AI use in multilingual English classrooms.

H4: Attitudes (ATT) toward unsolicited AI use positively influence behavioral intentions (BI) to adopt AI tools independently.

H5: Behavioral intentions (BI) positively influence actual usage (AU) of AI tools in multilingual English classrooms.

H6: It has been noted that for students, perceived ease of use (PEOU) and perceived usefulness (PU) are more strongly related than they are for teachers.

H7: It was noticed that students have a stronger relationship between perceived ease of use (PEOU) and attitudes (ATT) toward unsolicited AI use than teachers.

H8: Conversely, teachers, in contrast to students, are positively influenced by perceived usefulness (PU) about attitudes (ATT) directed towards unsolicited AI use.

H9: There exists a strong positive correlation between attitudes (ATT) and behavioral intentions (BI) among students compared to the case among teachers.

H10: Teachers reported a stronger correlation between behavioral intentions (BI) and actual usage (AU) than the students.

To illustrate further, Figure 3 below shows the relationships among perceived usefulness, perceived ease of use, attitude, behavioral intention, and actual use. This Student Research Model is based on the Technology Acceptance Model (TAM).

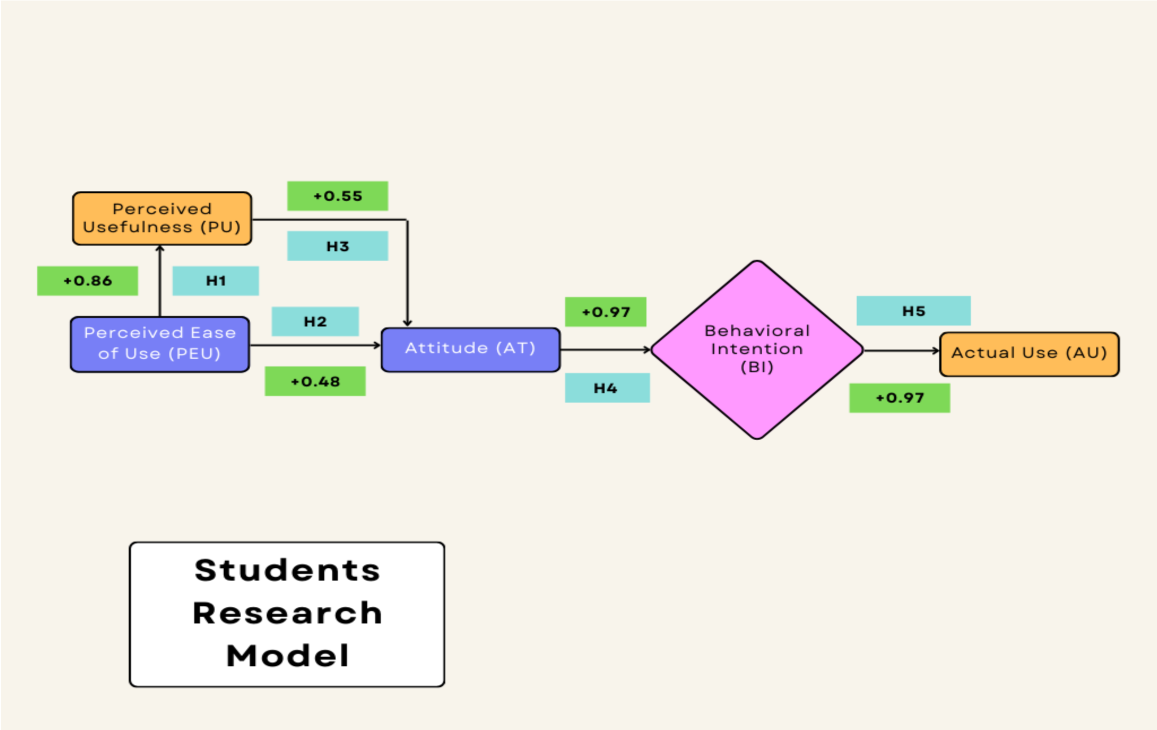


FIGURE 3. Students Research Model

Moreover, Figure 4 below illustrates the Teacher Research Model based on the Technology Acceptance Model (TAM) and shows the relationships among perceived usefulness, perceived ease of use, attitude, behavioral intention, and actual use.

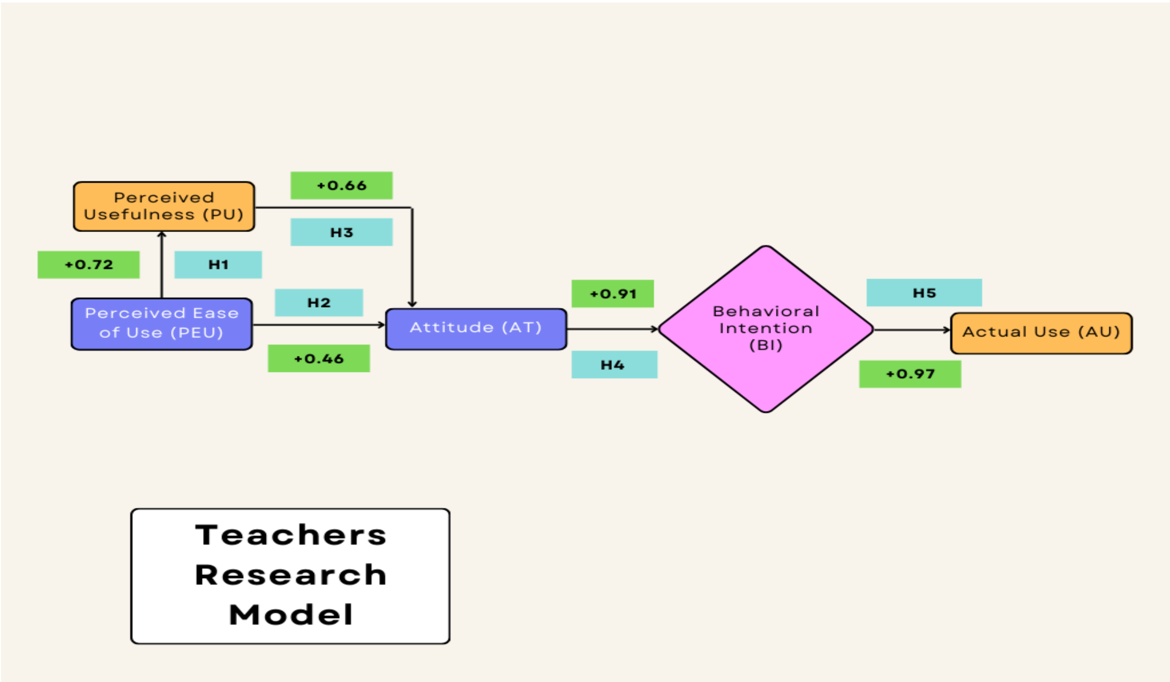


FIGURE 4. Teacher Research Model

Figure 5 is prepared to illustrate a proposed research framework based on the Technology Acceptance Model (TAM), which shows the relationships among perceived usefulness, perceived ease of use, attitude, behavioral intention, and actual use.

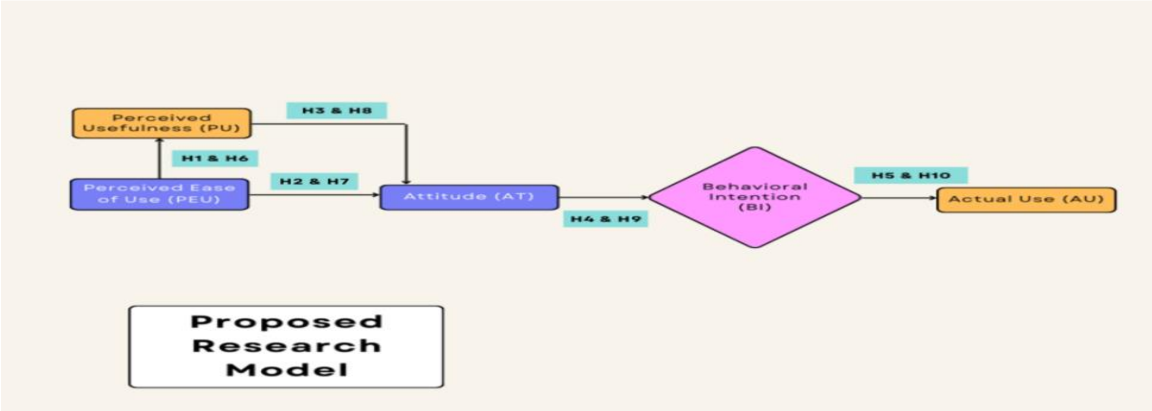


FIGURE 5. Proposed Research Model

Connection To Research Objectives

This study further argues that two of its RQs (RQ1 and RQ2) have already been addressed by the use of PEOU and PU variables to understand attitudes (ATT) and behavioral intentions (BI) towards self-directed use of AI tools. The TAM model is discussed extensively in AI literature but is rarely used in multilingual settings. H6 to H10 address the moderation - if any - effect of user groups on the construction of PU to BI and ATT to AU, among other TAM constructs. H5 assumes that AI integration into the classroom and or learning environment goes beyond the students' attempts to "see how far" they can get AI to respond to their requests on behalf of the teacher and maintains that AI use needs to enable the students' BI to translate into actual use (AU). Three frames of reference are invoked in the current study: ethical AI in Education, the actual or intended solicited AI in Education use scenarios norms across multilingual institutions, and pedagogical norms that operate in underexplored contexts (Zhang et al., 2023; Kumar et al., 2024; Qadhi et al., 2024). The study seeks to contribute to a better understanding of the strategies that foster ethical and effective integration of AI in multilingual educational contexts (Guan et al., 2023). From this perspective, the study responds to broader questions of how and why these shifts occur.

Material and Methods

This work adopts a quantitative research design that permits measuring the emergent components of ChatGPT usage in multimodal English classes. The primary motivation for using this methodology is to provide an empirically testable and generalizable understanding of the relations between the actors as postulated by the Technology Acceptance Model (TAM). Quantitative methods are the best fit for this research as they enable verification of the hypotheses in the set. Furthermore, the research questions about the disparity between student and teacher viewpoints (RQ1, RQ3, RQ4), the significant factors driving AI use (RQ2), and the moral and pedagogical dimensions regarding AI education (RQ5) fit well within the framework constructed by social factors. The stereotype attached to the PEOU, PU, ATT, BI, and AU, among other variables regarding AI adoption, is irrelevant, as the design carefully works with the fuzzy set. Consequently, this enables AI developers, educators, and policymakers worldwide in a multilingual context, well within the framework of a qualitative nature, with the help of current reputable figures (Dwivedi et al., 2023; Kohnke et al., 2023).

This research study focused on a sample group of 321 individuals, including 243 students and 78 teachers working in higher educational institutes across Riyadh, Jeddah, Dammam, and Medina. The Saudi Arabia regions selected for the study were strategically important due to their diverse population and culture; this was a critical part of the Saudi context higher education model. The chances of crowding out and selection were reduced to a minimum because the participants gained a lot of experience and exposure to AI tools in the context of multiple languages (English). Because of anticipated differences, Lee (2020) recommends a 3:1 student-to-teacher ratio, which is a positive factor in comparisons. Adequate representation was done by the Krejcie and Morgan (1970) method of estimating sample size. The approach enabled the representation and inclusion of the individual diversities that included languages and connectivity, geographical area, and qualifications that were sufficiently integrated within the Saudi higher educational system. As Tarhini et al. (2014) asserted, the relevant demographic information, such as age, gender, academic qualifications, and teaching experience, was collected on the participants so they could put the study into context. As Mostofa et al. (2021) remark, the multilingual type of the study is crucial when the authors want to investigate the ethical, behavioral, and pedagogic suggestions linked to the random use of AI, because the more languages, the more results can be understood. The institutions' Institutional Review Board (IRB), a participating institution among other partner institutions, was obtained. Informed consent was obtained from all participants, and confidentiality and anonymity were protected. The appropriate ethical principles for conducting this form of research, that is, on people, were considered (Ljubovic & Pajic, 2020; Noorbehbahani et al., 2022). The model utilized a teacher-specific and student-specific tool involving a two-dimensional Technology Acceptance Model (TAM) through a self-administered questionnaire developed for them. There are five key components: PEOU, PU, ATT, BI, and AU of AI. Using a cross-sectional descriptive survey, Oyelakun & Oluseyanu (2024) and Nguyen & Goto (2024) reported the use of questionnaires in which the respondents were asked to select the level of agreement with the statements on a five-point Likert scale ranging from Strongly Disagree to Strongly Agree.

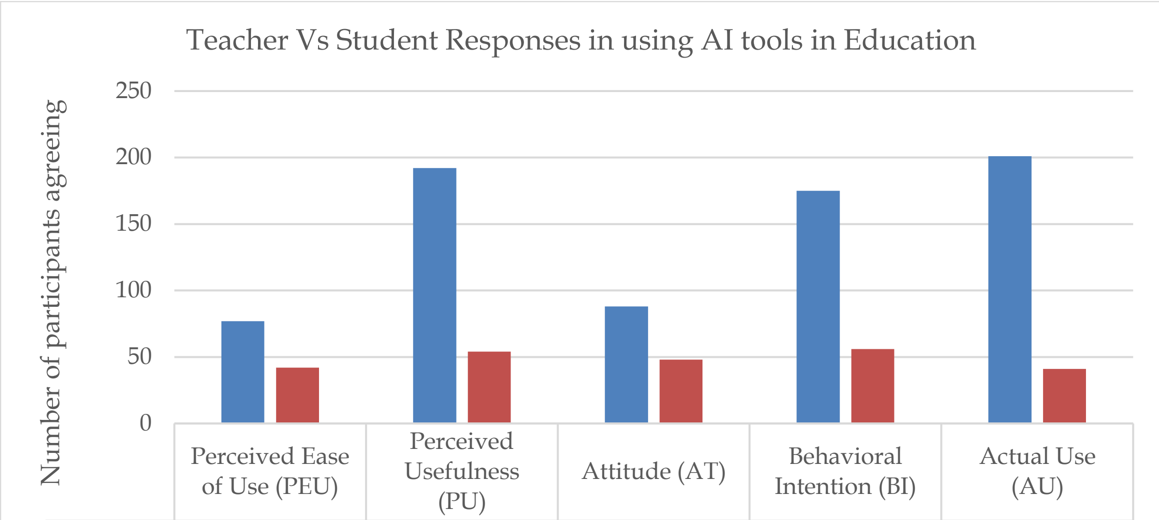
This specific study utilized a five-point Likert scale, which is beneficial due to the fact that it reduces respondent fatigue and allows for a diverse range of responses (Nishisato, 2014). This approach ensures two things. First, captures the widest range of detail while still minimizing the risk of fatigue. Fatigue risk questionnaires were paired with demographic questionnaires for proper participant feedback, which were also kept short and tested in a small audience. The evidence collected during this phase suggests the researchers' instrument was relevant and contained all the necessary research-aligned details. The researchers also believed the instrument was a simple, straightforward design, and did not make changes to the core tool. Then the researchers uploaded the final versions of the questionnaires and left them for two months to complete the data collection. The triangulation applied confirmed that research instruments tended to meet the study objectives. The survey was based on TAM scales (Davis, 1989; Venkatesh & Bala, 2008). The measurement of the construct was through a five-point Likert scale (1 = Strongly disagree, 5 = Strongly agree).

In order to determine the constructs' reliability and validity, confirmatory factor analysis with Cronbach's alpha (> 0.7) and Average Variance Extracted (AVE> 0.5) analyses were carried out.

Results and Discussion

Collected data was input into SPSS and Amos as per the objective of the study, as it was stated in the section of the dissertation methodology (Hair et al., 2019; Nishisato, 2014). As stated previously, some of the analysis was descriptive, which included the nature of the respondents and included the following: demographic variables, education qualifications, and teaching experience. This move ensured that the respondents thought that the sample was applicable, given the contextual factors that were relevant in the research. According to Cheung et al. (2023), the TAM model was detailed, with some of its different constructs, including Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude (ATT), Behavioral Intention (BI), and many others. The overall framework that was essential to examine and cognize the complexities of interrelationships and interactions between various constructs of the TAM was Structural Equation Modelling (SEM). The application of SEM in this instance was also appropriate because it is capable of answering and describing elaborate interdependencies among different constructs (Browen & Cudeck, 1993). This gave the researcher the ability to perform hypothesis tests and analyze variances, and contrasts among groups, as well as within groups and data points. The RMSEA, CFI, and TLI indices are the most widely used metrics for model fit assessment.

These indices were chosen because they assess the goodness of fit of a model to the data the model is attempting to explain (Bentler & Bonett, 1980; Cooper, 2023). The evidence was compelling enough to include these indices, thus establishing the results' reliability and validity and indicating the likely underlying structural relationships that justify the uninvited use of AI in multilingual education.



	Perceived Ease of Use (PEU)	Perceived Usefulness (PU)	Attitude (AT)	Behavioral Intention (BI)	Actual Use (AU)
Students	77	192	88	175	201
Teachers	42	54	48	56	41

FIGURE 6: Teacher vs Student Responses in Using AI Tools in Education

In Figure 6, teachers' and students' responses to AI tools in Education, by each of the received TAM components, are compared. It illustrates that, compared to teachers, students report a greater feeling of ease of use, perceived usefulness, behavioral intention, and actual use of AI tools.

The additional analysis to determine reliability and validity was done with a view to strengthening the measurement model. All the constructs had values greater than the generally agreed value in alpha of 0.7 (Nunnally, 1978), which denotes that the project lacks internal consistency.

The scores in all the composite reliability measures were more than the value of 0.7, and that supports the reliability of the instrument. All values of the Average Variance Extracted (AVE) are greater than 0.5, indicating that the models were used to capture a relevant amount of the variance of the respective indicators.

The outer loading rating of personal items was also between 0.632 and 0.992, which indicates sufficiently high reliability of each particular item.

Table 1
Summary of Constructs, Indicators, and Measurement Items in the TAM Framework

Constructs	Items	Outer Loading	Cronbach's Alpha	Composite Reliability	AVE
Attitude	Q27	0.801	0.790	0.922	0.760
	Q11	0.828			
	Q26	0.910			
	Q15	0.632			
Behavioral Intention	Q9	0.918	0.947	0.901	0.796
	Q14	0.705			
	Q6	0.974			
Actual Usage (AU)	Q5	0.991	0.923	0.921	0.791
	Q10	0.667			
	Q12	0.984			
Perceived Ease of Use	Q1	0.985	0.930	0.910	0.774
	Q2	0.720			
	Q3	0.923			
Perceived Usefulness	Q4	0.977	0.943	0.977	0.925
	Q7	0.992			
	Q13	0.988			
	Q22	0.894			

These findings support the soundness of the constructs utilized in the research and form a good basis to be tested in further sections.

Apart from reliability and convergent validity, discriminant validity was checked to guarantee that the constructs within the model measure separate dimensions and are not identical. Discriminant validity was tested by the Fornell-Larcker criterion, which tests the square root of the Average Variance Extracted (AVE) of each construct against the correlation coefficients of the other II constructs.

Table 2
Summary of the Metrics and the Discriminant Validity Statistics

Construct	ATT	BI	PEOU	PU	AU
ATT	0.981				
BI	0.947	0.949			
PEOU	0.475	0.926	0.951		
PU	0.587	0.536	0.824	0.747	
AU	0.847	0.739	0.801	0.521	0.946

The diagonal elements of the AVE yielded scores for each construct that were higher than the root mean square of correlation metrics for the other constructs, thus reinforcing evidence of discriminant validity. The strongest correlation of BI and ATT (0.947) was found, as it is one of the assumptions of the model that the attitude strongly correlates with the behavioral intentions. The strong discriminant valence assures that the constructs are not overlapping and are theoretically different as well, which proves the structural model's validity. The outcomes of this precondition are significant for hypothesis testing in further stages.

Hypotheses Testing

The hypotheses were evaluated through Structural Equation Modeling (SEM), and the outcomes are illustrated in Table 3. The analysis pointed out the presence of positive and negative interdependencies and the respective strengths of the connectedness of the constituents of the TAM for the teachers and the students. The analysis also noted intergroup variance regarding the interconnectedness of the incidents under study.

Results of Hypothesis Testing

Table 3
Results of testing the hypothesis:

Hypothesis	Path	SE	p-value	Combined	Students	Teachers	Hypothesis Status
H1	PEOU → PU	0.83	<0.001	0.83	0.86	0.72	Supported
H2	PEOU → ATT	0.48	<0.001	0.48	0.48	0.46	Supported
H3	PU → ATT	0.59	<0.001	0.59	0.55	0.66	Supported
H4	ATT → BI	0.95	<0.001	0.95	0.97	0.91	Supported
H5	BI → AU	0.97	<0.001	0.97	0.97	0.97	Supported
H6	PEOU → PU	+0.14	<0.001	-	-	-	Supported
H7	PEOU → ATT	+0.02	<0.001	-	-	-	Supported
H8	PU → ATT	+0.11	<0.001	-	-	-	Supported
H9	ATT → BI	+0.06	<0.001	-	-	-	Supported
H10	BI → AU	0.00	<0.001	-	-	-	Rejected

- H1 (PEOU → PU): both students and teachers agree that PEOU has the influence of an independent variable on PU. The association was noted to be stronger for students (14%).
- H2 (PEOU → ATT): the PEOU construct has a positive influence on the ATT construct in the context of the unprompted AI usage scenario. This influence is stronger for the students (2%).
- H3 (PU → ATT): the PU variable has a positive influence on the ATT variable. This influence is stronger for teachers (11%).
- H4 (ATT → BI): The ATT variable has a strong influence/impact on the BI variable. This impact is more pronounced for students (6%).
- H5 (BI → AU): The variable BI has a strong positive correlation with the AU variable in both populations (noted no intergroup variance).
- H10 (BI → AU): This hypothesis was rejected.

This analysis was aimed at bringing to the forefront the different behavioral patterns and attitudes of the teachers and students, and how these patterns and attitudes impact the use of AI tools in teaching in multilingual classroom settings.

The results corroborated the theorized linkages and underscored the predictive capability of its constructs in determining the unsolicited use of AI tool hypotheses (Whisenhunt et al., 2022).

Out of the hypotheses, PEOU would have a significant H1 and H2 standalone value that would allow it to be a metric for predicting PU and ATT, determining that users are likely to view AI tools as applicable and tend to formulate a positive attitude towards them when the tools are easy to utilize (Yan, 2023). This is consistent with the earlier TAM works as it affirms the relevance of simplicity and easy-to-comprehend design features for technology uptake (Tiwari et al., 2024; Venkatesh & Bala, 2012).

The results supported H3, which determined the positive correlation between PU and ATT. This implies that participants' beliefs about the usefulness of unsolicited AI technologies significantly influence their attitudes toward their use, which is consistent with previous findings regarding the role of utility in influencing the users of any product (Wang, 2024; Van Dis et al., 2023).

Group Comparisons: Students Vs. Teachers

The participants in this study had different perspectives regarding AI tools, which are summarized in the differences in viewpoints between Yu (2023) and the participants. Nonetheless, the rejection of H10, which states there is no difference in students and teachers in the transition from Behavioral Intention (BI) to Actual Usage (AU), conveys a lack of self-factors, which include institutional guidelines, AI tools, and supportive frameworks that are likely to affect both groups in the same direction. Therefore, this finding calls for policy adjustments, such as the establishment of a framework, as well as the improvement of balanced resource allocation to minimize the disparity between the intended and real utilization of AI in multilingual classrooms.

Students, in general, reported a low degree of AI utilization in their coursework, suggesting that in their case, the correlation between PEOU, ATT, and PU (Yusuf et al., 2024) was weaker, a finding contrary to Teo & Noyes (2014) who argued that being a digital native is, without a doubt, an advantage for students (Smith & Peloghitis, 2020).

Within the schooling system, the teachers had a stronger correlation, which increased their cognitive reasoning (Zawacki-Richter et al., 2019). Thus, watching educational videos should be more about the \\"usefulness\\" rather than PU, and, as Ertmer & Ottenbreit-Leftwich (2013; Nazaretsky et al., 2022; Stolpe & Hallström, 2024) point out, transform such insights and strategies into practical actions.

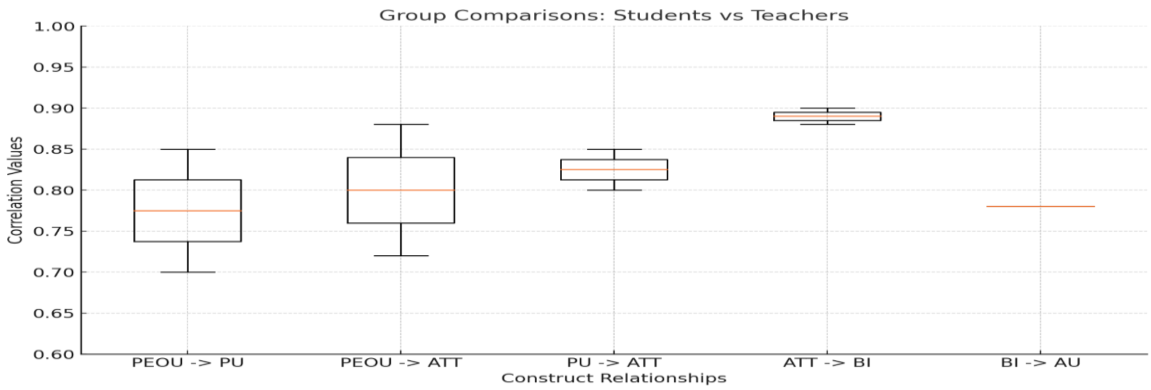


Figure 7: Group Comparisons - Students Vs Teacher

This figure highlights the gap between teachers and students in perceptions and, more importantly, the unprompted use of AI tools. Students are labeled digital natives, thus providing them an edge in simplicity bias reliance, while teachers have a more functional focus and institutional bias.

Conclusion

This study explored what drives students and teachers in higher education to use AI tools on their own in multilingual English learning settings, using the Technology Acceptance Model as a framework. By focusing on independently chosen rather than institutionally required AI use, the research adds to our understanding of how educational technology is adopted and brings attention to a less-studied aspect of AI integration. The results show that the main TAM factors—perceived ease of use and perceived usefulness—

still play a key role in shaping attitudes, intentions, and actual use of AI tools when there is no formal guidance.

The results reveal meaningful differences between students and teachers. Students demonstrated a stronger reliance on perceived ease of use in shaping their perceptions of usefulness, suggesting that interface simplicity and low operational barriers play a critical role in their engagement with AI tools. This challenges the assumption that digital nativity automatically translates into effective or sustained AI use. Teachers, by contrast, exhibited stronger associations between perceived usefulness, attitude, and actual usage, reflecting a more functional and pedagogically driven orientation toward AI adoption. These findings align with prior research indicating that educators prioritize instructional value and practical applicability over technological convenience.

Importantly, the absence of significant differences between students and teachers in the transition from behavioral intention to actual usage indicates the presence of shared external constraints. Factors such as limited institutional guidance, ethical ambiguity, data privacy concerns, and uneven access to AI resources appear to regulate AI use similarly across both groups. This suggests that unsolicited AI adoption is not solely driven by individual perceptions but is strongly shaped by contextual and environmental conditions. In multilingual English classrooms, where equity and linguistic diversity are central, these constraints may further complicate responsible and consistent AI integration.

Ethical considerations emerged as a critical moderating factor in the adoption process. While ease of use and usefulness remain influential, their effects are attenuated by concerns related to academic integrity, algorithmic bias, and data security. The findings indicate that positive attitudes toward AI do not automatically result in responsible usage when governance structures are absent. This underscores the need to situate AI adoption within broader ethical, pedagogical, and institutional frameworks rather than treating it as an individual or purely technological choice.

Recommendations

Based on these findings, there are several recommendations for policy, practice, and future research. First, higher education institutions should create clear and context-appropriate rules for using AI that cover ethics, academic honesty, data privacy, and how AI fits with teaching goals. These rules are especially important in multilingual English education, where unregulated AI use could increase existing inequalities and harm real language learning.

Second, there should be organized programs to help both students and teachers build their skills with AI. These programs should be tailored, since students usually care more about how easy tools are to use, while teachers focus on how useful they are for teaching. Training should go beyond just learning how to use the tools and instead help teachers use AI in ways that improve their teaching.

Third, those who design AI tools and educational materials should focus on user-centered design, making sure tools are both easy to use and clearly valuable for learning. For language learning, tools should match teaching methods that encourage communication and support multiple languages, so that AI helps with critical thinking and language use instead of replacing them.

Finally, future research should use long-term and mixed-method approaches to study how using AI on one's own affects language learning, independence, and teaching methods over time. Researchers should pay more attention to social and cultural factors, like family language habits and school culture, especially in Saudi and Gulf multilingual settings. Including a wider range of participants and more qualitative data would also help overcome the limits of self-reported information and similar samples.

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