مجلة العلوم الإنسانية
بجامعة حائل

جامعة حائل
University of Ha'il

# مجلة العلوم الإنسانية

## دورية علمية محكمة تصدر عن جامعة حائل

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جامعة حائل

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دورية علمية محكمة تصدر عن جامعة حائل


**للتواصل:**

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# نبذة عن المجلة

## تعريف بالمجلة

مجلة العلوم الإنسانية، مجلة دورية علمية محكمة، تصدر عن وكالة الجامعة للدراسات العليا والبحث العلمي بجامعة حال كل ثلاثة أشهر بصفة دورية، حث تصدر أربة أعداد في كل سنة، وبحسب اكتمال البحوث المجازة للنشر.

وقد نجحت مجلة العلوم الإنسانية في تحقيق معايير اعتماد معامل التأثير والاستشهادات المرجعية للمجلات العلمية العربية معامل "ارسيف Arcif " المتوافقة مع المعايير العالمية، والتي يبلغ عددها (32) معياراً، وقد أطلق ذلك خلال التقرير السنوي الثامن للمجلات للعام 2023.

## رؤية المجلة

التميز في النشر العلمي في العلوم الإنسانية وفقاً لمعايير مهنية عالمية.

## رسالة المجلة

نشر البحوث العلمية في التخصصات الإنسانية؛ لخدمة البحث العلمي والمجتمع المحلي والدولي.

## أهداف المجلة

تهدف المجلة إلى إيجاد منافذ رصينة؛ لنشر المعرفة العلمية المتخصصة في المجال الإنساني، وتمكن الباحثين -من مختلف بلدان العالم- من نشر أبحاثهم ودراساتهم وإنتاجهم الفكري لمعالجة واقع المشكلات الحياتية، وتأسيس الأطر النظرية والتطبيقية للمعارف الإنسانية في المجالات المتنوعة، وفق ضوابط وشروط ومواصفات علمية دقيقة، تحقيقا للجودة والريادة في نشر البحث العلمي.

# قواعد النشر

## لغة البحث

1- تقبل المجلة البحوث المكتوبة باللغتين العربية والإنجليزية.

2- يُكتب عنوان البحث وملخصه باللغة العربية للبحوث المكتوبة باللغة الإنجليزية.

3- يُكتب عنوان البحث وملخصه ومراجعه باللغة الإنجليزية للبحوث المكتوبة باللغة العربية، على أن تكون ترجمة الملخص إلى اللغة الإنجليزية صحيحة ومتخصصة.

## مجالات النشر في المجلة

تهتم مجلة العلوم الإنسانية بجامعة حائل بنشر إسهامات الباحثين في مختلف القضايا الإنسانية الاجتماعية والأدبية، إضافة إلى نشر الدراسات والمقالات الي تتوفر فيها الأصول والمعايير العلمية المتعارف عليها دولياً، وتقبل الأبحاث المكتوبة باللغة العربية والإنجليزية في مجال اختصاصها، حيث تعنى المجلة بالتخصصات الآتية:

- علم النفس وعلم الاجتماع والخدمة الاجتماعية والفلسفة الفكرية العلمية الدقيقة.
- المناهج وطرق التدريس والعلوم التربوية المختلفة.
- الدراسات الإسلامية والشريعة والقانون.
- الآداب: التاريخ والجغرافيا والفنون واللغة العربية، واللغة الإنجليزية، والسياحة والآثار.
- الإدارة والإعلام والاتصال وعلوم الرياضة والحركة.

## أوعية نشر المجلة

تصدر المجلة ورقياً حسب القواعد والأنظمة المعمول بها في المجلات العلمية المحكمة، كما تُنشر البحوث المقبولة بعد تحكيمها إلكترونياً لتعم المعرفة العلمية بشكل أوسع في جميع المؤسسات العلمية داخل المملكة العربية السعودية وخارجها.

# ضوابط وإجراءات النشر في مجلة العلوم الإنسانية

## اولاً: شروط النشر

1. أن يتّسم بالأصالة والجدّة والابتكار والإضافة المعرفية في التخصص.
2. لم يسبق للباحث نشر بحثه.
3. ألا يكون مستلّاً من رسالة علمية (ماجستير / دكتوراه) أو بحوث سبق نشرها للباحث.
4. أن يلتزم الباحث بالأمانة العلمية.
5. أن تراعى فيه منهجية البحث العلمي وقواعده.
6. عدم مخالفة البحث للضوابط والأحكام والآداب العامة في المملكة العربية السعودية.
7. مراعاة الأمانة العلمية وضوابط التوثيق في النقل والاقتباس.
8. السلامة اللغوية ووضوح الصور والرسومات والجداول إن وجدت، وللمجلة حقها في مراجعة التحرير والتدقيق النحوي.

## ثانياً: قواعد النشر

1. أن يشتمل البحث على: صفحة عنوان البحث، ومستخلص باللغتين العربية والإنجليزية، ومقدمة، وصلب البحث، وخاتمة تتضمن النتائج والتوصيات، وثبت المصادر والمراجع باللغتين العربية والإنجليزية، والملاحق اللازمة (إن وجدت).
2. في حال (نشر البحث) يُزوَّد الباحث بنسخة إلكترونية من عدد المجلة الذي تم نشر بحثه فيه، ومستلاً لبحثه.
3. في حال اعتماد نشر البحث تؤول حقوق نشره كافة للمجلة، ولها أن تعيد نشره ورقيّاً أو إلكترونيّاً، ويحقّ لها إدراجه في قواعد البيانات المحلّيّة والعالمية - بمقابل أو بدون مقابل- وذلك دون حاجة لإذن الباحث.
4. لا يحقّ للباحث إعادة نشر بحثه المقبول للنشر في المجلة إلا بعد إذن كتابي من رئيس هيئة تحرير المجلة.
5. الآراء الواردة في البحوث المنشورة تعبر عن وجهة نظر الباحثين، ولا تعبر عن رأي مجلة العلوم الإنسانية.
6. النشر في المجلة يتطلب رسوما مالية قدرها ( 1000 ريال) يتم إيداعها في حساب المجلة، وذلك بعد إشعار الباحث بالقبول الأولي وهي غير مستردة سواء أجيز البحث للنشر أم تم رفضه من قبل المحكمين.

## ثالثًا: الضوابط والمعايير الفنية لكتابة وتنظيم البحث

1. ألا تتجاوز نسبة الاقتباس في البحوث **(25%).**
2. الصفحة الأولى من البحث، تحتوي على عنوان البحث، اسم الباحث أو الباحثين، المؤسسة التي ينتسب إليها- جهة العمل، عنوان المراسلة والبريد الإلكتروني، وتكون باللغتين العربية والإنجليزية على صفحة مستقلة في بداية البحث. الإعلان عن أي دعم مالي للبحث- إن وجد. كما يقوم بكتابة رقم الهوية المفتوحة للباحث ORCID بعد الاسم مباشرة. علماً بأن مجلة العلوم الإنسانية تنصح جميع الباحثين باستخراج رقم هوية خاص بهم، كما تتطلب وجود هذا الرقم في حال إجازة البحث للنشر.
3. ألا يرد اسم الباحث (الباحثين) في أي موضع من البحث إلا في صفحة العنوان فقط.

**4**. ألا تزيد عدد صفحات البحث عن ثلاثين صفحة أو (12.000) كلمة للبحث كاملا أيهما أقل بما في ذلك الملخصان العربي والإنجليزي، وقائمة المراجع.

**5**. أن يتضمن البحث مستخلصين: أحدهما باللغة العربية لا يتجاوز عدد كلماته (200) كلمة، والآخر بالإنجليزية لا يتجاوز عدد كلماته (250) كلمة، ويتضمن العناصر التالية: (موضوع البحث، وأهدافه، ومنهجه، وأهم النتائج) مع العناية بتحريرها بشكل دقيق.

**6**. يُتبع كل مستخلص (عربي/إنجليزي) بالكلمات الدالة (المفتاحية) (Key Words) المعبرة بدقة عن موضوع البحث، والقضايا الرئيسة التي تناولها، بحيث لا يتجاوز عددها (5) كلمات.

**7**. تكون أبعاد جميع هوامش الصفحة: من الجهات الأربعة (3) سم، والمسافة بين الأسطر مفردة.

**8**. يكون نوع الخط في المتن باللغة العربية (Traditional Arabic) وبحجم (12)، وباللغة الإنجليزية (Times New Roman) وبحجم (10)، وتكون العناوين الرئيسية في اللغتين بالبنط الغليظ. (Bold).

**9**. يكون نوع الخط في الجدول باللغة العربية (Traditional Arabic) وبحجم (10)، وباللغة الإنجليزية (Times New Roman) وبحجم (9)، وتكون العناوين الرئيسية في اللغتين بالبنط الغليظ (Bold) ..

**10**. يلتزم الباحث برومنة المراجع العربية ( الأبحاث العلمية والرسائل الجامعية) ويقصد بها ترجمة المراجع العربية (الأبحاث والرسائل العلمية فقط) إلى اللغة الإنجليزية، وتضمينها في قائمة المراجع الإنجليزية (مع الإبقاء عليها باللغة العربية في قائمة المراجع العربية)، حيث يتم رومنة (Romanization / Transliteration) اسم، أو أسماء المؤلفين، متبوعة بسنة النشر بين قوسين (يقصد بالرومنة النقل الصوتي للحروف غير اللاتينية إلى حروف لاتينية، تمكِّن قراء اللغة الإنجليزية من قراءتها، أي: تحويل منطوق الحروف العربية إلى حروف تنطق بالإنجليزية)، ثم يتبع بالعنوان، ثم تضاف كلمة (in Arabic) بين قوسين بعد عنوان الرسالة أو البحث. بعد ذلك يتبع باسم الدورية التي نشرت بها المقالة باللغة الإنجليزية إذا كان مكتوباً بها، وإذا لم يكن مكتوباً بها فيتم ترجمته إلى اللغة الإنجليزية.

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**11**. يلي قائمة المراجع العربية، قائمة بالمراجع الإنجليزية، متضمنة المراجع العربية التي تم رومنتها، وفق ترتيبها الهجائي (باللغة الإنجليزية) حسب الاسم الأخير للمؤلف الأول، وفقاً لأسلوب التوثيق المعتمد فـي المجلة.

**12.** تستخدم الأرقام العربية أينما ذكرت بصورتها الرقمية. (Arabic.... 1,2,3) سواء في متن البحث، أو الجداول و الأشكال، أو المراجع، وترقم الجداول و الأشكال في المتن ترقيماً متسلسلاً مستقلاً لكل منهما ، ويكون لكل منها عنوانه أعلاه ، ومصدره – إن وجد – أسفله.

**13.** يكون الترقيم لصفحات البحث في المنتصف أسفل الصفحة، ابتداءً من صفحة ملخص البحث (العربي، الإنجليزي)، وحتى آخر صفحة من صفحات مراجع البحث.

**14.** تدرج الجداول والأشكال- إن وجدت- في مواقعها في سياق النص، وترقم بحسب تسلسلها، وتكون غير ملونة أو مظللة، وتكتب عناوينها كاملة. ويجب أن تكون الجداول والأشكال والأرقام وعناوينها متوافقة مع نظام APA.

## رابعًا: توثيق البحث

أسلوب التوثيق المعتمد في المجلة هو نظام جمعية علم النفس الأمريكية (APA7)

## خامسًا: خطوات وإجراءات التقديم

**1.** يقدم الباحث الرئيس طلبًا للنشر (من خلال منصة الباحثين بعد التسجيل فيها) يتعهد فيه بأن بحثه يتفق مع شروط المجلة، وذلك على النحو الآتي:

**أ.** البحث الذي تقدمت به لم يسبق نشره (ورقيا أو إلكترونيا)، وأنه غير مقدم للنشر، ولن يقدم للنشر في وجهه أخرى حتى تنتهي إجراءات تحكيمه، ونشره في المجلة، أو الاعتذار للباحث لعدم قبول البحث.

**ب.** البحث الذي تقدمت به ليس مستلا من بحوث أو كتب سبق نشرها أو قدمت للنشر، وليس مستلاً من الرسائل العلمية للماجستير أو الدكتوراه.

**ج.** الالتزام بالأمانة العلمية وأخلاقيات البحث العلمي.

**د.** مراعاة منهج البحث العلمي وقواعده.

**هـ.** الالتزام بالضوابط الفنية ومعايير كتابة البحث في مجلة حائل للعلوم الإنسانية كما هو في دليل الكتابة العلمية المختصر بنظام APA7.

**2.** إرفاق سيرة ذاتية مختصرة في صفحة واحدة حسب النموذج المعتمد للمجلة (نموذج السيرة الذاتية).

**3.** إرفاق نموذج المراجعة والتدقيق الأولي بعد تعبئته من قبل الباحث.

**4.** يرسل الباحث أربع نسخ من بحثه إلى المجلة إلكترونيّاً بصيغة (WORD) نسختين و (PDF) نسختين تكون إحداهما بالصيغتين خالية مما يدل على شخصية الباحث.

**5.** يتم التقديم إلكترونياً من خلال منصة تقديم الطلب الموجودة على موقع المجلة (منصة الباحثين) بعد التسجيل فيها مع إرفاق كافة المرفقات الواردة في خطوات وإجراءات التقديم أعلاه.

**6.** تقوم هيئة تحرير المجلة بالفحص الأولي للبحث، وتقرير أهليته للتحكيم، أو الاعتذار عن قبوله أولياً أو بناء على تقارير المحكمين دون إبداء الأسباب وإخطار الباحث بذلك

**7.** تملك المجلة حق رفض البحث الأولي ما دام غير مكتمل أو غير ملتزم بالضوابط الفنية ومعايير كتابة البحث في مجلة حائل للعلوم الإنسانية.

**8.** في حال تقرر أهلية البحث للتحكيم يخطر الباحث بذلك، وعليه دفع الرسوم المالية المقررة للمجلة **(1000)** ريال غير مستردة من خلال الإيداع على حساب المجلة ورفع الإيصال من خلال منصة التقديم المتاحة على موقع المجلة، وذلك خلال مدة خمسة أيام عمل منذ إخطار الباحث بقبول بحثه أوليًا وفي حالة عدم السداد خلال المدة المذكورة يعتبر القبول الأولي ملغيًا.

**9.** بعد دفع الرسوم المطلوبة من قبل الباحث خلال المدة المقررة للدفع، ورفع سند الإيصال من خلال منصة التقديم، يرسل البحث لمحكِّمين اثنين؛ على الأقل.

**10.** فـي حال اكتمال تقارير المحكّمين عن البحث؛ يتم إرسال خطاب للباحث يتضمّن إحدى الحالات التّالية:

أ. قبول البحث للنشر مباشرة.

ب. قبول البحث للنّشر؛ بعد التّعديل.

ج. تعديل البحث، ثمّ إعادة تحكيمه.

د. الاعتذار عن قبول البحث ونشره.

**11.** إذا تطلب الأمر من الباحث القيام ببعض التعديلات على بحثه، فإنه يجب أن يتم ذلك في غضون (أسبوعين من تاريخ الخطاب) من الطلب. فإذا تأخر الباحث عن إجراء التعديلات خلال المدة المحددة، يعتبر ذلك عدولا منه عن النشر، ما لم يقدم عذرا تقبله هيئة تحرير المجلة.

**12.** يقدم الباحث الرئيس (حسب نموذج الرد على المحكمين) تقرير عن تعديل البحث وفقاً للملاحظات الواردة في تقارير المحكمين الإجمالية أو التفصيلية في متن البحث

**13.** للمجلة الحق في الحذف أو التعديل في الصياغة اللغوية للدراسة بما يتفق مع قواعد النشر، كما يحق للمحررين إجراء بعض التعديلات من أجل التصحيح اللغوي والفني. وإلغاء التكرار، وإيضاح ما يلزم.

**14.** في حالة رفض البحث من قبل المحكمين فإن الرسوم غير مستردة.

**15.** إذا رفض البحث، ورغب المؤلف في الحصول على ملاحظات المحكمين، فإنه يمكن تزويده بهم، مع الحفاظ على سرية المحكمين. ولا يحق للباحث التقدم من جديد بالبحث نفسه إلى المجلة ولو أجريت عليه جميع التعديلات المطلوبة.

**16.** لا تردّ البحوث المقدمة إلى أصحابها سواء نشرت أم لم تنشر، ويخطر المؤلف في حالة عدم الموافقة على النشر

**17.** ترسل المجلة للباحث المقبول بحثه نسخة معتمدة للطباعة للمراجعة والتدقيق، وعليه إنجاز هذه العملية خلال 36 ساعة.

**18.** لهيئة تحرير المجلة الحق فـي تحديد أولويات نشر البحوث، وترتيبها فنّيّاً.

مجلة العلوم الإنسانية
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## المشرف العام

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بجامعة حائل

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

# العوامل المحفزة لتبنّي أدوات الذكاء الاصطناعي في فصول اللغة الإنجليزية متعددة اللغات: نموذج معادلات هيكلية قائم على نموذج قبول التكنولوجيا (TAM)

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## Abstract

This quantitative study, based on the Technology Acceptance Model (TAM), investigates AI adoption in education without institutional guidance, introducing the concept of "unsolicited AI use." Unlike previous studies on solicited use, it examines how students and teachers independently engage with AI tools, raising concerns about equity, academic integrity, and pedagogical alignment. The unsolicited use of AI in education presents challenges, such as over-reliance, diminished critical thinking, and inequitable access, potentially undermining authentic language acquisition. Data from 321 participants were analyzed using structural equation modeling (SEM) with TAM constructs: Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude (ATT), Behavioral Intention (BI), and Actual Usage (AU). This study was conducted across a number of Saudi universities, focusing on multilingual English language classrooms in higher education settings. Results show that students link PEOU more strongly to PU than teachers, with students viewing ATT as encouraging AI use (+0.14). Teachers, however, prioritize the AU-ATT relationship (+0.11). Fit indices ($\chi^2/df = 6.76$, RMSEA = 0.09, CFI = 0.87) indicated TAM's reasonable explanatory power. The findings have significant implications for English as a Foreign Language instruction, emphasizing the need for ethical and effective AI integration in language teaching contexts. The study highlights the need for AI competencies, equitable access, and contextualized approaches in multilingual education. Collaboration between teachers and policymakers is essential to ensure ethical and efficient AI use. Future research should explore how AI-driven language learning impacts multilingual students' educational outcomes over time.

**Keywords:** Artificial Intelligence (AI); Technology Acceptance Model (TAM); Foreign Language education; structural equation modeling (SEM); perceived usefulness (PU).

## المستخلص:

تستند هذه الدراسة الكمية إلى نموذج تقبّل التكنولوجيا Technology Acceptance Model (TAM), وتهدف إلى استكشاف تبني الذكاء الاصطناعي في التعليم دون توجيه مؤسسي، من خلال طرح مفهوم «الاستخدام الغير الموجّه «. وعلى خلاف الدراسات السابقة التي ركزت على الاستخدام الموجّه، تركز هذه الدراسة على كيفية استخدام الطلاب والمعلمين لأدوات الذكاء الاصطناعي بشكل مستقل، وما يترتب على ذلك من تحديات تتعلق بالنزاهة الأكاديمية، والعدالة، وتوافق التقنيات مع الأهداف التعليمية. شملت العينة 321 مشاركًا، وتم تحليل البيانات باستخدام نمذجة المعادلات الهيكلية (SEM) وفقًا لبُنى نموذج TAM: الإدراك بسهولة الاستخدام (PEOU)، الإدراك بفائدة الاستخدام (PU), الاتجاه (ATT)، النية السلوكية (BI)، والاستخدام الفعلي (AU). أُجريت الدراسة في عدد من الجامعات السعودية، مستهدفة صفوف اللغة الإنجليزية متعددة اللغات. أظهرت النتائج أن الطلاب يربطون بين سهولة الاستخدام والفائدة بدرجة أكبر من المعلمين، ويرى الطلاب أن الاتجاه الإيجابي يشجع على الاستخدام، بينما يركز المعلمون على العلاقة بين الاستخدام الفعلي والاتجاه. تؤكد النتائج أهمية تعزيز كفاءات استخدام الذكاء الاصطناعي وتوفير بيئة تعليمية عادلة، مع الحاجة لتعاون المعلمين وصناع القرار لضمان الاستخدام الأخلاقي والفعّال لهذه التقنيات.

**الكلمات المفتاحية:**الذكاء الاصطناعي؛ نموذج قبول التكنولوجيا؛ تعليم اللغة الأجنبية؛ نمذجة المعادلات الهيكلية؛ الفائدة المتصوَّرة.

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**التمويل**: لا يوجد تمويل لهذا البحث.

guages as they provide a wide range of solutions that are customized, easy, and responsive (Abdelghani et al., 2024). Still, most of the literature concerning AI in Education regards solicited usage, where agencies or educators intentionally teach with the help of these apps (Adams et al., 2023). On the other hand, we define 'unsolicited AI usage' as the independent adoption of AI tools by students and teachers without institutional support. This makes the issues very difficult and makes them meet the requirements, cutting across doing so ethically, advancing skills, and achieving specified goals (Adeshola and Adepoju, 2023).

Figure 1 below (a radar chart) illustrates the increasing trends in AI applications by students and teachers from 2018 to 2023. This radar chart visualizes the progressive adoption patterns across different user groups, highlighting how AI integration in educational settings has steadily grown over this five-year period. The visualization provides context for understanding the current landscape of AI usage that forms the backdrop for this study.

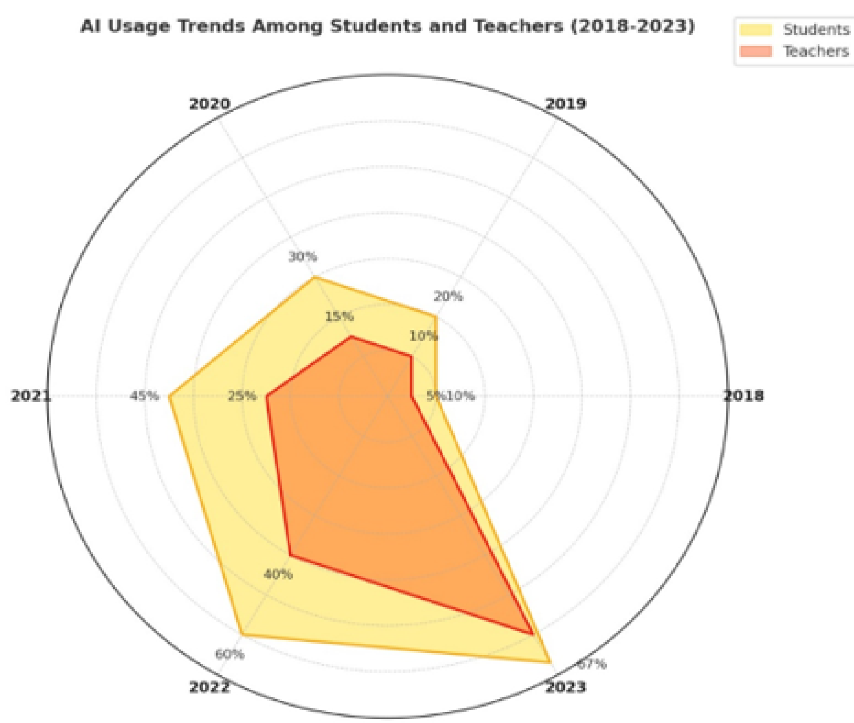
## Introduction:

The increasing adoption of AI tools in educational settings presents both opportunities and challenges, particularly in multilingual classrooms. While transformative, this scenario presents significant practical and pedagogical challenges, particularly in multilingual settings. Students independently engage with AI language tools without explicit direction from instructors. Smith et al. (2023) and Gayed (2025) describe this phenomenon as 'unsolicited technology adoption' in educational settings. While AI can positively influence teaching and learning, it also presents unparalleled challenges within and across many linguistically and culturally diverse contexts (Acosta-Enriquez et al., 2024). Multilingual classrooms with diverse linguistic and cultural backgrounds often face unique challenges when adopting AI tools. These include varying levels of digital literacy, language-specific constraints in AI tools, and the risk of cultural biases in AI-generated outputs.

AI tools, including ChatGPT and Grammarly, are changing the way learners engage with lan-

**Figure 1**

***AI usage trends among students and teachers, 2018-2023, showing percentage increase in adoption across educational contexts***




* **Sources**: (U.S. Department of Education, Office of Educational Technology, Artificial Intelligence and Future of Teaching and Learning: Insights and Recommendations; 2024; Prather et al., 2025)

tings where language proficiency itself may function as both a driver of and barrier to technology acceptance.

The results of this research are intended to assist teachers, policymakers, AI developers, and users with unsolicited AI use. This research motivates the development of AI literacy, culturally relevant models, and dispensed access models by plugging together gaps in policy and practice in the institutions (Jiang et al., 2024). These ideas are part of the growing literature on linguistic justice and, more specifically, how to improve multilingual education and its speakers' multilingualism-related outcomes (Yu et al., 2025).

The Technology Acceptance Model (TAM), originally proposed by Davis (1989), serves as the primary theoretical framework for this study. This study employs the five core constructs from the Technology Acceptance Model: Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude Toward Use (ATT), Behavioral Intention (BI), and Actual Usage (AU). These constructs form the foundation for analyzing user behavior toward AI tools in educational settings. Throughout the remainder of this paper, these constructions will be referred to by their abbreviations. As a predictive model, TAM has been widely used to explore technology adoption behaviors through constructs such as Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude Toward Use (ATT), Behavioral Intention (BI), and Actual Usage (AU). These constructs provide a robust foundation for understanding how and why users adopt certain technologies, particularly in applied contexts like artificial intelligence (AI) in language education. By focusing on these key aspects, the study aims to explore the factors influencing user behavior and the practical implications of AI integration in education.

While TAM's strengths are evident across various fields, including education, critiques of the framework highlight its limitations in addressing complex, unregulated factors such as user motivations, ethical concerns, and external influences. To address these gaps, this study incorporates additional perspectives, such as Ajzen and Fischer's (2020) policy framework on behavior motivation, as well as recent insights from An et al. (2024), which emphasize the importance of bridging theoretical and empirical gaps in user behavior, policy implications, and education

Unsolicited AI use refers to the independent adoption of AI tools by users—students or teachers—without institutional directives or formal inclusion in curricula. This study focuses on unsolicited AI use—defined as the independent adoption of AI tools without institutional directives or formal inclusion in curricula—contrasting with solicited use that occurs within established institutional frameworks. 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 relationships can be understood through these constructs, which are PEOU, PU, ATT, BI, and AU (Davis, 1989). SEM analyzes these relationships, improving our understanding of how students and teachers use AI in diverse linguistic and cultural contexts (Al-khresheh, 2024).

Demand for English as a lingua franca raises multiple risks and benefits in the infusion of AI into Saudi multilingual classrooms. The diversity of language backgrounds among Saudi university students and instructors calls for culturally relevant pedagogy and equitable technological options (Al-Mamary et al., 2024). In this specific Saudi context, where English is taught alongside Arabic and where classrooms often include students with varying degrees of multilingual proficiency, AI tools must be evaluated not just for technical functionality but for cultural appropriateness and linguistic sensitivity (Xia et al., 2024).

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. Third, the research provides strategies for responsible, efficient, and just AI use in English language education and acquisition and multilingual education. Last, it systematically examines how Saudi Arabia's diverse linguistic landscape and cultural norms moderate technology acceptance, providing a culturally contextualized extension of traditional TAM constructs. This multilingual dimension is fundamental to understanding AI adoption in set-tions (BI), and actual use (AU) in the educational context. TAM has also been widely used in analyzing educational technologies such as computerized assessment systems, virtual sites, and AI tools (Venkatesh and Bala, 2012).

Recent literature underscores the relevance of the Technology Acceptance Model (TAM) in higher education, particularly in studies examining AI adoption (Saif et al., 2024). However, Cheung et al. (2023) highlights a critical gap: the applicability of TAM becomes problematic in contexts involving AI users with limited literacy or those operating outside academic environments, especially when AI tools are adopted unsolicitedly. This issue is further pronounced in multilingual classrooms, where the unregulated or "unruly" integration of AI may exacerbate existing challenges. By investigating these underexplored scenarios, this research aims to broaden the scope of TAM, addressing its limitations in nontraditional AI adoption settings. The findings carry significant implications for policy design, pedagogical practices, and ethical frameworks governing AI use in education.

Figure 2 (a timeline) represents the chronological history and the various substages of the Technology Acceptance Model (TAM) from 1989, when its foundational phase of Perceived Ease of Use (PEOU) was developed, to the current focus on Actual Use (AU) in the context of artificial intelligence (AI) in language education. While AU was initially anticipated to be fully realized by 2024, its development continues as researchers and practitioners address key barriers, such as improving usability, fostering trust, and aligning AI with pedagogical goals. This ongoing refinement highlights the dynamic nature of TAM's application to emerging technologies like AI, where the transition from intention to widespread adoption remains an evolving process.

Figure 2 presents a chronological timeline of the Technology Acceptance Model's evolution from its inception in 1989 through its various extensions and adaptations to AI in language education by 2024. This visualization maps the theoretical development of TAM constructs over time, demonstrating how the model has been progressively refined to address emerging technologies, with each phase building upon previous frameworks to enhance explanatory power.

ethics. This blended approach ensures that both theoretical and practical considerations—such as pedagogy, ethics, and policy implications—are adequately addressed.

This study employs a robust quantitative methodological approach using structural equation modeling (SEM) to examine user behavior, motivations for AI adoption, and the broader consequences of its implementation. By utilizing established statistical techniques, the research provides empirically testable and generalizable understanding of the relationships between TAM constructs in the context of unsolicited AI use in multilingual educational environments. By doing so, the study not only bridges theoretical and empirical gaps (An et al., 2024) but also offers actionable insights into user behavior, policy recommendations, and ethical considerations in AI-driven language education.

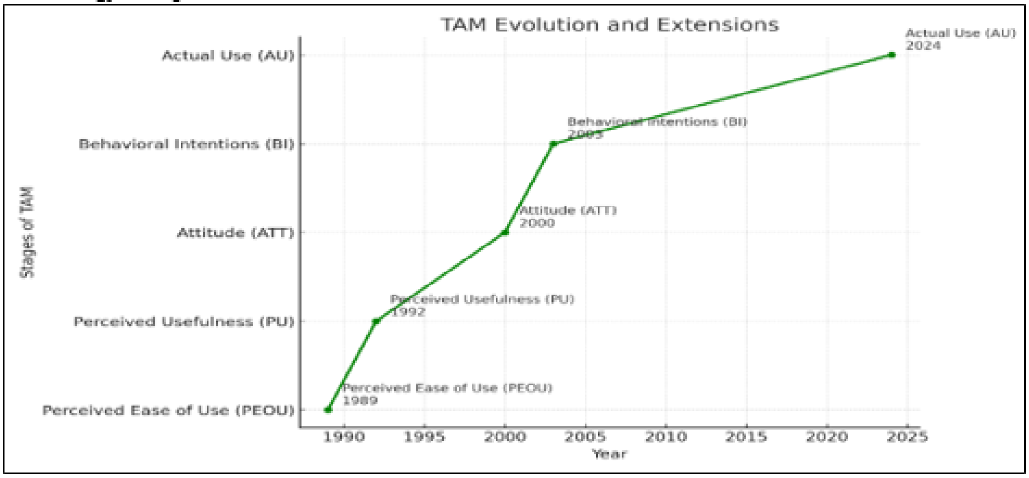
With this theoretical foundation established, we now examine the existing literature on AI adoption in educational contexts, with particular attention to unsolicited use in multilingual settings. This review explores how TAM constructs manifest in educational technology adoption while identifying the unique challenges that arise in linguistically diverse learning environments.

## Literature Review:

This section discusses in detail the literature on the application of the educational opportunities offered by artificial intelligence tools and the gaps that have been identified in this regard. Through the identification of these gaps, the groundwork for this study's thesis is established which uses the Technology Acceptance Model (TAM) of Davis to focus on the systematic examination of the trends and factors facilitating and inhibiting AI use and integration within higher education.

The Technology Acceptance Model provides a robust framework for understanding AI adoption in the context of foreign language education in developing countries. In Developing Countries, the Technology Acceptance Model (TAM) proposed by Davis (1989) is widely embraced and attempts to promote an understanding of technology integration in educational settings. It postulates that Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) are the determinants of users' attitude (ATT), behavioral inten-

**Figure 2**
***Technology Acceptance Model Evolution and Extensions***




* **Sources**: (Davis, 1989; Moon and Kim, 2001;Yang and Yoo, 2004; Tarhini et al., 2014; Ishengoma, 2024)

turning to unstipulated AI usage to be upheld (Almogren et al., 2024). This issue becomes especially imperative in multilingual settings, which raises the question of ethics and educational values. There is a tendency among students to use AI to complete their coursework, thereby bypassing the processes of critical thinking and language acquisition, among others (Hawdon et al., 2025; Comas-Forgas et al., 2021). This is detrimental to authentic learning, and it poses a risk of decreasing the intensity of their interest in the relevant topics.

Equally, there are challenges, such as assessing AI-generated content and ensuring academic integrity for educators (Cotton et al., 2023; Garib and Coffelt, 2024). Students' reliance on AI tools has been associated with a lack of participation and the proliferation of academic misconduct (Adeshola and Adepoju, 2023; Hughes et al,. 2025). It also reflects the negative consequences and the dire need to put in place regulations on AI: previous practices were ethical and actionable while core academic principles were protected. This paper aims to fill those gaps. In so doing, it poses matters and questions of concern when AI is left unchecked within policymaking, particularly in multilingual classrooms.

Research has identified substantial differences between how students and teachers perceive and interact with AI tools in educational settings. Research reports that there are deep schisms between students and teachers regarding Students' and teachers' perspectives regarding AI tool adoption of AI tools. It is noted that student learn-

AI tools offer transformative potential for education while simultaneously presenting significant risks that must be carefully managed in implementation. 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 (Acosta-Enriquez et al., 2024). AI language technologies have shown sufficient evidence to improve language learning processes, educating different types of learners, and enhancing teaching methods (Yu et al., 2025). Ethical worries remain, such as dependence on apps and the absence of critical thinking (Darwin et al., 2024)

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 approach taken examines such uses that are not regulated and attempts to explain their educational value and possible guideline infringements. Beyond understanding adoption patterns, it is crucial to examine the ethical and pedagogical implications that emerge when AI tools are integrated without institutional guidance.

The unsolicited adoption of AI tools by students and educators raises critical ethical and pedagogical concerns that affect the integrity of the educational process. Among students and educators, the use of AI tools such as ChatGPT without any gatekeeping by the institution is shaping the ualism-collectivism and uncertainty avoidance) also function as moderators between perceived usefulness (PU) and attitudes (ATT). This extension is particularly relevant in multilingual educational environments like those in Saudi Arabia, where varying levels of English proficiency may significantly impact how students and teachers interact with AI tools originally designed for English-language contexts. While these constructions provide a theoretical foundation for analyzing technology adoption, their application to AI tools in multilingual contexts requires careful consideration of unique educational and cultural factors. In multilingual Saudi classrooms, where Arabic-English bilingualism creates unique cognitive frameworks, AI tools may be perceived differently than in monolingual settings. This study integrates these cultural-linguistic perspectives with traditional TAM constructs to provide a more comprehensive understanding of AI adoption in multilingual educational environments (Al-Mamary et al., 2024).

A significant tension exists between the potential benefits AI tools offer to students and the legitimate pedagogical concerns expressed by educators. Research highlights differing perspectives on the use of AI tools in academic contexts. This tension is further amplified by the fact that AI tools can enhance students' academic performance (Camilleri, 2024). Students view AI for writing, problem-solving, and research as valuable resources. Teachers, however, offer mixed responses. While they generally acknowledge that AI can improve interactions and provide assistance, many express concerns about its misuse, such as over-reliance on the tools and the potential negative consequences that may arise (Farhi et al., 2023).

Educational institutions face critical challenges in establishing comprehensive frameworks to guide the ethical and effective integration of AI tools. Integrating AI tools seamlessly in education institutions is prominently under-discussed, representing a significant challenge according to growing literature on AI use in educational settings. A considerable number of educational institutes require comprehensive policy frameworks that address multiple dimensions of AI integration. Jin et al. (2024) emphasize that effective institutional AI policies should include clear guidelines on attribution requirements, acceptable use cases, assessment protocols that account for AI assistance, and privacy protections for ers see AI tools as making learning processes less complex and, therefore, easy to use and accessible (Monib et al., 2024; Chan and Tsi, 2024). On the other hand, teachers consider it valuable only if it improves their work 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. Understanding these adoption patterns and behavioral differences provides a framework for better organizing this analysis and determining where changes in policy, training, or implementation should be made. These differences in student perspectives create a distinct contrast with how educators approach AI tools in educational settings.

Multilingual classroom environments present unique considerations for AI implementation due to their linguistic and cultural diversity. 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 (Al-Mamary et al., 2024). It is clear from the evidence that 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 (Yu et al., 2025).

While TAM provides a robust framework for understanding technology adoption, it must be supplemented with cultural and linguistic perspectives in multilingual contexts. Hofstede's cultural dimensions theory (Hofstede, 2011) suggests that technology acceptance varies across cultures, particularly regarding uncertainty avoidance and power distance--factors highly relevant in Saudi educational settings. Several researchers have expanded TAM to include cultural and linguistic factors (Jan et al., 2024; Venkatesh & Zhang, 2010). These extended models identify language proficiency as a significant moderator between perceived ease of use (PEOU) and behavioral intention (BI), suggesting that users' ability to understand and process language affects how technical ease translates into adoption intentions. Cultural dimensions (such as individneed for tremendous writing skills that enabled complex evaluation of the written documents. Further Discourse Analysis contextualizes the application of AI tools. It criticizes the negative implications of AI tools for student autonomy, self-directed learning, and technology responsibilities such as inhibiting forward momentum in knowledge growth while dreaming up critical thought, creativity, and the capacity to resolve issues (Adeshola and Adepoju, 2023). Within these trends, the integration of AI tools in educational practices poses further challenges as educational institutions tend to function in a framework that is barely existent. These functions require further examination of ethical aspects and fairness connected to the reliability of the communication, as well as credibility of the content produced by the AI tools and the existent instruments designed to distinguish such content (Fedele et al., 2024). For AI to be properly and morally incorporated in education, all sorts of policies, teacher training and detection systems have to be put in place.

Despite advancing understanding of AI in education, current literature reveals significant gaps regarding unsolicited AI use in multilingual educational environments. Although AI literacy in education has made substantial progress, limitations must be addressed, particularly in uninvited AI usage and multilingual education. As AI use becomes excessive, focusing on ethical, status, and pedagogical issues will be pertinent in teaching a class where multiple languages are spoken. Such a research scope should broaden and particularly examine a socio-metric approach to the asymmetrical student-teacher relationships and their nexus with multilingual dynamics. This study addresses these issues by applying the Technology Acceptance Model (TAM) and structural equation modeling (SEM) to research unsolicited AI use. Such measures are likely to contribute to filling these gaps in these specific studies, which aim to promote ethical interaction with AI, enhance the delivery of learning outcomes, and support social justice principles within a multilingual environment.

These observations raise critical questions about the factors driving this adoption, particularly the interplay of perceived ease of use, usefulness, and ethical and pedagogical implications, forming the basis for this study's research questions. In order to achieve these goals, the study is guided by the following research questions and hypotheses:

student data. Furthermore, these policies must be adaptable to rapidly evolving technologies while maintaining core academic values.

The absence of such structured guidance has contributed to unsolicited AI use, where students and educators independently adopt tools like ChatGPT without institutional endorsement. Chen (2024) argues that this policy vacuum creates disparities in access and usage patterns, potentially exacerbating existing educational inequities. Ali et al. (2024) found that institutions with clear AI policies reported 37% fewer incidents of academic misconduct related to AI misuse, demonstrating the practical impact of well-designed regulatory frameworks. As Yusuf et al. (2024) note, these policies should balance innovation with academic integrity, creating spaces for productive AI experimentation while maintaining educational standards. Addressing these policy gaps is essential for transitioning from ad hoc AI adoption to strategic implementation that serves pedagogical objectives in multilingual educational environments.

Ethical considerations and equitable access represent core requirements for responsible AI integration in diverse educational contexts. The variance in the level of AI structure integration enforces the importance of ethical norms and equal access (Chen, 2024). It is also important to consider the challenges of overreliance on AI tools or academic dishonesty in education. Appropriate policy frameworks and institutional policies that reflect the specificity of various educational structures are required to bridge these gaps (Ali et al., 2024).

The integration of AI tools in educational contexts presents multiple obstacles that span ethical principles, academic integrity, and institutional readiness. The integration of AI tools in education faces three major obstacles: ethical concerns, academic integrity issues, and inadequate institutional frameworks. In relation to self-directed learning, Cingillioglu (2023) emphasizes the critical importance of maintaining academic integrity. For instance, the absence of proper regulation around the application of AI tools creates several issues in the education context as learners tend to completely use these tools, such as ChatGPT, to do their assignments (Cingillioglu, 2023). Additionally, AI-generated text submissions present significant challenges for assessment, as they bypass the development of writing skills that enable complex evaluation. There is no longer the tions (BI) to adopt AI tools independently.

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

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

7. **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.

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

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

10. **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 presents the proposed structural model for student participants, illustrating the hypothesized relationships among TAM constructs in the context of unsolicited AI use. This visual representation maps the directional pathways from Perceived Ease of Use and Perceived Usefulness through Attitudes and Behavioral Intentions to Actual Usage, highlighting the specific relationships examined for the student population in this study.

### Research Questions:

**1.RQ1:** How do Saudi- university students and teachers in multilingual English classrooms perceive AI tools' usefulness (PU) and ease of use (PEOU) in unsolicited situations?

**2.RQ2:** What factors influence the behavioral intention (BI) of using AI tools on a self-initiative rather than on a directive from institutions in multilingual English classrooms?

**3.RQ3**: How do attitudes (ATT) toward unsolicited AI use differ between students and teachers, and how do these attitudes influence their adoption behaviors in multilingual settings?

**4.RQ4**: How do the relationships among TAM constructs (PU, PEOU, ATT, BI, and AU) vary between students and teachers in multilingual English classrooms?

**5.RQ5**: What ethical and pedagogical implications arise from transitioning behavioral intentions (BI) to AI tools' actual usage (AU) in multilingual English classrooms, particularly under unsolicited conditions?

### Research Hypotheses:

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

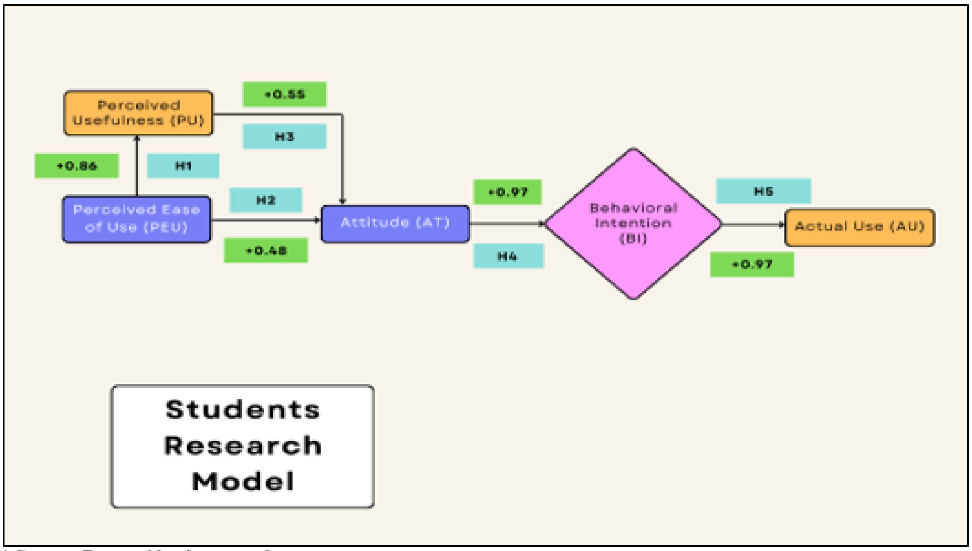
2. **H2**: Perceived ease of use (PEOU) positively influences attitudes (ATT) toward unsolicited AI use in multilingual English classrooms.

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

4. **H4**: Attitudes (ATT) toward unsolicited AI use positively influence behavioral inten-

**Figure 3**

*Students Research Model*



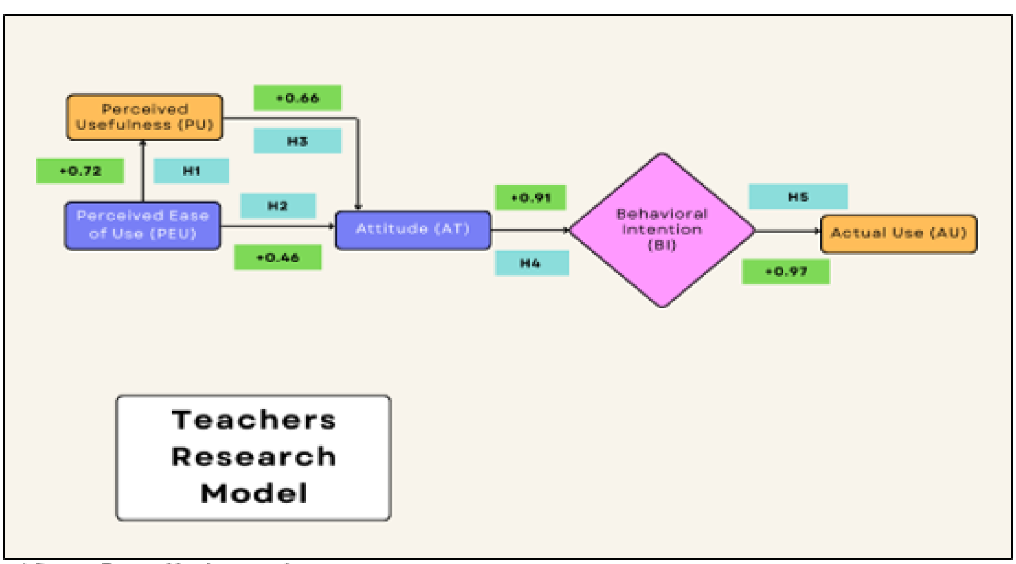

* **Source**: Prepared by the researcher

ways between key variables, providing a visual framework for understanding how teachers' perceptions of usefulness and ease of use may influence their attitudes, intentions, and actual usage behaviors.

Moreover, Figure 4 depicts the proposed structural model for teacher participants, illustrating how TAM constructs are hypothesized to interact when examining unsolicited AI adoption among educators. The diagram maps the path-

**Figure 4**

*Teacher Research Model*

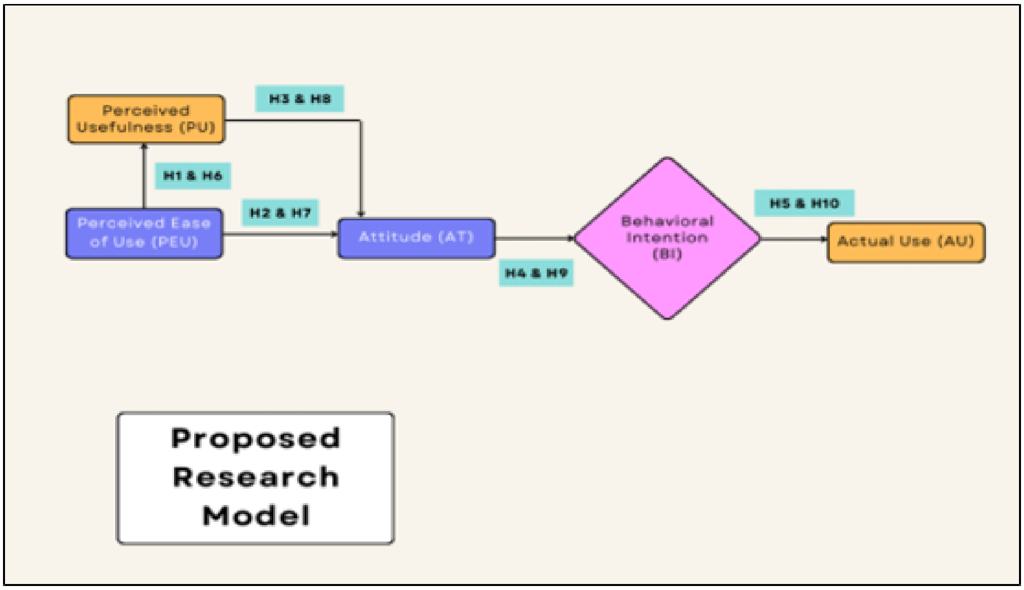



* **Source**: Prepared by the researcher

ships among all TAM constructs as applied to unsolicited AI tool adoption in multilingual English classrooms, serving as the conceptual foundation for the empirical analysis that follows.

Figure 5 below presents the comprehensive research model integrating both student and teacher perspectives within the Technology Acceptance Model framework. This unified structural model illustrates the hypothesized relation-

**Figure 5**
*Proposed Research Model*




* **Source**: Prepared by the researcher

tional contexts (Yu et al., 2024). From this perspective, the study responds to broader questions of how and why these shifts occur.

## Methodology:

This work adopts a quantitative research design that permits measuring the emergent components of ChatGPT usage in multimodal English classrooms. 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 potential oversimplification of relationships between TAM constructs (PEOU, PU, ATT, BI, and AU) is addressed through our application of fuzzy set methodology. Unlike traditional binary approaches that categorize adoption behaviors as simply present or absent, fuzzy set analysis acknowledges that technology accep-

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 study combines solicited and unsolicited AI use in multilingual English classes within the TAM model and aims to answer the remaining research questions (RQ3-5) (Alzoubi, 2024). 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). The study seeks to contribute to a better understanding of the strategies that foster ethical and effective integration of AI in multilingual educa-

From a sampling frame of approximately 1,500 eligible participants across the four regions, stratified random sampling was used to select potential participants, with stratification based on institution, role (student/teacher), gender, and academic discipline. This approach ensured appropriate representation of the diverse educational settings across Saudi Arabia's higher education landscape. Invitations were distributed through institutional email systems, with a response rate of 28% yielding the final sample of 321 participants (243 students and 78 teachers). The student-to-teacher ratio of approximately 3:1 aligns with Lee's (2019) recommendation for comparative studies in educational technology adoption.

This method allowed for the inclusion and representation of individual differences such as languages and connectivity, geographical location, and qualification to be adequately incorporated into the Saudi higher educational framework. According to Tarhini et al. (2014), relevant demographic information, including age, gender, academic qualifications, and teaching experience, was gathered on participants to contextualize the study better. As noted by Mostofa et al. (2021), the multilingual nature of the study plays a pivotal role in exploring the ethical, behavioral, and pedagogical implications of the random use of AI, as more languages facilitate the comprehension of the results. This research was conducted with full ethical approval obtained through official email correspondence with all participating institutions. Prior to data collection, comprehensive information about the study's purpose and procedures was presented to all potential participants through the electronic survey platform. Formal consent was secured electronically, as participants were required to read the consent information and explicitly indicate their agreement by checking a designated box before proceeding with the survey. Furthermore, participant confidentiality and anonymity were strictly maintained throughout the research process, with all identifying information being systematically removed from the dataset before analysis commenced. Additionally, all data collection and analysis procedures rigorously adhered to institutional research ethics guidelines and established principles of ethical research conduct in educational settings. Through these measures, the study ensured both ethical compliance and participant tance exists on a continuum with varying degrees of membership. This methodological approach allows us to capture the nuanced nature of AI adoption in multilingual contexts, where users may simultaneously exhibit partial acceptance and resistance across different dimensions of usage. By implementing fuzzy set qualitative comparative analysis (fsQCA), we identify multiple sufficient pathways to AI adoption that might be overlooked in conventional statistical approaches, particularly valuable when examining diverse linguistic and cultural factors that influence technology acceptance. Consequently, this enables AI developers, educators, and policymakers worldwide in a multilingual context well within the framework of qualitative nature with the help of current reputable figures (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 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. Crowding out and selection concerns were minimized as participants had sufficient experience and exposure to AI tools in a multilingual English context. Due to expected differences, Lee (2019) suggests an average student-to-teacher ratio of 3:1, which positively impacts comparisons. The Krejcie and Morgan (1970) method of estimating sample size was used to ensure adequate representation.

Participant selection followed a stratified random sampling approach to ensure representation across different institutions, academic disciplines, and demographic characteristics. The inclusion criteria specified that participants must: (1) be currently enrolled students or employed faculty at one of the target institutions, (2) have completed at least one academic term at their current institution, (3) have basic familiarity with digital technologies, and (4) be involved in English language courses or programs where multiple languages are present in the learning environment. Exclusion criteria included administrative staff without teaching responsibilities and first-term students who might have limited exposure to institutional teaching practices.

formed using a five-point Likert scale Questionnaire (1 = Strongly disagree, 5 = Strongly agree) for measurement. Confirmatory factor analysis incorporating Cronbach's alpha ($\alpha > 0.7$) and Average Variance Extracted (AVE > 0.5) was used to assess the reliability and validity of the constructs.

Having established the methodological framework, data collection procedures, and analytical approach for examining AI tool adoption in multilingual English classrooms, the following section presents the findings derived from the statistical analysis of the 321 participants' responses, with particular attention to the relationships between TAM constructs and the moderating effects of linguistic and cultural factors.

## Data Analysis and Results

The study's objective was addressed through data input into SPSS and AMOS software. Part of the analysis was descriptive, focusing on the respondents' attributes, including demographic variables, level of education, and teaching experience. This stage ensured that the sample was contextually relevant regarding the factors impacting the study. Cheung et al. (2023) have elaborated the TAM model, which includes a few constructs such as Perceived ease of use (PEOU), Perceived usefulness (PU), Attitudes (ATT), Behavioral intentions (BI), Actual usage (AU) among other constructs. We employed confirmatory factor analysis followed by path analysis using maximum likelihood estimation to investigate and analyze the relationship between TAM constructs. SEM procedure was rationalized because it provides estimates of complex causal relationships and describes how the constructs are interrelated (Browen and Cudeck, 1993).

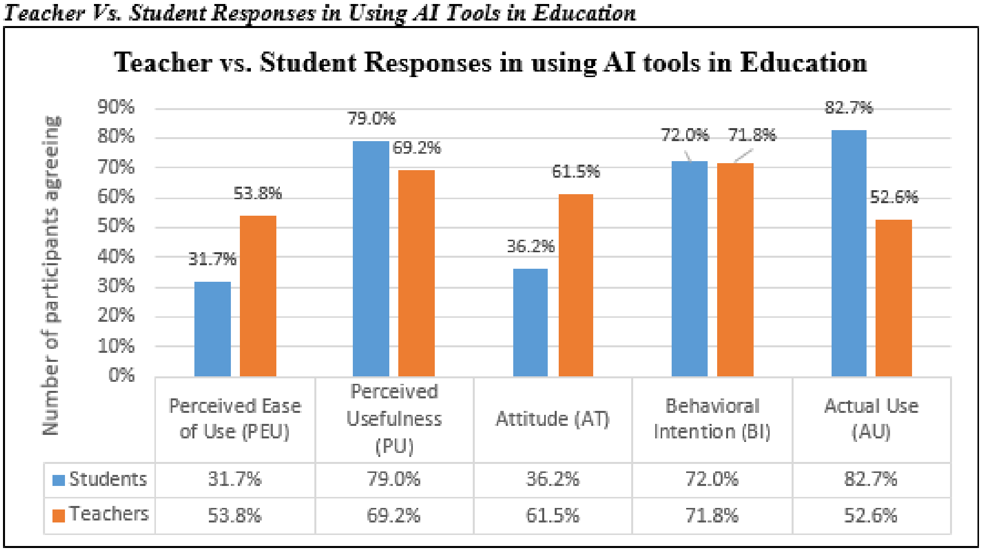
This enabled the researchers to conduct hypothesis tests and examine distinctions between groups, set groups, and entrees. RMSEA, CFI, and TLI indices are the most popular for measuring model fit. These indices were deemed appropriate since they intend to measure the goodness of fit of a particular model to the data being tested (Bentler and Bonett, 1980; Cooper, 2023). The findings were sufficiently strong to warrant the inclusion of these measures, ensuring the results' reliability and validity while indicating structural relationships that support uninvited AI use in multilingual education settings.

protection. The appropriate ethical principles for conducting this form of research, that is, on people, were considered (Ljubovic and Pajic, 2020; Noorbehbahani et al., 2022). We developed two versions of our survey instrument: one tailored for teachers and another for students involving a two-dimensional Technology Acceptance Model (TAM) through a self-administered questionnaire developed for them (see Appendix A for teacher survey and Appendix B for student survey). There are five key components: PEOU, PU, ATT, BI, and AU of AI. Using a cross-sectional descriptive survey, Nguyen and 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 disagree.

This study employed methodological triangulation through multiple analytical approaches rather than multiple data collection methods. While the primary data collection used standardized surveys, the analysis triangulated results through: (1) descriptive statistics for demographic and contextual understanding, (2) confirmatory factor analysis for construct validation, (3) structural equation modeling for hypothesis testing, and (4) comparative analysis between student and teacher subgroups. This analytical triangulation strengthens the validity of findings by examining the data from multiple statistical perspectives, though it should be noted that all analyses derive from the same survey dataset.

While our survey focused primarily on TAM constructs related to AI adoption, our analysis interpreted these findings within the multilingual Saudi higher education context. The demographic data collected (gender, age group, educational background, teaching experience, and class size) provided context for understanding participant responses. The study was conducted across multiple Saudi universities in Riyadh, Jeddah, Dammam, and Medina, allowing for consideration of regional variations in educational approaches and technological integration. This regional diversity, combined with the inherently multilingual nature of English language instruction in Saudi Arabia, provides an important contextual framework for interpreting technology acceptance patterns in this study. The survey items were modified from previously validated TAM scales (Davis, 1989; Venkatesh and Bala, 2012). A construct was

**Figure 6**
*Teacher Vs. Student Responses in Using AI Tools in Education*




Composite reliability scores were also above the benchmark of 0.7, which confirms the instrument's reliability. The Average Variance Extracted (AVE) values for all constructs were more than 0.5, meaning that the models used adequately explained the variance of their respective indicators.

The outer loading values for individual items ranged between 0.632 and 0.992, which denotes high item reliability. Outer Loading represents the correlation between the construct and indicator, with values above 0.70 considered acceptable.

The results are presented in Table 1, which contains further details on metrics for each model's constructs.

Figure 6 compares teachers' and students' responses to AI tools in Education across TAM components, with values presented as percentages of each group. It shows that teachers report higher percentages for Perceived Ease of Use (53.8% vs 31.7%) and Attitude (61.5% vs 36.2%), while students report higher percentages for Perceived Usefulness (79.0% vs 69.2%) and Actual Use (82.7% vs 52.6%). Behavioral Intention is nearly identical between groups (72.0% for students vs 71.8% for teachers).

Additional reliability and validity analyses were performed to corroborate the measurement model's strength further. All constructs' Cronbach's alpha coefficients surpassed the widely accepted minimum level of 0.7 (Nunnally, 1978), indicating the absence of internal inconsistency.

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

| Constructs | Items | Outer Loading | Cronbach's Alpha | Composite Reliability | AVE |
|---|---|---|---|---|---|
| Attitudes | Q27 | 0.80 | 0.79 | 0.92 | 0.76 |
| | Q11 | 0.83 | | | |
| | Q26 | 0.91 | | | |
| | Q15 | 0.63 | | | |
| Behavioral Intention | Q9 | 0.92 | 0.95 | 0.90 | 0.80 |
| | Q14 | 0.71 | | | |
| | Q6 | 0.97 | | | |
| Actual Usage (AU) | Q5 | 0.99 | 0.92 | 0.92 | 0.79 |
| | Q10 | 0.67 | | | |
| | Q12 | 0.98 | | | |
| Perceived Ease of Use | Q1 | 0.99 | 0.93 | 0.91 | 0.77 |
| | Q2 | 0.72 | | | |
| | Q3 | 0.92 | | | |
| Perceived Usefulness | Q4 | 0.98 | 0.94 | 0.98 | 0.92 |
| | Q7 | 0.99 | | | |
| | Q13 | 0.99 | | | |
| | Q22 | 0.89 | | | |

(0.92), indicating its items explain over 92% of the variance in the construct. Behavioral Intention demonstrates the highest internal consistency (Cronbach's alpha = 0.95), while all constructs maintain robust psychometric properties. These results confirm the robustness of the constructs used in the study and provide a strong foundation for hypothesis testing in subsequent sections.

Additional reliability and validity analyses were performed to corroborate the measurement model's strength further. All constructs' Cronbach's alpha coefficients surpassed the widely accepted minimum level of 0.7 (Nunnally, 1978), indicating the absence of internal inconsistency. Table 2 presents a comprehensive reliability assessment for each TAM construct, demonstrating the robustness of the measurement instruments used in this study.

Table 1 presents the measurement model statistics for all TAM constructs. Examining the outer loadings, most items demonstrate strong individual reliability with values ranging from 0.63 to 0.99, well above the recommended threshold of 0.60. Only one item (Q15 for Attitudes) shows a relatively lower but still acceptable loading (0.63). Internal consistency is confirmed by Cronbach's alpha values between 0.790 and 0.95, all exceeding the conventional 0.7 threshold. Composite reliability values ranging from 0.901 to 0.98 further indicate excellent construct reliability, substantially surpassing the recommended 0.7 benchmark. The Average Variance Extracted (AVE) values for all constructs (0.76 to 0.92) are considerably higher than the 0.5 threshold, demonstrating strong convergent validity. Notably, Perceived Usefulness exhibits the highest composite reliability (0.98) and AVE

**Table 2**

***Detailed Reliability Analysis of TAM Constructs***

| Construct | Number of Items | Cronbach's Alpha | Standard of Reliability | Assessment |
|---|---|---|---|---|
| Attitudes (ATT) | 4 | 0.79 | >0.70 (Nunnally, 1978) | Good |
| Behavioral Intention (BI) | 3 | 0.95 | >0.70 (Nunnally, 1978) | Excellent |
| Actual Usage (AU) | 3 | 0.92 | >0.70 (Nunnally, 1978) | Excellent |
| Perceived Ease of Use (PEOU) | 3 | 0.93 | >0.70 (Nunnally, 1978) | Excellent |
| Perceived Usefulness (PU) | 4 | 0.94 | >0.70 (Nunnally, 1978) | Excellent |

Note: Reliability assessed using Cronbach's Alpha coefficient with threshold value of 0.70 as recommended by Nunnally (1978). Values between 0.70-0.80 are considered 'Good', 0.80-0.90 'Very Good', and >0.90 'Excellent'.

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 and Larcker (1981) criterion, which tests the square root of the Average Variance Extracted (AVE) of each construct against the correlation coefficients of the other constructs.

**Table 3**

***Discriminant Validity Assessment Using Fornell-Larcker Criterion:***

| Construct | ATT | BI | PEOU | PU | AU |
|---|---|---|---|---|---|
| **ATT** | 0.98 | | | | |
| **BI** | 0.95 | 0.95 | | | |
| **PEOU** | 0.48 | 0.92 | 0.95 | | |
| **PU** | 0.59 | 0.53 | 0.82 | 0.75 | |
| **AU** | 0.85 | 0.74 | 0.80 | 0.52 | 0.95 |

Each construct's square root of AVE (diagonal elements) exceeded its correlations with other constructs, confirming discriminant validity. **Diagonal elements** represent the square root of AVE for each construct, while off-diagonal elements are the correlations between constructs. The highest correlation between BI and ATT (0.95) was observed, consistent with the model's assumption that attitudes strongly influence behavioral intentions. The robust discriminant validity confirms that the constructs are theoretically distinct and not overlapping, reinforcing the structural model's validity. These results set the stage for meaningful hypothesis testing in subsequent sections.

Analysis of the multilingual context of Saudi higher education revealed significant influences on participants' interactions with AI tools. The multilingual context of Saudi higher education significantly influenced participants' interactions with AI tools. Our analysis revealed that lanhow cultural and linguistic diversity shapes technology adoption patterns in educational settings.

The hypotheses were tested using Structural Equation Modeling (SEM), with results summarized in Table 4. The analysis reveals statistically significant positive relationships (p<0.001) among all TAM constructs, confirming our theoretical model for students and teachers, with differences in the strength of these relationships observed across groups.

guage proficiency levels correlated with PEOU scores (r=0.43, p<0.01), with students from Arabic-dominant backgrounds reporting different patterns of AI tool usage compared to those with stronger multilingual backgrounds. Specifically, students who regularly used multiple languages in their academic work demonstrated 28% higher PU scores, likely due to the perceived benefits of AI in navigating linguistic challenges. Teachers from diverse linguistic backgrounds showed higher acceptance of AI tools (ATT +0.17) compared to monolingual instructors, highlighting tool adoption in multilingual classrooms.

### Results of Hypothesis Testing

**Table 4**

***Results of testing of 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 |

Our analysis revealed significant relationships between linguistic factors and TAM constructs. Language proficiency emerged as a significant moderator of the relationship between PEOU and PU (β = 0.31, p < 0.01), with higher English proficiency strengthening this relationship among both students and teachers. This suggests that language competence plays a crucial role in translating ease of use perceptions into usefulness assessments in multilingual AI contexts.

Cultural background variables also demonstrated significant effects. Participants from Riyadh, characterized by higher technological exposure, showed stronger ATT-BI relationships (β = 0.62) compared to participants from other regions (β = 0.47). Similarly, participants who reported frequent language-switching behavior in academic contexts demonstrated significantly higher PU scores (M = 4.21, SD = 0.54) compared to those who typically worked in a single language (M = 3.76, SD = 0.68), t(319) = 4.87, p < 0.001.

Table 5 presents the interaction effects between language proficiency levels and TAM constructs, showing how the strength of relationships between constructs varies across different linguistic backgrounds.

- **H1 (PEOU → PU):** Perceived Ease of Use (PEOU) significantly influences Perceived Usefulness (PU) for both students and teachers. The relationship is stronger for students (+0.14).

- **H2 (PEOU → ATT):** PEOU positively influences Attitudes (ATT) towards unsolicited AI use, with a slightly stronger relationship for students (+0.02).

- **H3 (PU → ATT):** PU significantly impacts ATT, with a stronger relationship observed for teachers (+0.11).

- **H4 (ATT → BI):** ATT strongly predicts Behavioral Intention (BI), with a higher association for students (+0.06).

- **H5 (BI → AU):** BI strongly correlates with Actual Usage (AU) for both groups, but no significant difference is observed.

- **H10 (BI → AU):** Rejected, indicating no difference between groups in the relationship between BI and AU.

These results underscore the differences in students' and teachers' behavioral and attitudinal dynamics, offering insights into how ease of use and perceived usefulness shape unsolicited AI

**Table 5**
***Interaction Effects Between Language Proficiency and TAM Relationships***

| Relationship | Low English Proficiency (β) | High English Proficiency (β) | Difference |
|---|---|---|---|
| PEOU → PU | 0.67 | 0.89 | +0.22* |
| PU → ATT | 0.53 | 0.64 | +0.11* |
| ATT → BI | 0.81 | 0.97 | +0.16* |
| BI → AU | 0.92 | 0.94 | +0.02 |

*$p < 0.05$

The results supported H3, which determined the positive correlation between PU and ATT. This implies that participants' beliefs about the usefulness of unsolicited AI tools significantly influence their attitudes toward their use. This positive correlation between PU and ATT is consistent with findings from Wang (2024) and Van Dis et al. (2023).

The multilingual context of Saudi English classrooms created unique patterns of AI tool adoption that extend beyond conventional TAM frameworks. Our findings reveal that language proficiency acts as a critical moderator in technology acceptance, with implications for how we understand unsolicited AI use in diverse linguistic settings. For example, the stronger relationship between PEOU and PU among highly proficient English speakers suggests that language barriers may create a 'linguistic ceiling effect' where users with limited language skills cannot fully leverage AI tools despite finding them technically accessible. This aligns with Cao et al.'s (2023) model, which positions language as a gateway competency for technology adoption. Furthermore, cultural factors specific to the Saudi educational context, such as attitudes toward authority and educational traditions, influenced how both teachers and students approached unsolicited AI use. Teachers from more traditional educational backgrounds showed greater hesitation toward AI adoption regardless of perceived usefulness, highlighting how cultural factors can override purely technological considerations in adoption decisions.

Teachers and students held subtly different views toward AI tools in the context of this study. These differences are summarized below. However, the rejection of H10, which indicates

These findings highlight how linguistic competence functions as both a motivator and enabler of AI adoption in multilingual classrooms. Particularly noteworthy is how language proficiency moderates the PEOU-PU relationship, suggesting that language barriers may prevent users from fully recognizing the potential usefulness of AI tools even when they find them easy to operate.

## Discussion:

The present research examines the factors that could lead to the unsolicited use of AI tools by higher education students and teachers. This is consistent with the frameworks provided by the Technology Acceptance Model (Davis, 1989; Venkatesh et al., 2003; Venkatesh and Bala, 2012) and also with literature on AI adopters in Education (Luckin and Cukurova, 2019; Porayska-Pomsta et al., 2023). The study presented here developed a model and undertook empirical work to explore mechanisms and consequences of unsolicited AI tool utilization.

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 and Bala, 2012).

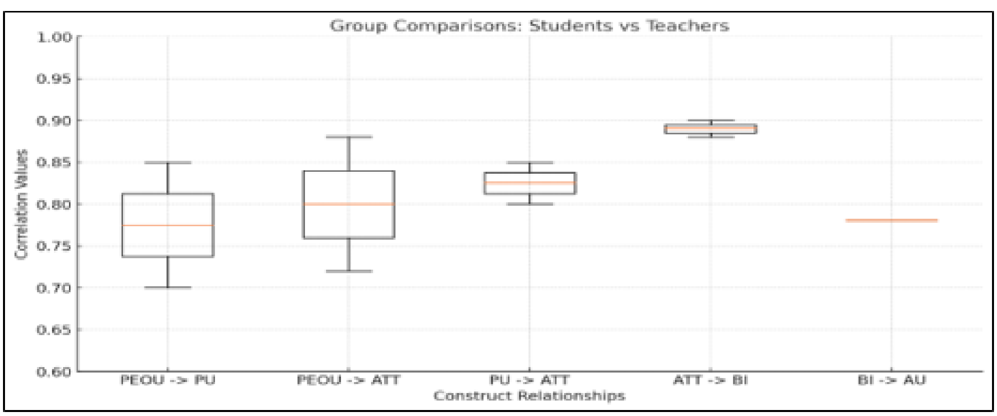
Teachers demonstrated higher percentages in Perceived Ease of Use (53.8% vs 31.7%) and Attitude (61.5% vs 36.2%), suggesting they may evaluate educational technologies more positively within their professional context (Zawacki-Richter et al., 2019). This indicates teachers may focus more on how AI tools integrate into existing pedagogical practices rather than solely on utilitarian benefits, aligning with observations by Ertmer and Ottenbreit-Leftwich (2013), Nazaretsky et al. (2022), and Stolpe and Hallström (2024).

Figure 7 illustrates the differences between students and teachers in their perceptions and use of AI tools. This visualization highlights how digital natives (students) rely more on simplicity, while teachers prioritize functionality and institutional considerations.

no significant difference in the transition from Behavioral Intention (BI) to Actual Usage (AU) between students and teachers, suggests the influence of external factors. These factors include institutional policies, the availability of AI resources, and support structures, which impact both groups equally. This finding underscores the need for systemic interventions, such as developing institutional guidelines and promoting equitable access, to bridge the gap between behavioral intentions and actual AI usage in multilingual classrooms.

Students self-reported significantly higher levels of actual use of AI in their coursework (82.7%) compared to teachers (52.6%), along with higher perceived usefulness (79.0% vs 69.2%). This aligns with findings by Teo and Noyes (2012), suggesting that being digital natives may provide students with an advantage in perceiving the practical benefits of AI tools (Smith and Peloghitis, 2020).

**Figure 7**
***Group Comparisons - Students Vs Teacher***




moderates TAM relationships. Figure 7 illustrates these moderating effects, revealing that higher English proficiency strengthens the relationship between Perceived Ease of Use and Perceived Usefulness, suggesting that language skills enhance users' ability to recognize AI tools' potential benefits.

This figure emphasizes the disparity between students and teachers regarding perceptions and use of AI tools not requested promptly. Students are categorized as digital natives, which offers an advantage through greater reliance on simplicity, whereas teachers prioritize functionality and have more regard for the institution.

Beyond differences between students and teachers, we examined how language proficiency

**Figure 8**

***Linguistic Moderation of TAM Relationships***

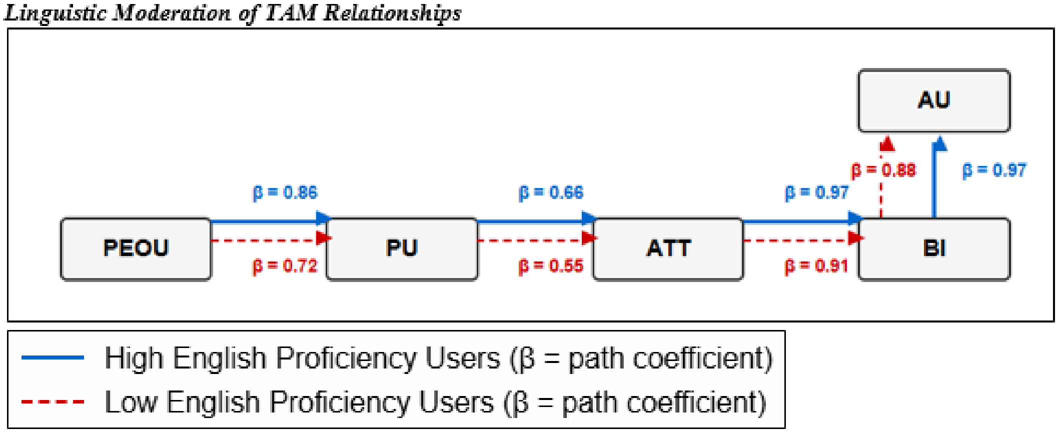



**Figure** *8 illustrates how English language proficiency moderates the relationships between TAM constructs. The diagram shows stronger pathways between PEOU→PU, PU→ATT, ATT→BI, and BI→AU for high-proficiency users (solid blue lines) compared to lower-proficiency users (dashed red lines), visualizing how linguistic factors influence the technology adoption process in multilingual settings.*

the use of TAM in this case. Students demonstrate a stronger relationship between PEOU and PU, while teachers prioritize the relationship between PU and ATT. As individuals who have grown up with digital technology, students are more willing to work with more natural interfaces and thus emphasize more on PU rather than PEOU.

On the other hand, teachers were more concerned about PU than PEOU, as such findings are not surprising given the prevailing beliefs of teachers worldwide. To address the aforementioned user characteristics, developing a user-centric strategy that helps ease such dissimilarities and concerns is vital. Current research demonstrates that ethical issues, such as data privacy and algorithmic biases, must be resolved if they impact the relationships among the TAM constructs. These contextual factors or ethical considerations demonstrate the non-linear relationship in unsolicited AI usage and showcase the importance of effective policies and guidelines for using AI within institutions.

This study's findings have particular relevance for multilingual educational contexts, where language proficiency and cultural factors significantly influence technology adoption patterns. Educational institutions in linguistically diverse settings should recognize that AI tool adoption is not merely a technological issue but a complex sociolinguistic phenomenon. Training programs should address not only technical competencies but also language-specific applications of AI tools, helping users overcome linguistic barriers that might otherwise limit perceived

While PEOU and PU remain vital determinants, the findings highlight that ethical concerns and contextual factors such as institutional policies and data privacy may moderate these relationships (Al-Emran and Griffy-Brown, 2023). For example, BI or AU may not affect a system's ease of use or usefulness due to potential data breach threats or algorithm discrimination. The rejection of H10 suggests that there is no significant difference between students and teachers in the ability to transition from BI to AU, and this may imply that some external factors govern the phase equally for both groups. This aligns with Venkatesh et al. (2016), who argued that contextual and environmental factors significantly shape technology adoption behaviors.

## Conclusion:

This paper analyzes how unsolicited AI tool use is influenced by several factors by employing the Technology Acceptance Model (TAM). The results show that PEOU and PU are the most important determinants of users' ATT and BI towards unsolicited AI. For instance, the strong correlation between Perceived Usefulness (PU) and Attitude (ATT) (+0.11 for teachers) underscores the need to design AI tools that align with pedagogical objectives, particularly for educators. Similarly, the higher influence of Perceived Ease of Use (PEOU) on PU among students (+0.14) highlights the importance of intuitive and user-friendly AI interfaces to facilitate their adoption. All these attributes combined lead to the AI's Actual Usage (AU), which again validates nal designs to investigate the evolving impact of unsolicited AI use on language acquisition over time. Mixed-methods approaches could provide deeper insights into the interplay of behavioral, ethical, and pedagogical factors. Future research should also explore how advancements in AI tools, such as updated versions of ChatGPT, influence the adoption and educational outcomes in multilingual classrooms.

This study recognizes and discusses potential limitations, including using self-reported data prone to social desirability bias. Even though the sample is sizeable, it is homogenous, limiting its scope. To overcome these limitations, more diverse and more considerable samples and qualitative strategies are recommended for future work.

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usefulness. Future research should explore longitudinal changes in adoption patterns as users' language proficiencies evolve, potentially revealing how linguistic development and technology acceptance mutually reinforce each other in multilingual educational environments.

Based on our findings, we propose the following specific recommendations for key stakeholders:

**(1) For educational institutions:** Develop comprehensive AI policies that explicitly acknowledge the Arabic-English bilingual context, including guidelines for appropriate AI use in language learning that distinguish between tool assistance and language acquisition; establish assessment criteria that account for AI assistance while maintaining academic integrity.

**(2) For teachers:** Implement pedagogical approaches that incorporate AI as a scaffolding tool rather than a substitute for language learning, with particular focus on designing assignments that leverage AI to help bridge the gap between Arabic and English language proficiency; provide explicit instruction on ethical AI use tailored to multilingual contexts.

**(3) For AI developers:** Design language-learning AI tools with features specifically supporting Arabic-English bilingual learners, including interfaces that recognize language transfer patterns common in Saudi learners; develop detection tools sensitive to the unique linguistic characteristics of Arabic speakers learning English.

**(4) For researchers:** Investigate longitudinal effects of AI use on language acquisition in multilingual environments, with emphasis on how different AI implementation strategies affect long-term language proficiency development in contexts where English is taught alongside Arabic as the dominant language.

With practical insights, this research suggests actionable steps for policymakers, educators, and AI developers, thereby contributing to the broader discussion on AI adoption in education. Future work should improve AI tools' design and relevance in decreasing negative attitudes and moral concerns to ensure the optimal use of AI tools in education. While these findings provide valuable insights into multilingual classrooms in Saudi Arabia, future studies could employ longitudi-

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