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# Mapping Digital Engagement of English Teachers: A Hybrid Approach

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Teachers' role takes an essential position in determining the success of technology integration. Thus, evaluating teachers' attitudes and behaviour relating to technology is critical. Typically, researchers use Davis (1989)'s Technology Acceptance Model (TAM) framework for assessing teachers' technology acceptance, but this model stresses the linear relationship between teachers' psychological perceptions and their behaviour, and fails to consider the heterogeneity among teachers. This study creates a hybrid framework that combines TAM with typology, which is then applied by examining 33 English teachers in a Chinese, examination-oriented school. After administering structured questionnaires and conducting follow-up interviews, the researchers analysed the data using descriptive statistics, independent samples t-tests, one-way ANOVA, Pearson's correlation analysis and multiple linear regression. The results showed that among cautious practitioners (n = 21) perceived usefulness (PU) and perceived ease of use (PEOU) had a positive impact on the actual behaviour, with PU being a stronger predictor. However, interactive innovators (n = 12) had higher intrinsic motivation, resulting in an insignificant correlation between PU/PEOU and ATU. Background variables (teaching experience, school stage and prior training) had no significant effect on PU or PEOU in this context. The hybrid model reveals heterogeneity in teachers' technology integration, providing a basis for differentiated training and policymaking. However, the study is limited by its small sample size and specific context. Future research could expand the sample size, incorporate additional variables for categorising teacher types and further refine the hybrid model to inform digital educational practices.

Keywords: teachers' perspectives, technology acceptance model (TAM), clustering analysis, Chinese public school, technology integration

## INTRODUCTION

Nowadays, technology adoption in education has become a global phenomenon, and it is reshaping instructional approaches and pedagogical interactions (Laaraj, 2025). In this trend, teachers as the main agents of implementation hold a pivotal position to determine the success or failure of classroom integration (Miramon et al., 2024). Consequently, examining teachers' acceptance of technology is essential (Gouseti et al, 2024).

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There are various theoretical frameworks that have been developed to conceptualise attitudes and behaviours towards technology. Davis (1989)'s Technology Acceptance Model (TAM), which offers a psychological pathway to examine how individuals evaluate and adopt technology, stands out. Based on this foundation, substantial empirical studies have spawned to validate or extend TAM across different educational contexts (e.g., Johar, 2021; Wangdi et al., 2023). However, much existing TAM research has been grounded in Western contexts or private school settings, where exam-oriented pressure may be less prevalent (Han & Sa, 2022). The voices and perspectives from educators in Chinese public schools who are under great pressure from the school/college entrance examination tend to be neglected. This study aims at a public K–12 school located in Shenzhen, one of China's leading cities with competitive atmosphere and high technology coverage in education (Fang & Liu, 2023). In 2023, this city witnessed a surge of teacher attrition due to salary reduction, leading to a hiring shift towards younger teachers who are highly educated from top universities (Yaqin, 2025). These young teachers are usually digital natives and confront a unique blend of educational policy reform, performance pressure as well as evolving expectations. Thus, the exploration of their technology adaptation is significant. While TAM offers a powerful framework for probing teachers' technology acceptance, most studies on TAM take a linear approach to verify relationships between variables, failing to explore heterogeneity among teachers. To improve it, this study creates a new model that combines the TAM model with a clustering analysis of teachers' typology.

The study utilises this hybrid model in a Chinese educational context, tring to answer the following questions:

RQ1: How do teachers' background variables (teaching age, school level, and prior technology training) influence their perceived usefulness (PU) and perceived ease of use (PEOU) of digital technologies?

RQ2: To what extent do PU and PEOU predict the actual frequency of digital technology use (ATU) in English teaching, and do these relationships differ across teacher profiles?

## LITERATURE REVIEW

### Underpinned model

Proposed by Davis (1989, p.3), TAM believed that before using technology, users would make subjective evaluations based on their PU and PEOU. PU refers to whether users believe that the technology helps improve work efficiency; PEOU concerns whether the technology is easy to use (Davis, 1989). These two elements are closely related. PEOU not only directly affects usage intention but also indirectly enhances the motivation for technology adoption by increasing PU. Subsequently, Venkatesh and Davis (2000) expanded the model by introducing external variables such as social influence and experience feedback to enrich PU. Time changing, TAM has evolved and been supplemented, but its essential framework has remained. This research adopts classic TAM (Davis, 1989) as a blueprint to further discuss relationships(see Figure 1 below).

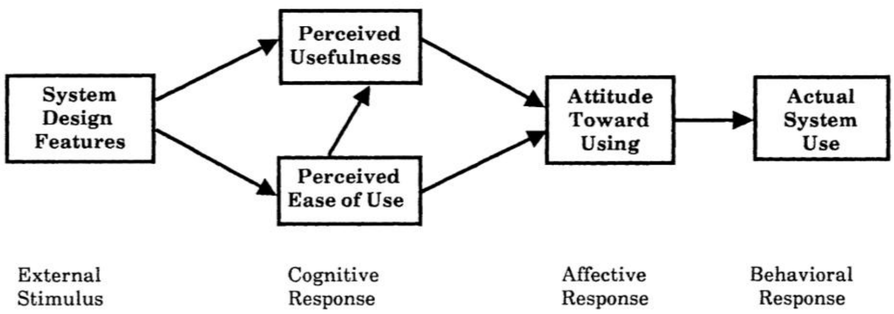


Figure 1
TAM proposed by Davis (1989)

In the education field, TAM has been widely used as theoretical guidance to explain teachers' willingness to adopt various educational technologies in practice (Scherer et al., 2019). PU and PEOU determine teachers' attitudes towards using, while they will be influenced by many other external factors. These relevant variables are flexible and may be adjusted in consonance with the specific research context. For example, in software application research, users' computer anxiety (CA) is often incorporated into the TAM framework to explain their technology adoption behaviour more comprehensively (Li et al., 2008). Thus, TAM can exhibit structural variations in different contexts, highlighting the research significance of exploring subjective variables in specific domains. Studies that explore the factors of teachers' technology integration are abundant, including educational level, gender, personal experience, etc (e.g., Khlaif, 2018; Babić, 2012). This study introduces teachers' personal background variables (teaching age, school level, and prior training), which are frequently discussed to explore their potential impact on PU and PEOU.

Studies on teaching experience find that since young teachers are more proficient in technology operations, they have a higher technology acceptance than veteran teachers who may have technology anxiety or path dependence (Inan & Lowther, 2010). Besides, teachers' willingness also decreases with the increase of the school level (Xia et al., 2023). Teachers in lower grades prefer to use technology to encourage interaction. In higher grades, however, teachers are probably influenced by exam pressure and pay more attention to knowledge transfer and training. As a result, digital technology is sometimes regarded as inefficient and time-consuming. As to technology training experience, Tondeur et al. (2017) found that teachers who received systematic technology training are more likely to notice its potential.

The core path hypothesis of the TAM model holds the view that PU and PEOU not only directly affect individuals' technology intentions, but also ultimately affect their actual use behaviour through attitude variables (Davis, 1989). In other words, measuring teachers' subjective perception of the *usefulness* and *ease of use* of technology can predict their adoption and application of educational technology to a certain extent (Saliva, 2015). So how to quantifying PU and PEOU?

Many studies (e.g., Alzoubi, 2024; Tondeur et al., 2017; Natasia et al., 2022) design Likert scale questionnaire items to measure PU and PEOU for data analysis. For PU, common measuring indicators include: whether technology can improve students' learning performance and efficiency, and whether it helps improve teachers' own teaching efficiency and teaching quality (Natasia et al., 2022; Martín-García et al., 2022). With reference to these dimensions, this study measures PU through a Likert scale questionnaire in questions: "Digital technology improves my teaching efficiency", "Digital technology increases students' interest in learning English" and "Digital technology makes my class more vivid". The measurement indicators of PEOU concentrate on the ease of use, regardless of user convenience or equipment operation (Natasia et al., 2022). The questionnaires for measuring PEOU in this study are designed as "I can flexibly choose suitable tools to meet different teaching needs" and "I can fully understand and actually operate these technical tools".

**The hybrid model**

Although TAM can effectively explain the linear relationship between teachers' psychological perceptions and their behaviour when using digital technology, it assumes homogeneity among teachers by calculating averages, which may obscure significant differences within the target group (Huang et al., 2024). To reveal the complexity and diversity within a specific educational context, this study creates a hybrid model that uses TAM as a foundation and incorporates cluster analysis to explore acceptance and usage characteristics of digital technology in language education among different types of teacher in a public school — a typical, exam-oriented educational context in China. Since this study is expected to use this hybrid model, one crucial step is to classifies teachers into representative clusters based on meaningful dimensions. So, which dimensions are meaningful?

Witter and Hattie (2024) examined belief systems, teaching practices, and students' perceptions of teaching effectiveness in order to identify three distinct groups of teacher quality. Huang et al. (2024) examined teachers' self-efficacy in three areas: classroom management, instruction and student engagement. It is evident that the dimensions used to classify teachers are not fixed, yet they are meaningful enough to inform practical, targeted support strategies for different groups of teachers. General demographic information, such as gender or age, is not widely used as it often offers limited explanatory power. Instead, more studies engage with behavioural and psychological dimensions as the typological basis, since these are more actionable and context-sensitive when offering professional development.

In line with this perspective, this study provides a practical lens through which to view teachers' habitual digital usage, their pedagogical purpose, perceived difficulties, and expected support from the teachers' own perspective. Such typological insights construct teacher profiles that go beyond demographic segmentation and offer a richer, more actionable understanding of how technology is perceived and used in school settings (Lau & Jong, 2023).

After determining teacher categories, the hybrid model requires the researcher to further re-examine the relationships among TAM model variables (PU, PEOU, and ATU) within each teacher group. This two-stage analysis aids in understanding the internal structure of the TAM model across different teacher types.

## METHOD

### Participant and Instruction

This study sets the context in a 12-year public school in Shenzhen, China, involving 36 English teachers from primary, middle and high school levels. The questionnaire was sent to the teachers' workgroup in the form of an online questionnaire star on WeChat, and eventually 33 valid questionnaires were received. The questionnaire was designed with a total of 14 questions. Considering the participants' language background, the questionnaire was in Mandarin. Among them, Q1-3 collects teachers' basic information, including teaching age, school level and whether received training. Q4 and Q7-11 were measured by a 5-point likert scale (1 stands for completely disagree and 5 for completely agree). Q7-9 measure PU, Q10-11 measure PEOU, and Q4 evaluates the ATU. The rest, Q5–6 and Q12–13, provide the basis for constructing a teacher profile. A follow-up interview was conducted with participants voluntarily. All participants were fully informed of the purpose of this study, and data were collected only after obtaining their informed consent. Participants have the right to withdraw at any time. All collected data will be anonymised and stored securely to prevent disclosure.

### Stage1: Typological Clustering of Teachers' Digital Practices

Since the silhouette score peaked (=.087) at k = 2 (see figure7), analysis of teachers' tool usage, instructional purposes, perceived challenges, and support needs ultimately generated two clusters that are interactive innovators and cautious practitioners.

*Interactive innovators* (n=12) refers to those who actively incorporate diverse digital tools, especially for listening, output tasks, and autonomous learning. Their motivation stems from pedagogical engagement and classroom vitality goals. They embrace change, but inadequate technical support and unreliable infrastructure always hold them back. They have a strong desire for better technical support. *Cautious practitioners* (n = 21) primarily use digital technology for exam-oriented purposes. Their caution stems from concerns about classroom management, time constraints and the inefficiency of certain tools. They are not completely reluctant to use technology; rather, they prefer to use it efficiently, especially for examinations.

This typology highlights differences in motivation among teachers. Due to the small sample size (n = 33), only two groups were identified. While this limits the scope for explanation to some extent, it is still meaningful in indicating the need for future research to move away from one-size-fits-all training and tailor it to each type of teacher.

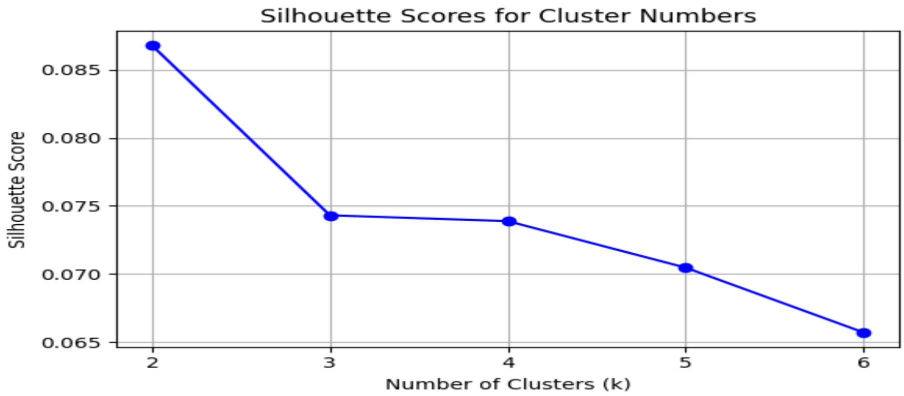


Figure 2
Silhouette Scores for Different Cluster Numbers (k = 2 to 6).

Table 1
Clusters

| Cluster | Size (n) | Top Features | Interpretation |
|---|---|---|---|
| Cluster 1 | 12 | Listening tools; Output tasks; Autonomous learning; Infrastructure concern; Tech support | Interactive innovators |
| Cluster 2 | 21 | Systematic training; School support; Moderate tool use; Cost/time concern; Few tools; Preference for simplified resources | Cautious practitioners |

**Path Hypothesis and Variable Construction**

Based on classic TAM framework proposed by Davis (1989) and the findings in the educational field (e.g., Teo, 2011; Tondeur et al., 2017), this study proposed a contextual research model to examine the factors that influence teachers' technology integration in a Shenzhen public school setting. The model consists of three dimensions: (1) teachers' background, (2) their PU and PEOU, and (3) their ATU.

In this model, PU and PEOU are key mediating variables which reflect the teachers' attitudes towards technology. Whether their attitudes determine their actual behaviour needs to be verified. Teaching age (Q1), teaching stage (Q2), and prior technology training(Q3) are external variables which are waiting to evaluate how to influence PU and PEOU. In turn, PU and PEOU are hypothesised to predict ATU (Q4) in English teaching. Thus, here are the hypotheses waiting to be verified in this study:

$H_1$: Teachers' background variables (teaching experience, school level and prior technology training) will affect their PU and PEOU.

$H_2$: PU and PEOU will positively predict ATU.

Table 2
Variable Construction

| Variables | Questionnaire survey item | Measurement |
|---|---|---|
| PU | Q7, Q8, Q9 | Mean score |
| PEOU | Q10, Q11 | Mean score |
| ATU | Q4 | single item |
| teaching age | Q1 | Categorical (e.g. ≤5, 6–15, ≥16) |
| school level | Q2 | Primary / Middle / High |
| training | Q3 | Yes/No |

The hypothesis validation process evaluates the relationships among TAM variables by calculating their means within each cluster. This study then provides explanations within and across clusters based on the unique Chinese setting.

**Data Analysis**

All the data from the questionnaire was exported in Excel format, and the researchers used Python to further clean and analyse them. The study presents some descriptive analysis about the participants' demographic information, PU, PEOU and ATU. These descriptive data were visualised by Python in the form of bar charts, pie charts, box plots, etc.

To answer RQ1, the study conducted independent-samples t-tests and one-way ANOVA (Park, 2009). Specifically, t-tests compared PU and PEOU between teachers who had received technology training and those who had not, while one-way analysis of variance (ANOVA) examined group differences in PU/PEOU appertaining to teaching experience and school level (Park, 2009). For RQ2, this study analysed data by Pearson correlation analysis and multiple linear regression (Shi & Conrad, 2009). Correlation analysis tried to explore the relationships among PU, PEOU and usage frequency. Regression analysis, on the other hand, evaluated the predictive power of PU and PEOU on usage frequency. The study set statistical significance at $p < 0.05$. Since RQ2 involves two groups of PU, PEOU and ATU, we define the relevant variables in cluster1 (*Interactive innovators*) as $PU_i$, $PEOU_i$ and $ATU_i$, while in cluster2 (*Cautious practitioners*) as $PU_c$, $PEOU_c$ and $ATU_c$.

Before doing data analysis, the study used the Shapiro–Wilk test and Levene's test to evaluate the normality of the data distribution and the homogeneity of variances separately. The results show that the data within each group are approximately normally distributed ($p_1 > 0.05$) and that the assumption of homogeneity of variances is met ($p_2 > 0.05$).

Responses to Q5, 6, 12 and 13 were transformed into a binary matrix using one-hot encoding to represent each teacher's usage of tools, motivation, perceived barriers and support needs. The study then employed the K-means clustering algorithm based on this matrix to group participants into distinct profiles. The optimal number of clusters was determined by both the elbow method and the silhouette coefficient (Saputra et al.,2020). Finally, the study interpreted and labelled each cluster based on shared characteristics.

### Validity and Reliability

This study examined both the content validity and internal consistency reliability of the questionnaire.

In terms of validity, the questionnaire was adapted from TAM framework. The items that measure PU and PEOU were informed by related studies that had verified their validity. Additionally, there was a pilot questionnaire survey conducted before the formal distribution. Two English teachers from the same school provided feedback on revising the wording of the questions, removing ambiguity and ensuring better alignment with real teaching practices. All questions were in Mandarin, which made the questionnaire more comprehensible to participants.

For reliability, internal consistency of the core constructs was assessed by Cronbach's alpha (Adamson & Prion, 2013). The PU scale (Q7–Q9) produced 0.82, and the PEOU scale (Q10–Q11) yielded 0.76. Both exceeded the 0.70 threshold for acceptable reliability (Nunnally, 1978). These results indicated that the scales were internally consistent and suitable for further statistical analysis. Since the actual usage variable (Q4) was measured with a single item, no internal reliability test was applied.

## FINDINGS AND DISCUSSION

### Descriptive Analysis

The descriptive results of the participants' demographic information and their responses to core variables including PU, PEOU, and actual usage frequency are presented in this section to give an overall perception.

Figure3 and Table3 show the concrete demographic profile of the 33 English teachers. The figure indicates that the studied school has a relatively high proportion of educators at the beginning of their careers. Following the salary reduction in Shenzhen, many veteran teachers left and the Shenzhen Education Bureau recruited numerous recent master's degree graduates. These new teachers are required to undergo various training programmes during their first year, including digital technology training. Thus, teachers with less than 5 years of teaching experience have generally received training in digital technology. However, nearly half of the teachers have never received any digital training, and these teachers are roughly evenly distributed across primary, middle, and high school levels.

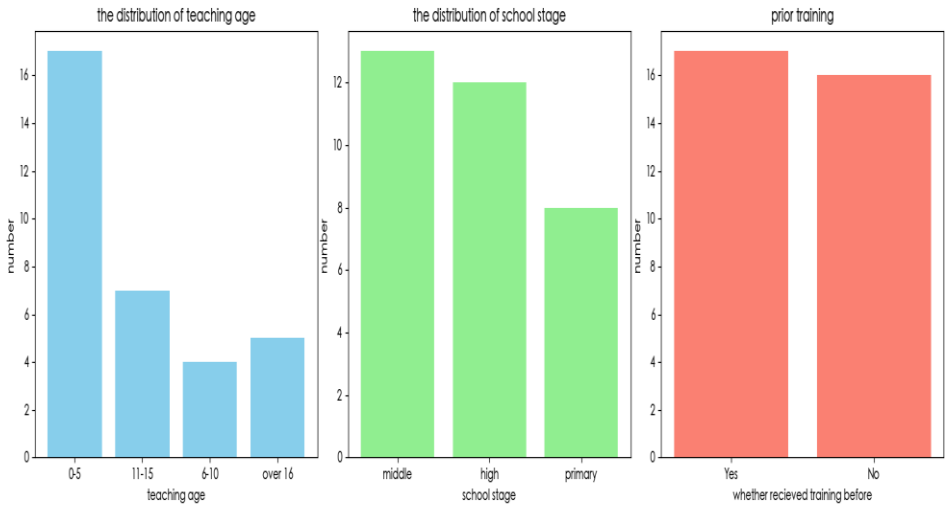


Figure 3
Demographic profile

Table 3
Demographic information

| Variable | Category | Frequency | Percentage(%) |
|---|---|---|---|
| Teaching experience | ≤5 years | 17 | 51.52 |
| | 6–10 years | 4 | 12.12 |
| | 11-15 years | 7 | 21.21 |
| | ≥16 years | 5 | 15.15 |
| School Level | Primary | 8 | 24.24 |
| | Middle | 13 | 39.39 |
| | High school | 12 | 36.36 |
| Technology Training | Yes | 17 | 51.52 |
| | No | 16 | 48.48 |

The values of teachers' PU, PEOU and ATU are shown in Table4 and visualised in the form of a boxplot (Figure4). Each variable is calculated as a mean score from the relevant items in the Likert scale questionnaire.

PU (M = 3.79) suggests that generally teachers see digital technology as a beneficial tool for improving teaching efficiency and classroom engagement. The relatively narrow interquartile range shows consistency in their positive views. The lower median (M = 3.35) and more dispersed responses for PEOU reveal a greater divergence of views. While most teachers considered digital tools to be manageable, a small proportion reported difficulties in understanding or applying these tools effectively. Regarding actual usage frequency, there is noticeable variability among teachers. Although teachers expressed positive attitudes in both the PU and the PEOU, significant differences in usage are observed among participants, with some reporting limited adoption. This suggests that behavioural implementation is influenced by some factors beyond subjective attitudes, which need to be explored further.

Table 4
Mean and standard deviation of PU, PEOU and usage frequency

| Variable | Mean | Standard Deviation |
|---|---|---|
| Perceived Usefulness (PU) | 3.788 | 0.975 |
| Perceived Ease of Use (PEOU) | 3.348 | 0.972 |
| Actual Technology Usage (ATU) | 4.0 | 1.061 |

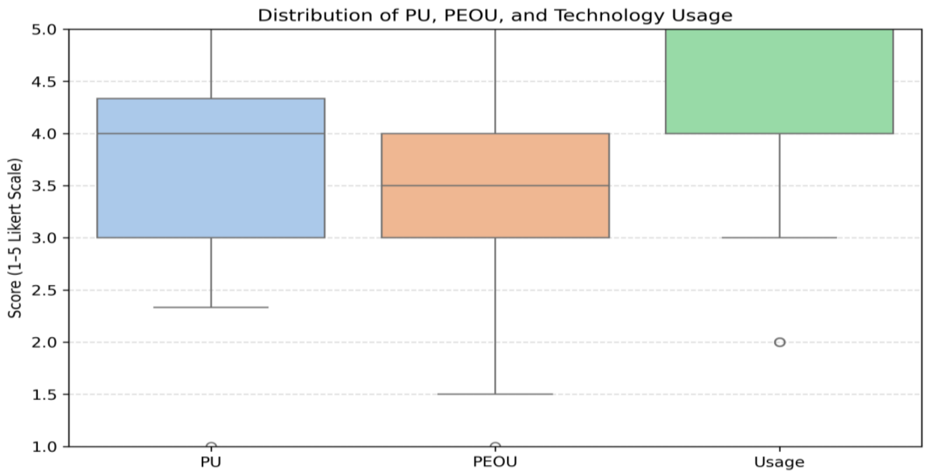


Figure 4
Distribution of PU, PEOU and usage frequency

**Regarding to $H_1$: Difference in PU and PEOU across background variables**

Whether background variables in Q1-3 significantly influence PU and PEOU is examined by an independent-samples T-test and one-way ANOVA.

To evaluate the prior training factor, this study conducted T-test (shown in Table5). The results show that teachers who had received prior technology training reported slightly higher PU (M = 4.24, SD = 0.55) compared to those without training (M = 4.03, SD = 0.49). However, this difference is not statistically significant, t(31) = 1.03, p = .310. For PEOU, trained teachers also reported higher scores (M = 3.92, SD = 0.58) than untrained teachers (M = 3.43, SD = 0.62). This difference approaches statistical significance, t(31) = 1.88, p = .070, which suggests a possible trend in favour of training experience.

Table 5
The prior training factor, t-test

| Group | N | PU Mean (SD) | PEOU Mean (SD) |
|---|---|---|---|
| Trained | 17 | 4.24 (0.55) | 3.92(0.58) |
| Untrained | 16 | 4.03 (0.49) | 3.43(0.62) |
| t-value | | 1.03 | 1.88 |
| p-value | | .310 | .070 |

To examine the teaching age variable, a one-way ANOVA was conducted across four teaching age groups. The PU and PEOU values, which were calculated based on relevant questionnaire items, are presented in Table6 and visualised in Figure5. As shown in Table5, the ANOVA results revealed no statistically significant differences in PU among the four teaching age groups, $F(3, 29) = 1.65$, $p = 0.20$. Similarly, no significant differences were found in PEOU, $F(3, 29) = 1.43$, $p = 0.25$.

These results suggest that teaching experience did not significantly affect teachers' PU or PEOU in this sample.

Table 6
The teaching age variable

| teaching age | PU M | PU SD | PEOU M | PEOU SD |
|---|---|---|---|---|
| 0-5 | 3.92 | 0.79 | 3.41 | 0.78 |
| 6-10 | 2.83 | 0.99 | 2.50 | 0.91 |
| 11-15 | 4.05 | 0.65 | 3.71 | 0.64 |
| >16 | 3.73 | 1.61 | 3.30 | 1.72 |

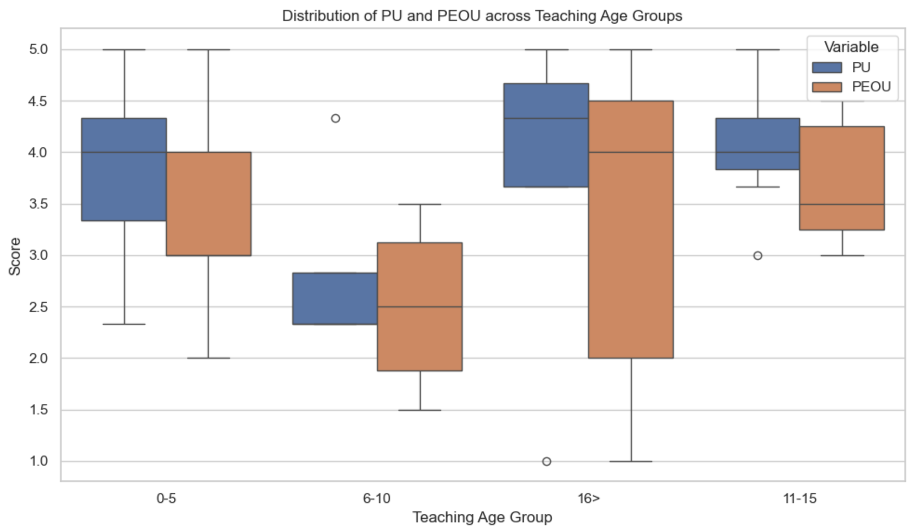


Figure 5
The teaching age group

Table 7
Teachers' PU or PEOU

| Variable | F-value | P-value | Significance |
|---|---|---|---|
| PU | 1.65 | 0.20 | Not significant |
| PEOU | 1.43 | 0.25 | Not significant |

The same testing procedures were applied to the teaching stage factor (see Table7, 8 and Figure6). The study finds that the mean values of both PU and PEOU at the primary school level are higher. This trend may reflect the greater flexibility and emphasis on interactivity at this level, where digital tools are often made for boosting student engagement. In contrast, high school teachers, who face examination pressures and a rigid curriculum, may view digital technologies as too burdensome to accept.

Table 8
The teaching stage factor

| teaching stage | PU M | PU SD | PEOU M | PEOU SD |
|---|---|---|---|---|
| primary | 4.04 | 0.92 | 3.00 | 0.76 |
| middle | 3.31 | 0.73 | 3.08 | 0.79 |
| high | 4.14 | 1.10 | 3.88 | 1.11 |

For PU, the results reveal a marginally non-significant difference among the three school levels ($F(2, 30) = 2.95$, $p = .068$). The same result is found for PEOU, $F(2, 30) = 3.16$, $p = .057$. While neither difference is statistically significant, these near-threshold results provide preliminary evidence that school level could be a contextual factor that influences teachers' attitudes towards technology acceptance.

Table 9
The teaching stage factor

| Variable | F-value | P-value | Significance |
|---|---|---|---|
| PU | 2.95 | 0.068 | Not significant |
| PEOU | 3.16 | 0.057 | Not significant |

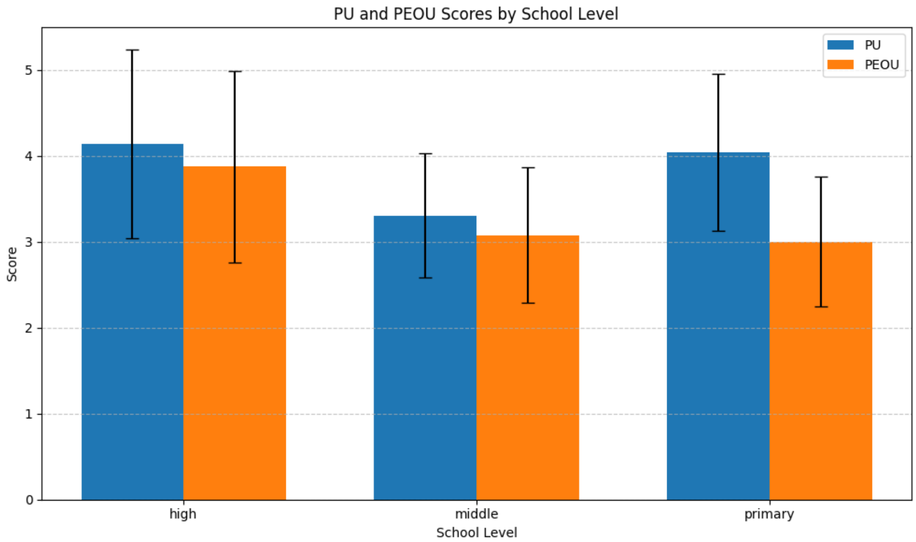


Figure 6
The teaching stage factor

**Regarding to $H_2$: Predictive Power of PU and PEOU on ATU**

Table 10
PU and PEOU

| Interactive innovator | *r* | *p* |
|---|---|---|
| $PU_i$ and $ATU_i$ | 0.329 | 0.296 (not significant) |
| $PEOU_i$ and $ATU_i$ | 0.283 | 0.373 (not significant) |
| Cautious practitioners | *r* | *p* |
| $PU_c$ and $ATU_c$ | 0.664 | 0.001 (significant) |
| $PEOU_c$ and $ATU_c$ | 0.283 | 0.029 (significant) |

Results from the Pearson correlation analysis showed that both PU and PEOU among cautious practitioners were significantly and positively correlated with ATU. This dominant TAM pathway suggests that teachers in this group are more likely to increase their usage frequency if they find a teaching technology useful and easy to use. However, in the interactive innovator group, the correlation between PU/PEOU and ATU was not significant, possibly because their PU/PEOU/ATU scores were already high, resulting in a ceiling effect with little intragroup variation. It is easy to see that interactive innovators already have a strong inner motivation, which makes them less aware of the technology itself.

Moreover, to examine the predictive capability of $PU_c$ and $PEOU_c$ concerning $ATU_c$ further, a multiple linear regression was performed. The model specification is as follows:

$$\text{UsageFreq}_{Q4} = \beta_0 + \beta_1(\text{PU}) + \beta_2(\text{PEOU}) + \epsilon$$

Table 11
The variance

| Predictor | B (Unstandardised) | SE | t | p | 95%CI |
|---|---|---|---|---|---|
| Constant | 1.064 | 0.579 | 1.838 | 0.076 | [-0.118, 2.247] |
| PU | 0.642 | 0.198 | 3.237 | 0.003 | [0.237, 1.046] |
| PEOU | 0.151 | 0.199 | 0.760 | 0.453 | [-0.255, 0.557] |

The model accounts for 47.9% of the variance in usage frequency. $PU_c$ proved to be a significant predictor ($p$ = 0.003), whereas $PEOU_c$ did not reach statistical significance ($p$ = 0.453). This shows that, among a group of cautious practitioners, teachers' perceived usefulness (PU) was the driving factor in actual technology usage. These findings partly corroborate $H_2$ while confirming TAM's proposition that users' PU is a stronger factor contributing to intention and practice.

## CONCLUSION

This study expands the TAM model by combining typologies and provides practical evidence in a Chinese context. The findings regarding cautious practitioners reaffirm the TAM rule that both PU and PEOU show positive correlations with ATU, with PU emerging as a stronger predictor. The new framework revealed findings that went beyond existing TAM conclusions and highlighted some inconsistencies. However, due to the limited sample size (n = 33), the findings may be specific to this context and not be acceptable in another. Additionally, inconsistencies with prior research do not mean that the prior hypothesis is incorrect and should be completely rejected. What this study aims to do is to provide new inspiration for the current TAM framework by conducting a case study in a specific exam-oriented context.

The relationships between PU and PEOU across background variables differ from hypothesis 1. Neither teaching age nor prior training had statistically significant effects on PU or PEOU. Explanation could be the availability of digital technology and the universality of baseline digital skills among teachers today are levelling the field. Even untrained teachers may develop comparable digital competence through informal learning, peer sharing, or self-experimentation with everyday platforms. Follow-up discussions with participants who volunteered for interviews provide further support for this assumption, adding that, since many teachers in this school are young digital natives, their familiarity with technology may diminish the perceived need for structured training. Data also reveals that although the mean PEOU score was higher among trained teachers (M = 3.92) than untrained ones (M = 3.43), the difference did not reach statistical significance. After discussing with participants, this study found a possible explanation. Interviewers believe that many training programmes were too theoretical and decontextualised to substantially enhance perceived ease of use. This suggests future training should be tool-specific and practically oriented to better support technology integration.

The effect of school level on PU/PEOU was marginally significant, with a descending order from primary school to high school. Further interviews explain that since a primary school teacher has the relatively lower exam pressure and more flexible curriculum, they are more open-minded for exploration. In contrast, one high school interviewee explicitly rejected technology for being "inefficient" and "useless". These two completely different views may be rooted in the intensity of exam-oriented instruction at higher grade levels in China's education system. In this context, the only standard by which the efficiency is evaluated is whether it can improve students' grades. Therefore, the potential impact of exam expectations and students' maturity greatly influences teachers' choices. This suggests that digital promotion should consider the broader policy and institutional context in which teachers operate.

The teacher typology complements the linear TAM model, which highlights the heterogeneous nature of technology integration in a Chinese school. Interactive innovators actively integrate digital tools, but are often hindered by infrastructure limitations or inadequate technical support. For this group, technology workshops should move beyond "why-so" sessions, as they are already motivated. Instead, "how-to" sessions on design thinking and the creation of student-centred digital tasks should be introduced. The willingness of using technology for cautious practitioners rely heavily on external factors, since the PU is a dominant factor.  Therefore, school leaders should organise formal, systematic sessions for this group to arise their awareness of using technology while teaching. Public acknowledgement and incentives for digital experimentation are also necessary. Since cautious practitioners, who tend to excel at higher school levels, avoid complex or time-consuming tools due to cost, exam pressure or the perceived irrelevance of such tools to student outcomes, highly targeted professional development sessions that align with their textbook and exam format are welcomed.

This study proposes a hybrid TAM-typology model that balances cognitive and behavioural factors with the heterogeneity of teaching practices. Future research could introduce additional variables, such as culture, policy pressures and student characteristics, to categorise teacher types from a more practical perspective. This would provide more targeted references for teacher training, policy-making and the promotion of digital education. Additionally, future studies could increase the sample size, which can provide implications for a wider context.

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