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Examining the Factors Affecting Vocational and Technical College Students' Acceptance of Automated Written Corrective Feedback: A TAM-Based Quasi-Experimental Approach

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Abstract: The quasi-experimental study investigates the acceptance and effects of the Automated Written Corrective Feedback (AWCF) system iWrite among Chinese vocational and technical college students, applying the Technology Acceptance Model (TAM). The study included 112 students, who were categorized into an experimental group (n = 54) that utilized iWrite for writing feedback and revision and a control group (n = 58) that received traditional teacher-led feedback. Writing proficiency was measured by content, language use, and structure-based pre- and post-tests. Compared with the control group, the experimental group had statistically significant improvements in total writing scores. The results of the TAM-based survey showed a generally positive attitude toward iWrite, with Perceived Usefulness (PU) as the highest mean score. Structural equation modeling confirmed critical pathways of the TAM: PEOU → PU → AT → BI, with Perceived Ease of Use (PEOU)'s direct effect on BI nonsignificant, suggesting that PU, rather than PEOU, predominantly influences acceptance in this educational setting. This study supports the pedagogical efficacy of the iWrite system and contributes methodologically by developing and validating a modified TAM framework specifically designed for vocational and technical college students in China. The results provide a technical framework to upgrade AWCF systems to better meet the practical learning needs of this particular user group. Thus, the study advocates the judicious integration of AWCF systems into vocational and technical college English syllabuses, particularly in cases where the educational benefits are clear and aligned with the practical learning objectives of students.

Keywords: Automated Written Corrective Feedback (AWCF), Technology Acceptance Model (TAM), iWrite feedback, vocational and technical college students, EFL writing

1. Introduction

The 2020 College English Teaching Guide advocates technology-assisted, personalized learning, a paradigm shift in accordance with the global trends in AI and big data [1]. Meta-analyses confirm the pedagogical potential of automated feedback, leading to a medium-sized positive effect on writing performance (g = 0.55) [2]. At the same time, recent technological advances have enabled the development of intelligent scoring systems based on deep learning for higher vocational settings, which have shown significant accuracy and reliability in English composition evaluation [3].

Automated Written Corrective Feedback (AWCF) employs natural language processing (NLP) to address the limitations of traditional WCF and enables instant, consistent, and scalable feedback on grammar, syntax, and organization [4]. This timeliness allows for real-time corrections and reduces student anxiety and increases self-efficacy through guided practice [5, 6]. The use of this technology is necessary to increase the effectiveness and quality of learning English [7].

The integration of AI and NLP technology has been driven by the national AI in education policy in 2017, and the feedback methods have been revolutionized, with online and automated feedback being more common in higher education [8, 9]. The advent of AI-powered AWCF technologies introduces an innovative approach to the systematic inefficiency of traditional writing feedback. These solutions can offer timely, reliable, and personalized feedback, which could ease teachers' work and provide students with the scalable practice opportunities they need [4, 5].

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However, the acceptance of AWCF has been critically underexplored among Chinese vocational and technical college students, a population with unique, pragmatically oriented learning needs and heterogeneous digital literacy, despite the potential of AWCF to reduce anxiety and promote autonomy. Acceptance of these tools is an important step in successful implementation in this unique English as a Foreign Language (EFL) context.

This study is theoretically based on the following literature review. First, the analytical framework is the Technology Acceptance Model (TAM). Second, the empirical findings on AWCF acceptance are synthesized, and finally, a justification for the use of the iWrite platform in this context is provided.

2. Literature Review

2.1. Theoretical framework

The study used the TAM [10] to analyze the users' behavioral intentions and adoption decisions, which are critical to realizing potential learning outcomes. TAM provides a theoretical framework for analyzing this practical aspect and the factors that influence acceptance or rejection of technology. This section reviews empirical studies on factors that influence students' behavioral intentions and actual use of AWCF systems.

The students' adoption of AWCF is predominantly driven by the two main components of the TAM: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), which are influenced by a multitude of external factors pertaining to the educational context.

PU is the degree to which a student believes that using AWCF will improve their learning performance. This is the main determinant of the adoption intention. Students perceive feedback as more useful when they perceive it as accurate, detailed, and comprehensible [11, 12]. People tend to appreciate and use a tool that is capable of providing specific explanations for errors, rather than merely detecting them, as the former creates the feeling of learning and progressing. Moreover, PU is closely associated with extrinsic motivators, such as the potential for achieving higher scores on assignments and meeting course requirements, as well as intrinsic motivators, including the desire to improve writing skills for personal or professional goals [13]. The perceived relevance of the tool to the future professional communication needs of vocational and technical college students (e.g., drafting clear emails and reports) significantly influences their PU.

PEOU is a major initial barrier to adoption and refers to the extent to which the use of a system is perceived as free of effort. A complicated interface, confusing codes for feedback, or a cumbersome procedure may immediately turn off students regardless of the potential usefulness of the tool [14]. It depends on factors such as the student's computer self-efficacy and previous experience with similar technologies. In the context of vocational and technical colleges where students have varying levels of digital literacy, it is important to offer a simple and accessible user experience. The TAM includes PEOU, which is suggested to have a positive influence on PU because a user-friendly product is often perceived as more useful [10].

Acceptance does not mean much involvement in deep learning. Research has shown that students use AWCF to different extents: Some students interact superfluously without a complete understanding and accept all suggestions just to get a higher automated score or for the sake of assignment requirements [12]. A recent systematic review indicates that although Automated Writing Evaluation (AWE) feedback can enhance writing quality, its efficacy is influenced by learners' competence levels and the availability of human scaffolding, implying that feedback quality alone does not ensure profound involvement [15].

Conversely, some students demonstrate profound engagement by thoroughly assessing suggestions, seeking to understand the underlying rationale, making informed decisions about accepting or rejecting feedback, and employing the tool as a resource for inquiry and hypothesis testing related to language rules [16]. The acceptance considerations for vocational and technical college students depend on their personal situations. They seem to operate in a very pragmatic and utilitarian way. They are likely to appreciate AWCF more if its applicability is closely related to the actual competencies needed for their future jobs (e.g., writing a correct technical report) rather than to theoretical academic writing [17]. Additionally, students with lower initial proficiency might get more frustrated when trying to comprehend the feedback, possibly leading to a faster rejection of the tool. Conversely, individuals may also achieve more rapid and significant enhancements in accuracy, perhaps boosting their self-efficacy and, thus, their perceived use of the tool [18].

2.2. iWrite for Automated Written Corrective Feedback

Following a rigorous selection process that included an evaluation of the accessibility of the tool in the specific educational context of China, iWrite was selected as the most suitable platform for conducting the present study. The iWrite system is a digital platform for writing instruction and assessment, developed by the Foreign Language Teaching and Research Press and the National Research Center for Foreign Language Education in China [19]. Launched in 2015, it is a significant effort to utilize artificial intelligence to improve English writing pedagogy in China.

Teachers create virtual classrooms and then invite students to join by using the invitation codes. The platform enables teachers to assign writing tasks with deadlines, and students can submit their work on time. One of the most useful features is the real-time monitoring of progress: teachers can check whether students have completed the task, review their work, and manage e-portfolios of writing. This all-in-one solution improves the management of writing work, as it works as a digital portfolio.

The system's core is the automatic assessment and feedback on the students' writing. It uses advanced algorithms based on NLP techniques trained on large corpora of English written by Chinese learners to assess essays according to the three-part framework of Language, Content, and Structure [20]. iWrite is designed to support a hybrid model of feedback. Instructors can review machine-generated assessments, add their own comments, and control the writing process (e.g., assign work, track drafts, and manage revisions). This feature enables a holistic approach to writing development [21].

Upon submission of a piece of writing, students receive immediate, thorough feedback. The method typically identifies specific errors (e.g., grammatical flaws, inappropriate word choices) and provides detailed ratings and descriptive evaluations for each dimension (content, language use, structure) [22]. This allows learners to identify specific mistakes as well as general strengths and weaknesses in their writing. Apart from the practical aspects of iWrite, the pedagogical potential is essentially founded on its technical architecture. A detailed analysis shows the basic differences from conventional writing aid software.

2.3. Theoretical comparison with alternative AWCF tools

This study focuses on iWrite, but a theoretical comparison with mainstream AWCF tools helps contextualize its unique features. In contrast to generic tools such as Grammarly, which primarily emphasizes grammatical precision [23], iWrite's technical framework is unique due to its training on an extensive corpus of writing from Chinese EFL learners [24]. This enables its NLP algorithms to deliver feedback that is more aligned with prevalent transfer errors committed by Chinese students [24]. Moreover, in contrast to earlier systems that provided solely error detection, iWrite employs a tripartite assessment model (content, language, structure), necessitating a more advanced algorithm to assess and score these aspects comprehensively. The technical specificity may elucidate the substantial improvements noted in the "Content" sub-score in our study, indicating that the algorithmic design of the system directly influences pedagogical results.

The methodological approach developed in this study, combining TAM-based acceptance measurement and quasi-experimental writing proficiency evaluation, can be used in comparative analyses of different AWCF systems, toward a comparative research framework. The present study focuses on iWrite, but the same methodological framework could be applied in future research to compare iWrite with other platforms such as Grammarly, Pigai, or Criterion. Individual AWCF systems have been evaluated in isolation, but there are few comprehensive evaluations of their different impacts on writing outputs and user acceptance [25, 26], and comparative studies would fill an important gap in the literature. This work also contributes methodologically with a validated and replicable framework for further comparative studies.

The iWrite system's technical capabilities operate as an integrated teaching and feedback system, and a key question is: How do the main users, students, perceive and use its automated feedback? The mere implementation of a technology tool does not guarantee that it will be useful for instruction or accepted by the users. Research shows that acceptance of students is a multidimensional issue that is influenced by tool design, PU, social context, and individual learner characteristics. Engagement isn't an either-or phenomenon, but a continuum of mechanical to intentional. Chinese vocational and technical college students have a large gap in the application of this knowledge. While there are studies of student acceptance in the university setting [11, 12], the characteristics of vocational and technical college students have not been adequately explored. These characteristics include their motivational driver, different levels of proficiency, and career goals. Initial evidence from the Chinese vocational colleges suggests that iWrite can significantly improve technical accuracy and grammatical regulations among the lower-proficiency students. However, these studies mostly focus on writing results instead of the psychological acceptance mechanism of the students [27]. Recent studies on AI-driven writing pedagogy in application-oriented institutions indicate that the intelligent feedback system of iWrite can enhance writing skills and learning motivation [28]. The present TAM models have not been adequately validated and contextualized for this demographic segment.

Research Novelty and Contributions

This study makes several unique contributions to fill these gaps. Methodologically, it blends quasi-experimental assessment with TAM-based acceptance analysis into a dual-outcome framework, thereby creating a direct link between PU and measurable learning gains. Empirically, it draws on Chinese vocational and technical college students, an under-researched population whose career-oriented learning orientations may be qualitatively different and may influence AWCF acceptance. Technically, it demonstrates that PU fully mediates the PEOU–BI relationship, contrary to generic TAM assumptions, and highlights the importance of feedback accuracy over interface usability. Finally, it offers a validated, reproducible framework for future comparative assessments of AWCF platforms.

Research Questions

The objective of this research was to investigate the acceptance level and influencing factors of the AWCF provided by iWrite among Chinese vocational and technical students after intervention, with two specific research questions:

a. To what extent does AWCF from iWrite impact the vocational and technical college students' EFL writing performance (total score, content, language use, and structure)?
b. What is the level of acceptance of AWCF from iWrite, and what factors influence their acceptance among Chinese vocational and technical college students in their writing?

3. Research Methodology

3.1. Statement of methodological contribution

This section clearly outlines the methodological, empirical, and technical contributions this study aims to make. The study adopts a quasi-experimental approach based on TAM to address two research gaps. Although TAM is widely used in educational technology research, its application to vocational and technical college students, who have hands-on learning needs and different levels of digital literacy, has not been sufficiently explored. This study contributes methodologically by expanding and validating a modified TAM framework suitable for this population.

This study adds objectively to the literature by combining objective performance data with subjective measures of acceptance to assess the relationship between perceived and real efficacy, in contrast to previous research that largely focused on writing outputs. This combined approach allows a more comprehensive understanding of the effectiveness of AWCF.

Based on the results of structural equation modeling (SEM), we propose three evidence-based recommendations for the development of the AWCF system: (a) the significance of accuracy and relevance of feedback in NLP models, (b) the importance of integrating usability heuristics in essential utility functions, and (c) the importance of enhancing explainable AI (XAI) capabilities for delivering perceived value feedback.

3.2. Research design

This study employed a quasi-experimental, pretest–post-test control-group design supplemented by a TAM-based questionnaire to examine vocational and technical college students' acceptance of AWCF via the iWrite system and its effect on their English writing proficiency.

3.3. Participants

The objectives of this research are to investigate students' acceptance of AWCF, identify factors influencing their acceptance, and explore recommendations for its effective integration into present and future English writing classes. A total of 112 first-year Automotive Repair majors from a vocational and technical college in Sichuan, China, participated in the study. The participants consist of 54 students from the experimental class (EC) and 58 students from the control class (CC).

3.3.1. Instruments

This study addressed the research questions utilizing the following instruments: (1) the iWrite AWCF platform, (2) writing tests comprising a pretest and a post-test, and (3) the TAM questionnaire.

3.3.2. Intervention

Both EC and CC classes are instructed by the same teacher, with identical course materials, syllabi, and writing assignments, but they receive two distinct writing feedback methodologies. The participants in the EC employed iWrite to submit their essay drafts, thereafter correcting their writings for better versions. They submitted their final drafts to the teacher for evaluation after obtaining iWrite AWCF. The participants in the CC composed their essay drafts using a paper-and-pencil style and received conventional teacher comments during class.

3.4. Data collection

Data collection involved the administration of a pretest and post-test to measure the participants' English writing performance before and after receiving traditional writing feedback and the iWrite AWCF intervention. In discussing research on students' acceptance of AWCF and the influencing factors, the researcher must strive for both brevity and thoroughness. Thus, the TAM questionnaire collected information on four main dimensions—(1) Perceived Usefulness (PU), (2) Perceived Ease of Use (PEOU), (3) Attitude Toward Use (AT), and (4) Behavioral Intention to Use (BI)—assessed with 5-point Likert scale statements and closed-ended questions.

3.5. Data analysis

Quantitative data from the pretest and post-test were analyzed by SPSS AU. Descriptive statistics (means and standard deviations) were calculated for all writing scores. To examine within-group differences (pretest vs post-test), a paired-sample t-test was used for both groups. An independent-samples t-test was used to compare post-test scores between experimental and control groups.

Descriptive statistics (means and standard deviations) were computed for each construct in the TAM questionnaire data. Then, confirmatory factor analysis (CFA) and SEM were conducted as inferential statistics to test the hypothesized relationships among PU, PEOU, AT, and BI.

4. Findings

4.1. Findings for writing tests (RQ1)

This study evaluates three important dimensions according to the CET-4 English writing assessment criteria: content (relevance, depth, logic, and originality), language use (vocabulary, grammar, sentence variety, and style), and structure (introduction, body paragraphs, and conclusion), with a maximum score of 25 points. The three sections are weighted 40% (10 points), 40% (10 points), and 20% (5 points).

The pretest and post-test data were the writing outcomes of the final examination of the first and second semesters of 2024–2025, evaluated by two proficient EFL teachers. The final examination adopted a standardized proposition, uniform evaluation, and rigorously consistent assessment standards, and the writing topic was selected from the CET-4 writing repository of iWrite.

To look into the first study question about the efficacy of iWrite, the writing test results were examined and contrasted between the EC and CC.

The pretest scores were analyzed using an independent-samples t-test to determine the comparability of the EC and CC before the intervention. Descriptive results (Table 1) indicated comparable mean scores for both groups on the total score (EC: M = 15.83, SD = 3.20; CC: M = 15.56, SD = 3.04) and all subscales. There were no significant differences between the groups in the total score ($t(110) = -0.12$, $p = 0.903$), content ($p = 0.806$), language use ($p = 0.868$), and structure ($p = 0.194$) as shown in the t-test results (Table 2). The minimal values of Cohen's d (between $|0.07|$ and $|0.11|$) also indicate that any preexisting differences were negligible. Thus, the two groups were comparable in English writing proficiency at the beginning of the study.

Table 3 presents the descriptive statistics of the post-test for both groups. Paired-samples t-tests were conducted to assess the enhancement within each group following the intervention period.

The EC demonstrated statistically significant and large improvements in all areas measured using the iWrite AWCF system (Table 4). The total score increased notably from the pretest (M = 15.83) to the post-test (M = 17.87), and there was a strong pretest–post-test correlation ($r = 0.866$, $p < 0.001$). Major improvements were found in content ($p < 0.001$), language use ($p < 0.001$), and structure ($p = 0.003$). Findings showed that the use of AWCF was related to significant improvements in students' writing proficiency.

In contrast, the CC, which received conventional training, showed a different pattern (Table 5). There was no significant

Table 1
Results of the pretest

		N	Mean	Std. deviation	Std. error mean
Total score	EC	54	15.83	3.20	0.44
	CC	58	15.56	3.04	0.40
Content	EC	54	6.49	1.76	0.24
	CC	58	6.35	1.48	0.20
Language use	EC	54	6.53	1.62	0.22
	CC	58	6.34	1.89	0.25
Structure	EC	54	2.81	0.88	0.12
	CC	58	2.87	.86	0.11

Table 2
Independent-samples *t*-test for pretest

		Levene's p	*t*	*df*	*p*	Mean difference	95% CI for mean difference	Cohen's *d*
Total score	EC	0.349	–0.12	110	0.903	0.27	[–0.89, 1.43]	0.09
	CC							
Content	EC	0.786	–0.25	110	0.806	0.14	[–0.46, 0.74]	0.09
	CC							
Language use	EC	0.919	–0.17	110	0.868	0.19	[–0.46, 0.84]	0.11
	CC							
Structure	EC	0.064	1.31	110	0.194	–0.06	[–0.38, 0.26]	–0.07
	CC							

Table 3
Results of the post-test

		N	Mean	Std. deviation	Std. error mean
Total score	EC	54	17.87	2.75	0.37
	CC	58	16.55	2.52	0.33
Content	EC	54	7.24	1.30	0.18
	CC	58	6.64	1.34	0.18
Language use	EC	54	7.40	1.47	0.20
	CC	58	6.95	1.15	0.15
Structure	EC	54	3.23	0.92	0.13
	CC	58	2.96	1.09	0.14

Table 4
Paired samples statistics of EC

Pair		N	Mean	Std. deviation	Std. error mean	Correlation coefficient	Sig. (2-tailed)
Pair 1	Pretest total score	54	15.83	3.20	0.44	0.866	0.000
	Post-test total score	54	17.87	2.75	0.37		
Pair 2	Pretest content	54	6.49	1.76	0.24	0.726	0.000
	Post-test content	54	7.24	1.30	0.18		
Pair 3	Pretest language use	54	6.53	1.62	0.22	0.718	0.000
	Post-test language use	54	7.40	1.47	0.20		
Pair 4	Pretest structure	54	2.81	.88	0.12	0.437	0.003
	Post-test structure	54	3.23	.092	0.13		

Table 5
Paired samples statistics of CC

Pair		N	Mean	Std. deviation	Std. error mean	Correlation coefficient	Sig. (2-tailed)
Pair 1	Pretest total score	58	15.56	3.04	0.40	0.215	0.105
	Post-test total score	58	16.55	2.52	0.33		
Pair 2	Pretest content	58	6.35	1.48	0.20	0.178	0.180
	Post-test content	58	6.64	1.34	0.18		

(*Continued*)

Table 5
(*Continued*)

Pair		N	Mean	Std. deviation	Std. error mean	Correlation coefficient	Sig. (2-tailed)
Pair 3	Pretest language use	58	6.34	1.89	0.25	–0.127	0.344
	Post-test language use	58	6.95	1.15	0.15		
Pair 4	Pretest structure	58	2.87	0.86	0.11	0.130	0.330
	Post-test structure	58	2.96	1.09	0.14		

increase in the total score from pretest (M = 15.56) to post-test (M = 16.55) (p = .105). Pretest and post-test associations were small and not statistically significant across all sub-scales. The improvement of language use and structure was not statistically significant (p = .344 and p = .330, respectively). This suggests that traditional teaching methods had little effect on improving writing skills during the trial.

The primary analysis to assess the efficacy of the AWCF intervention compared the post-test results of the two groups. An independent-samples t-test of the post-test data (Table 6) indicated a statistically significant advantage for the EC over the CC on the overall writing score, with a medium effect size ($t(110)$ = 2.36, p = 0.020, Cohen's d = 0.50). The mean difference was 1.32 points (95% CI [0.34, 2.30]).

At the sub-scale level, this advantage was influenced by a substantial and significant difference in the content sub-score (p = 0.040, Cohen's d = 0.45). The EC surpassed the CC in language utilization; however, this disparity was not statistically significant (p = 0.104). The structural difference was also not statistically significant (p = 0.284)

4.2. Findings for TAM questionnaire (RQ2)

Students from EC completed the TAM questionnaire (Appendix 1) to evaluate their views on AWCF. The measure consists of closed-ended questions employing a 5-point Likert scale, spanning from "strongly disagree" (1) to "strongly agree" (5). The framework includes four constructs of the TAM, adapted from the studies of Davis [10] and later TAM instruments [29, 30]: PEOU (5 items), PU (12 items), AT (5 items), and BI (4 items).

Before assessing the structural correlations, the validity and reliability of the measuring model were tested. A CFA was conducted for the four constructs: PU, PEOU, AT, and BI.

Table 7 shows that all standardized factor loadings were statistically significant ($p < 0.001$) and greater than the minimum value of 0.60. They ranged from 0.62 (PEOU2) to 0.88 (PU3), suggesting that all items were strong indicators of their respective latent constructs.

Table 8 presents the descriptive statistics for the perception of students for the iWrite system. Mean scores of all the constructions were above the scale midpoint, indicating a general positive acceptance. The highest score was obtained by PU (M = 3.82, SD = 0.71), indicating that students perceived the AWCF tool as being especially useful to improve their writing. The following metrics were AT (M = 3.75, SD = 0.79), BI (M = 3.64, SD = 0.82), and PEOU (M = 3.58, SD = 0.85).

The model fit indices in Table 9 indicated an excellent match to the data (χ^2/df = 2.1, Comparative Fit Index (CFI) = 0.94, Root Mean Square Error of Approximation (RMSEA) = 0.06), validating the postulated four-factor structure of the TAM.

Furthermore, the constructs demonstrated high reliability and validity. As shown in Table 8, the Cronbach's alpha values were all above 0.80 for all structures, indicating excellent internal consistency. The analysis of convergent validity from Table 10 shows that all constructs of the TAM meet the psychometric standards for internal consistency. All four constructs of the TAM showed excellent composite reliability (CR = 0.86–0.93) and adequate convergent validity (AVE = 0.51–0.54), exceeding the suggested threshold of 0.50 [31], confirming that each latent construct adequately represents its measured variables.

Discriminant validity was also established. Table 11 shows that the square root of the average variance extracted (AVE) for each construct (diagonal elements) is greater than its correlations with other constructs (off-diagonal elements), thus supporting the distinctiveness of each construct and its greater variance shared with its own indicators in comparison to other constructs in the model.

Table 6
Independent samples *t*-test for post-test

		Levene's p	t	df	p	Mean difference	95% CI for mean Difference	Cohen's d
Total score	EC	0.219	2.36	110	0.020	1.32	[0.34, 2.30]	0.50
	CC							
Content	EC	0.706	2.07	110	0.040	0.60	[0.11, 1.09]	0.45
	CC							
Language use	EC	0.021	1.64	110	0.104	0.45	[-0.04,0.94]	0.34
	CC							
Structure	EC	0.518	1.08	110	0.284	0.27	[–0.10,0.64]	0.27
	CC							

Table 7
Standardized factor loadings for all TAM constructs (n = 54)

Construct	Item code	Factor loading (λ)	p-value
Perceived Usefulness (PU)	PU1	0.78	<0.001
	PU2	0.82	<0.001
	PU3	0.88	<0.001
	PU4	0.85	<0.001
	PU5	0.79	<0.001
	PU6	0.83	<0.001
	PU7	0.76	<0.001
	PU8	0.81	<0.001
	PU9	0.84	<0.001
	PU10	0.77	<0.001
	PU11	0.80	<0.001
	PU12	0.83	<0.001
Perceived Ease of Use (PEOU)	PEOU1	0.75	<0.001
	PEOU2	0.62	<0.001
	PEOU3	0.71	<0.001
	PEOU4	0.68	<0.001
	PEOU5	0.73	<0.001
Attitude Toward Use (AT)	AT1	0.81	<0.001
	AT2	0.79	<0.001
	AT3	0.83	<0.001
	AT4	0.85	<0.001
	AT5	0.77	<0.001
Behavioral Intention (BI)	BI1	0.86	<0.001
	BI2	0.84	<0.001
	BI3	0.82	<0.001
	BI4	0.83	<0.001

Table 8
Descriptive statistics and reliability of TAM constructs

Construct	No. of items	Mean (M)	Standard deviation (SD)	Cronbach's α
Perceived Usefulness (PU)	12	3.82	0.71	0.93
Perceived Ease of Use (PEOU)	5	3.58	0.85	0.86
Attitude Toward Use (AT)	5	3.75	0.79	0.88
Behavioral Intention (BI)	4	3.64	0.82	0.89

Table 9
TAM construct validation

Fit indices	Obtained value	Threshold criteria	Interpretation
χ^2/df	2.1	<3	Excellent fit
CFI	0.94	>0.90	Good fit
RMSEA	0.06	<0.08	Acceptable fit

Table 10
Convergent validity analysis of TAM constructs

Construct	Number of items	Composite reliability (CR)	Average variance extracted (AVE)	Interpretation
Perceived Usefulness (PU)	12	0.93	0.52	CR： Excellent AVE： Acceptable

(*Continued*)

Table 10
(*Continued*)

Construct	Number of items	Composite reliability (CR)	Average variance extracted (AVE)	Interpretation
Perceived Ease of Use (PEOU)	5	0.86	0.51	CR: Excellent AVE: Acceptable
Attitude Toward Use (AT)	5	0.88	0.53	CR: Excellent AVE: Acceptable
Behavioral Intention (BI)	4	0.89	0.54	CR: Excellent AVE: Acceptable

Note: All constructs satisfied the recommended thresholds for CR (>0.70) and AVE (>0.50).

Table 11
Discriminant validity

Construct	PU	PEOU	AT	BI
PU	0.72			
PEOU	0.51	0.71		
AT	0.67	0.43	0.73	
BI	0.69	0.38	0.72	0.74

Note: Diagonal elements (bold) represent the square root of AVE.

The findings in Table 12 support basic TAM constructs but reveal contextual specificities. The relatively weak association between PEOU and BI (r = 0.38) indicates that functionality (PU) may be a more important driver of adoption than usability (PEOU) for AWCF solutions, a tendency found in specialized educational technology [32]. The strong association between AT and BI (*r* = 0.72) highlights the importance of emotional evaluations in technology adoption decisions.

The study used an SEM to test the proposed relationships within the TAM framework. The model had a better fit (χ^2/df = 2.1, CFI = 0.94, RMSEA = 0.06). Table 13 presents the path coefficients and their significance. The findings show that PEOU had a significant positive effect on PU (β = 0.48, $p < 0.001$), confirming the hypothesis that easier-to-use technology is perceived as more valuable. PU was a strong and significant predictor of AT (β = 0.54, $p < 0.001$). Attitude Toward Use emerged as a robust and significant predictor of students' Behavioral Intention to use the iWrite system (β = 0.61, $p < 0.001$). The direct effect of PEOU on BI was not statistically significant (β = 0.12, p = 0.142), indicating that PEOU's influence on BI is fully mediated by PU and AT in this case. The R-squared values show that the model explains a substantial amount of the variance in the endogenous variables, 23% for PU, 29% for AT, and 53% for BI. The inter-construct correlation matrix (Table 12) supports these relationships, demonstrating strong and significant positive correlations between all constructs, with the strongest relationship found between AT and BI (r = 0.72, p < 0.01).

Table 12
Inter-construct correlation matrix

	PU	PEOU	AT	BI
PU	1			
PEOU	0.51**	1		
AT	0.67**	0.43**	1	
BI	0.69**	0.38*	0.72**	1

Notes: *$p < 0.05$, **$p < 0.01$ (two-tailed). n = 54.*

Table 13
SEM tested the hypothesized TAM paths

Path	β	p-value	R^2
PEOU → PU	0.48	<0.001	0.23
PU → AT	0.54	<0.001	0.29
AT → BI	0.61	<0.001	0.53
PEOU → BI	0.12	0.142	

Model Fit: χ^2/df = 2.1, CFI = 0.94, RMSEA = 0.06.

5. Discussion

The purpose of this study was to investigate the effect of an Automated Writing Corrective Feedback (AWCF) system, iWrite, on writing performance in vocational and technical college students and to determine their adoption of the technology. The findings provide strong evidence of the effectiveness of the tool and valuable insights into the psychological variables underlying the adoption.

5.1. Main findings

The outcomes result in two major findings. First, iWrite had a medium-sized statistically significant effect on students' overall writing proficiency (Cohen's d = 0.50), with the largest gain in the content sub-score (d = 0.45). This finding is consistent with the growing body of research evidence that has supported the positive effects of AWCF on the development of L2 writing [33]. The significant improvement, especially in content, indicates that the prompt and the continuous feedback from iWrite may have freed up cognitive resources, allowing students to devote more attention to higher-order concerns such as idea development and organization, rather than worrying too much about surface-level errors.

Second, the model of acceptance based on the TAM was mostly supported: PU was a significant predictor of AT, which was a predictor of BI, and the model explained 53% of the variance in BI. The direct path from PEOU to BI was not significant (β = 0.12, p = 0.142), indicating that for these students, usefulness perceptions fully mediate the effect of usability on adoption intentions.

Importantly, these two findings are not independent. The objective improvement in writing performance, especially in content development, is the empirical validation of students' subjective perception of iWrite as useful (PU, M = 3.82). The interaction of perceived and actual efficacy creates a dynamic virtuous cycle: the successful use of the tool enhances its perceived value, which in turn improves the attitude and intention for continued use, resulting in lasting engagement and long-term improvement.

5.2. Theoretical and technical implications

This study expands TAM to the understudied population of Chinese vocational and technical college students and demonstrates that the core paths of the model are still applicable in this context (R^2 = 53% for BI). The nonsignificant direct PEOU → BI relationship (β = 0.12, p = 0.142) is contrary to classic TAM studies [14] but is consistent with recent findings on AI-driven educational tools, where PU often overshadows ease of use as a direct predictor of intention [34]. We interpret this as evidence that, for pragmatically orientated learners, instrumentality—evidence that a tool contributes to writing improvement— is more important than subjective usability. The full mediation model (PEOU → PU → AT → BI) indicates that PU is the primary psychological lever for adoption in this context.

The interpretation has direct technical implications for the design of AWCF systems. First, the high factor loadings across all PU items (λ = 0.76–0.88) suggest that developers should concentrate on feedback accuracy and pedagogical relevance in their NLP models. Recent evaluations show that commercial tools such as Grammarly achieve precision rates from 67% to 90% depending on the error type [35], and Large Language Model (LLM)-based feedback research further highlights the need to adapt the feedback to the learners' knowledge gaps [36, 37]. Second, the fully mediated model suggests that usability heuristics should be embedded as augmentations to core utility functions, rather than as independent features [38]. Third, the nonsignificant PEOU→BI path suggests that systems should focus on "perceived value feedback"—that is, using XAI functionalities that generate meta-feedback explaining how correcting an error improves writing quality or aligns with professional requirements [39–42]. Finally, the high R^2 for BI (53%) validates TAM as a diagnostic instrument for system assessment across technology iterations [34, 43].

5.3. Practical implications

Several practical implications follow for EFL instruction in vocational and technical colleges. First, AWCF systems such as iWrite can be used as a supporting tool to enhance writing instruction, especially in large classrooms where teacher feedback on an individual level is not feasible. Second, when introducing such tools, instructors should highlight the pedagogical value of such tools—how the system's feedback helps students meet writing goals for the course or career—rather than ease of use. The finding of the full mediation of PU in the PEOU–BI relationship implies that usefulness arguments are more persuasive to this population. Third, the significant enhancement of content scores indicates that AWCF may be a scaffold for the higher-order writing skills to boost learners' confidence in idea generation and organization.

5.4. Limitations and recommendations

However, some limitations should be acknowledged despite the positive findings. First, while the study demonstrates significant short-term progress, one semester constrains any conclusions about long-term retention of writing improvements or sustainability of positive attitudes. Future research can be conducted with longer intervention time and more diverse students.

Second, this study examined one AWCF system (iWrite) in a specific college context. The quasi-experimental design guarantees strong internal validity, but the absence of cross-system comparison constrains the generalizability of the results in terms of the comparative effectiveness of different AWCF platforms. Future research should take the same methodological approach to compare iWrite with other systems (e.g., Grammarly, Pigai, Criterion) across different institutions to build a comparative evidence base to inform system choice and developmental priorities.

Third, this study depends on self-reported TAM data, which is prone to social desirability bias—students may overstate their positive attitudes to please the teacher-researcher. Moreover, the writing post-test was a standardized CET-4 assessment. Although this guarantees reliability, it may not entirely reflect the transferability of abilities acquired through iWrite to more genuine, unrestricted writing assignments (e.g., emails, reports) that are relevant to vocational and technical college students' future professions. Future research ought to integrate more ecologically valid writing evaluations.

Furthermore, this study provides an abundance of acceptance data, but it is unclear whether the novelty of the AWCF system will wane or if students will use "gaming" strategies such as superficial acceptance of all ideas with no thorough cognitive process to obtain higher automated scores [12]. Future longitudinal studies combining an analysis of log data with eye-tracking or think-aloud protocols could shed light on qualitative dimensions of "engagement" and the distinction between deep, meaningful learning and strategic superficial compliance. By correlating students' interaction patterns with the system (e.g., time spent on feedback, revision attempts) with their learning outcomes, we can establish a more objective "Engagement with AI Feedback" metric [44, 45], which would serve as a significant technical benchmark for assessing the effectiveness of human-computer interaction in educational AI. Recent learning analytics developments have demonstrated that process data from digital learning environments can provide detailed insights into how learners interact with automated feedback [46, 47]. These objective measurements enhance self-reported data and facilitate a more thorough comprehension of the mechanisms that govern feedback effectiveness [45].

6. Conclusion

This study concludes that the iWrite AWCF system effectively enhances the writing performance of vocational and technical college students and is positively welcomed by them. The strong predictive capability of the TAM model suggests that students are inclined to adopt technology they deem truly beneficial for their academic achievement. The results advocate for the deliberate use of AWCF tools in EFL writing curricula, highlighting their potential to improve learning and engage students when their educational significance is effectively conveyed and acknowledged.

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Ethical Statement

All subjects provided informed consent for inclusion before participating in the study. The study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the human research ethics committee of the Department of Foreign Languages at Nanchong Vocational and Technical College in China (Reference No.: NCZYWGY-2025-0301).

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in Figshare at https://figshare.com/s/78ad5d90995db17b3cde.

Author Contribution Statement

Xiaomin Deng: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Supyan Hussin:** Validation, Writing – review & editing, Supervision, Project administration. **Nur Ainil Sulaiman:** Writing – review & editing, Supervision.

References

[1] Bhutoria, A. (2022). Personalized education and artificial intelligence in the United States, China, and India: A systematic review using a human-in-the-loop model. *Computers and Education: Artificial Intelligence*, *3*, 1–18. https://doi.org/10.1016/j.caeai.2022.100068

[2] Fleckenstein, J., Liebenow, L. W., & Meyer, J. (2023). Automated feedback and writing: A multi-level meta-analysis of effects on students' performance. *Frontiers in Artificial Intelligence*, *6*, 1–11. https://doi.org/10.3389/frai.2023.1162454

[3] Feng, S., Yu, L., & Liu, F. (2024). Scoring method of English composition integrating deep learning in higher vocational colleges. *Scientific Reports*, *14*(1), 7287. https://doi.org/10.1038/s41598-024-57419-x

[4] Hosseini, M., Rasmussen, L. M., & Resnik, D. B. (2024). Using AI to write scholarly publications. *Accountability in Research*, *31*(7), 715–723. https://doi.org/10.1080/08989621.2023.2168535

[5] Akgun, S., & Greenhow, C. (2022). Artificial intelligence in education: Addressing ethical challenges in K-12 settings. *AI and Ethics*, *2*(3), 431–440. https://doi.org/10.1007/s43681-021-00096-7

[6] Nazari, N., Shabbir, M. S., & Setiawan, R. (2021). Application of artificial intelligence powered digital writing assistant in higher education: Randomized controlled trial. *Heliyon*, *7*(5), 1–9. https://doi.org/10.1016/j.heliyon.2021.e07014

[7] Pan, Q., & Dapat, R. O. (2023). Evaluation of higher vocational English curriculum toward enhanced program implementation. *Evaluation*, *5*(1), 1–5. https://doi.org/10.54097/jeer.v5i1.11548

[8] Shang, H. F. (2022). Exploring online peer feedback and automated corrective feedback on EFL writing performance. *Interactive Learning Environments*, *30*(1), 4–16. https://doi.org/10.1080/10494820.2019.1629601

[9] Shi, H., & Aryadoust, V. (2024). A systematic review of AI-based automated written feedback research. *ReCALL*, *36*(2), 187–209. https://doi.org/10.1017/S0958344023000265

[10] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

[11] Wu, F., & Xie, G. (2024). Research on the influence of perceived quality on users' continuance usage intention of online live streaming class platforms: The mediating role of flow experience and the moderating impact of perceived usefulness. *Frontiers in Psychology*, *15*, 1–13. https://doi.org/10.3389/fpsyg.2024.1455597

[12] Guo, Q., Feng, R., & Hua, Y. (2022). How effectively can EFL students use automated written corrective feedback (AWCF) in research writing? *Computer Assisted Language Learning*, *35*(9), 2312–2331. https://doi.org/10.1080/09588221.2021.1879161

[13] Wong, E. Y. C., Hui, R. T. Y., & Kong, H. (2023). Perceived usefulness of, engagement with, and effectiveness of virtual reality environments in learning industrial operations: The moderating role of openness to experience. *Virtual Reality*, *27*(3), 2149–2165. https://doi.org/10.1007/s10055-023-00793-0

[14] Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

[15] Aldosemani, T. I., Assalahi, H., Lhothali, A., & Albsisi, M. (2023). Automated writing evaluation in EFL contexts: A review of effectiveness, impact, and pedagogical implications. *International Journal of Computer-Assisted Language Learning and Teaching*, *13*(1), 1–19. https://doi.org/10.4018/IJCALLT.329962

[16] Storch, N. (2018). Written corrective feedback from sociocultural theoretical perspectives: A research agenda. *Language Teaching*, *51*(2), 262–277. https://doi.org/10.1017/S0261444818000034

[17] Yang, H., Gao, C., & Shen, H. Z. (2024). Learner interaction with, and response to, AI-programmed automated writing evaluation feedback in EFL writing: An exploratory study. *Education and Information Technologies*, *29*(4), 3837–3858. https://doi.org/10.1007/s10639-023-11991-3

[18] Bai, X., & Nordin, N. R. M. (2025). Human-AI collaborative feedback in improving EFL writing performance: An analysis based on natural language processing technology. *Eurasian Journal of Applied Linguistics*, *11*(1), 1–19. https://doi.org/10.32601/ejal.11101

[19] Guo, Y., & Xiong, W. (2024). The impact of English writing instruction integrated with automated evaluation systems on college English teachers—iWrite 2.0 system as an example. *Open Journal of Modern Linguistics*, *14*(6), 1159–1169. https://doi.org/10.4236/ojml.2024.146061

[20] Chen, J. W., Tu, H. L., Chang, C. H., Hsu, W. C., Wang, P. C., Liao, C. H., & Chen, M. (2025). Automated evaluation of reflection and feedback quality in workplace-based assessments by using natural language processing: Cross-sectional competency-based medical education study. *JMIR Medical Education*, *11*, 1–13. https://doi.org/10.2196/81718

[21] Warschauer, M., & Ware, P. (2006). Automated writing evaluation: Defining the classroom research agenda. *Language Teaching Research*, *10*(2), 157–180. https://doi.org/10.1191/1362168806lr190oa

[22] Chen, M., & Cui, Y. (2022). The effects of AWE and peer feedback on cohesion and coherence in continuation writing. *Journal of Second Language Writing*, *57*, 100915. https://doi.org/10.1016/j.jslw.2022.100915

[23] Omelianchuk, K., Liubonko, A., Skurzhanskyi, O., Chernodub, A., Korniienko, O., & Samokhin, I. (2024). Pillars of grammatical error correction: Comprehensive inspection of contemporary approaches in the era of large language models. In *Proceedings of the 19th Workshop on Innovative Use of NLP for Building Educational Applications*, 17–33.

[24] Xu, J. (2019). The construction of iWriteBaby Chinese learner's English corpus. *Corpus Linguistics/Yuliaoku Yuyanxue*, *6*(1), 105–109.

[25] Zhai, N., & Ma, X. (2022). Automated writing evaluation (AWE) feedback: A systematic investigation of college students' acceptance. *Computer Assisted Language Learning*, *35*(9), 2817–2842. https://doi.org/10.1080/09588221.2021.1897019

[26] Sanosi, A. B., & Mohammed, M. O. M. (2024). The effectiveness of automated writing evaluation: A structural analysis approach. *Int International Journal of Evaluation and Research in Education*, *13*(2), 1216–1226. https://doi.org/10.11591/ijere.v13i2.25372

[27] Xu, X., Baharum, B., & Izzuan, H. (2024). The application of blended teaching based on iWrite system in college English writing classes. *Pakistan Journal of Life & Social Sciences*, *22*(2), 1–14. https://doi.org/10.57239/PJLSS-2024-22.2.00476

[28] Shen, Y., Shao, X., Tan, J., Chen, X., Chen, H., Pu, S., . . . , & Zhu, L. (2025). A study on AI-based English writing pedagogy: A case study of application-oriented higher education institutions. In Y. Ping, F. Meng, H. Jiang, & W. Fu (Eds.), *Proceedings of the 2025 International Conference on Education Research and Training Technologies*, 205–211. Atlantis Press.

[29] Bailey, D. R., Almusharraf, N., & Almusharraf, A. (2022). Video conferencing in the e-learning context: Explaining learning outcome with the technology acceptance model. *Education and Information Technologies*, *27*(6), 7679–7698. https://doi.org/10.1007/s10639-022-10949-1

[30] Sun, P. P., & Mei, B. (2022). Modeling preservice Chinese-as-a-second/foreign-language teachers' adoption of educational technology: A technology acceptance perspective. *Computer Assisted Language Learning*, *35*(4), 816–839. https://doi.org/10.1080/09588221.2020.1750430

[31] Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.2307/3151312

[32] Hyland, K., & Rodrigo, I. H. (2007). English for academic purposes: An advanced resource book. *Miscelánea: A Journal of English and American Studies*, *35*, 99–108.

[33] Zhang, Z. V., & Hyland, K. (2022). Fostering student engagement with feedback: An integrated approach. *Assessing Writing*, *51*, 100586. https://doi.org/10.1016/j.asw.2021.100586

[34] Rathore, J., Singh, A., & Rao, U. (2026). Validation of an extended technology acceptance model framework incorporating organisational culture and trust in AI usage within hospitals: A cross-sectional study. *Journal of Clinical and Diagnostic Research*, *20*(4), 6–11. https://doi.org/10.7860/JCDR/2026/84554.22732

[35] Luo, N., Wang, Y., Zhang, Z. V., Zhou, Y., & Zhao, R. (2026). Impact of prompt sophistication on ChatGPT's output for automated written corrective feedback. *ReCALL*, *38*(2), 240–254. https://doi.org/10.1017/S095834402510044X

[36] Coyne, S., Galvan-Sosa, D., Spring, R., Guerraoui, C., Zock, M., Sakaguchi, K., & Inui, K. (2025). Annotating errors in English learners' written language production: Advancing automated written feedback systems. In *International Conference on Artificial Intelligence in Education,* 292–306. https://doi.org/10.1007/978-3-031-98459-4_21

[37] Degraeuwe, J., & Moerman, T. (2025). *Retrieval-augmented generation for automated written corrective feedback: From dataset to human evaluation*. In *Proceedings of the 35th Meeting of Computational Linguistics in the Netherlands*, 292–306. https://doi.org/10.1007/978-3-031-98459-4_21

[38] Lehnert, F., Doublet, S., & Sim, G. (2025). Designing usability/user experience heuristics to evaluate e-assessments administered to children. *Computer Standards & Interfaces*, *92*, 103933. https://doi.org/10.1016/j.csi.2024.103933

[39] Khosravi, H., Shum, S. B., Chen, G., Conati, C., Tsai, Y. S., Kay, J., . . . , & Gašević, D. (2022). Explainable artificial intelligence in education. *Computers and Education: Artificial Intelligence*, *3*, 1–22. https://doi.org/10.1016/j.caeai.2022.100074

[40] Ayanwale, M. A. (2025). Building trust in AI-powered assessment through explainable machine learning models. In *Proceedings of the ACM Global on Computing Education Conference*, *2*, 403–404. https://doi.org/10.1145/3736251.3747313

[41] Choi, W. C., Lam, C. T., Pang, P. C. I., & Mendes, A. J. (2025). A systematic literature review of explainable artificial intelligence (XAI) for interpreting student performance prediction in computer science and STEM education. In *Proceedings of the 30th ACM Conference on Innovation and Technology in Computer Science Education*, 221–227. https://doi.org/10.1145/3724363.3729027

[42] Swamy, V., Romano, D., Desikan, B. S., Camburu, O. M., & Käser, T. (2025). iLLuMinaTE: An LLM-XAI framework leveraging social science explanation theories towards actionable student performance feedback. In *Proceedings of the AAAI Conference on Artificial Intelligence*, *39*(27), 28431–28439. https://doi.org/10.1609/aaai.v39i27.35065

[43] Al Rian, A., Rohan, A., Yoshi, A. M., Talukder, T., Faruque, M. O., Chowdhury, S. N., & Rabbani, M. G. (2024). Development and empirical validation of an information technology acceptance framework. *Journal of Business and Management Studies*, *6*(6), 36–47. https://doi.org/10.32996/jbms.2024.6.6.3

[44] Dong, L. (2025). Development and validation of a multidimensional ChatGPT feedback engagement scale in second language writing. *System*, *135*, 103875. https://doi.org/10.1016/j.system.2025.103875

[45] Schiller, R., Fleckenstein, J., Mertens, U., Horbach, A., & Meyer, J. (2024). Understanding the effectiveness of automated feedback: Using process data to uncover the role of behavioral engagement. *Computers & Education*, *223*, 105163. https://doi.org/10.1016/j.compedu.2024.105163

[46] Schiller, R., Fleckenstein, J., Höft, L., Horbach, A., & Meyer, J. (2025). On the role of engagement in automated feedback effectiveness: Insights from keystroke logging. *Computers & Education*, *238*, 1–20. https://doi.org/10.1016/j.compedu.2025.105386

[47] Lang, C., Siemens, G., Wise, A. F., Gašević, D., & Merceron, A. (2022). *The handbook of learning analytics*. Canada: Society for Learning Analytics Research. https://doi.org/10.18608/hla22

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Appendix 1

Questionnaire of Technology Acceptance Model (TAM)

Notes: Please thoroughly review the following questions and provide an accurate assessment of TAM on AWCF. These questions are specifically crafted to assess AWCF, so there are no definitive correct or incorrect responses.

Please place a "√" on the appropriate number to rate the following items regarding "Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Toward Use (AT), Behavioral Intention to Use (BI)," using a scale of 1–5:				
1 Strongly Disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly Agree
Part 1 Perceived Usefulness (PU)				
1. Being acquainted with AWCF and relevant tools helps improve my writing proficiency.				1 2 3 4 5
2. AWCF is useful in EFL writing.				1 2 3 4 5
3. Utilizing AWCF enhances the efficacy of my English writing.				1 2 3 4 5
4. Use of AWCF leads to my increased productivity in English writing.				1 2 3 4 5
5. AWCF enables me to accomplish tasks more quickly when revising for English writing.				1 2 3 4 5
6. AWCF has improved the quality of my English writing.				1 2 3 4 5
7. AWCF makes it easier to writing English composition.				1 2 3 4 5
8. AWCF gives me greater control over English writing processes.				1 2 3 4 5
9. The use of AWCF increases the effectiveness of performing English writing tasks.				1 2 3 4 5
10. Using AWCF gives me access to a lot of information.				1 2 3 4 5
11. AWCF provides thorough information for my writing correction purposes.				1 2 3 4 5
12. The advantages of AWCF in writing feedback processes outweigh the disadvantages.				1 2 3 4 5
Part 2 Perceived Ease of Use (PEOU)				
1. It is easy for me to use AWCF in revising English writing.				1 2 3 4 5
2. It is easy for me to learn to use tools concerning AWCF.				1 2 3 4 5
3. Use of AWCF paves the way for English writing feedback.				1 2 3 4 5
4. My interaction with AWCF in revising English composition processes has been clear and understandable.				1 2 3 4 5
5. Using AWCF enables me to have more accurate corrective writing feedback.				1 2 3 4 5
Part 3 Attitude Towards Use (AT)				
1. I think positively about using AWCF for correcting English essays.				1 2 3 4 5
2. Using AWCF for revising English writing is a wise idea.				1 2 3 4 5
3. AWCF tools are worth to use within the English writing process.				1 2 3 4 5
4. I plan on using AWCF for writing revision processes on a regular basis in the future.				1 2 3 4 5
5. Using AWCF within the writing revision process is pleasant.				1 2 3 4 5
Part 4 Behavioral Intention to Use (BI)				
1. I intend to use AWCF regularly during English writing tasks.				1 2 3 4 5
2. I intend to frequently use AWCF for revising English essays.				1 2 3 4 5
3. Assuming I have access to AWCF for revising English essays, I intend to adopt it.				1 2 3 4 5
4. Given that I have access to AWCF for revising English essays, I predict that I would adopt it.				1 2 3 4 5