Mediating effect of ambiguity tolerance in automated writing evaluation research model

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ABSTRACT

In light of the advancement of generative artificial intelligence (GenAI) technology-empowered automated writing evaluation (AWE) system represents a revolutionary paradigm at the forefront of mobile assisted English learning (MAEL). Numerous empirical studies have been carried out to test the efficacy of automated writing corrective feedback in writing assistance. However, it has seldom been investigated from the cognitive stance of AWE technology enhanced embodied learning. Embodied cognitive linguistics intensifies that learning experience is enhanced in the process of conceptualizing the empirical world. Therefore, the current study explores technology characteristics and individual characteristics incorporating the psychological construct of ambiguity tolerance. Emanating from psychology, ambiguity tolerance describes people's preponderance to manage uncertainties and unpredictable challenges in the learning process. This study utilized the partial least square structural equation modeling (PLS-SEM) method to analyze 679 valid questionnaire responses via SPSS 29 and SmartPLS 4. The results elucidated that the AWE research model incorporating the technology acceptance model (TAM model), task technology fit model (TTF model), and individual characteristics could predict the user's adoption of AWE software in the completion of writing tasks. Moreover, ambiguity tolerance functions as an effective mediator in the GenAI technology-empowered automated writing evaluation research model. This study provides technical implications for AWE developers to design AWE software suitable for individual characteristics. Future research could combine qualitative research methods with multivariant statistical approaches to meticulously investigate the interaction of literacy cultivation and emotional intelligence in the utilization of AWE technology for academic purposes in the GenAI era.

Keywords: *Generative artificial intelligence, Ambiguity tolerance, Automated writing evaluation, Mobile assisted English learning, Partial least square structural equation modeling, Technology acceptance model, Task technology fit model, Individual characteristics.*

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Highlights of this paper

- The structural equation modeling investigation shows that personality trait ambiguity tolerance serves as an effective mediator in automated writing evaluation research model.
- AWE technology enhanced embodied learning has offered us deeper insights into writing literacy cultivation in language education.
- Questionnaire back-translation method is utilized to mitigate common method bias and enhance accuracy, precision, reliability, and validity.

1. INTRODUCTION

Section 1 introduces the research background, previous studies on ambiguity tolerance and the AWE platform, knowledge gaps, significance, research purposes, and research questions of this study.

1.1. An Introduction to Research Background

With evolving technology progressing with leaps and bounds in pedagogical areas, the application of GenAI-empowered automated writing evaluation (AWE) tools in writing practices is groundbreaking (Brown, Liu, & Norouzian, 2023). The voyage of learning a second language or a foreign language is a complex procedure that is composed of multifaceted and multimodal components, in meanwhile, several psychological and cognitive factors play an indispensable part in language education (Baumann & Eiroa-Orosa, 2016; Nunes, Cordeiro, Limpo, & Castro, 2022). The new era of Artificial Intelligence Generated Content (AIGC) has added technological elements to language education and literacy cultivation, which creates more intensive, immersive, and impressive learning environments (Divekar* et al., 2022; Grant & Metz, 2022). GenAI-empowered AWE technology is subsumed to AIGC which refers to new content generated by artificial intelligence to complement the traditional content approaches to provide writing corrective feedback (Grant & Metz, 2022). Writing literacy is a basic literacy to accommodate in modern society which has received global recognition (Nunes et al., 2022). Writing is of paramount importance in emotion regulation, feeling expression, post-traumatic stress healing, note-taking, knowledge retrospect and daily record in educational settings of daily lives (Graham, 2018; Nunes et al., 2022). Given that writing literacy constitutes a fundamental basic skill in cultivating K12 literacy, researchers and scholars have garnered escalating interest in the efficacy of AWE tools on writing proficiency in the GenAI-dominant age (Carless & Boud, 2018; Nunes et al., 2022).

1.2. Previous Studies on AWE and Ambiguity Tolerance

A vast body of literature has investigated the effectiveness of AWE platform encompassing systematic reviews, bibliometric analyses, statistical analyses, empirical studies, qualitative and quantitative studies. Shadiev and Feng (2023) comprehensively reviewed 43 automated corrective feedback tools and posited positive influence on writing literacy cultivation in language learning. Nunes et al. (2022) systematically reviewed the effective instructional AWE programs application among Grades 1–12 and the users' perception of AWE systems. AWE software can function as an effective replacement for human raters in the assistance of writing calibration, evaluation, correction, refinement, and polish (Nunes et al., 2022). AWE technology provides correction suggestions and recommendations according to individual mistakes encountered in real-time writing practice with decreased human effort expenditure (Brown et al., 2023; Ranalli, 2021). It is worth noting that the AWE software platform provides instant and individualized synchronous corrective feedback differentiated with users. The notable benefits of higher level of ambiguity tolerance exist in ambiguity tolerance degree also differentiated among different language users with several influential factors such as self-efficacy (Endres, Chowdhury, & Milner, 2009) motivation (Lowe, 2020) multilingualism (Dewaele & Li, 2013; Jean-Marc Dewaele & Wei, 2014) engagement (Chu, Lin, Chen, Tsai, & Wang, 2015; Yu, Wang, & Xia, 2022) and learning outcomes (Chu et al., 2015; Yu et al., 2022).

Moreover, educators and practitioners attach importance to catering to students' psychological conditions and cultivating personality traits. Psychologists also attach importance to personality traits and psychological well-being. The higher-order personality traits have received assiduous research attention. In psychology, the Big Five personality traits refer to five dimensions that are utilized to delineate peculiarities of personality (Costa & McCrae, 1992). The Big Five personality model encompassing openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism constitutes the higher-order personality traits (OCEAN, (Marengo, Davis, Gradwohl, & Montag, 2021; Montag & Panksepp, 2017)). While scant attention has been paid to lower-order personality traits such as ambiguity tolerance (Budner, 1962; Furnham & Ribchester, 1995; Wei & Hu, 2019). It is noteworthy that lower-order personality traits also exert a positive influence on language learning achievements. Psychological capital is a conclusive term including self-efficacy, grit, resilience, and optimistic attitudes which is also referred to as a positive psychological condition. A particular function of psychological capital is to reduce the detrimental influence of ambiguity intolerance due to cultural shock or other sociocultural circumstances (Baumann & Eiroa-Orosa, 2016; Budner, 1962; Furnham & Ribchester, 1995). These qualities are helpful for learners to cultivate resilience and maintain mental well-being so as to achieve satisfactory writing proficiency and language learning outcomes (Baumann & Eiroa-Orosa, 2016; Ranalli, 2021).

1.3. Knowledge Gaps and Significance of this Study

Although multiple factors moderate the effectiveness of AWE technology in the promotion of writing proficiency, the mediation effect of the psychological construct ambiguity tolerance in using AWE tools has barely been investigated. Following this line, the current study is carried out to complement this missing link and probe into the efficacy of ambiguity tolerance in determining writing proficiency, attitudes, and continuance intention to use AWE technology to enhance the writing experience. The major knowledge gaps that remain in the AWE relevant studies are that insufficient studies investigate the efficacy of nuanced psychological and cognitive factors that determine the adoption of AWE technology in writing enhancement in language education. It is thus meaningful to delve deeper into the role of the individually different psychological construct ambiguity tolerance in the adoption of AWE technology. However, in the context of AWE technology-facilitated writing practice, ambiguity tolerance has not yet been investigated as a mediator in the relationship between technology characteristics, individual characteristics, and task technology fit. Accordingly, we assume that by adding ambiguity tolerance, we can thoroughly comprehend the individualized psychological construct as an effective mediator influencing the attitude and ensuing intention to use AWE technology.

1.4. Research Purposes and Questions

From the perspective of cognitive linguistics and psycholinguistics, a vast body of literature has investigated the interactive effects of learning engagement, learning motivation, self-efficacy, and ambiguity tolerance on learning effectiveness (Dewaele & Li, 2013; Endres et al., 2009; Lowe, 2020). The existing empirical evidence showed that these variables work together to strengthen learning outcomes. AWE platforms provide verbatim calibration for users who have the necessity to write English articles. Students, scholars, journalists, and academic research fellows are the potential users and broader audience of the AWE platform. Users hold positive attitudes toward the broader ubiquity and individualized help provided by the AWE platform. Since the contention positive mediator of ambiguity tolerance is validated, this study aims to provide implications for educators and practitioners to strengthen AT levels in the cultivation of writing literacy.

The current study aims to investigate the mediating effect of ambiguity tolerance on writing proficiency, attitude, and continuance intention to use AWE tools to facilitate writing. Based on the prominent task technology fit model (TTF model), and technology acceptance model (TAM model), the current study utilized the partial least square structural equation modeling (PLS-SEM) approach to calculate parameters in the proposed AWE research model (see Figure 1). We proposed the hybrid research model with an integration of the TTF model for AWE technology utility and the TAM model for the attitudes toward continuance intention to use AWE technology. Complementing these theoretical preliminaries, the model adds psychological constructs and other determinants, including ambiguity tolerance (AT), writing engagement, writing motivation, automated written corrective feedback (AWCF), AWE self-efficacy, and writing proficiency. This empirical study aims to answer three research questions.

RQ1: What are the constructs within the GenAI-empowered AWE research model?

RQ2: How about the specific predictive power of the current AWE research model?

RQ3: Can ambiguity tolerance function as an effective mediator in the AWE research model at a statistically significant level?

2. THEORETICAL PREMISES

This section provides theoretical preliminaries and statistical evidence for the composition of the theoretical constructs in the AWE research model.

2.1. Theoretical Framework Supporting the AWE Research Model

The design philosophy of generative artificial intelligence empowered AWE research model is rooted in Vygotskian sociocultural theory which suggests that human cognition involves mediated social interactions and the learning process is closely connected with the context (Vygotsky & Cole, 1978; Wertsch, 1989). Mediation is recognized as a decisive construct in sociocultural theory (Lantolf & Thorne, 2006; Lantolf, Xi, & Minakova, 2021). The sociocultural theory perspective views language as a multimodal and coherent interaction. Tracing back to the Vygotskian theory of social origins of indirect (mediated) memory, the psychological factor serves as a mediator in the learning process (Vygotsky & Cole, 1978). From the embodied cognitive stance, AWE technology enhanced embodied learning theory elicits actual use of the AWE platform in the improvement of EFL writing tasks (Schilhab & Groth, 2024). Embracing the ubiquity of generative artificial intelligence-empowered automated writing evaluation tools, it is imperative to explore the mediating effect of ambiguity tolerance within the AWE model. Therefore, we add the psychological construct ambiguity tolerance as a latent variable in the AWE research model to explore its direct and indirect effects on writing proficiency, attitude towards AWE, and continuance intention to use AWE technology (see Figure 1). Figure 1 The theoretical construct of the AWE research model is funded on the incorporation of TTF model, individual characteristics, the potential mediator ambiguity tolerance, and the TAM model.

2.2. Statistical Evidence for AWE Research Model Composition

It is instructive to administrate factor analysis on IBM SPSS Statistics 29 to provide statistical evidence for the integration of theoretical models as an AWE research model. As is shown in Figure 2 The scree plot, there are a totally of 40 components in accordance with the 40-item questionnaire. The eigenvalue drops sharply and became horizontal at component number three, so the third point is the cut-off point. It is equivalent to the three components in the component matrix (Çokluk, Şekercioğlu, & Büyüköztürk, 2021). From a statistical standpoint, this translates to the 40 components can be subsumed into three categories (Reijer, Otter, & Jacobs, 2024). Correspondingly, our research model is composed of three subsections, that is, task technology fit model (TTF model), individual characteristics, and technology acceptance model (TAM model). As is shown in Figure 1 Theoretical constructs of the AWE research model, the psychological construct ambiguity tolerance serves as a mediator in connecting the TTF model, individual characteristics, and TAM model. Ambiguity tolerance associated with the constructs of the TTF model and individual characteristics with writing proficiency, attitude towards AWE, and continuance intention to use AWE software.

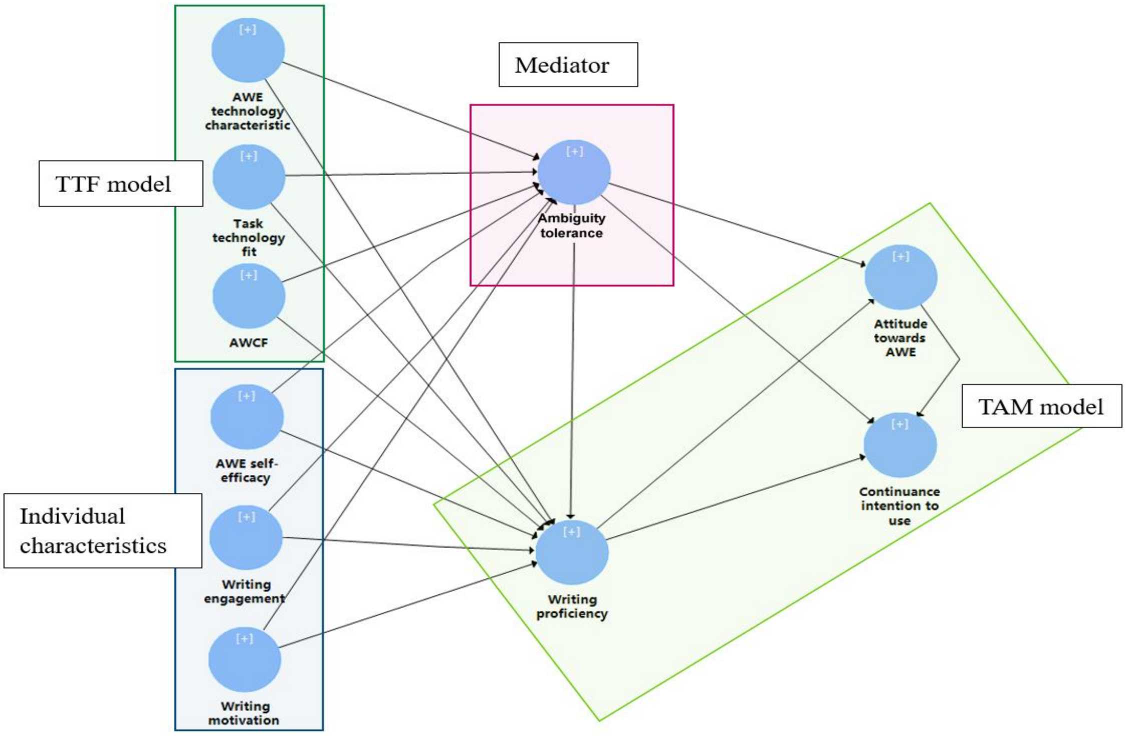

Figure 1. Theoretical constructs of the AWE research model.

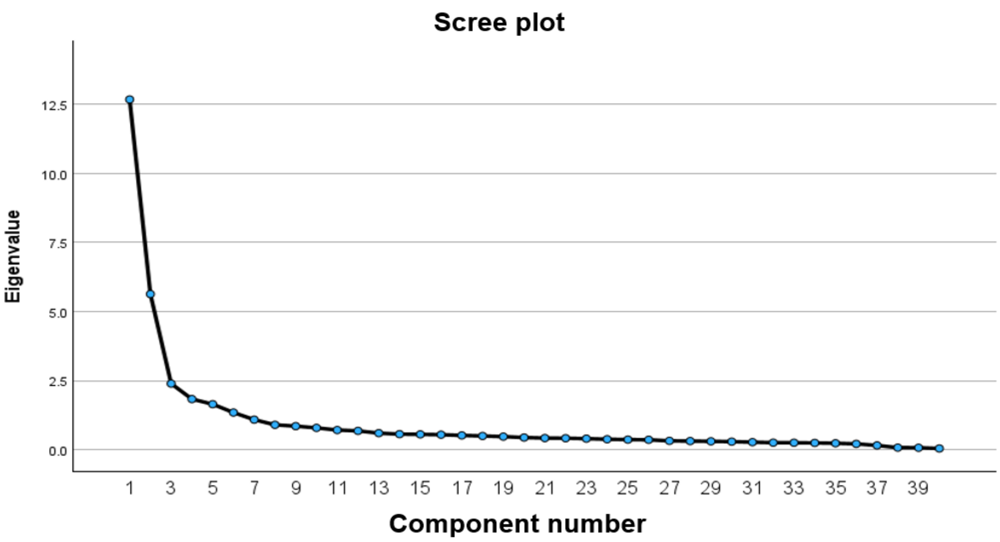

Figure 2. The scree plot.

3. LITERATURE REVIEW

Section 3 provides theoretical evidence in previous studies for the connection between the constructs in the research model. Specifically, we refer to literature on the positive influence of individual characteristics and task technology fit model (TTF model) on ambiguity tolerance, and the mediating effect of ambiguity tolerance on the relationship between individual characteristics, TTF model, and technology acceptance model (TAM model). Research hypotheses are thus proposed based on theoretical evidence from former studies.

3.1. Ambiguity Tolerance as the Proposed Mediator

Users' psychological factors are of paramount importance in their perception and adoption of AWE (Ding & Zou, 2024). Emanating from psychology, ambiguity tolerance is conceived as language learners' capability to adapt to uncertainties and unpredictable circumstances encountered in the learning process without feeling disappointed and uncomfortable (Furnham & Marks, 2013; Furnham, Richards, & Paulhus, 2013). Ambiguity tolerance was first proposed by Frenkel-Brunswik (1949) as an individual difference (ID) variable. Since then, many scholars have shared their definitions from multiple perspectives and gauged the concepts of ambiguity tolerance with numerous ambiguity tolerance scales (Budner, 1962; Furnham & Ribchester, 1995). Ambiguity tolerance is defined as a predisposition to receive ambiguous occasions relatively agreeable and preferable (Budner, 1962). Herman, Stevens, Bird, Mendenhall, and Oddou (2010) redefined ambiguity tolerance and reiterated AT measurement. Ambiguity tolerance, frequently referred to as tolerance of ambiguity or uncertainty tolerance, is deemed an indispensable psychological construct in cross-cultural communication and multilingual and multicultural learning environments (Dewaele & Li, 2013; Van Compernolle, 2016). The emblematic features of ambiguity-tolerant people are motivated to try new things and actively involved in the learning task (Kamran & Maftoon, 2012). Paralkar and Knutson (2023) corroborated that ambiguity tolerance plays a vital role in managing academic pressure and positively influencing academic learning outcomes. Ambiguity tolerance is a reflection of knowledge and information receiving and accessing processes in which attributes are personally different (McLain, Kefallonitis, & Armani, 2015). Ambiguity tolerance constitutes a major component of the positive psychological constructs (Dewaele & Li, 2013; Van Compernolle, 2016). Chen (2023) demonstrated that ambiguity tolerance mediates learner autonomy and learning achievement in EFL education. AT is demonstrated to be relevant with the indicator of age, elder citizens tend to possess the wisdom of life and a higher level of ambiguity tolerance, albeit, without achieving a statistically significant result (Dewaele & Li, 2013; Van Compernolle, 2016). Moreover, AT is positively relevant to multilingualism, AT level is strongly pertinent to the proficiency level of a second or third language (Dörnyei & Ryan, 2015; Rubin, 1975; Van Compernolle, 2017; Wei & Hu, 2019).

Many scholars have investigated and developed the benchmark of the ambiguity tolerance assessment scale (Budner, 1962; Furnham & Ribchester, 1995; Herman et al., 2010). The current study aims to delve deeper into the psychological and cognitive factors influencing the actual use of AWE tools. Considering the active influence of positive psychology in the pedagogical sphere, it is imperative to explore the educational meaning of ambiguity tolerance in the perception and adoption of the AWE platform. Enlighted by Jiang, Yang, and Zheng (2023) study which has corroborated the moderation effect of ambiguity tolerance on the influence of conversational cues on social presence in the application of chatbots for pedagogical purposes. In regard to the active role of ambiguity tolerance in education, the current study took ambiguity tolerance as a decisive mediator in the proposed AWE research model to meticulously investigate its role in employing AWE software to promote writing. Considering the effective role of ambiguity tolerance in cross-cultural language education contexts and personality trait cultivation, it is meaningful to explore ambiguity tolerance as a mediator in AWE-facilitated writing proficiency.

The construct of ambiguity tolerance in the current AWE research model is built based on former studies of its role in the adoption of artificial intelligence chatbots (Jiang et al., 2023). Ambiguity tolerance is supposed to function as a mediator in the proposed AWE research model. The manifest variables of ambiguity tolerance are adapted from AT scales in previous studies (Budner, 1962; Jiang et al., 2023).

Ambiguity tolerance (Budner, 1962; Jiang et al., 2023).

AT1: When I am using AWE software, I am not bothered by the situation when the generated feedback is unclear.

AT2: When I am using AWE software, I prefer to deal with complex problems rather than simple ones.

AT3: When I am using AWE software, I don't avoid issues where there seems to be more than one best solution.

AT4: It never bothers me that even when the automated corrective feedback is hard to understand.

3.2. Task Technology Fit Model (TTF Model)

The TTF model is initially proposed by Goodhue and Thompson (1995). The current study incorporates AWE technology features into the TTF model which is designated with automated writing corrective feedback (AWCF), AWE technology characteristics, and task technology fit as latent variables. TTF model postulates that AWE technology characteristics constitute an important construct in the TTF model.

3.2.1. AWE Technology Characteristics

AWE systems are designed as computer programs or plug-ins in Microsoft Word. The mainstream of the AWE functions can be divided into two branches, i.e., automated correction and automated evaluation (Ding & Zou, 2024). Featured with synchronous corrective feedback, AWE technology is attracting assiduous attention from educators and students. Framed under the theoretical preliminaries of writing feedback literacy (Dong, Gao, & Schunn, 2023; Hyland & Hyland, 2019) social interaction theory (Mead, 1934) and sociocultural theory (Vygotsky & Cole, 1978) AWE technology characteristics incorporate providing synchronous computer-mediated corrective feedback (SCMC). AWE technology is a useful tool and a powerful replacement for human raters with the assistance of English article writing (Almusharraf & Alotaibi, 2023). AWE technology characteristics encompass the function of grammar checkers (Ranalli, 2021) accuracy assurance, users' writing proficiency development, facilitating users' confidence, and attracting continuance intention to use the AWE platform in future endeavors. The manifest variables of AWE technology characteristics are adapted from previous studies (Ke, Sun, & Yang, 2012; Pituch & Lee, 2006; Zhai & Ma, 2022).

AWE technology characteristics Ke et al. (2012); Pituch and Lee (2006) and Zhai and Ma (2022).

ATC1: AWE provides synchronous computer-mediated corrective feedback.

ATC2: AWE offers authentic corrective recommendations.

ATC3: AWE helps to facilitate my EFL writing with multiple merits.

ATC4: AWE provides effective corrective feedback across the boundaries of time and space.

3.2.2. Automated Writing Corrective Feedback (AWCF)

Automated writing corrective feedback (AWCF) is operationally conceptualized as specific synchronous corrective feedback from a micro-level, including spelling, collocation, and punctuation which is provided by the AWE platform (Roscoe, Wilson, Johnson, & Mayra, 2017). Writing assessment literacy, as a subconstruct of feedback literacy, is the theoretical preliminary of AWCF (Carless & Boud, 2018). As feedback constitutes a vital component of writing assessment, AWCF offers constructive, instant, and thorough corrective feedback, liberating human raters from the calibration mundane (Wilson & Czik, 2016; Woodworth & Barkaoui, 2020). AWE system is designed with GenAI, latent semantic analysis, machine learning (ML) and natural language processing (NLP) algorithms, and big data model (Wilson & Roscoe, 2020). The three most popular AWE tools such as Grammarly, Pigai, and Criterion are used didactically to provide authentic automated writing corrective feedback (AWCF) concerning recommended corrections of various erroneous forms of linguistic errors, structural, and semantic compositions (Sanosi, 2022). With the widespread proliferation of generative artificial intelligence, synchronous feedback is automatically generated through AWE software so as to provide timely and individualized writing corrective hints (Nunes et al., 2022). Equipped with predetermined knowledge, AWE computer systems provide comprehensive and authentic corrective suggestions compared with teacher feedback or peer feedback. AWE systems provide comprehensive corrective feedback at a textual level concerning mechanic, stylistic, structural, organizational, and content issues (Moore & MacArthur, 2016). AWE system serves as a useful tool in providing seamless, expeditious, convenient, and convincing correction suggestions. To gauge the efficacy of AWCF, the manifest variables of AWCF technology characteristics are adapted from previous studies.

AWCF Zhai and Ma (2022) and Li et al. (2019).

AWCF1: AWE software provides instant calibration.

AWCF2: AWE software provides timely calibration of the spelling.

AWCF3: AWE software provides timely calibration on the grammar use.

AWCF4: AWE software provides timely calibration of the coherence.

3.2.3. Task Technology Fit

The task technology fit model attaches importance to the specific technological characteristics to meet the specific demands of individual needs (Goodhue & Thompson, 1995)). Catering to the proposed AWE research model, task refers to the writing assignment. Technology refers to the AWE platform to facilitate GenAI enhanced writing experience. TTF model incorporates AWE technology could meet the individual need of fulfilling writing tasks with satisfactory results of enhanced writing proficiency (Almusawi & Durugbo, 2024; Dahri, Yahaya, Al-Rahmi, Almogren, & Vighio, 2024; Goodhue, 1995; Goodhue & Thompson, 1995). In the proposed AWE research model, a writing task is precisely referred to as a series of actions in the completion of a writing assignment. To delve into the efficacy of the manifest variables of task technology fit are adapted from previous studies.

Task technology fit adapted from Isaac, Aldholay, Abdullah, and Ramayah (2019); (Li et al., 2019);

TTF1: The AWE platform is fit for the requirements of my writing.

TTF2: The AWE platform is suitable for helping me complete writing assignments.

TTF3: The AWE platform is helpful in the assistance of hard writing assignments.

TTF4: The AWE platform is necessary for the completion of my writing assignment.

3.3. Individual Characteristics

Apart from technology characteristics, individual characteristics are vital components in the AWE research model which includes AWE self-efficacy, writing engagement, and writing motivation.

3.3.1. AWE Self-Efficacy

AWE self-efficacy, a subconstruct of computer self-efficacy, is conceived as an individual's appraisal, confidence, and evaluation of their capability to finish writing assignments with the aid of the AWE platform (Bruning &

Kauffman, 2016; Dahri et al., 2024; Zhai & Ma, 2022). Higher AWE self-efficacy individuals tend to hold a positive attitude toward the perceived usefulness and ease of use of AWE (Han & Shin, 2016; Li et al., 2019; Zhai & Ma, 2022). AWE self-efficacy measurement is adapted from the 22-item Self-Efficacy for Writing Scale (SEWS; Bruning, Dempsey, Kauffman, McKim, and Zumbrunn (2013)). Educators recognized the usability, efficiency, and desirability of AWE systems, they supported using AWE tools to strengthen students' writing self-efficacy (Wilson & Czik, 2016). AWE self-efficacy might facilitate writing proficiency and attitudes toward the continuance intention to use AWE tools. To further investigate the efficacy of AWE self-efficacy, the manifest variables of AWE self-efficacy are adapted from previous studies (Compeau & Higgins, 1995; Terzis & Economides, 2011).

AWE self-efficacy adapted from Compeau and Higgins (1995) and Terzis and Economides (2011).

ASE1: I could complete a writing task using AWE if someone showed me how to do it first.

ASE2: I could complete a writing task using AWE if I could call someone for help if I got stuck.

ASE3: I could complete a writing task using AWE if I had only the software manuals for reference.

ASE4: I could complete a writing task using AWE if there was no one around to tell me what to do as I go.

3.3.2. Writing Engagement

Fredricks, Blumenfeld, and Paris (2004) proposed the tripartite constructs of engagement encompassing affective, behavioral, and cognitive engagement. Ellis (2009) escalated the student engagement in receiving written corrective feedback. In light of previous research, writing engagement in GenAI-empowered AWE-facilitated writing practice is described as the degree of involvement with the software in the completion of writing assignments, a feeling of entertainment and concentration (Pelet, Ettis, & Cowart, 2017). Students with high writing engagement are prone to be absorbed in AWE-assisted writing tasks which leads to a higher level of writing proficiency (Ranalli, 2021). AWE system serves as a vibrant mechanism to furnish writing practice by adding correction and polishing, which improves and develops the cultivation of writing literacy (Ellis, 2009; Hyland & Hyland, 2019). The AWE system is a powerful tool that works better than human raters in providing effective feedback on students' writing assignments. There is an enhanced writing engagement acknowledged by AWE platform users, the synchronous feedback enhances their immersion and devotion in the writing task completion (Nunes et al., 2022; Palermo & Thomson, 2018). To further explore the efficacy of AWE self-efficacy, the manifest variables of AWE self-efficacy are adapted from previous study (Parsons et al., 2023).

Writing engagement adapted from Parsons et al. (2023).

WENG1: When working on the writing assignment, I was interested in what I was writing.

WENG2: When working on the writing assignment, I felt good.

WENG3: I kept trying on writing assignments even if it was difficult.

WENG4: When working on the writing assignment, I thought carefully about the words I used.

3.3.3. Writing Motivation

Emanating from psychology, writing motivation is conceptualized as a psychological construct determining students' preference, passion, and participation in second language writing tasks. Since writing comprises an essential content of language education, the L2 writing process is conceived as a complicated activity that requires cognitive engagement and problem-solving skills. Wring motivation also catalyzes for students to accomplish their writing tasks in the language learning process. Writing motivation, a subconstruct of learning motivation, is defined as the inner power or internal drive to participate in the GenAI AWE-facilitated writing assignment (Wilson & Czik, 2016). Writing motivation and AWE technological characteristics exert a mutual influence, and these factors work together to cultivate individuals' writing literacy (Wilson & Czik, 2016). Individuals with a higher level of writing motivation have more propensity to use AWE tools to promote writing proficiency and polish the language (Wilson & Roscoe, 2020). It is deemed an indispensable property in individuals' willingness to use GenAI AWE tools. GenAI AWE tools motivate students, which affects writing performance and positive attitudes toward the use of technology to assist writing practice (Wilson & Roscoe, 2020). Social network sites have been corroborated to be a vital component of the attitudes toward continuance intention to use the AWE system because important, intimate, or reliable people (for example, a respectable teacher) use the technology, students are prone to follow their teacher's behavior (Roscoe et al., 2017). There is an escalating motivation acknowledged by AWE system users that automated writing corrective feedback provided by AWE platform helps to boost their confidence and motivation in the revision and reorganization of writing assignments (Nunes et al., 2022; Palermo & Thomson, 2018).

To further delve into the efficacy of writing motivation, the manifest variables of writing motivation are adapted from previous study (Steve Graham et al., 2023).

Writing motivation adapted from Steve Graham et al. (2023).

WMOT1: I like working on writing assignments with a computer.

WMOT2: I am eager to accomplish each writing assignment with a computer.

WMOT3: I enjoy the process of typing on a computer to finish a writing assignment.

WMOT4: I enjoy the completion of a writing assignment with a computer.

3.4. Technology Acceptance Model (TAM Model)

The TAM model was initially postulated by Davis (1989) built on the theory of reasoned action (TRA; Icek Ajzen and Fishbein (1973)) and theory of planned behavior (TPB; Ajzen (1985)) the TAM model has been adapted to fit various types of technology and is designed to foresee the actual use of a particular technology. There are newly emerged and updated versions of TAM model. To put it more specific, technology acceptance model 2 (TAM2; Venkatesh and Davis (2000)) technology acceptance model 3 (TAM3; Venkatesh and Bala (2008)) and the unified theory of acceptance and use of technology (UTAUT; Venkatesh, Morris, Davis, and Davis (2003)). From a cognitive stance, the current AWE research model incorporates writing proficiency, attitude, and continuance intention to use the AWE system to facilitate writing proficiency. Continuance intention to use or behavioral intention to use describes users' willingness to adopt AWE technology to facilitate writing in future practices. Despite the multiple adapted TAM versions, continuance intention to use is decided by three core variables: usefulness, ease of use, and attitude towards use (Davis, 1989). Technology resistance, a concept contrary to technology acceptance, is defined as a user's unwillingness towards the application of a technology. Technology resistance theory posits the negative effect wrought by technology. Although multiple TAM-based empirical studies have been carried out to test the efficacy of a specific technology, the inconsistent findings come from different sample sizes, research model designs, moderating variables, and various path coefficients. The manifest variables of behavioral intention to use and attitudes toward AWE are adapted from previous studies (Ke et al., 2012; Lee, Yoon, & Lee, 2009).

Behavioral intention to use (Lee et al. (2009).

BITU1: I intend to use AWE software to facilitate my writing in the future.

BITU2: I want to recommend AWE software to facilitate my writing.

BITU3: I expect my use of AWE software to continue in the future.

BITU4: I think AWE software should be implemented in my writing.

Attitudes toward AWE (Ke et al., 2012).

ATT1: I like using AWE software to help me facilitate the writing.

ATT2: I have a generally favorable attitude towards using AWE software.

ATT3: I believe it is a good idea to use AWE software to help me correct my writing mistakes.

ATT4: I prefer to use AWE software to enhance my writing.

3.5. Writing Proficiency

Writing proficiency is conceived as a decisive indicator in measuring the quality of the article in boosting L2 writing literacy. In the AWE research model, writing proficiency is measured through a questionnaire based on the self-defined measurement scales in the current empirical study. Writing proficiency is measured by improved linguistic expression, cohesiveness, accuracy, and professional expression. Writing proficiency is proven to be moderated by a series of factors, including the AWE technology characteristic, individuals' psychological construct, and personality traits. Users' attitudes toward AWE systems play a vital role in the actual use of AWE. AWE self-efficacy, motivation, and engagement are classified as individual factors. AWCF, task technology fit, and technology characteristics are grouped as the TTF model. Implementation of automated writing corrective feedback can facilitate writing proficiency in boost writing literacy (Molloy, Boud, & Henderson, 2020). GenAI-empowered AWE tools provide instant and spontaneous feedback from multiple perspectives concerning spelling, grammatical, and syntactic corrections (Rad, Alipour, & Jafarpour, 2023). AWE system provides individually characterized and learner-specific feedback based on personalized language proficiency levels (Ai, 2017). The current study chose the "self-report writing proficiency scale" to measure different writing proficiency levels. This research reorganized the items and selected four items. The four questionnaire items are measured via a 5-point Likert scale.

Writing proficiency (Bruning et al., 2013; Sun, Wang, & Kim, 2022).

WP1: I can think of appropriate words to describe my ideas with the assistance of AWE technology.

WP2: I can cohesively write a paragraph with the assistance of AWE technology.

WP3: I can write a passage with proper grammatical structures with the assistance of AWE technology.

WP4: I make improvements in writing with the assistance of AWE technology.

4. RESEARCH METHODOLOGY

Section 4 delineated the research design, prior estimation of sample sizes demographic data of participants, statistical approaches, and SEM method.

4.1. Prior Estimation of Sample Sizes

G*Power software is endowed with the computation power for prior estimation of sample sizes required based on a number of predictors. Since in the SEM models, there are mainly regression relations between constructs. We administrated an estimation of sample size utilizing the recommended F-test and regression analysis on G*Power 3.1 software based on the total number of predictors (see Figure 3). When determining sample size, the program should be configured for the F tests as a test family, linear multiple regression as a statistical test, and compute the required sample size as a type of 'A prior' power analysis. In the current study, the number of predictors (independent variables) is 9. Then sample sizes are generated, the estimated total sample size for the current study is 114. From a statistical standpoint, this means 114 is an eligible sample size for the current study. In the actual data collection process, we acquired 679 effective and eligible questionnaires. 679 is deemed as a good sample size which has surpassed the threshold of the prior estimation of 114.

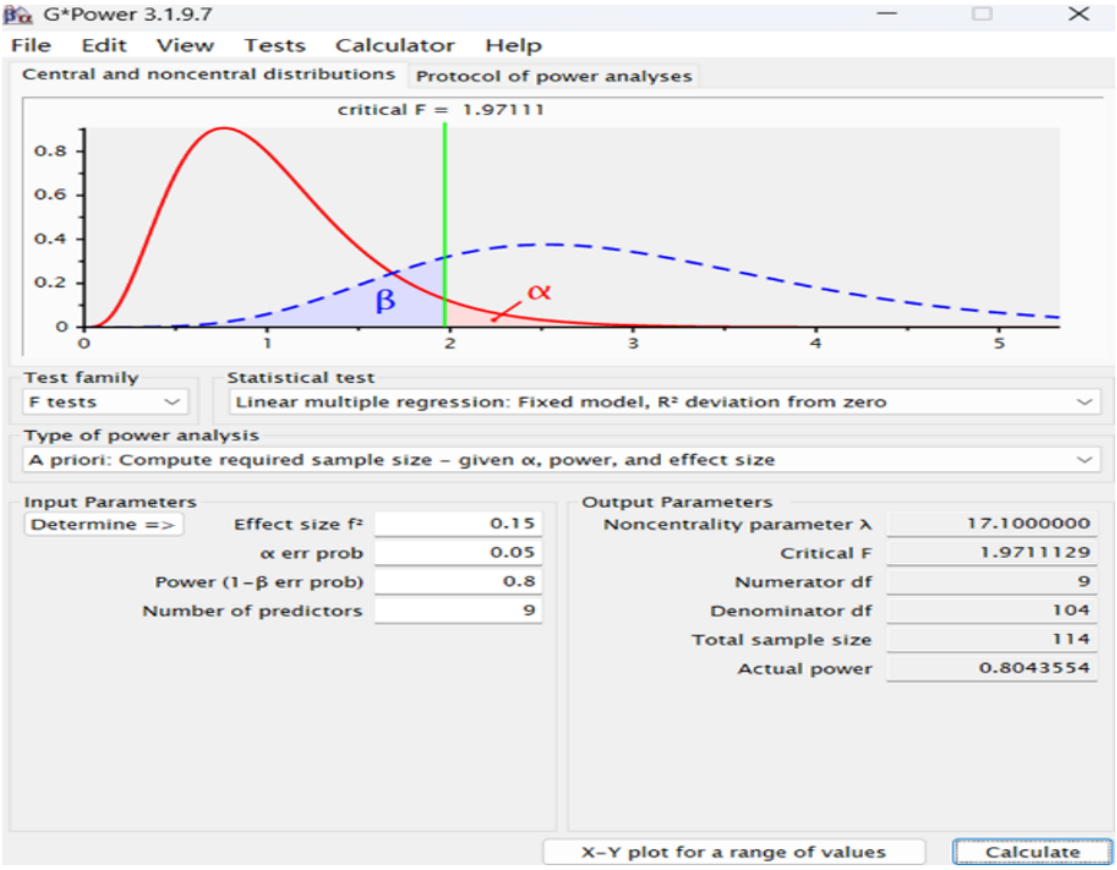

Figure 3. Prior estimation of sample sizes on G*power.

Note: Here * is taken as a component part for the holistic name of the statistical software G*power.

4.2. Quantitative Survey Data Collection

The questionnaire is designed with forward and backward translation methods to avoid ambiguous expressions due to cultural differences (Rad et al., 2023). Five earnest, stringent, and assiduous scholars were invited to check the design and original references of the questions and reached an agreement on the final affirmation of the questionnaire. The current research is obliged to follow the research protocols and the academic regulations. The researchers disseminate paper questionnaires during the breaks from November 1, 2023 to January 1, 2024. The research claimed that the respondents' data is confidential and only used for academic research purposes. The questionnaire is composed of two sections. The first section includes the selection of willingness to fill out the questionnaire and participate in the survey, and participants' information of gender, age, major, and educational level. The second section consists of 40 items (observed variables) to measure 10 latent variables in the AWE research model: ATC, TTF, AWCF, ASE, WENG, WMOT, AT, WP, ATT, and CITU. The 40 items of observable variables are measured by five-point Likert scales, anchored on "1 strongly disagree" and "5 strongly agree".

The demographic data of participants is precisely tabulated in Table 1. According to the consent question, 679 students agreed to participate in the survey, and 121 students were unwilling to participate. There is almost an even distribution in the genders. Participants were predominantly undergraduates, with a medium number of masters, and a small number of Ph.Ds. A majority of the participants majored in Arts and Humanities, Science, and Engineering, and a minority of the population majored in Agriculture and Medicine. The research design fits multiple majors since students have to write English articles for academic purposes.

Table 1. The demographic characteristics of participants.

Item	Genre	Frequency	Proportion
Willingness to participate	Yes	679	84.9%
Valid responses (N=679)	No	121	15.1%
Gender	Female	336	49.5%
	Male	343	50.5%
Educational levels	Undergraduates	430	63.3%
	Master's degree	213	31.4%
	Ph.D	36	5.3%
Major	Arts and humanities	502	73.9%
	Science	102	15.0%
	Engineering	58	8.5%
	Agriculture	11	1.6%
	Medicine	6	0.9%

4.3. Modeling and Data Analysis

The researchers conducted the normality test on Statistical Package for the Social Sciences program (IBM SPSS Statistics 29) for the skewness and kurtosis of each construct which is essential and fundamental for the higher-order statistical analysis under the guideline of Kline (2023). If the values are within the limits, the statistical data is displayed with normal distribution. After the precise normality estimation procedure "analyze-descriptive statistics-descriptives" via SPSS 29, the study items are reported with a satisfactory normal distribution. This research utilized the second-generation statistical method PLS-SEM to test research hypotheses. Evidence from the P-P Plot and QQ Plot suggests that the research data comprehensively meets the requirements of normal distribution.

4.4. The Rationales for PLS-SEM

Partial least square structural equation modeling (PLS-SEM) is the second-generation statistics. PLS outperforms covariance-based structural equation modeling (CB-SEM) and other forms of SEM for the following reasons. First, the latent construct can be measured by one item, however, at least four items are required for one construct in CB-SEM. Second, since data collection is a random process in humanities and social sciences, data is often distributed non-normally. Ten-item scales are employed to reduce non-normal distribution. PLS does not require assumptions of normality distribution, and deals with non-normal data equally well. Third, PLS could precisely estimate interaction effects incorporating moderation (Bontis, Booker, & Serenko, 2007). Khan et al. (2019) comprehensively reviewed the main reasons for the popularity of PLS-SEM as methodological research. The current study chose SmartPLS software to conduct PLS calculation, bootstrapping, and PLS prediction (Ringle, Wende, & Becker, 2024). Structural equation modeling method can be administrated via multiple software, encompassing Amos, EQS, GSCA Pro, LISREL, Matlab, Mplus, Python package (Igolkina & Meshcheryakov, 2020) Simulink, SPSS, Stata, SmartPLS, and R packages sem (Hair et al., 2021) lavaan, OpenMx. Taken together the premise of ease of use and usefulness, the researchers chose SmartPLS to accomplish statistical analysis.

Implementing statistical functions, SmartPLS 4 is a popular software for calculating PLS-SEM algorithm, Bootstrapping, and PLSpredict indicators. PLS-SEM fits the condition of small sample sizes but multiple latent constructs (Fornell & Bookstein, 1982). Following Hair and Alamer (2022) research steps, we calculated the indicators of the measurement model and structural model respectively employing the PLS-SEM algorithm. We investigated the indirect effect, namely, mediation effects employing Bootstrapping function. Progressively, we assessed predictive power and explanatory power by employing the PLSpredict function.

4.5. Common Method Bias

When the research data was collected from participants from similar backgrounds, the model was perceived to be contaminated with common method bias (Kock, 2015, 2017). Since the researchers disseminated the questionnaires among students from similar educational backgrounds, that is, higher education. It is necessary to detect the underlying common method bias. The contamination of common method bias is severe when participants share a similar background. The researchers implemented a back-translation method and distributed the for participants to mitigate common method bias and enhance accuracy, precision, reliability, and validity (Cohen, Cohen, West, & Aiken, 2003; Trajković, 2008).

Harman Wold developed Harman's single-factor test to detect whether the model is contaminated with common method bias, which is the most commonly used method (Wold, 1980). Methodologically, researchers upload all the variables to administrate an exploratory factor analysis and confirmatory factor analysis (CFA) (Kock, Berbekova, & Assaf, 2021; Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Kock (2020) introduced that when AVE is higher than the threshold of 0.5, the dataset is discerned to be contaminated by common method bias. In other words, the administration of Harman's single-factor test could successfully detect common method bias in the research data.

According to the benchmark KMO value designated by Kaiser, the value of KMO > 0.9 is marvelous, > 0.8 is meritorious, > 0.7 is middling, > 0.6 is mediocre, > 0.5 is miserable, and < 0.5 is unacceptable (Hair, Hult, Ringle, & Sarstedt, 2022; Khan et al., 2019). Framed by this guideline, Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO value) of the current research data equals 0.915 which achieves a marvelous level. The significance value of our statistical data< 0.001 suggests that the statistical data included in our study do not generate a similar matrix, that is, differ to a large extent. Taken together with KMO and Bartlett's Test, the statistical data is in proxy multivariate normally distributed and fits for factor analysis.

5. RESULTS

Section 4 summarized the statistical results of PLS-SEM to examine the research hypotheses of the AWE research model.

5.1. RQ1 Measurement Model Assessment

Partial least square structural equation modeling (PLS-SEM) is the second generation of multivariate analysis. SmartPLS 4 is utilized to test the structural and measurement models. The measurement model was utilized to test the relationship between latent constructs and observed variables which are composed of reflective indicators in the proposed model. PLS-SEM examines the measurement model with indicators of loadings, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and Heterotrait-Monotrait (HTMT) ratio of correlation for the reflective model, while redundancy analysis, VIF, significance and relevance of the indicator weights for the formative model. Theoretically, collinearity statistics variance inflation factors (VIF) are utilized to evaluate multicollinearity. The ideal threshold of VIF is lower than 3 which suggests the absence of multicollinearity. Routinely, Cronbach's alpha values exceeding the threshold of 0.708 suggest good internal consistency, convergent validity and reliability.

In the reflective measurement model, the recommended internal consistency reliability ranges from 0.70-0.90 with Cronbach's alpha value as the lower bound and the composite reliability (CR) as the upper bound. The statistical data for the proposed AWE research model is precisely tabulated in Table 2. Cronbach's alpha value of ambiguity tolerance=0.871, attitude=0.826, continuance intention to use=0.869, writing engagement=0.861, writing motivation=0.880, automated written corrective feedback=0.775, AWE self-efficacy=0.871, AWE technology characteristics=0.883, task technology fit=0.848, writing proficiency=0.827. The composite reliability (CR) value of ambiguity tolerance=0.912, attitude=0.884, continuance intention to use=0.910, writing engagement=0.900, writing motivation=0.917, automated written corrective feedback=0.855, AWE self-efficacy=0.911, AWE technology characteristics=0.919, task technology fit=0.898, writing proficiency=0.885. Hence, reflective indicators corroborate the internal consistency reliability is eligible. In the assessment of the measurement model, the HTMT ratio of correlation is implemented to evaluate discriminant validity (see Table 3). Square root values of AVE displayed on the diagonal are higher than off-diagonal values (the correlation estimates) (Shahzad, Shahzad, Dilanchiev, & Irfan, 2022). The analysis results show that the comprehensive tested parameters reach a satisfactory level, the reliability and validity are consolidated.

There is a consistency in the value of factor loading, VIF, Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE). These values tend to report higher or lower values accordantly in the same vein. The overall internal consistency of the measurement scale for the research questionnaire items was administrated via SPSS 29 with Cronbach's alpha resulting in a high-reliability coefficient of 0.938. RQ1 the constructs within the Gen-empowered AWE research model is explicitly explained with theoretical preliminaries and statistical evidence well explained in this section through measurement model assessment.

Table 2. The assessment of the outer model.

Latent variable	Item	Factor loading	Outer VIF values	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
Ambiguity tolerance	AT1	0.798	1.848	0.871	0.912	0.723
	AT2	0.871	2.209			
	AT3	0.870	2.215			
	AT4	0.851	2.417			
Attitude	ATT1	0.872	2.515	0.826	0.884	0.657
	ATT2	0.871	2.425			
	ATT3	0.885	2.573			
	ATT4	0.767	1.616			
Continuance Intention to use	CITU1	0.837	2.157	0.869	0.910	0.718
	CITU2	0.857	2.356			
	CITU3	0.865	2.293			
	CITU4	0.882	2.498			
Writing engagement	WENG1	0.792	1.758	0.861	0.900	0.692
	WENG2	0.732	1.615			
	WENG3	0.889	2.379			
	WENG4	0.820	1.884			
Writing motivation	WMOT1	0.743	1.520	0.880	0.917	0.733
	WMOT2	0.801	1.486			
	WMOT3	0.800	1.690			
	WMOT4	0.743	1.436			
Automated written corrective feedback	AWCF1	0.846	2.242	0.775	0.855	0.596
	AWCF2	0.858	2.638			
	AWCF3	0.793	1.595			
	AWCF4	0.889	2.814			
AWE self-efficacy	ASE1	0.771	1.604	0.871	0.911	0.719
	ASE2	0.839	1.996			
	ASE3	0.861	2.285			
	ASE4	0.845	2.064			
AWE technology characteristics	TC1	0.869	2.145	0.883	0.919	0.740
	TC2	0.843	2.001			
	TC3	0.797	1.786			
	TC4	0.816	1.854			

Latent variable	Item	Factor loading	Outer VIF values	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
Task technology fit	TTF1	0.851	2.255	0.848	0.898	0.688
	TTF2	0.886	2.529			
	TTF3	0.852	2.185			
	TTF4	0.835	2.370			
Writing proficiency	WP1	0.795	1.792	0.827	0.885	0.659
	WP2	0.813	1.788			
	WP3	0.874	2.275			
	WP4	0.761	1.503			

Table 3. The Heterotrait-Monotrait Ratio (HTMT) testing results.

	AT	ATT	CITU	WENG	WMOT	AWCF	ASE	TTF	ATC	WP
AT										
ATT	0.070									
CITU	0.656	0.080								
WENG	0.689	0.125	0.442							
WMOT	0.697	0.077	0.344	0.736						
AWCF	0.551	0.134	0.388	0.700	0.535					
ASE	0.650	0.070	0.474	0.636	0.603	0.514				
TTF	0.739	0.154	0.507	0.725	0.625	0.503	0.543			
ATC	0.063	0.088	0.070	0.103	0.056	0.118	0.051	0.155		
WP	0.764	0.113	0.463	0.740	0.648	0.583	0.763	0.715	0.115	

Note: AT: Ambiguity tolerance; ATT: Attitude; CITU: Continuance intention to use; ENG: Engagement; MOT: Motivation; AWCF: Automated written corrective feedback; ASE: AWE self-efficacy; TTF: Task technology fit; TC: Technology characteristics; WP: Writing proficiency.

5.2. RQ2 Structural Model Assessment

PLS-SEM measures the structural model with indicators of (1) checks of collinearity: tolerance (TOL) coefficients and variance inflation factor (VIF), (2) predictive power coefficients endogenous constructs' explanatory power R^2, (3) f^2 change effect values, (4) PLSpredict outer model's predictive power Stone-Geisser's Q^2(Geisser, 1974; Stone, 1974). Theoretically, PLSpredict function is utilized to evaluate the out-of-sample predictive power (Shmueli, Ray, Estrada, & Chatla, 2016). (5) Coefficient of determination R^2 is utilized to assess in-sample predictive power, and R^2 is irrelevant to out-of-sample predictive power (Rigdon, 2012). R^2 is a measurement of endogenous constructs' explanatory power (Shmueli & Koppius, 2011). Routinely, R^2 value ranges from 0 to 1, higher R^2 stands for good explanatory power. As a rule of thumb, R^2 values of 0.25, 0.50, and 0.75 describe weak, moderate, and substantial predictive power (Henseler, Ringle, & Sinkovics, 2009). As is displayed in Figure 4, our model could explain 0.499, 0.588, 0.439, and 0.405 of the variance in ambiguity tolerance, writing proficiency, attitude, and continuance intention to use AWE. The AWE research model is founded on an integration of three theoretical research models encompassing TTF model, individual characteristics, and TAM model. The current AWE research model demonstrates a relatively high explanatory power (R^2 values of 0.405) about the users' behavioral intention to use AWE platform. Q^2 value is a combination of the outer model's prediction and the inner model's explanatory power (Sarstedt, Ringle, & Hair, 2017). By default, Q^2 values of 0, 0.25, and 0.50 describe the small, medium, and substantial predictive power of the PLS-SEM model. As is tabulated in Table 4, Q^2 values of 0.486, 0.552, 0.397, and 0.285 suggest that the exogenous construct demonstrates a medium to substantial prediction relevance for the endogenous construct of the AWE research model. RQ2 the specific predictive power of the current AWE research model is answered through structural model assessment.

Table 4. Predictive power statistics.

Construct	Q^2	R^2
Ambiguity tolerance	0.486	0.499
Writing proficiency	0.552	0.588
Attitude towards AWE	0.397	0.439
Continuance intention to use AWE	0.285	0.405

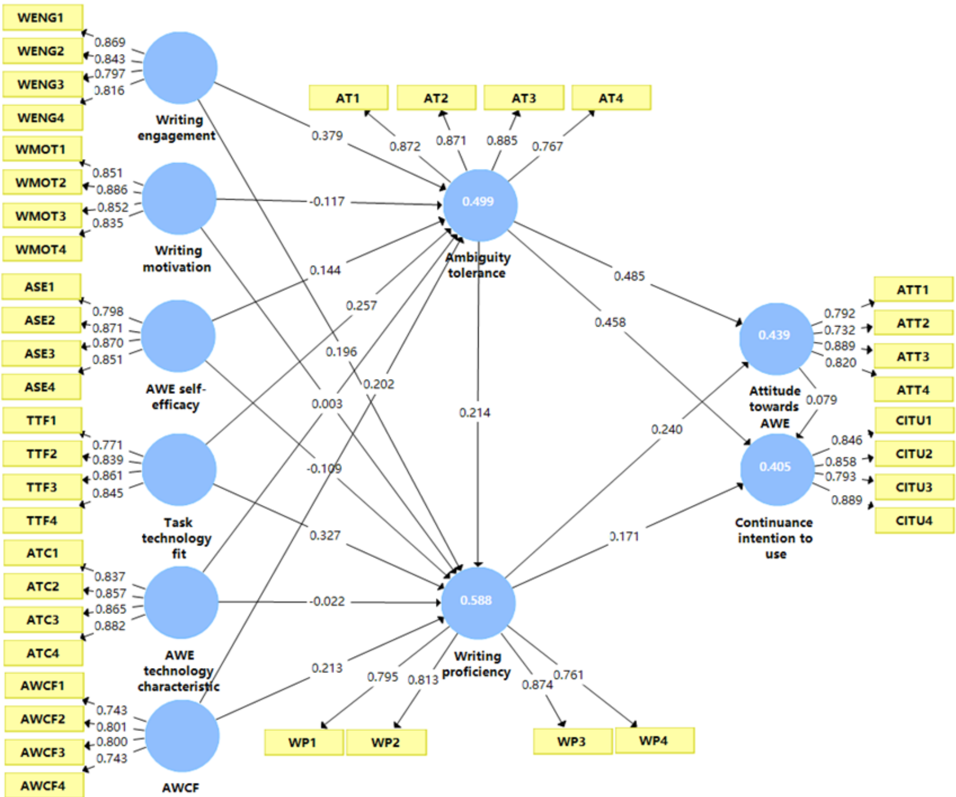

Figure 4. PLS-SEM diagram (Valid estimation model).

The fourth step is discriminant validity assessment. Normally, Fornell-Larcker criterion and the heterotrait-monotrait Ratio (HTMT) are utilized to evaluate discriminant validity. Fornell-Larcker criterion introduces a classic metric that requires a comparison between each construct's AVE and the squared inter-construct correlation of that construct and other reflective constructs in the SEM (Fornell & Larcker, 1981). However, Fornell-Larcker criterion is corroborated as inferior in the precision of discriminant validity (Henseler, Ringle, & Sarstedt, 2015). As suggested by Radomir and Moisescu (2020) the Fornell-Larcker criterion can be dismissed in the assessment of discriminant validity. We hence excluded the Fornell-Larcker criterion in the current study. The heterotrait–monotrait ratio (HTMT) of correlations is a preferable supplement for discriminant validity assessment (Henseler et al., 2015).

5.3. RQ3 Mediation Effect of Ambiguity Tolerance

The researchers investigated the mediating role of ambiguity tolerance in using AWE technology. The 13 mediation paths and parameters of the mediation effect of ambiguity tolerance are precisely tabulated in Table 5. In Fig. 4 the valid estimation model of the AWE research model, the psychological construct ambiguity tolerance acts as a mediator in connecting two latent variables. We observed that the personality trait ambiguity tolerance acts as a mediator in connecting the relationship between technology characteristics, task technology fit, AWE self-efficacy, motivation, AWCF, engagement, writing proficiency, attitudes towards AWE, and continuance intention to use (CITU). Mediation analysis corroborates that ambiguity tolerance is an effective mediator towards the attitudes and continuance intention to use GenAI-empowered AWE tools in facilitating writing proficiency.

The parameters of the specific indirect effect path show the mediating effect of ambiguity tolerance in the proposed AWE research model. The mediation analysis is realized through the bootstrapping method, a nonparametric procedure that is utilized to examine the statistical power of PLS-SEM the path coefficient. By default, the basic settings of bootstrapping methodology are with 5000 subsamples (Davison & Hinkley, 1997). Based on the percentile method in the bootstrapping calculation, p-value<0.05 and 95% confidence intervals do not include zero indicating the statistical significance of the mediation model. Thus, the 13 hypotheses of the mediation role of ambiguity tolerance in using AWE tools are supported.

Table 5. The 13 mediating effects of ambiguity tolerance in the model.

Number	Specific indirect effect path	Specific indirect effects	Standard deviation	Bootstrapping 95%CI	T statistics	P values
1	AWCF -> Ambiguity tolerance -> Attitude towards AWE	0.098	0.023	[0.061, 0.136]	4.340	<0.001
2	AWCF -> Ambiguity tolerance -> Continuance intention to use	0.092	0.023	[0.055, 0.132]	3.960	<0.001
3	AWCF -> Ambiguity tolerance -> Writing proficiency	0.043	0.015	[0.021, 0.071]	2.824	0.005
4	Task technology fit -> Ambiguity tolerance -> Attitude towards AWE	0.124	0.026	[0.085, 0.169]	4.868	<0.001
5	Task technology fit -> Ambiguity tolerance -> Writing proficiency -> Attitude towards AWE	0.013	0.004	[0.007, 0.020]	3.185	0.001
6	Task technology fit -> Ambiguity tolerance -> Continuance intention to use	0.118	0.024	[0.080, 0.158]	4.938	<0.001
7	Task technology fit -> Ambiguity tolerance -> Writing proficiency -> Continuance intention to use	0.009	0.004	[0.004, 0.016]	2.427	0.015
8	Task technology fit -> Ambiguity tolerance -> Writing proficiency	0.055	0.015	[0.032, 0.080]	3.730	<0.001
9	Writing engagement -> Ambiguity tolerance -> Attitude towards AWE	0.184	0.027	[0.140, 0.227]	6.929	<0.001
10	Writing engagement -> Ambiguity tolerance -> Writing proficiency -> Attitude towards AWE	0.019	0.006	[0.011, 0.030]	3.299	0.001
11	Writing engagement -> Ambiguity tolerance -> Continuance intention to use	0.173	0.028	[0.128, 0.219]	6.301	<0.001
12	Writing engagement -> Ambiguity tolerance -> Writing proficiency -> Continuance intention to use	0.014	0.005	[0.007, 0.023]	2.756	0.006
13	Writing engagement -> Ambiguity tolerance -> Writing proficiency	0.081	0.019	[0.050, 0.113]	4.209	<0.001

Note: SD: Standard deviation. CI: Confidence intervals.

The 13 mediating effects of ambiguity tolerance are demonstrated in the AWE research model.

1: Ambiguity tolerance significantly mediates AWCF and attitude towards AWE.

2: Ambiguity tolerance significantly mediates AWCF and continuance intention to use.

3: Ambiguity tolerance significantly mediates AWCF and writing proficiency.

4: Ambiguity tolerance significantly mediates task technology fit and attitude towards AWE.

5: Ambiguity tolerance significantly mediates task technology fit, writing proficiency, and attitude towards AWE.

6: Ambiguity tolerance significantly mediates task technology fit and continuance intention to use.

7: Ambiguity tolerance significantly mediates task technology fit, writing proficiency, and continuance intention to use.

8: Ambiguity tolerance significantly mediates task technology fit and writing proficiency.

9: Ambiguity tolerance significantly mediates writing engagement and attitude towards AWE.

10: Ambiguity tolerance significantly mediates writing engagement, writing proficiency, and attitude towards AWE.

11: Ambiguity tolerance significantly mediates writing engagement and continuance intention to use.

12: Ambiguity tolerance significantly mediates writing engagement, writing proficiency, and continuance intention to use.

13: Ambiguity tolerance significantly mediates writing engagement and writing proficiency.

The results of mediation analyses showed that amongst the total number of 39 mediation effects of ambiguity tolerance scrutinized in the proposed AWE research model, 13 mediation pathways are statistically significant at the 0.05 level. This indicates ambiguity tolerance is an effective intermediary construct in linking the independent and dependent variables. As is precisely tabulated in Table 5, the 13 mediating effects in the AWE research model depict multiple indirect effect pathways amongst the constructs. However, through statistical calculation, the researchers found that ambiguity tolerance failed to report a positive mediating effect on the relationship between AWE self-efficacy and writing proficiency. Ambiguity tolerance is not an effective mediator in connecting writing motivation and writing proficiency at a statistically significant level. Moreover, ambiguity tolerance is not an effective mediator between AWE technology characteristics and writing proficiency.

6. DISCUSSION

Section 6 enumerated the rationale and significance of the theoretical contribution, practical implications, contribution, and novelty of the current study. This section is a comparison of the findings in the current study with former studies.

6.1. Theoretical Contribution

6.1.1. The Positive Effect of the TTF Model on Writing Proficiency

RQ1 the constructs within the GenAI-empowered AWE research model is answered through theoretical and statistical investigations. This study corroborated that the TTF model encompassing AWE technology characteristics, task technology fit, and AWCF positively influence writing proficiency. TTF model is targeting on the features, functions, and utility of the AWE platform. The current empirical study corroborated that the AWE platform is indeed a promising tool in the assistance of writing quality improvement. Our finding resonates with numerous researchers and scholars who favored AWE studies (Bagheri & Rassaei, 2022; Brown et al., 2023; Ding & Zou, 2024; Huawei & Aryadoust, 2023). Driven by sophisticated NLP and machine learning algorithms, AWE tools are powerful and helpful in providing convincing corrective feedback (Stevenson & Phakiti, 2014). The amplification effectiveness of the AWE software attracts an escalating number of students to take the AWE platform as a reliable assistant in English essay writing.

6.1.2. The Positive Effect of Individual Characteristics on Writing Proficiency

The current study corroborates the positive effects of individual characteristics including AWE self-efficacy, writing engagement, and writing motivation. The current study validated the indispensable role of individual characteristics in determining writing proficiency. We summarized three findings. First, AWE self-efficacy is negatively pertinent to writing proficiency. Second, writing engagement contributes to enhanced writing proficiency. Third, higher writing motivation leads to better performance in the accomplishment of writing assignments. It is worth noting that the positive influence of individual characteristics, psychological constructs, and cognitive demands in the adoption of AWE technology resonating with previous investigations to a large extent (Rad et al., 2023). Sauro (2009) proposed that speedy delivery of recommended corrections could efficaciously attract learners' attention. The marking of erroneous expressions and inappropriate collocation also awoke users' ensuing intention to use AWE tools (Ranalli, 2021). Individual's writing motivation and writing engagement are proven to be positive predictors of writing proficiency (Wilson & Czik, 2016; Wilson & Roscoe, 2020). Individuals are prone to be affected by their role models, teachers, and intimate friends in the intention to use AWE tools (Wilson & Roscoe, 2020).

6.2. Practical Implications

The current study provides practical implications for AWE platform developers, software designers, AWE users, educators, practitioners, researchers, academic research fellows, and students. AWE-relevant studies are promising in future endeavors. The findings shed light on AWE developers to design software that fits individual cognitive feedback needs. It is recommended that AWE platform developers and software designers upgrade the AWE software platform according to individual needs. It is easy for users to learn to use and be skillful at adopting AWE software to enhance writing quality from multifaceted levels encompassing lexical, syntactical, and semantic factors. It is reasonable for educators and practitioners to incorporate AWE technology in language education. It is rationale for educators and practitioners to help students foster ambiguity tolerance which is a good property in cross-cultural communication and education. It is promising and groundbreaking for researchers and academic research fellows to keep tracing AWE-relevant academic research orientation in the GenAI-dominant era. The positive predictors of AWE-facilitated writing proficiency are composed of technology characteristics and individual characteristics. Individual characteristics encompassing AWE self-efficacy, writing engagement, and writing motivation are positively pertinent to ambiguity tolerance and writing proficiency. The TTF model of the AWE writing program including technology characteristics, TTF, and AWCF positively influences ambiguity tolerance and writing proficiency. Ambiguity tolerance functions as an effective mediator in connecting the TTF model and continuance intention to use AWE writing programs. It is confirmed that the TTF model and individual characteristics are important determinants of the attitudes toward the AWE writing program. The perceived usefulness of AWE feedback and the enhanced writing proficiency are persuasive for students to continue to use GenAI-empowered AWE tools (Ding & Zou, 2024; Zhai & Ma, 2022).

6.3. Contribution and Novelty

RQ2 the specific predictive power of the current AWE research model is well explained through the evaluation of the structural model. This study is the first endeavor employing structural equation modeling to incorporate the cognitive and psychological construct of ambiguity tolerance with the application of the AWE platform. Through explicit investigation, this study consolidates the positive effect of ambiguity tolerance on the efficacy of AWE-facilitated writing proficiency. The proposed AWE research model corroborates that ambiguity tolerance incrementally improves writing proficiency, and the reciprocal effects need further investigation. AWE technology users' ambiguity positively predicts writing proficiency, attitudes toward AWE technology, and continuance intention to use AWE technology. Among the mediation relations in the proposed AWE research model, 13 mediation paths were statistically significant. Our findings are in alignment with previous studies. Although researchers and scholars have shown their escalating interest in personality trait ambiguity tolerance, it has never been studied under the context of AWE-facilitated writing improvements (Bagheri & Rassaei, 2022). The findings in the current study are resonating with previous studies. A series of SEM and hierarchical regression analyses have proved multilingualism, language proficiency, age, and educational level are indicators of ambiguity tolerance (Dewaele & Li, 2013; Wei, Kang, & Wang, 2022). Bagheri and Rassaei (2022) designed comparative experimental study among Iranian EFL learners and validated the positive role of ambiguity tolerance and direct feedback in the enhancement of writing performance. The mediation effect of ambiguity tolerance in the AWE research model is consistent with Wei et al. (2022) who have adopted SEM to provide an affirmative answer on the positive role of ambiguity tolerance in facilitating language learning. As Vygotsky and Cole (1978) puts it, the mediating effect is a higher stage of development behavior. RQ3 ambiguity tolerance is corroborated as an effective mediator in the AWE research model at a statistically significant level. Based on the theoretical premise of the mediation effect or the indirect effect in the learning process, the current study demonstrates the efficacy of psychological constructs in enhancing writing literacy in language education. Ambiguity tolerance functions as an effective mediator in connecting the task technology fit model (TTF model), individual characteristics, and technology acceptance model (TAM model).

The positive role of ambiguity tolerance in educational settings has been investigated in numerous studies. Endres et al. (2009) found the mediation effect of ambiguity tolerance in the connection of task complexity and self-efficacy. According to Endres et al. (2009) the mediation effect of ambiguity tolerance only existed in complex task completion but disappeared in moderate or less complex tasks. Chen (2023) corroborated the mediating role of ambiguity tolerance influencing the relationship between learner autonomy and learning achievement in the EFL pedagogical context. Ravindran and Iyer (2014) pointed out ambiguity tolerance acts as a mediator in deciding the cause-effect influence of self-efficacy and filling knowledge gaps. In the accomplishment of tough tasks, self-efficacy is positively pertinent to ambiguity, and these attributes work together to strengthen learning performance (Endres et al., 2009). Multilingual beliefs and psychological well-being are essential in language education such as learning English as a second language (ESL) or learning English as a foreign language (EFL) context (Dewaele & Li, 2013; Van Compernolle, 2016). Through statistical investigation, the current study corroborated that AWE technology characteristics, task technology fit, and writing engagement are demonstrated to be positive predictors of ambiguity tolerance and these constructs work together to facilitate writing proficiency and learning outcomes with the application of GenAI-empowered AWE tools.

7. CONCLUSION

This section is designated to summarize the contributions and research implications concerning personality trait ambiguity tolerance and GenAI-empowered AWE technology. The findings obtained through statistical investigation are expected to corroborate that ambiguity tolerance functions as a bridge linking the TTF model, individual characteristics, and TAM model in the proposed AWE research model. The empirical findings demonstrate a satisfactory correlation in the 13 mediation paths. The results of the path coefficient prove that ambiguity tolerance works as an effective mediator in facilitating writing proficiency which attracts students and research fellows' future application of the AWE software. In addition, the AWE research model has a small to moderate explanatory power of ambiguity tolerance, writing proficiency, attitude, and continuance intention to use AWE with R^2 ranging from 0.405 to 0.588. Besides, Q^2 values demonstrate a medium to substantial predictive power of the AWE research model.

The current study provides pedagogical suggestions for calculating L2 learners' writing literacy, facilitating writing engagement, boosting writing motivation, and strengthening AWE self-efficacy under the particular circumstances of employing specific AWE technology tools Grammarly, Pigai, Criterion, and so on. The moderating effects of multiple variables that determine AWE-enhanced writing proficiency can be classified into AWE technology elements and individual characteristics. One of the merits of the PLS-SEM model is that the constructs in the research model are appropriate, flexible, and selected based on theories of learning analytics and individual needs to enhance writing feedback literacy in the GenAI settings (Rad et al., 2023; Winstone & Carless, 2020). Although a counter-example suggests that being over-dependent on AWE tools hinders cognitive engagement and contributes to blind acceptance of the recommended corrections (Koltovskaia, 2020) the vast body of empirical studies has corroborated the improved writing proficiency leads to frequent adoption of AWE tools in the future (Abdullah & Ward, 2016).

8. LIMITATIONS AND FUTURE WORKS

Notwithstanding the promising development of AWE software for pedagogical purposes. This research is not with no flaws. The current study is estimated to have three limitations. The first limitation is the time span and participants of this empirical study.

The uneven distribution of the participants' majors due to the dissemination of questionnaires in a language-featured university within two months which is referred to as a cross-sectional study. The merits of cross-sectional study are that it provides preliminary statistical evidence for more detailed and enhanced empirical studies in the future. The demerits are that the temporal association is weak so it is prone to be contaminated with common method bias.

The researchers employed statistical techniques to diminish the potential effects of common method bias. The second limitation is that the current study incorporates ten latent variables to explore the effectiveness of the GenAI-empowered AWE system. Admittedly, ten constructs are a little bit more in a research model which leads to too many paths. Thus, the specific statistics for path coefficients are excluded in the article. The third limitation is that the proposed AWE research possesses a small to moderate explanatory power which is less satisfying.

Due to the limitations of the current study, it is plausible that future research could concentrate on the focal constructs in the efficacy of AWE technology. It is advisable for scholars to conduct empirical study methods to further delve into the benefits of AWE technology in writing literacy cultivation. The current study mainly focuses on quantitative studies of the empirical data with only one open-ended question which is insufficient for qualitative study.

Thus, future studies could put more emphasis on qualitative research so as to comprehensively investigate the factors that determine the efficacy of AWE applications for educational purposes. Popular qualitative research methods include action research, case studies, ethnography, grounded theory, mixed methods, narrative inquiry, and phenomenology (Heigham & Croker, 2009).

Moreover, future studies could incorporate the ethical, moral, humanity, and social science issues toward the application of the AWE software platform and other prevalent GenAI-empowered writing tools such as Chat Generative Pre-Trained Transformer (ChatGPT).

Future research could merge qualitative research methods with multivariant statistical approaches to meticulously investigate the interaction of literacy cultivation and emotional intelligence in the utilization of AWE technology for academic purposes in the GenAI era (Divekar* et al., 2022).

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