Understanding the dynamics of motivation and learning behaviors in augmented-reality-based writing courses

Abstract

Augmented reality (AR) has emerged as a valuable tool in writing education, with the goal of enhancing students' learning. However, questions persist about the consistency of motivation among students and their classroom performance when participating in educational experiences driven by augmented reality. This study focused on an AR-driven writing course, employing cluster analysis to identify different writing improvement profiles by examining the pre- and post-test scores of 87 primary school students. Subsequently, the study delved into differences in their motivation levels and the frequency of learning behaviors (e.g., disordered behaviors, raising hands). The analysis identified five distinct writing improvement profiles, categorized as the Advanced, High-achievers, Persistent, Indifferent, and Diligent groups and different levels of motivation and learning behavior frequency were observed among these groups. The Advanced, High-achievers, and Diligent groups showed significant improvements in certain dimensions of their writing motivation (e.g., curiosity, boredom, competition) within the AR-driven writing course, while such enhancements were not observed in the Persistent and Diligent groups. Additionally, the Indifferent group demonstrated a lack of motivation toward AR-based learning activities, evidenced by increased technical difficulties and disorderly behaviors. Variances were also found in students' sequential behavior patterns among different groups. These findings shed light on the dynamics of motivation and learning behaviors among students in different writing improvement profiles within AR-based writing courses, offering valuable insights for a more comprehensive understanding of the dynamics at play in such educational settings.

Keywords: Augmented and virtual reality; Applications in subject areas; Elementary education; Improving classroom teaching

1. Introduction

Proficiency in written communication is an essential prerequisite for achievement, not only within academic settings but also in broader life contexts, emphasizing its importance as a core competency for continuous learning (UNESCO, 2017). This capability is as an indispensable tool for learners, enabling them to demonstrate their grasp of subject matter through the completion of written tests, compositions, and reports, while also enhancing their comprehension by articulating their thoughts on class materials (Bangert-Drowns et al., 2004). However, acquiring proficiency in writing is a multifaceted and challenging developmental process. A substantial number of students fall short of reaching the requisite level of writing skill by the end of compulsory education (Veiga Simão et al., 2016). Students often encounter difficulties in transforming abstract concepts or emotions into concrete written expressions. They may face challenges in accessing relevant knowledge or experiences stored in their long-term memory and occasionally contend with a lack of motivation towards writing tasks (Berninger, 1999). These difficulties are echoed in the study of Flower (1994) and Hayes (1996), who assert that writing is not solely a cognitive but also a social process that thrives in authentic contexts. Clear objectives, content, genre, audience, and available resources are crucial supports for this endeavor. A well-designed authentic writing context is often considered a means to inspire proficient writing and to overcome writer's block (Chen et al., 2022b). Through this authentic context, students can forge links between their prior knowledge and the writing scenario in which they work, thereby nurturing an earnest and engaged articulation of their sentiments in writing (ibid).

Augmented reality (AR), as one of the immersive technologies, provides learners with the chance to engage in authentic learning experiences directly related to the subject matter, thereby elevating the process of writing education (Li et al., 2023). This is achieved by enabling authentic and interactive learning experiences, which entail superimposing virtual elements in text, image, or video forms onto the actual environment to facilitate interactions among students (Azuma, 1997). Research consistently demonstrates that the authentic and interactive aspects of AR function as a powerful bridge, effectively connecting students' existing knowledge and experiences with the learning material while nurturing their empathy and helping them to overcome emotional barriers in writing education (Li et al., 2023; Wang, 2017). While contextual factors undoubtedly contribute to the development of writers, the Writer(s)-within-Community (WWC) model (Graham, 2018) places a crucial emphasis on examining individual writer-specific factors. Of these, writing motivation emerges as a significant individual factor, determining not only whether writers engage in writing, but also the level of effort they invest in, the steps they take, and their interactions within the writing community (ibid). For example, a student's motivation levels may fluctuate, influencing their readiness to approach a particular paper (referred to as state motivation) or to engage in writing as a whole (referred to as trait motivation). These motivational dynamics, to a certain degree, align with their effectiveness in attaining success in writing (Camping, Graham, & Harris, 2023). However, it is worth noting that writing motivation is an implicit variable often assessed through self-reported surveys, which may be susceptible to response bias and ceiling effects. It is suggested that observational data, such as classroom behaviors, should be integrated to enhance the predictive power in assessing learners' achievement (Li et al., 2023). With the use of sequential data analysis, it is also possible to identify patterns in students' behaviors, shedding light on their learning processes through the examination of observational data (Li et al., 2023). This allows us to uncover specific behavioral sequences that manifest at rates significantly higher than expected by chance (Chen et al., 2023b). Ultimately, it can enable us to better understand the factors influencing students' achievements and motivation levels in their learning pursuits.

However, there are limited empirical studies delving into the connections between writing achievements and motivation in the context of AR-based writing activities using these advanced statistical approaches. This gap in the research is particularly notable when considering students with different writing improvement profiles which can be detected using clustering approaches. Moreover, none of the previous studies we reviewed explored the behavior patterns exhibited by students with different writing improvement profiles in the context of AR-based writing activities. Therefore, the primary objective of this study is to bridge these existing research gaps by examining the dynamics of student motivation and learning behaviors in AR-based writing activities. This can offer novel insights for researchers and can also help educators design more effective writing activities, thanks to a deeper understanding of how students engage with and perceive the integration of AR in writing education.

The subsequent section provides a comprehensive overview of the theoretical frameworks utilized in this study. Following this, the methodology, results and discussion sections are presented. More specifically, we employed a clustering analysis method to probe different writing improvement profiles in AR-based writing learning. We investigated whether those with different writing improvement profiles exhibited mean differences in their learning motivation and behavior frequencies, respectively. Additionally, we conducted a sequential analysis to examine the ways in which learners with different writing improvement profiles vary in their approaches to participating in AR-based writing courses. Lastly, we conducted semi-structured interviews with students representing different writing improvement profiles to gain deeper insights into their perceptions of AR-based writing courses. Using these approaches, this study aims to address the following four questions:

RQ1: Do students display different writing improvement profiles that can be characterized into different groups in the context of AR-based writing courses?

Hypothesis 1: According to Li et al. (2023), a range of factors including prior knowledge and engagement may yield different trajectories of improvement in AR-based writing activities. Thus, we hypothesize that students immersed in AR-based writing courses will display different writing improvement profiles.

RQ2: Do students with different writing improvement profiles demonstrate different levels of learning motivation in the context of AR-based writing courses?

Hypothesis 2: It is well-established that students participating in writing courses demonstrate different levels of learning motivation (e.g., Graham et al., 2022). Thus, we hypothesize that students with different writing improvement profiles will also display different levels of learning motivation in AR-based writing courses.

RQ3: Do students with different writing improvement profiles demonstrate different learning behavior patterns in the context of AR-based writing courses?

Hypothesis 3: According to Graham et al. (2017), a correlation has been established between writing achievements and learning behavior patterns. Thus, we hypothesize that students with different writing improvement profiles will display different learning behavior patterns in AR-based writing courses.

2. Theoretical framework

2.1. AR and its application in writing education

AR is an immersive technology that aims to deepen learning interactions by overlaying digital information onto physical settings (Chen et al., 2022b). It incorporates sensory and visual components, sharing similarities with a three-dimensional environment, which can significantly enhance the learning process. These enhancements manifest through collaborative interactions, heightened engagement of the learners' primary senses, and the visual representation of information (Specht et al., 2011). In contrast to virtual reality (VR), which isolates the user from the real world using specialized headsets like Oculus Rift or Samsung Gear VR (Popolo, Schneider & Hyde, 2018), AR operates without the need for such specialized equipment, readily accessible through computers or mobile devices. This accessibility renders it particularly suitable for educational settings. AR's distinct attributes, including sensory immersion, navigational flexibility, and interactive manipulation, serve to cultivate a sense of presence and satisfaction among learners, thereby enhancing the overall learning experience (Bokyung, 2008). As noted by Chiang et al. (2014) and Santos et al. (2014), these AR features have the potential not only to impact students' learning outcomes but also to exert a positive influence on their psychological factors. These encompass motivation, positive attitude, engagement, satisfaction, and confidence, collectively enhancing the educational experience. For example, Akçayır et al. (2016) investigated the effects of the use of AR in science laboratories on university students' laboratory skills and attitudes towards laboratories. The results obtained over a 5-week application demonstrated a significant enhancement in the development of the students' laboratory skills, alongside a notable improvement in their attitudes towards physics laboratories. In another study by Chen et al. (2022a), the authors implemented AR-enhanced learning to investigate the effects of English proficiency levels (less proficient and proficient) on junior high school students' English learning effectiveness, motivation and attitude. The outcomes indicated that students demonstrated positive motivation toward learning in the AR-enhanced contextualized learning environment. Proficient learners displayed higher motivation levels in terms of self-efficacy, proactive learning and learning value.

Given its substantial potential impact, research has empirically demonstrated the effectiveness of AR in enhancing students' writing proficiency (Abdelrahim, 2023; Allagui, 2021; Wang, 2017). For instance, in a recent investigation by Li et al. (2023) focusing on elementary school students' writing courses, the advantages and challenges of employing AR to enhance writing achievements were explored. Researchers developed an AR-based approach on the basis of the motivational model, which leveraged motivational strategies to augment the learning experience. The study's findings highlighted the effectiveness of the AR approach in improving students' writing performance, specifically in terms of enhancing feature descriptiveness and fostering innovative thinking. Furthermore, it led to a reduction in the occurrence of students' distracted behaviors. The study also proposed that the AR-based approach provided even greater benefits for students with higher levels of engagement compared to those with lower levels of engagement. In Abdelrahim's (2023) study, the impact of critical analysis based on AR technology on the development of critical thinking and critical writing was explored. The study involved two groups of undergraduates (n = 120), with the experimental group utilizing critical analysis based on AR and the control group utilizing online instruction via a learning management system without AR. The findings revealed that the experimental group outperformed the control group in critical thinking and writing. Critical thinking elements were effectively integrated into the critical writing of the experimental group.

The recent systematic reviews similarly highlight the potential of AR in education, showing that it can promote students' writing achievements (Allagui, 2021; Li et al., 2023; Wang, 2017). More specifically, AR enables students to immerse themselves in experiences related to those in the real world, fostering emotions and sensations (Li et al., 2023). This immersive quality can serve as a powerful tool to motivate and engage students, particularly in the area of writing education, where students need to characterize events, express feelings or imagine objects (ibid). AR's capacity to evoke such authentic experiences makes it highly relevant and valuable in enhancing students' writing skills (ibid). However, there are limited studies that delve into the variables impacting students' participation in AR-based writing activities, as well as the dynamics between these variables and students' writing performance.

2.2. Student motivation

Student motivation is the inclination of a student to actively engage in a learning activity (Keller & Litchfield, 2002). It involves the processes that initiate and sustain goal-directed activities, constituting a multidimensional construct that encompasses various beliefs (Pintrich & Schunk, 2002). The relationship between student motivation and academic achievement is listed as one of the most extensively studied areas of research. It is suggested that students who exhibit high levels of motivation in their learning process tend to demonstrate heightened levels of engagement, increased effort, and ultimately, improved academic success (Theall, 1999). Conversely, the absence of motivation can serve as a significant barrier impeding learner achievement (Jeamu, Kim, & Lee, 2008). This viewpoint is further substantiated by Pintrich (1999), who affirmed the role of motivation in fostering and sustaining self-regulated learning, ultimately leading to enhanced academic performance. Similarly, Schmidt (2007) maintains that motivation has the potential to shape the “what, when and how” of the learning process, significantly augmenting the likelihood of engaging in activities conducive to learning and achieving better outcomes.

More specifically, the influence of motivation on writing has garnered increased theoretical and empirical attention from scholars in the past two decades (Graham et al., 2022). According to Hayes (1996), writing motivation includes students’ beliefs, goals and personal attributes associated with writing. Motivated learners proactively initiate learning to achieve their goals and find enjoyment and perseverance in the writing learning process (Graham et al., 2022). In an empirical study conducted by Ng et al. (2022), the authors found that writers with different levels of motivation were driven by different aspects of writing motives. Curious and averagely motivated writers were primarily motivated by curiosity and involvement, those with weaker motivation were predominantly driven by the pursuit of grades, and unmotivated writers did not exhibit clear motives for writing. Given the influence of motivation on writing performance (Ekholm et al. 2018), researchers have explored the effects of various pedagogical strategies on writing motivation. A recent survey emphasized that understanding the relationship between student motivation and writing achievements holds the potential to shed light on the impact of specific pedagogical strategies (Camacho et al., 2021). Limited research has delved into this aspect in the context of AR-based writing activities. Our aim is to bridge this gap by investigating how student motivation is linked with their writing achievement profiles in AR-based writing courses.

In this study, we use the Writer(s)-within-Community model (WWC, Graham, 2018) as a theoretical framework for understanding motivation. The WWC model contends that writers’ motivations include beliefs about writing motives, the value and utility of writing, interests and attitudes, competence, writing identity, and reasons for success/failure. To assess writing motivation in alignment with the WWC model, we employ the Writing Motivation Questionnaire (WMQ, Graham et al., 2022), a progressively utilized self-reported instrument. It was developed to assess learners’ motivational orientation and their willingness to write (Graham et al., 2022). The WMQ is structured to evaluate seven dimensions of writing motives, including curiosity (the desire to write driven by interest in the writing topic), involvement (the aspiration to write for positive experiences), competition (the motivation to outperform others in writing), grades (the drive to achieve higher grades through writing), emotional regulation (the use of writing to overcome negative emotions), relief from boredom (writing to pass the time) and social recognition (writing in search of praise and approval from others). Empirical data gathered from American 4th and 5th graders' responses confirmed the seven-factor model outlined in the WMQ (Graham et al., 2022). Subsequent studies conducted with student samples from Portuguese (Limpo et al., 2020) and Chinese contexts (Ng et al., 2022) offered additional empirical support for the validity of the writing motives instrument. In this work, we use the WMQ to assess the motivation levels of primary school students in AR-based writing courses.

2.3. Sequential analysis for learning behavior patterns

The identification of learning behavior patterns is regarded as a reliable method to capture the holistic state of students' attention, persistence and motivation in their learning process (Sun & Lin, 2022). This approach grants a thorough insight into students' engagement and commitment to the learning process. Moreover, it complements the statistical analysis of data by revealing the dynamic aspects of the learning process (Li et al., 2023). Sequential analysis, as introduced by Bakeman and Gottman in 1997, is a technique employed for analyzing data gathered in a sequential or time-ordered manner. It places an emphasis on the swift succession of behaviors, examining the transition from one behavior to another within a short timeframe (Hou, 2015). Recognized as an effective coding method, it proves particularly valuable when examining classroom learning behaviors over an extended period. Consequently, it provides a valuable tool for comprehending the intricate patterns of students' behavior (Chen et al., 2023b).

Many studies have applied sequential analysis to investigate various aspects of student behavior, including peer discussions, cognitive processes and attention behaviors (Chen et al., 2023b; Hou, 2015; Sun et al., 2018). In their study, Li et al. (2023) explored the sequential patterns of students' learning behaviors in a motivational AR-based writing course. They identified nine categories of learning behaviors, distributed across three dimensions: behaviors related to the course, behaviors related to the observational activity, and distracted behaviors, with three categories in each dimension. The researchers classified and coded students' behaviors based on the classroom videos. The findings suggested that students utilizing the motivational AR-based learning approach placed a greater emphasis on the observational process compared to traditional AR-based learning approach. Moreover, the group employing the motivational AR-based approach exhibited less distracted behaviors.

Similarly, Chen et al. (2023b) used a video recording to capture students' classroom behaviors and investigate how the peer feedback-based spherical video-based virtual reality (PF-SVVR) approach influenced students' writing learning process. They categorized students' classroom behavior into eight types, namely answering questions, observing the SVVR content, discussing with peers, completing the task learning sheets, listening to the teacher's instruction or peers' answers, raising hands, having trouble with the use of SVVR, and disorder in the classroom. The results of their study indicated that students in the PF-SVVR group tended to exhibit less disorderly behaviors than those in the conventional SVVR group. In this study, we derived and adapted an existing coding scheme for classroom learning behaviors in AR-based writing courses. This scheme was developed based on the coding approaches of Li et al. (2023) and Chen et al. (2023b), tailored to the specific context of our investigation, thus yielding an appropriate framework for analyzing students' learning behavior patterns in AR-based writing courses.

3. Methodology

3.1. Research context and participants

This study was conducted in two classes of a Chinese writing course, each lasting three weeks, with 100 minutes of instruction per week, at an elementary school in southeast China. AR materials were integrated into the curriculum to offer students an authentic learning experience, with the goal of enhancing their motivation and fostering active learning behaviors. Following the Chinese Curriculum Standards for Full-Time Compulsory Education, we selected "Mysterious Adventure" as the overarching theme for the entire writing learning program.

The AR learning materials utilized in this study were developed by Aibuke Limited[1]and include a book titled "Wild Animals Exploration" along with a corresponding application (app) called "Wild Animals Exploration" (see Fig. 1). The book comprises three segments: illustrations of the animals, descriptive paragraphs about each animal, and an interactive AR module. The app offers features for capturing photos of the animals, interacting with them (e.g., using gestures to engage a tiger in hunting), and a mute button to control audio (refer to Fig. 2). Specifically designed to complement the content of the book, the app provides students with an immersive experience. Through the app, students not

[1]http://wxbookdown.dazzleeye.net/

only viewed authentic 3D scenarios but also interacted with the animals, performing tasks like using gestures to entice a tiger into hunting or capturing a photo of the tiger. The app was installed on tablets, and students were paired up based on their classroom seating arrangements (i.e., student A and his/her deskmate).

Figure 1 Examples of the AR learning materials

Figure 2 Introduction of the Functions of the AR App

Despite the integration of AR materials, the writing courses were devised based on the ARCS model proposed by Keller (1987). This theory has been substantiated as an effective framework for designing AR-based writing activities, encompassing four stages: attention, relevance, confidence, and satisfaction (Li et al., 2023). The specific procedures of the AR-based learning activities are shown in Figure 3. Fifteen types of animals were selected for the course, with five types featured in each session.

Each type of animal includes figures illustrating the animal, paragraphs describing the animal, and an AR module for interacting with the animal.

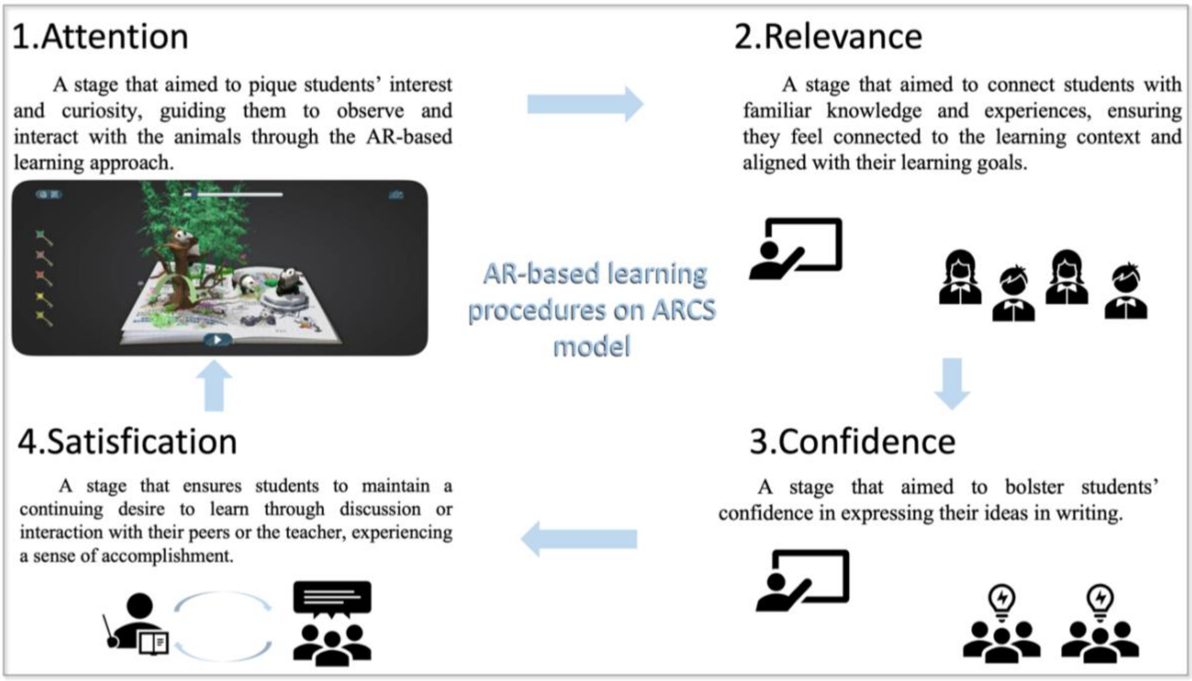


Figure 3 AR-based learning procedures on the ARCS model

As shown in Table 1, a total of 87 primary school students were enrolled in the course, comprising 54 boys with an average age of 10.47 (ranging from 9-12) and 33 girls with an average age of 10.16 (ranging from 9 to 11). 18.5 percent of the boys reported previous experience with AR and 15.2 percent of the girls had previous experience with AR. Initially, a sample of 90 students was recruited for this study. Three students (all boys) were eliminated due to incomplete pre- or post-writing tests. Participants were recruited during the second semester of the 2022–2023 academic year, and we received authorization to conduct the courses during the instructional period. Data collection took place from 18th May to 16th June 2023, and underwent review and approval by the Institutional Review Board of the first author's affiliated institution. Parental consent was obtained for each participant, and parents were provided with documentation explaining the experiment. Furthermore, standard ethical institutional procedures were followed to guarantee participant anonymity (e.g., name, class), and all the participants were informed of the voluntary nature of their participation, with the option to withdraw at any time during the experiment. Prior to the first session of the course, the instructor administered pre-tests evaluating their writing performance (focused on the theme of "My hometown") and learning motivation. Following the final session of the course, post-tests were conducted assessing their writing performance (focused on the theme of "Mysterious Adventure") and learning motivation. Both the pre- and post-tests consist of free-form writing tasks on a specific topic (i.e., My hometown, Mysterious Adventure) with no constraints on the structure or style. The course instructor collected all written manuscripts and questionnaires, which were subsequently delivered to the authors of this paper.

Table 1 Participant demographic information

	Boys	*SD*	Min	Max	Girls	*SD*	Min	Max
Average age	10.47	0.915	9	12	10.16	0.767	9	11
N	54				33			
Previous experience with AR	18.5%				15.2%			

3.2. Instruments

3.2.1. Rubric of writing performance

The evaluation of pre- and post-writing performance was conducted using the rubric for descriptive Chinese writing developed by Li et al. (2023). This rubric encompasses four key dimensions: organization, expression, creativity, and accuracy. Organization entails a well-structured composition with appropriate levels of detail and coherent paragraphing, effectively conveying the core elements of the writing. Expression involves the adept use of rhetorical devices like metaphors and the incorporation of sensory verbs to convey emotions and intricate details within the writing. Creativity embodies the distinctive and innovative aspects of the theme, narrative perspective, and evidential presentation. Accuracy demands a precise focus on content, meticulous word choice, adherence to punctuation norms, and the absence of glaring linguistic errors. Each dimension accounts for 25% of the total score, with a perfect score of 100 for the writing assessment.

The students' pre-test and post-test writings were assessed by two highly experienced Chinese teachers with over a decade of teaching experience in Chinese writing. These grading teachers followed a back-to-back, double-blinded assessment approach. A Pearson correlation analysis of their grading scores revealed a significant correlation ($r = 0.825$, $p < 0.000$). The final scores for the students' writing performance were determined by averaging the scores given by the two teachers.

3.2.2. Learning motivation questionnaire

The Writing Motivation Questionnaire (WMQ; Graham et al., 2022) was employed to assess the motivations of Chinese students in relation to writing. These motivations encompass curiosity (e.g., "I write because I enjoy contemplating specific subjects"), involvement (e.g., "I write because I can craft and immerse myself in mental adventures"), grade (e.g., "I write because it aids in my scholastic achievement"), competition (e.g., "I write because it enables me to outperform my classmates"), emotional regulation (e.g., "I write because it brings me a sense of well-being"), boredom ("I write to stave off boredom"), and social recognition (e.g., "I write because my parents deem it important for me to excel in writing"). Each motivational category was evaluated through four items, utilizing a 5-point Likert scale (1=Not true at all; 5=Very true). The questionnaire, originally in English, was translated into Chinese by the first author. Additionally, two experienced professors with over a decade of experience in educational psychology research ensured expert validity through the meticulous review and refinement of the translation to ensure its appropriateness. In total, 28 items were employed to gauge these seven distinct writing motivations. The original scale's reliability was measured by Omega (ω) coefficients, yielding values of 0.78 for curiosity, 0.74 for involvement, 0.66 for social recognition, 0.78 for competition, 0.74 for grade, 0.87 for emotional regulation, and 0.76 for boredom.

The reliability of the questionnaire in the present study, following all modifications, demonstrated strong internal consistency with Cronbach's α of 0.831 and ω of 0.836 for the overall questionnaire. Moreover, the seven subscales exhibited commendable reliability: curiosity (Cronbach's $\alpha = 0.64$; $\omega = 0.812$), involvement (Cronbach's $\alpha = 0.606$; $\omega = 0.779$), boredom (Cronbach's $\alpha = 0.737$; $\omega = 0.859$), emotional regulation (Cronbach's $\alpha = 0.795$; $\omega = 0.896$), grade (Cronbach's $\alpha = 0.839$; $\omega = 0.919$), competition (Cronbach's $\alpha = 0.732$; $\omega = 0.871$), social recognition (Cronbach's $\alpha = 0.651$; $\omega = 0.802$). The questionnaire's validity was established through an exploratory factor analysis (EFA) using SPSS 25.0. The Kaiser-Meyer-Olkin (KMO) value, reaching 0.80, and the significance level of Bartlett's test, falling below 0.05, affirmed the suitability of the questionnaire items for factor analysis (Field, 2009). Principal component analysis (PCA) results indicated the presence of eight significant components, each with eigenvalues surpassing 1. These components collectively accounted for an impressive 64.576% of the total items. A confirmatory factor analysis was performed using Mplus 8, following the specifications outlined in the WMQ. The analysis revealed a well-fitting 7-factor model which showed an acceptable fit to the data (χ^2 = 467.768, df = 329, p < 0.001; CFI = 0.88; TLI = 0.86; RMSEA = 0.058 (0.045 – 0.069); SRMR = 0.07). All the item factor loadings (0.44 - 0.83) were significant, p < 0.001. The values of Composite Reliability (CR) for the seven subscales of the questionnaire were acceptable with values greater than 0.7 (Fornell & Larcker, 1981), and the Average Variance Extracted (AVE) was acceptable with values greater than 0.5 (Peterson, 2000).

3.2.3. Coding scheme of classroom learning behaviors

Table 2 shows the coding scheme developed in this study, based on the classroom learning behavior coding framework introduced by Chen et al. (2023b). To ensure the coding scheme's effectiveness, we enlisted the expertise of three observers experienced in coding classroom behaviors to validate the applicability of the codes and their definitions. Responses from these experts affirmed that the coding scheme effectively measures the intended constructs. Subsequently, we identified a total of ten different learning behaviors of students in this study, namely, answering questions (SA), observing and interacting with the AR content (SO), discussing with peers (SDP), completing the task learning sheets (SC), looking over the task learning sheets from their peers (SLP), listening to the teacher's instruction or peers' answers (SL), reading aloud together (SRT), raising hands (SR), having trouble with the use of AR (SH), disorder in the classroom (SD), to identify variations in student behaviors across different clusters. Detailed information about the coding scheme can be found in Table 2.

All participants' behaviors were recorded using the Micro-classroom's integrated camera, commencing at the outset of each class session. Video recordings for analysis were edited to capture the dynamics of student learning behaviors. Each video segment had a duration of approximately 75 minutes, accounting for the exclusion of time spent on equipment adjustments, maintenance of the class order and breaks. Participants' behaviors were encoded chronologically in 15-second time slots. Two second-year graduate students in educational technology with experience in encoding classroom learning behaviors conducted the behavioral coding. Before the coding work began, we provided coders with comprehensive explanations of the classification and the meaning of the ten behavior codes. To determine the coding reliability, the learning behaviors of 10 randomly selected students (11.5%) were blind-coded by the two coders. Inter-coder reliability was assessed using Cohen's kappa, yielding an acceptable level of agreement (k = 0.815) (Cohen, 1968). Any initial disparities were discussed between the two coders until a consensus was reached. Following the establishment of coding reliability, the remaining participants' learning behaviors were independently coded by two researchers.

Table 2 Coding scheme of classroom learning behaviors (Chen et al., 2023b)

Code	Behaviors	Description
SA	Answering questions	Students answer the questions raised by the teacher.
SO	Observing and interacting with the AR content	Students engage with AR content using a tablet, allowing them to observe and interact with the virtual elements.
SDP	Discussing with peers	Students discuss with their peers what they have seen in AR content.
SC	Completing the task learning sheets	Students complete task learning sheets based on the AR materials
SLP	Looking over the task learning sheets from their peers	Students look over the task learning sheets from their peers
SL	Listening to the teacher's instruction or peers' answers	Students listen to the teacher's instructions or the answers of their peers.
SRT	Reading aloud together	Students read aloud together with the guidance of the teacher.
SR	Raising hands	Students raise their hands to either contribute their thoughts or respond to questions posed by the teacher.
SH	Having trouble with the use of AR	Students have trouble with the use of AR.
SD	Disorder in the classroom	Students behave disorderly (e.g., wandering, dazing).

3.3. Data analysis

In this study, we employed both quantitative and qualitative data to delve into the dynamics of students' learning in the context of AR-based writing instruction. Kurtosis and skewness statistics were meticulously examined for each variable, as outlined in Table 3. Notably, our observations indicated a normal distribution, as evidenced by kurtosis values falling within the range of −2 to +2, and skewness values within −7 to +7 (West, Finch, & Curran, 1995). The testing of normality assumptions yielded satisfactory outcomes, validating the application of parametric analysis methods such as *t*-tests and ANOVA. Furthermore, comprehensive tests were conducted to ensure that the assumptions of homogeneity were upheld without violation.

For the first research question, we employed an unsupervised machine learning approach known as k-means clustering using MATLAB. This approach was employed to classify participants into different groups based on two variables: pre-test and post-test writing performance. It aimed to facilitate the identification of specific writing improvement profiles among students enrolled in AR-based writing courses. To alleviate the influence of divergent grading standards between pre-test and post-test writing performance, we integrated standardized scores for these variables in our analysis, following the methodology proposed by Wu (2020). The Elbow method was employed to determine the optimal number of clusters. Furthermore, various visualizations, including the Silhouette and Davies-Bouldin methods, were utilized to identify the optimal cluster count. The ideal clustering configuration was expected to exhibit a pronounced elbow (Kaufman & Rousseeuw, 1990), maximal Silhouette values (Rousseeuw, 1987), and minimized Davies-Bouldin value (Davies & Bouldin, 1979).

Furthermore, we conducted descriptive statistics using SPSS 25.0 to outline the characteristics of participants within each group. For the examination of group mean differences in writing performance indices, we applied either the one-way ANOVA or Welch's ANOVA, as recommended by Delacre et al. (2017), contingent on the results of Levene's tests for equality of variances. In the event of a statistically significant omnibus test, we employed Tukey's Honest Significant Difference (HSD) procedure under the assumption of homogeneous variances. Conversely, if the homogeneity of variances was not met, we opted for the Games-Howell test (Kassis et al., 2021) in post-hoc analysis to mitigate the potential inflation of the Type I error rate. After this, we conducted pair *t*-tests to compare pre- and post-writing performance among students in different clusters. This analysis aimed to elucidate the distinct improvement profiles within each cluster and assign them appropriate labels for identification.

In addition, considering that strong performance in the pre-test did not guarantee exceptional results by the course's end, we extended our analysis to include assessments of the writing motivation and learning behaviors exhibited by students with various learning improvement profiles. This provides a more thorough comprehension of their learning dynamics. For the examination of writing motivation, we utilized a paired sample *t*-test to uncover the impact of AR-based writing courses on student writing motivation among clusters. Subsequently, ANOVA tests were employed to examine the group mean differences in writing motivation indices. In the event of a statistically significant omnibus test, we carried out Tukey's HSD procedure to further investigate specific group differences. Regarding the analysis of classroom learning behaviors, we calculated the ratio of each behavior within different clusters. ANOVA tests were then applied to examine the group mean differences in classroom learning behavior indices. Again, in the case of a statistically significant omnibus test, we carried out Tukey's HSD procedure to further investigate specific group differences. Then, we conducted a sequential behavioral analysis using General Sequential Querier (GSEQ) to illustrate the behavior transaction patterns among each student cluster.

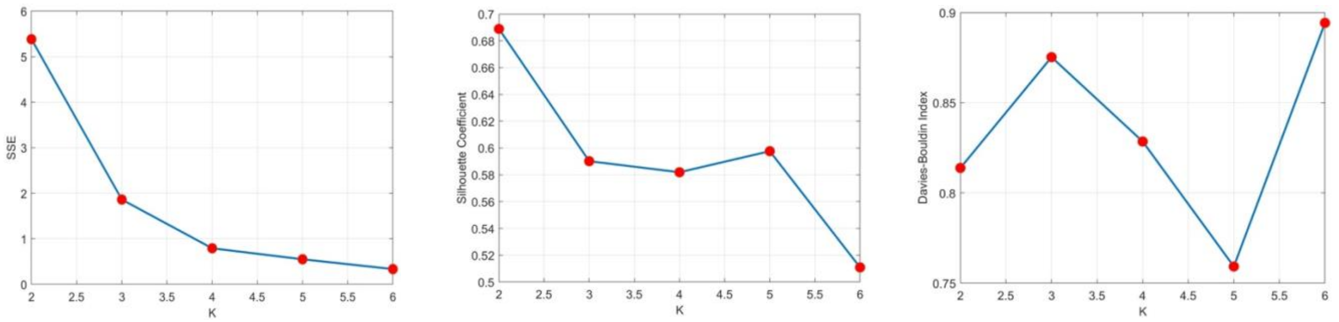
Table 3 Kurtosis and skewness statistics of dependent variables

Variables	Dimensions	Kurtosis	Skewness
Writing performance	Pre-test	0.251(SE =0.511)	-0.624(SE =0.258)
	Post-test	0.893(SE =0.511)	-1.097(SE = 0.258)
Learning motivation	Pre-questionnaire		
	Curiosity	1.237(SE =0.511)	-0.582(SE = 0.258)
	Involvement	1.205(SE =0.511)	-0.611(SE = 0.258)
	Boredom	0.078(SE =0.511)	-0.789(SE = 0.258)
	Emotional regulation	-0.679(SE =0.511)	-0.299(SE = 0.258)
	Grades	-0.506(SE =0.511)	-0.236(SE = 0.258)
	Competition	-0.3(SE =0.511)	0.158(SE = 0.258)
	Social recognition	0.263(SE =0.511)	0.388(SE = 0.258)
	Post-questionnaire		
	Curiosity	-0.066(SE =0.511)	-0.667(SE = 0.258)
	Involvement	0.743(SE =0.511)	-0.767(SE = 0.258)
	Boredom	0.694(SE =0.511)	-1.052(SE = 0.258)
	Emotional regulation	0.027(SE =0.511	-0.8(SE = 0.258)
	Grades	-0.716(SE =0.511)	-0.294(SE = 0.258)
	Competition	-0.763(SE =0.511)	-0.058(SE = 0.258)
	Social recognition	-0.707(SE =0.511)	-0.064(SE = 0.258)
Learning behavior	SA frequency	1.266 (SE =0.511)	1.581 (SE = 0.258)
	SO frequency	0.801 (SE =0.511)	2.305 (SE = 0.258)
	SDP frequency	0.202 (SE =0.511)	0.103 (SE = 0.258)
	SC frequency	-0.338 (SE =0.511)	4.67 (SE = 0.258)
	SLP frequency	0.074 (SE =0.511)	-1.676 (SE = 0.258)
	SL frequency	-1.408 (SE =0.511)	3.046 (SE = 0.258)
	SRT frequency	-1.943 (SE =0.511)	7.528 (SE = 0.258)
	SR frequency	3.047 (SE =0.511)	10.403 (SE = 0.258)
	SH frequency	2.762 (SE =0.511)	7.836 (SE = 0.258)
	SD frequency	2.199 (SE =0.511)	6.395 (SE = 0.258)

4. Results

4.1. RQ1: Do students display different writing improvement profiles that can be characterized into distinct groups in the context of AR-based writing courses?

As shown in Figure 2, we applied the Elbow, Silhouette, and Davies-Bouldin methods to determine the most suitable number of clusters (k) for delineating writing improvement profiles. The Elbow method yielded a distinct “elbow” point, indicating an optimal k value around 4 (refer to Figure 2 (a)). Simultaneously, the Silhouette method revealed two potential optimal Ks for the K-means clustering algorithm. As illustrated in Figure 2 (b), k = 2 exhibited the highest average silhouette coefficient, with k = 5 ranking the second. Additionally, the visualization from the Davies-Bouldin method indicated that k = 5 represented the most favorable choice for the K-means clustering algorithm (refer to Figure 2 (c)). Consequently, we opted for K = 5 as the optimal number of clusters for classifying learners based on their writing improvement profiles in the AR-based learning environment.



(a) Elbow method (b) Silhouette method (c) Davies-Bouldin method

Fig 2 The Elbow method, Silhouette method, and Davies-Bouldin method

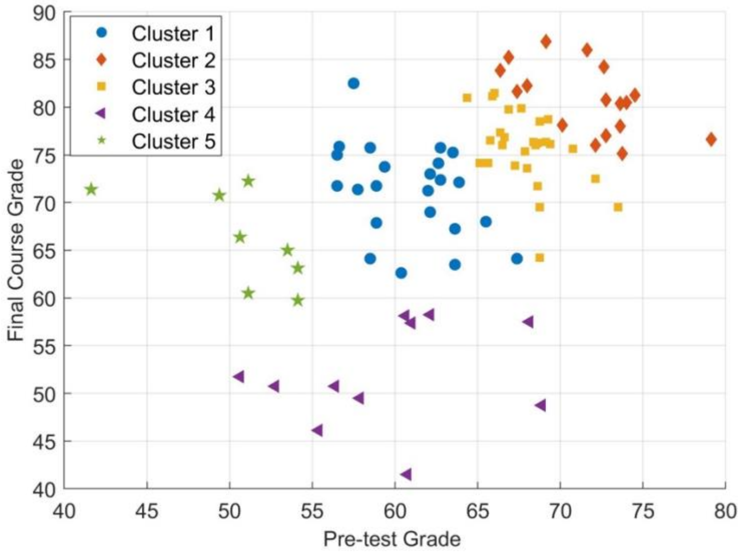


Fig 3 The scatter plot of the five cluster classification results for students' pre-test and final course grades

To validate the effectiveness of the 5-cluster scheme illustrated in Fig. 3, we examined whether students belonging to different clusters exhibited statistically significant variations in their pre-test and final course grades. The pre-test of writing performance demonstrated a rejection of the null hypothesis regarding variance homogeneity according to Levene's test ($F = 4.191$, $p < .01$), while the post-test of writing performance demonstrated an acceptance of the null hypothesis regarding variance homogeneity according to Levene's test ($F = 1.006$, $p > 0.05$). Consequently, Welch's ANOVA test was conducted for the pre-test and the one-way ANOVA test was applied for the post-test. The outcomes substantiated notable distinctions among the five clusters, accompanied by substantial effect sizes ($F = 61.753$, $p < .001$, $\eta^2 = 0.78$ for pre-test grades; $F = 82.194$, $p < .01$, $\eta^2 = 0.80$ for post-test grades), as outlined in Table 4. When considering pre-test grades, Cluster 1 demonstrated notably lower scores in comparison to Clusters 2 and 3, but notably higher scores when compared to Cluster 5. Cluster 2, on the other hand, exhibited significantly higher scores compared to Clusters 3, 4, and 5. Cluster 3 displayed significantly lower scores than Clusters 4 and 5. Similarly, Cluster 4 showed significantly lower scores compared to Cluster 5. In terms of final course grades, Cluster 1 achieved significantly lower scores than Clusters 2 and 3, but notably higher scores when compared to Clusters 4 and 5. Clusters 2 surpassed Clusters 3, 4, and 5. Cluster 3 outperformed Clusters 4 and 5. Lastly, Cluster 4 displayed significantly lower scores in comparison to Cluster 5.

Table 4 Welch's ANOVA test for pre-test and one-way ANOVA test for post-test of writing performance among learning improvement profiles

	Mean	SD	Welch's or one way ANOVA	p	η^2	Post-hoc
Pre-test	64.10	7.00	61.753***	< 0.001[a]	0.78	1 < 2 ***; 1 < 3 ***; 1 > 5 **; 2 > 3 **; 2 > 4 ***; 2 > 5 ***; 3 > 4 **; 3 > 5 ***; 4 < 5 **
Post-test	71.59	9.66	82.194***	< 0.001[b]	0.8	1 < 2 ***;1 < 3 **; **1 > 4 *****; 1 > 5 *; 2 > 3 **; 2 > 4 ***; 2 > 5 ***; 3 > 4 ***; 3 > 5 ***; 4 < 5 ***

*p** < 0.05; *p*** < 0.01; *p**** < 0.001; 1 = Cluster 1; 2 = Cluster 2; 3 = Cluster 3; 4 = Cluster 4; 5 = Cluster 5

a The Games-Howell procedure

b Tukey's Honest Significant Difference (HSD)

As illustrated in Table 5, Cluster 1, comprising 24 students, demonstrated a commendable advancement, achieving an average increase of approximately 10 points (t = -7.74, p < 0.001), elevating their scores from 61 to 71. This notable progress was labelled as the "Advanced group". Meanwhile, Cluster 2, comprising 17 students, attained the highest grades in both pre- and post-tests, distinguishing them as the "High-achievers group". Cluster 3 exhibited a consistent advance, with a relatively lower increase of about 7 points (t = -7.64, p < 0.001), moving from 68 to 75, labelled as the "Persistent group". However, the 11 students in Cluster 4, who initially performed nearly on par with Cluster 1 in the pre-test, experienced a noticeable decline and received the lowest scores in their final course grades (t = 3.69, p < 0.01), leading to their label as the "Indifferent group". In contrast, despite their lower performance in the pre-test, 8 students in Cluster 5 displayed significant improvement (t = -11.82, p < 0.01) by the end of the course, raising their scores from 50 to 66, and were labelled as the "Diligent group".

Table 5 Paired sample t-test for the writing performance among learning improvement profiles

	Groups	*N*	*M*	*SD*	*t*
Cluster 1: Advanced group	Pre-test	24	60.99	3.03	-7.74***
	Post-test		71.34	4.78	
Cluster 2: High-achievers group	Pre-test	17	71.67	3.32	-6.13***
	Post-test		80.82	3.63	
Cluster 3: Persistent group	Pre-test	27	67.94	2.07	-7.68***
	Post-test		75.65	3.90	
Cluster 4: Indifferent group	Pre-test	11	59.5	5.73	3.69**

	Post-test		51.85	5.48	
Cluster 5: Diligent group	Pre-test	8	50.7	4.07	-11.82***
	Post-test		66.14	4.91	

$p^{**} < 0.01$; $p^{***} < 0.001$

4.2. RQ2: Do students with different learning improvement profiles demonstrate different levels of learning motivation in the context of AR-based writing learning activities?

We conducted a paired sample *t*-test method to examine whether AR-based learning activities led to different improvements in students' learning motivation. As shown in Table 6, there were significant improvements in students' learning motivation in the Advanced group ($t = -3.61$, $p < 0.01$ for curiosity; $t = -2.65$, $p < 0.05$ for boredom; $t = -3.18$, $p < 0.01$ for emotional regulation; $t = -2.83$, $p < 0.01$ for competition), High-achievers group ($t = -3.26$, $p < 0.01$ for curiosity; $t = -2.22$, $p < 0.05$ for involvement; $t = -4.29$, $p < 0.01$ for boredom), and Diligent group ($t = -2.52$, $p < 0.05$ for curiosity; $t = -3.34$, $p < 0.05$ for involvement; $t = -2.51$, $p < 0.05$ for competition; $t = -2.6$, $p < 0.05$ for social recognition). Conversely, no significant improvement was observed in the Persistent and Indifferent groups.

Table 6 Paired sample *t*-test for the learning motivation among learning improvement profiles

	Cluster 1: Advanced group			Cluster 2: High-achievers group			Cluster 3: Persistent group			Cluster 4: Indifferent group			Cluster 5: Diligent group		
	(N=24)			*(N=17)*			*(N=27)*			*(N=11)*			*(N=8)*		
	M	SD	*t*	M	SD	*t*	M	SD	*t*	M	SD	*t*	M	SD	*t*
Pre-curiosity	3.70	0.64	-3.61**	3.88	0.70	-3.26**	3.53	0.92	-0.65	3.55	0.60	-0.65	3.69	0.78	-2.52*
Post-curiosity	4.36	0.66		4.47	0.57		3.60	1.00		3.5	0.96		4.28	0.99	
Pre-involvement	3.85	0.55	-1.60	3.68	0.74	-2.22*	3.60	0.87	-0.70	3.52	0.84	-0.70	3.59	0.78	-3.34*
Post-involvement	4.13	0.77		4.09	0.61		3.70	1.01		3.73	0.87		4.5	0.68	
Pre-boredom	3.63	0.98	-2.65*	3.87	0.93	-4.29**	4.15	0.69	-0.68	3.80	0.80	-0.68	3.94	0.65	-2.16
Post-boredom	4.06	1.00		4.49	0.69		4.28	0.75		3.48	0.98		4.19	0.74	
Pre-emotional regulation	3.26	1.03	-3.18**	3.66	1.13	-1.46	3.29	0.93	-1.19	2.93	1.15	-1.19	3.5	1.12	-2.13

Post-emotional regulation	3.91	1.07		3.94	1.08		3.49	1.16		3	1.18		4.09	0.86	
Pre-grades	3.51	1.10	-1.97	3.91	0.81	-1.46	3.64	0.82	-0.44	3.30	0.85	-0.44	3.28	0.77	-1.77
Post-grades	3.93	0.90		4	0.75		3.71	0.93		2.95	0.71		3.81	0.84	
Pre-competition	3.15	1.06	-2.83**	3.54	1.07	-1.61	3.02	0.82	-1.07	3.18	0.80	-1.07	2.75	0.69	-2.51*
Post-competition	3.75	0.94		3.78	1.24		3.24	1.04		2.55	0.77		3.5	0.89	
Pre-social recognition	3.10	0.94	-1.74	2.76	0.91	-1.73	2.91	0.81	-1.27	2.73	0.68	-1.27	2.88	0.48	-2.6*
Post-social recognition	3.55	1.07		3.23	1.19		3.13	1.02		2.86	1.37		3.28	0.54	

*p** < 0.05; *p*** < 0.01

To delve into the intricacies of students' learning motivation within AR-based learning activities across different clusters, we conducted a one-way ANOVA analysis. Both the pre- and post-tests for learning motivation exhibited conformity with the null hypothesis of variance homogeneity ($F = 0.581$, $p > 0.05$ and $F = 1.732$, $p > 0.05$ for pre- and post-curiosity; $F = 0.742$, $p > 0.05$ and $F = 0.979$, $p > 0.05$ for pre- and post-involvement; $F = 1.568$, $p > 0.05$ and $F = 0.571$, $p > 0.05$ for pre- and post-boredom; $F = 0.26$, $p > 0.05$ and $F = 0.254$, $p > 0.05$ for pre- and post-emotional regulation; $F = 1.346$, $p > 0.05$ and $F = 0.579$, $p > 0.05$ for pre- and post-grades; $F = 1.549$, $p > 0.05$ and $F = 1.093$, $p > 0.05$ for pre- and post-competition; $F = 0.831$, $p > 0.05$ and $F = 1.254$, $p > 0.05$ for pre- and post-social recognition).

As shown in Table 7, no significant differences were observed across all dimensions of the pre-test of students' learning motivation among the different clusters. However, notable differences emerged when examining specific dimensions of the post-test of learning motivation (i.e., $F = 5.16$, $p < 0.01$, $\eta^2 = 0.201$ for curiosity, $F = 2.64$, $p < 0.05$, $\eta^2 = 0.114$ for boredom, $F = 3.01$, $p < 0.05$, $\eta^2 = 0.128$ for grades, and $F = 3.44$, $p < 0.05$, $\eta^2 = 0.144$ for competition) with medium to large effect sizes. Thus, a post-hoc test was performed to scrutinize these significant differences in dimensions of learning motivation among different clusters. As outlined in Table 6, the Advanced group demonstrated significantly higher levels of curiosity than the Persistent group, and excelled in curiosity, grades and competition when compared to the Indifferent group. Similarly, the High-achievers group exhibited notably higher levels of curiosity than the Persistent group, and outperformed the Indifferent group in curiosity, boredom, grades and competition. The results reported here reveal that the

Advanced and High-achievers groups may possess heightened learning motivation in AR-based learning activities compared to the Persistent and Indifferent groups.

Table 7 ANOVA test for learning motivation among learning improvement profiles

	Pre- or post- test	Mean	SD	F	p	η^2	Post-hoc[a]
Curiosity	Pre-test	3.66	0.75	0.65	0.628	—	
	Post-test	4.03	0.92	5.16^{**}	0.001	0.201	$1 > 3^{*}$; $1> 4^{*}$; $2 > 3^{*}$;$2 > 4^{*}$
Involvement	Pre-test	3.68	0.75	0.54	0.709	—	
	Post-test	3.97	0.85	2.03	0.098	—	
Boredom	Pre-test	3.89	0.84	1.29	0.282	—	
	Post-test	4.15	0.88	2.64^{*}	0.04	0.114	$2 > 4^{*}$
Emotional regulation	Pre-test	3.33	1.04	0.92	0.457	—	
	Post-test	3.69	1.12	2.02	0.099	—	
Grades	Pre-test	3.58	0.91	1.13	0.35	—	
	Post-test	3.74	0.90	3.01^{*}	0.023	0.128	$1> 2^{*}$; $2 > 4^{*}$
Competition	Pre-test	3.15	0.94	1.26	0.292	—	
	Post-test	3.42	1.07	3.44^{*}	0.012	0.144	$1> 4^{*}$; $2 > 4^{*}$
Social recognition	Pre-test	2.91	0.82	0.59	0.668	—	
	Post-test	3.24	1.08	0.88	0.481	—	

$p^{*} < 0.05$; 1 = Cluster 1; 2 = Cluster 2; 3 = Cluster 3; 4 = Cluster 4; 5 = Cluster 5

a Tukey's Honest Significant Difference (HSD)

4.3. RQ3: Do students with different learning improvement profiles demonstrate different learning behavioral patterns?

To identify the differences in learning behavior patterns among students with different learning improvement profiles, we employed either ANOVA or Kruskal-Wallis tests. Given that the behavior data for SA, SO, SDP, SC, SLP, and SL demonstrated a normal distribution (refer to Table 3) and exhibited conformity with the null hypothesis of variance homogeneity (F = 1.132, $p > 0.05$; F = 1.111, $p > 0.05$; F = 1.537, $p > 0.05$; F = 1.479, $p > 0.05$; F = 1.412, $p > 0.05$), a one-way ANOVA test was performed. In the case of SL, which demonstrated a rejection of the null hypothesis regarding variance homogeneity according to the Levene test, Welch's ANOVA was utilized. Furthermore, for behavior variables SRT, SR, SH, and SD, which did not exhibit a normal distribution (refer to Table 3), a Kruskal-Wallis test was conducted. As shown in Table 8, notable differences in student behaviors were observed in terms of SRT, SH, and SD among the five clusters. Conversely, no significant difference was found in the remaining seven behaviors. Subsequent post-hoc analyses revealed specific patterns within the clusters: High-achievers group exhibited a significantly higher frequency of SRT compared to Diligent group; Persistent group demonstrated a significantly lower frequency of SH compared to Indifferent group; Advanced group showed a significantly higher frequency of SD compared to Indifferent group; High-achievers group showed a significantly higher frequency of SD compared to Indifferent group.

Table 8 ANOVA or Kruskal-Wallis test for learning behavior among learning improvement profiles

	Advanced group	High-achievers group	Persistent group	Indifferent group	Diligent group	*F*	*p*	Post-hoc[d]
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)			
SA	5.42 (1.14)	6.47 (1.49)	7.19 (1.21)	2.45 (0.90)	4.88 (1.47)	1.54	0.197[a]	
SO	110.79 (1.41)	109.59 (1.84)	109.78 (1.29)	111 (2.00)	115 (4.73)	0.81	0.521[a]	
SDP	8.08 (0.43)	8.71 (0.79)	9.85 (0.52)	8 (0.95)	7.88 (1.38)	1.71	0.155[a]	
SC	256.92 (3.73)	252.88 (4.69)	245.37 (4.35)	233.09 (10.97)	259.13 (15.50)	2.17	0.08[a]	
SLP	11.92 (1.38)	13.53 (1.71)	15.41 (1.50)	12.73 (2.18)	12 (3.37)	0.81	0.52[a]	
SL	416.96 (6.12)	419.65 (6.20)	406.48 (8.05)	378.91 (13.90)	369 (28.53)	2.46	0.069[b]	
SRT	3.46 (0.12)	3.82 (0.10)	3.56 (0.10)	3.55 (0.16)	2.63 (0.42)	13.53**	0.009[c]	2 > 5*
SR	8.25 (3.16)	9 (3.13)	4.3 (1.79)	7.82 (2.85)	3 (1.09)	4.60	0.331[c]	
SH	0.46 (0.23)	0.94 (0.37)	0.11 (0.08)	0.91 (0.37)	0.25 (0.25)	12.13*	0.016[c]	3 < 4*
SD	33.29 (5.22)	30.71 (5.12)	53.96 (10.36)	105.55 (25.05)	82 (30.88)	12.91*	0.012[c]	1> 4*; 2 > 4*

*p** < 0.05; 1 = Cluster 1; 2 = Cluster 2; 3 = Cluster 3; 4 = Cluster 4; 5 = Cluster 5

a One-way ANOVA

b Welch's ANOVA

c Kruskal-Wallis test

d Multiple comparison correction by Bonferroni

We extended our analysis by examining the frequency of each possible combination of learning behaviors. Fig. 4 presents the behavioral transition diagrams of each cluster. In these diagrams, the black lines indicate statistically significant transitions between two behaviors, the yellow lines show significant behaviors do not occur in the Indifferent group, and the blue lines indicates significant behaviors do not occur in the Diligent group. Each line is labelled with a z value. When z > 1.96, it signifies that a sequential behavior reached a statistically significant level within %95 confidence interval. A higher z-value indicates a more robust behavioral transaction. The arrows in the diagrams indicate the direction of transfer for each sequence, while the thickness of the directional line serves as an indicator of the strength of the behavioral transaction.

The analysis results indicate that in the Advanced group, a total of 18 learning behaviors reached a statistically significant level. In the High-achievers, Persistent, Indifferent, and Diligent groups, there were 17, 21, 15, and 16 learning behaviors, respectively, that reached this significant level. Among the behaviors of SR, SL, and SA, each cluster demonstrated different transaction patterns. In the Advanced group, students who attentively listened to the teacher demonstrated different behaviors. Those who had the opportunity raised their hands to respond to the teacher's questions and then returned to listening to the teacher (SL→SR→SA→SA→SL). On the other hand, if they did not have the chance to answer the question, they simply reverted to listening to the teacher (SL→SR→SR→SL→SL). In the High-achievers group, students who had the opportunity raised their hands to respond to the teacher's questions and then returned to listening to the teacher (SR→SA→SA→SL). Conversely, when they did not have the chance to answer the question, they would revert to listening to the teacher (SR→SR→SL→SL). In the Persistent group, students who attentively listened to the teacher also demonstrated different behaviors. Those who had the opportunity raised their hands to respond to questions and then returned to listening (SL→SR→SA→SA→SL), or they continued raising their hands before returning to listening (SL→SR→SA→SA→SR→SL). If they did not have the chance to answer the question, they simply returned to listening (SL→SR→SL). Additionally, attentive students in the Persistent group were also inclined to answer questions proposed by the teacher (SL→SA). In the Indifferent group, students who were actively engaged in listening to the teacher, when given the opportunity, raised their hands to address the teacher's questions and then reverted to active listening (SL→SR→SR→SA→SA). If they did not have a chance to respond, they promptly resumed their focus on the teacher (SL→SR→SR→SL→SL). In contrast to the previous four clusters, the Diligent group exhibited no behavioral transition between SR and SA. Students actively engaged in listening to the teacher may have raised their hands, expressing a desire to answer questions, and then promptly return their focus to the teacher (SL→SR→SR→SL→SL). Alternatively, students actively engaged in listening to the teacher might be invited by the teacher to answer questions and then promptly return their focus to the teacher (SL→SA→SA→SL→SL). The results presented here indicate that, with the exception of students in the Indifferent group, the AR-based learning approach appeared to be effective in redirecting students' attention back to the teacher after they had finished answering questions raised by the teacher.

The Advanced, High-achievers, and Diligent groups presented similar behavioral transaction patterns among SRT, SLP, and SDP. Students who reviewed their peers' learning sheets for the task often engaged in discussions with their peers and then revisited their peers' task learning sheets (SLP→SDP→SDP→SLP→SLP). In the Persistent group, students who reviewed their peers' task learning sheets often engaged in discussions with their peers without revisiting the sheets (SLP→SLP→SDP→SDP). Notably, there were interactions between SRT and SL. Attentive students in the Persistent group also participated in group reading sessions guided by the teacher (SL→SRT→SRT→SL→SL). In the Indifferent group, no behavioral transaction was found between SLP and SDP. As for SC, SH, SO, and SD behaviors, the Advanced, High-achievers, Persistent, and Indifferent groups presented similar transactional patterns. Students engaging with AR content on tablets might face challenges in its use (SO→SH→SH→SO→SO). Conversely, the Diligent group exhibited no transactional patterns among these behaviors.

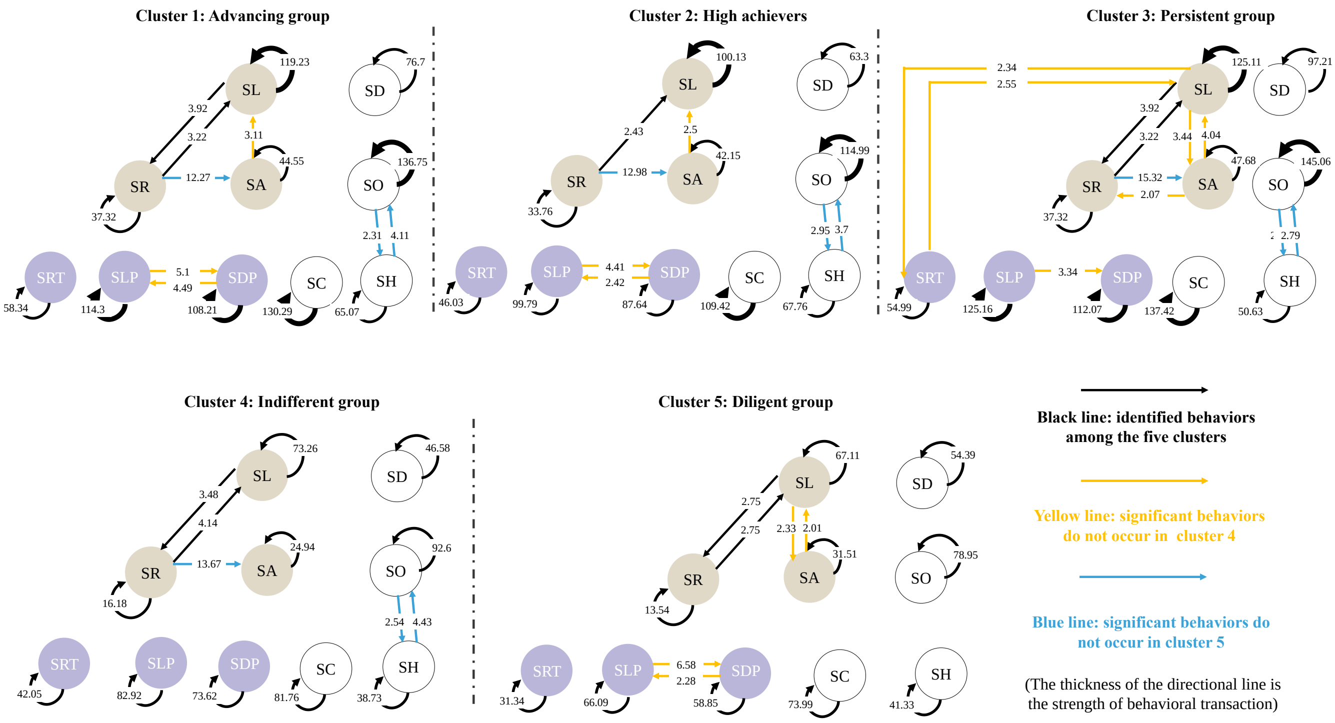


Fig. 4 The behavioral transition diagrams of the five clusters

5. Discussion, implications and limitations

In this study, we investigated the manner in which elementary school students interact with AR technology in the context of writing education and its implications for their achievement. Our focus was on elucidating the motivational factors that influence their engagement and their observed learning behaviors. We initially applied the k-means cluster analysis method to identify different writing improvement profiles using their pre- and post-writing scores. Subsequently, we identified the dynamics of student motivation and learning behaviors in different writing improvement profiles within the AR-based learning environment. Our discussion of the research findings addresses the three research questions initially posed, their relationship to the previous literature, and offers further suggestions for instructional practices.

5.1. Writing improvement profiles

In addressing RQ1, our findings reveal that students engaged in AR-based writing activities can be classified into five different clusters: the Advanced, the High-achievers, the Persistent, the Indifferent and the Diligent groups. The ANOVA test for the post-test of students' writing performance revealed a significant difference between the Advanced and the Indifferent groups, while no such difference was observed in the pre-test of writing performance. These results substantiate hypothesis 1 of the study, suggesting that students immersed in AR-based writing courses are likely to benefit at different degrees, exhibiting different writing improvement profiles. These outcomes further confirm prior research findings (e.g., Ng et al., 2022; Yu et al., 2022) that not all students adapt well when participating in educational experiences driven by AR. AR allows for a more immersive and interactive learning experience. Some students may thrive in these environments and show significant improvement in their writing skills, while others might not benefit from it as positively (Li et al., 2023). Individual learning preferences, engagement levels, and the adaptability of students to the specific instructional methods are among the potential reasons for these varied outcomes (ibid). Furthermore, successful performance is indicative not only of skill levels but also of the confidence individuals have for performing in specific domains and contexts (Bandura, 1997). The utilization of AR may introduce technical or usage challenges (Chen et al., 2023a), and students have different levels of self-efficacy regarding the use of VR. Those with a higher self-efficacy are likely to undertake specific tasks and sustain their engagement even when faced with difficulties, in contrast to those starting from a lower self-efficacy (ibid).

5.2. Learning motivation in different writing improvement profiles

In addressing RQ 2, we conducted an analysis of students' average learning motivation across the five identified clusters. Students in the Advanced, High-achievers, and Diligent groups demonstrated significant enhancements in their learning motivation for AR-based learning. Conversely, the Persistent and Indifferent groups did not exhibit the same level of improvement. This discovery supported the conclusion drawn by Liao and Wu (2023), who observed that students in the Indifferent and Persistent groups may display relatively lower levels of learning motivation. Several factors may contribute to this finding. Firstly, as mentioned earlier, not all students thrive in AR-based learning environments. Some learners may prefer traditional methods owing to their familiarity and comfort with the established approaches they are accustomed to (Chen et al., 2023a). Alternatively, others may find it challenging to adapt to the technical aspects of AR (e.g. X,Y,Z), hindering their comfort and confidence in utilizing AR tools (ibid). These challenges may encompass difficulties in operating devices and comprehending software interfaces (ibid). Secondly, different students have diverse learning preferences and needs. What proves effective for one student in an AR-based approach may not yield the same results for another (Li et al., 2023). Our findings revealed that the Persistent group demonstrated a higher writing performance than the Advanced and Diligent groups in their post-writing test, but they demonstrated lower improvement between the pre- and post-tests. In addition, significant improvements in writing motivation was observed in both the Advanced and Diligent groups and no such improvement was observed in the Persistent group. These results indicate that writing motivation may act as a mediator, influencing the enhancement of writing performance in AR-based learning contexts. This viewpoint is also supported with evidence from a recent systematic review conducted by Camacho, Alves and Boscolo (2021). Their review highlighted that the majority of the studies they examined reported moderate positive associations between motivation levels and writing proficiency which appears to be the case for AR interventions as well.

Moreover, we found significant variations in learning motivation among different writing improvement profiles. These outcomes supported our second hypothesis, revealing that students with diverse writing improvement profiles exhibited varying levels of writing motivation and demonstrated differing levels of motivation driven by various factors. This observation parallels the findings of Liao and Wu (2023), underlining the importance of varying motivation levels among students with different learning improvement profiles. As suggested in the self-determination theory, students motivated by different factors may exhibit variations in their performance (Ryan & Deci, 2000). Researchers indicated that autonomous writers, motivated by internal rewards, tend to produce higher-quality work as they hold a genuine appreciation for writing and are inherently interested in the subject matter (De Smedt et al., 2018). Conversely, controlled writers, motivated by external rewards, often experience heightened stress levels associated with writing, leading to relatively lower writing achievements (ibid). Also, we identified that in AR-based writing activities, curiosity, boredom, grades and competition aspects play essential roles as motivational factors influencing students to achieve more productive writing improvement profiles. Specifically, students who exhibit greater curiosity, show concern for their grades, display a competitive spirit, and experience less boredom tend to make more significant advances in their writing improvement profiles. These findings are also highlighted in previous studies. For instance, Rocha et al. (2019) demonstrated the predictive power of curiosity in writing quality. Ng et al. (2022) highlighted that students' grades-focused writing motivation, driven by culturally significant considerations such as seeking social approval and outperforming peers in school, serves as key motivational drivers for improved performance in writing. Furthermore, as suggested by Camping et al., (2020), relief from boredom appears to be a relatively weak incentive for writing, as we identified a significant difference only between the High-achievers group and the Indifferent group. The findings suggest several implications for educators in shaping effective pedagogical practices. First, teachers are encouraged to design writing courses with creative and engaging themes to enhance students' curiosity that can further motivate them. Second, educators can establish transparent grading criteria, provide constructive feedback, and foster an open dialogue about assessment expectations. This approach can alleviate anxiety and motivate students to actively engage in the writing process (Chen et al., 2023b). Third, educators can design writing challenges, contests, or collaborative projects with an element of friendly competition, encouraging students to invest more effort in their writing tasks (Graham et al., 2017).

5.3. Sequential behavior patterns in different writing improvement profiles

In addressing RQ 3, our investigation uncovered substantial distinctions in classroom behavior frequencies among students with different writing improvement profiles. This included activities like reading aloud together, seeking assistance, and occurrences of disordered behavior. We observed that the High-achievers group were more inclined to follow the teacher's instructions for collective reading aloud, whereas the Diligent group tended not to. This phenomenon appears to be closely linked to their respective attitude towards learning tasks. The High-achievers group, characterized by their exceptional writing performance in both pre- and post-tests, consistently displayed attentiveness and active participation throughout the entire learning process. On the other hand, the Diligent group, who initially displayed the lowest writing performance in their pre-test, tended to become actively engaged primarily when AR technology was integrated. This suggests that their engagement levels were influenced by the introduction of AR technology, which likely sparked their enthusiasm for learning. Notably, the Indifferent group demonstrated a tendency to encounter technical problems, evidenced by their heightened frequency of seeking assistance compared to their peers. This phenomenon might be attributed to their disinterest or lack of motivation in utilizing AR, leading to a reduced focus on overcoming challenges in the learning process. This is further evident from their increased frequency of disordered behaviors, suggesting a decreased focus on overcoming obstacles associated with AR usage. The findings serve as additional support for the conclusions drawn in RQ 2, which identified that students in the Indifferent group exhibited no significant fluctuation in their motivation towards AR-based learning activities. As the Indifferent group have the lowest final course grade, this finding aligns with the observations made by Liao and Wu (2023), suggesting that students who achieved the lowest final course grades tended to be less motivated in course learning.

In analyzing the different sequential behavior patterns within each group, several noteworthy observations also come to light. Except for the Indifferent group, the AR-based learning approach effectively redirected students' focus back to the teacher after they had finished answering the teacher's questions. Moreover, in contrast to the Indifferent group, the remaining four groups consistently displayed behavior transactions between SLP (looking over the task learning sheets from their peers) and SDP (discussing with peers), as well as SL (listening to the teacher's instruction or peers' answers) and SA (answering questions). These discoveries signify that in AR-based learning, aside from the Indifferent group, the majority of students gravitate towards engaging in discussions with their peers when reviewing others' task learning lists, and most students are inclined to listen attentively to the teacher after completing their responses to questions. These findings align with the outcomes identified by Li et al. (2023), underscoring the efficacy of the AR-based approach in intensifying students' focus on the writing learning process. Compared to the Diligent group, the other four groups consistently displayed behavior transactions between SR (raising hands) and SA (answering questions), as well as SO (observing and interacting with the AR content) and SH (having trouble with the use of AR). These findings indicate that in AR-based learning, apart from those in the Diligent group, the majority of students are inclined to raise their hands to respond to the teacher, and they may encounter some technical problems when observing the AR materials. While the AR-based learning process was thoughtfully designed, some students still encountered technical challenges (such as …..). The majority of students viewed these hurdles as minor and did not believe they significantly impacted their learning outcomes. However, a small subset of students, particularly those in the Indifferent group, struggled to adapt, which may have affected their performance. This underscores the importance, as highlighted by Allagui (2021), of designing user-friendly AR tools, a consideration that researchers should prioritize in all EdTech interventions. Additionally, we observed that the Persistent group engaged in behavior transactions between SRT (reading aloud together) and SL (listening to the teacher's instruction or peers' answers). Despite the fact that students in this group may not be primarily motivated by the use of AR in their writing learning process (as suggested by the results for RQ2), they maintain a positive attitude towards their learning tasks. This is evident in their adherence to the teacher's instructions, such as reading aloud.

Based on these findings, practitioners can enhance their implementation of AR for writing education in the following aspects: First, personalized AR-based activities should be designed considering the needs and requirements of students with a diverse set of writing learning ability and motivation. For example, incorporating artificial intelligence (AI) into AR-based activities holds the potential to accommodate diverse levels of writing motivation among students, ensuring that the technology enriches the writing experience for every student, irrespective of their varying learning abilities. Second, the improvement of students' writing motivation is crucial, given the positive relationship between motivation and writing performance. Teachers can, for instance, integrate gamification elements into AR-based writing activities, introducing challenges, rewards, and progression levels to make the learning process more enjoyable and motivating for students. Finally, the development of a more user-friendly interface for AR tools is essential to eliminate difficulties that students may face in the learning process.

5.4. Limitations

Despite our efforts to uncover the dynamics of student motivation and learning behaviors in AR-based writing courses, our study had several limitations. Firstly, we did not account for demographic factors such as age and gender, which are known to be critical influencers of learning achievements. Future studies should consider incorporating students' demographic data into their data analyses. Secondly, our study suggested the potential mediating effects of writing motivation on students' writing outcomes, but it did not establish definitive causal relationships. Thus, we aim to incorporate mediation analysis in future research to gain deeper insights into the relationship between writing motivation and learning outcomes in the context of AR-based learning. Third, our sequential behavior data analysis did not take into account time series segmentation (e.g., by course session), which limited our ability to interpret specific learning behaviors within individual course sessions. To enhance the comprehensibility of AR's influence on classroom learning behaviors among students with different improvement profiles, researchers can present classroom behavior patterns on a session-by-session basis. This would facilitate a more detailed understanding of how AR impacts students' learning behaviors throughout their course journey.

6. Conclusions

The current research extends prior work on AR-based writing learning in three key ways, advancing both theory and practice. First, we utilized unsupervised machine learning, specifically the K-means cluster method, to identify different writing profiles within AR-based writing learning activities. We conducted a comparative analysis of writing motivation and learning behaviors across these groups, reaffirming the link between higher writing motivation and improved outcomes while uncovering underlying factors such as curiosity, grade focus, competitiveness, and reduced boredom in writing motivation, associated with more focused and organized behaviors. Notably, not all students demonstrated equal proficiency in adapting to AR-based learning activities, with lower writing motivation linked to underperformance. Second, we enriched the literature by revealing that students in different writing improvement profiles exhibited unique combinations of motives, as assessed through an enhanced motivational questionnaire derived from WMQ. Third, our findings empirically supported the idea that students in different writing improvement profiles displayed divergent sequential behavior patterns throughout the classroom learning process. To improve the effectiveness of AR-supported writing education in primary schools, these differences in motivation and behaviors of students should be taken into account accordingly in pedagogical interventions.

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