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Extending Technology Acceptance Model to higher-education students' use of digital academic reading tools on computers

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Abstract

Digital academic reading tools on computers bring multiple benefits to higher-education students. Through structural equation modeling methods, this study contributes to the following findings: (1) Perceived ease of use, perceived usefulness, and lecturers' positive responses significantly predict students' positive attitudes toward digital academic reading tools on computers; (2) perceived ease of use, lectures' positive responses, and expectations of academic achievement are significantly positive predictors of students' perceived usefulness of these tools; (3) attitudes and expectations of academic achievement significantly predict students' positive intentions to use these tools; (4) academic experience significantly predicts students' negative attitudes toward these tools; (5) perceived ease for collaborative learning and self-efficacy are significantly positive predictors of students' perceived ease of using these tools. Findings in this study may contribute to understanding the external factors influencing students' acceptance and use of digital academic reading tools on computers with a substantial explanatory power of the proposed model ($R^2 = 64.70–84.20\%$), which may benefit researchers, instructors, students, and technology designers.

Keywords: Technology acceptance model, Digital reading, Computer-assisted language learning, Academic reading

Introduction

Digital learning tools and e-learning environments have attracted avid interest in academic research, promoting reading performances in higher education (Kuhn et al., 2022). Controversies exist regarding the exact definitions of digital learning tools (particular educational technologies) and e-learning environments (broader contexts combining technological, learning, and pedagogical aspects) (Moore et al., 2011). Unclear definitions do not prevent researchers from conducting an increasing amount of research on various technologies in educational contexts. Broadly referring to tasks in academic contexts, students' academic work benefits from the rapid development of digital reading tools. Particularly, academic reading ability is crucial to English for Academic Purposes that encompasses a series of skills and knowledge for using English effectively for academic purposes and in academic contexts (DiCerbo et al., 2014). In a digital era, reading is facilitated by computer programs that allow for highlighting important content, attaching comments, re-organizing digital reading sources, sharing resources, and collaborating online simultaneously (Pálsdóttir, 2019). Digital reading tools have sparked research on them from technological and educational perspectives. The diverse functions of digital reading tools demonstrate their suitability and functionality for academic purposes despite inconsistent conclusions regarding reading performances with different media (Inie et al., 2021). Higher-education students, teachers, and other researchers need to read updated academic materials, which familiarizes them with previous findings and state-of-art progress in a particular research area. The related resources can only receive timely updates when they use digital reading tools and materials. Consequently, digital academic reading plays a fundamental role in research and learning in higher education.

Instructors have actively introduced digital reading tools and resources into their courses, given that these tools can enhance the effectiveness of academic reading and research-related work (Arshad & Ameen, 2017). In higher education, students may hold inconsistent attitudes toward such technological transformation. Active research on the mechanisms whereby educational technologies can be accepted by their users significantly contributes to understanding the characteristics of particular users and technologies in education (Keskin et al., 2016). However, digital reading tools on computers are rarely investigated regarding technological acceptance. More specifically, influencing factors related to academic work have not been integrated into technology acceptance models, such as expectation, efficacy, external support, and experience related to academic work (Habibi et al., 2022; Leong et al., 2018). As digital technologies are prevalent in higher education, it is significant to explore how digital reading tools can be integrated into teaching practice and how students may accept them. Extending technology acceptance models is a pathway to effectively introducing digital reading tools into practice.

This study adopts structural equation modeling methods to introduce six external factors to the traditional Technology Acceptance Model so that the extended model can attain a higher explanatory and predictive power. In this way, we will explore the influences of academic, psychological, and experiential factors and examine how these factors contribute to explaining and predicting students' acceptance and actual use of digital reading tools on computers for academic purposes in higher education. This article will unfold with the following structure. First, we will review studies related to digital reading tools, academic reading, and technology acceptance. Based on the existing literature, we will propose an extended and hypothesized technology acceptance model to include some less-investigated factors. Then, we will introduce our research methods and results, testing the proposed model and hypotheses. Findings will be used for theoretical and practical implications about technology integration, digital literacy cultivation, instructions about academic English reading, and other potential areas.

Literature review

Digital reading for academic English

The active practice of digital academic reading in educational contexts has been inspired largely by the advantages of digital academic reading, such as convenient resource-sharing, timely material updates, digital note-taking, and facilitated self-regulated learning.

Pioneered by Prensky's investigation on games in learning (2001), studies on digital tools for academic reading have thrived. Researchers on digital reading tools for academic materials have explored the potential of electronic documents for academic reading (Qayyum, 2008). Previous studies also investigated electronic journals, which allowed close updates of reading materials (Arshad & Ameen, 2017). Although some studies reported that students preferred printed texts for e-books (e.g., Woody et al., 2010), electronic reading technologies have significantly developed. With the popularity of mobile-assisted learning, Li summarized various contents for academic libraries in Chinese (2013). Recent researchers have specified educational contexts and finer-grained elements for academic reading studies. Electronic books and digital learning systems could enhance students' self-regulated learning, self-efficacy, and academic achievements (Chen & Su, 2019). Collaborative learning could also be facilitated by digital reading tools, which promoted learners' academic performances (Rodríguez et al., 2017). Video integration enhanced the effectiveness of digital academic reading (Baker et al., 2021). Researchers have widely supported the multi-faceted benefits of digital reading tools on various technologies and media for academic purposes.

To identify primary research issues, we used the Core Collection on Web of Science on 23 January 2023, with the keyword "digital academic reading" searched in "Topic" (i.e., titles, keywords, and abstracts of publications in the database). Visualizing 413 studies with popular software, VOSviewer (Van Eck & Waltman, 2010), Fig. 1 demonstrates that 219 keyword items (minimum occurrences being three in the literature search results) could be clustered into nine groups according to their co-occurrences. The visualization map revealed the hot keyword items by large nudes and less-investigated topics by smaller ones. Clustering keyword items was performed automatically by the program based on the co-occurrence relations in the included literature. Cluster 1 and 5 indicated

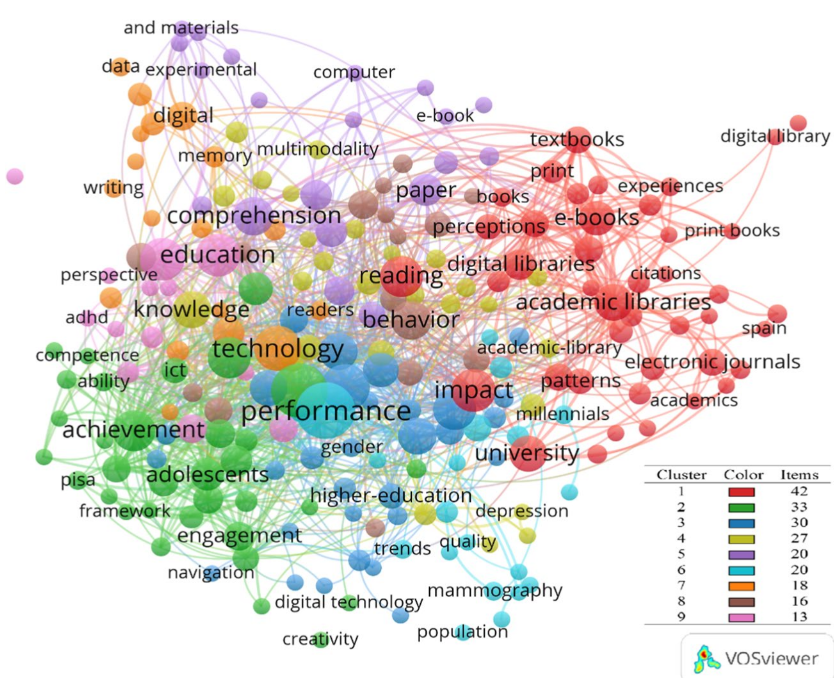

Fig. 1 Keyword items visualization related to digital academic reading

that digital resources (libraries, e-books, and journals) were popular research topics. Cluster 2, 3, and 6 indicated that researchers focused on learners' abilities, such as information technology-mediated communication, academic achievement, and reading performance. Cluster 4 suggested research interest in various learning contexts, represented by COVID-19 and teacher training. Through the literature search, visualization, and clustering, we could summarize that the existing literature has extended their research interest to digital reading sources, related competence, learning outcomes, and various application contexts.

The findings in literature visualization could be confirmed through a systematic review based on the search results. Following a literature filtration paradigm suggested by the Preferred Reporting Items of Systematic reviews and Meta-Analyses (PRISMA) flowchart (Page et al., 2021), we screened the search records according to a set of systematic criteria (cf. Duran et al., 2006). Based on relevance evaluation and quality assessment, the literature filtration led us to only 19 empirical studies and one literature review article related to digital academic reading studies in higher education contexts. We examined the search records by reading their titles, abstracts, and keywords. Four articles focused on academic libraries in the era of digitalization (e.g., Tbaishat, 2018), two on special educational needs in higher education (e.g., Alsalem, 2018), and three on a broader research theme of academic literacy, including reading competence (e.g., Lea & Jones, 2011). Ten empirical studies concentrated on particular digital reading devices, such as specialized e-book readers, iPad, and mobile phone (e.g., Gourlay, 2015; Soroya & Ameen, 2020); four empirical studies compared printed and digital reading materials, considering students' preferences and learning effectiveness (e.g., Eden & Eshet-Alkalai, 2013). A thorough review of these studies identified similar research trends found by the clustering results: Digital reading tools on computers for academic purposes in higher education have rarely been investigated, especially from a perspective of technology acceptance research. To probe into the less-investigated technologies and contexts, this study intended to explore factors influencing students' acceptance and use of digital reading tools on computers in higher education contexts.

Technology Acceptance Model and its developments

Technology Acceptance Model (TAM) was proposed by Davis (1989) to evaluate students' acceptance of four programs. Davis's study established in the original model the relationships between perceived usefulness, perceived ease of use, attitudes, and behavior or actual use of the programs (Davis, 1989). The traditional model was developed to explain and predict technology users' acceptance concerning multiple factors, but it remains open to emerging constructs (Cheung & Vogel, 2013) since factors in the original Technology Acceptance Model did not characterize much detail about technology use and acceptance. The model was extended to TAM 2 (the Extended Technology Acceptance Model) by Venkatesh and Davis, who added social and cognitive factors, such as experience and voluntariness (2000), encouraging studies to further examine moderating effects of these factors (Venkatesh & Bala, 2008). Venkatesh and Bala's model (known as TAM 3) could provide a 40–53% explanation of technology users' behavioral intention by synthesizing 17 variables (2008). Another prevalent technology acceptance model was proposed by Venkatesh et al. (2003), known as the Unified Theories of

Acceptance and Use of Technology (UTAUT). It was proposed based on eight technology acceptance models, including the traditional Technology Acceptance Model (see Williams et al., 2015; Zhang & Yu, 2022 for a full list of the component models). According to Venkatesh et al. (2003), the Unified Theories of Acceptance and Use of Technology had an even higher explanatory power (adjusted $R^2 = 69\%$) for users' intention to use certain technologies than the component models. Venkatesh later extended this model into the extended Unified Theories of Acceptance and Use of Technology (UTAUT 2), adding "hedonic motivation, price value, and habit" to enhance this model's explanatory power (2012).

Extending the Technology Acceptance Model to digital academic reading tools on computers

Incorporating new factors into the established technology acceptance models and applying them to diverse contexts have been two popular research directions for technology acceptance, especially with structural equation modeling methods. Extending the traditional Technology Acceptance Model by adding new constructs was a common approach to enhance the explanatory power for technology use in various fields. Individual, psychological, social, and cognitive factors were dominant in the previous literature, especially in educational research. Perceived security, relevance, and personal investment were integrated into the traditional Technology Acceptance Model by Wang et al., (2022b), where relevance and personal investment contributed to students' use of a popular online learning application in China. Wang, Yu, et al.'s study integrated five external factors into the Technology Acceptance Model, yielding a moderate level of explanatory power (R^2 between 33 and 67%) (Wang et al., 2022b). Psychological factors have been introduced into the Technology Acceptance Model or the Unified Theories of Acceptance and Use of Technology, such as openness, perseverance of effort, and emotional stability (Zhang & Yu, 2022). Regarding academic reading with e-books, Luo et al. (2021) incorporated social and controlling tools into technology acceptance models, while academic performance and achievements were not investigated. Digital social reading platforms also demonstrated positive effects on higher-education students' writing skills and comprehension (Burhan-Horasanlı, 2022), while the acceptance of the platform was not particularly investigated. Keskin et al. (2016) investigated factors like students' attitudes and perceived usefulness of technology, but their study did not adopt a structural equation modeling method to formulate the extended model.

The existing literature rarely considered academic and psychological in explaining using digital academic reading tools on computers. This study aimed to incorporate them into the traditional Technology Acceptance Model. Figure 2 combines academic work-related factors, psychological constructs, and the traditional Technology Acceptance Model. The proposed model demonstrates the relationships explored in this study. Before our proposals of new external concepts, we would introduce the hypotheses in the traditional Technology Acceptance Model. To commence with, the traditional concepts in the Technology Acceptance Model were adapted for this study and defined as follows: *Perceived usefulness* (PU) measures the degree to which users believe that using digital reading tools on computers could facilitate their academic performances;

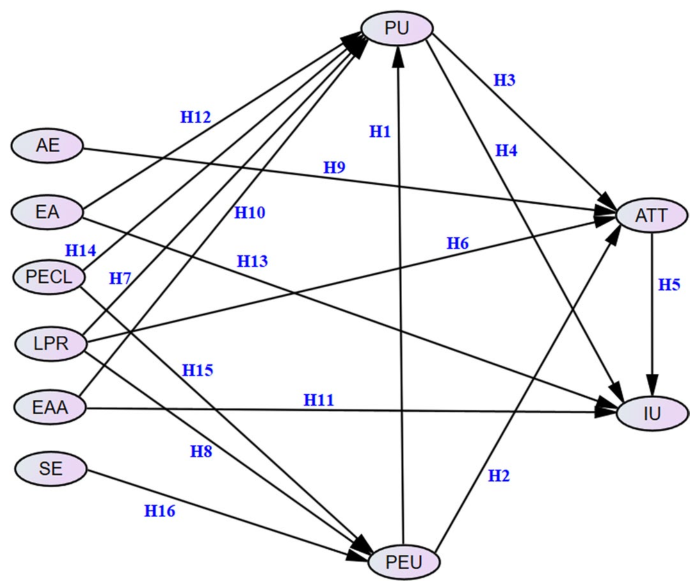

Fig. 2 A hypothesized model with new constructs explaining and predicting higher-education students' accpetance and actual use of digital academic reading tools on computers. *AE* academic experience, *EA* ease of access to academic reading materials, *PECL* perceived ease for collaborative learning, *LPR* lecture's positive response, *SE* self-efficacy, *EAA* expectation of academic achievement, *PU* perceived usefulness, *PEU* perceived ease of use, *ATT* attitude, *IU* intention to use

perceived ease of use (PEU) refers to the degree to which users believe that using digital reading tools on computers for academic purposes does not require too much effort; *attitude* (ATT) refers to the degree to which users are interested in using digital reading tools on computers for academic purposes; *intention to use* (IU) refers to users' behavioral purposes of using digital reading tools on computers for academic goals (Cheung & Vogel, 2013; Davis, 1989).

Five hypotheses would be tested in this study considering these four traditional variables. According to similar research using the traditional Technology Acceptance Model, such as Wang et al., (2022b) and Luo et al. (2021), we would test the hypotheses in the traditional Technology Acceptance Model regarding higher-education students' use of digital academic reading tools on computers. H1, 2, 3, and 5 were adapted from widely tested hypotheses in technology acceptance modeling research, and these paths were supported in contexts of various educational technologies (Arpaci et al., 2023; Wang et al., 2022b). This study would test these four hypotheses to extend the Technology Acceptance Model to a new context from higher-education students' perspectives, that is, digital academic reading tools for academic purposes on computers. In contrast, the predictive role of perceived usefulness toward intention to use was rather inconsistent. A considerable body of research found insignificant results regarding the predictive role (e.g., Deng & Yu, 2023; Wang et al., 2022b). However, many researchers found that perceived usefulness has a significantly positive role in predicting (continuous) intention to use, such as in Wang et al. (2022a) and Arpaci et al. (2023). Confronted with such inconsistencies in the existing literature, we intended to test the predictive role of perceived usefulness toward intention to use by H4. The following were hypotheses tested in this study concerning the traditional Technology Acceptance Model:

H1: Higher-education students' perceived ease of use positively predicts their perceived usefulness of digital academic reading tools on computers.
H2: Higher-education students' perceived ease of use positively predicts their attitudes toward digital academic reading tools on computers.
H3: Higher-education students' perceived usefulness positively predicts their attitudes toward digital academic reading tools on computers.
H4: Higher-education students' perceived usefulness positively predicts their intentions to use digital academic reading tools on computers.
H5: Higher-education students' attitudes positively predict their intentions to use digital academic reading tools on computers.

In addition to the traditional Technology Acceptance Model, this study intended to incorporate six constructs related to academic contexts. We aimed to provide a stronger explanatory and predictive model for students' use of digital reading tools on computers for academic purposes in higher education. Some of the following constructs were rarely introduced into technology acceptance studies, while rationales existed to support their impacts on students' use of digital academic reading tools on computers. The following sections will introduce these concepts separately, and rationales will be provided for the proposed hypotheses.

Lecture's positive response (LPR)

The lecturer's response is defined in this study as a lecturer's reaction to students' use of digital academic reading tools on computers. This concept was derived from teachers' attitudes toward educational technologies, which has been popular in recent studies on introducing technologies to teaching practice. For example, the values of information communication technologies perceived by teachers would positively influence their attitudes toward the related educational policies and technology applications (Hong et al., 2022). Teachers' attitudes toward educational technologies could be a critical factor in whether technology integration into the classroom is successful and whether students could accept them (Yu & Yu, 2019; Raygan & Moradkhani, 2022). However, few studies focused on the correlation between teachers' attitudes toward technologies and students' use of digital academic reading tools on computers. As teachers' attitudes could positively predict the outcomes of technology integration, they might also be positively related to students' attitudes and actual use of educational technologies. Therefore, in this study, we intended to test the following hypotheses:

H6: Lecturers' positive responses positively predict higher-education students' attitudes toward digital academic reading tools on computers.
H7: Lecturers' positive responses positively predict higher-education students' perceived usefulness of digital academic reading tools on computers.
H8: Lecturers' positive responses positively predict higher-education students' perceived ease of use of digital academic reading tools on computers.

Academic experience (AE)

In the Extended Technology Acceptance Model (Venkatesh & Davis, 2000), researchers have included experience as a moderator in the relationships between influencing factors and the use of technologies. Defined as prior involvement in using certain technologies, the experience would significantly influence the acceptance of technologies (Leong et al., 2018). In contrast, this study intended to investigate students' experience with academic work rather than educational technologies. Also, different from the moderating effect of experience in some technology acceptance models, this study would investigate the influence of academic experience on the acceptance and use of digital academic reading tools on computers. The rationale was that experience in academic work could allow students to better perceive how digital academic reading could contribute to their academic work. In this sense, the academic experience could strengthen the intention to use digital reading tools on computers for academic purposes. Therefore, we would test the following hypothesis:

> **H9**: Higher-education students' academic experience positively predicts their attitudes toward digital academic reading tools on computers.

Expectation of academic achievement (EAA)

The concept of expectation was derived from the Expectation-Confirmation Theory, for example, in Persada et al. (2022). In this study, we intended to explore the impacts of higher-education students' academic expectations. From a psychological perspective, the hope theory attempted to establish the relationship between expectations and actual achievements, which was further extended to academic contexts (Levi et al., 2014). Many researchers revealed that academic expectations could lead to students' arduous efforts for achievements (Levi et al., 2014). However, empirical evidence also suggested the negative impacts of expectation when it caused academic stress (Calaguas, 2012). The role of expectation could be inconsistent, but critical as to whether it could contribute to academic efforts and achievements. Academic expectations might encourage higher-education students to choose efficient learning tools actively (Teo et al., 2023). The academic expectations and technological use for academic purposes could be related. Therefore, we intended to test the following hypotheses:

> **H10**: Higher-education students' expectations of academic achievement positively predict their perceived usefulness of digital academic reading tools on computers.
> **H11**: Higher-education students' expectations of academic achievement positively predict their intentions to use digital academic reading tools on computers.

Ease of access to digital resources (EA)

One of the benefits of educational technologies was considered the openness of digital resources and the increased opportunities for learners (Haleem et al., 2022; Kuhn et al., 2022). Nevertheless, more important might be how much students could benefit from open resources and digital reading tools on computers. Studies have extensively explored the benefits of electronic reading tools on mobile phones and tablets, suggesting students' enhanced learning motivation and enjoyment (Ciampa, 2016). Copyright issues and restrictions on resource sharing could challenge access to digital resources. Considering benefits and limitations, students' perceived ease of access to digital resources might impact their perceived usefulness and intentions to use digital reading tools on computers for academic purposes. This study intended to test the following hypotheses:

> **H12**: Higher-education students' perceived ease of access to digital resources positively predicts their perceived usefulness of digital academic reading tools on computers.
> **H13**: Higher-education students' perceived ease of access to digital resources positively predicts their intentions to use digital academic reading tools on computers.

Perceived ease for collaborative learning (PECL)

Enhanced resource sharing allowed by digital devices and the Internet was one of the benefits of using digital academic reading tools on computers. Perceived ease of use was a critical component in the traditional Technology Acceptance Model, which was relatively general and referred to individuals' perceived ease of using a particular system (Davis, 1989). This study would further specify the perceived ease and explore how higher education students could benefit from using these tools for collaborative learning. Collaborative learning has been a popular learning strategy in current educational contexts, especially for peer assessment activities (Lin & Yu, 2023). Established on Vygotsky and Cole's theory of the Zone of Proximal Development (1978), collaborative learning has yielded significant enhancements of learning effectiveness and achievements in technology-enhanced learning with the introduction of computers (AbuSeileek, 2012; Ebadijala & Moradkhani, 2023). Researchers suggested that the advantages of using digital reading tools could facilitate collaborative learning. Digital learning media improved young learners' collaborative learning performances (Lieberman et al., 2009). Digital reading tools were integrated into primary education, seeking its advantages in promoting collaborative learning (Rodríguez et al., 2017). Convenient collaborative annotation tools could also enhance students' academic reading performances (Chen & Chen, 2014). However, adopting digital reading tools on computers for academic purposes was not investigated much in higher education contexts regarding the impacts of these benefits on students' technology acceptance and actual use. Considering the positive effects of collaborative learning and technology integration in education, this study intended to test the following hypotheses:

> **H14**: Higher-education students' perceived ease of using digital reading tools on computers for collaborative learning positively predicts their perceived usefulness.
> **H15**: Higher-education students' perceived ease of using digital reading tools on computers for collaborative learning positively predicts their perceived ease of use.

Self-efficacy (SE)

Self-efficacy is defined as people's belief in their ability to overcome challenges in achieving the expected targets; more specifically, teacher and computer self-efficacy were conceptualized (Schwarzer & Luszczynska, 2008). Researchers studying technology acceptance were interested in computer self-efficacy proposed by Marakas et al. (1998), including the general aspect and other specific ones in different application contexts. In this study, self-efficacy refers to individuals' belief in their ability to use digital reading tools on computers to achieve academic purposes. It would focus on realizing the expected functions with digital reading tools, while expectations would be measured from a general perspective of academic achievements. Previous studies have contributed to the positive correlation between self-efficacy and perceived ease of use (Habibi et al., 2022). This study would extend the correlation between self-efficacy and perceived ease of using digital reading tools on computers for academic purposes in higher education by the following hypothesis:

> **H16**: Higher-education students' self-efficacy in using digital academic reading tools on computers positively predicts their perceived ease of use.

Methods

Survey instrument design

First, we designed our survey questionnaire using the literature review and the established scales for corresponding variables. The questionnaire included 44 questions: For the first section, three questions were asked to request participation consent and record participants' genders and educational levels. The second section consisted of ten variables, each measured by four statements. References for these variables were as follows: AE, EA, LPR; SE (Schwarzer & Jerusalem, 1995), EAA; PU, PEU, PECL (David, 1989; Venkatesh et al., 2012); ATT (Davis, 1989; Razmak & Bélanger, 2018); IT (Al-Shahrani, 2016; Davis, 1989; Venkatesh et al., 2011). Some variables were not investigated in the previous literature, where the statements would demonstrate our innovative explorations. We strictly followed the patterns for other established scales and tested these items with statistical approaches. Concerns might arise regarding our question designs for the less-investigated constructs. However, we would combine validity and reliability tests for all variables to validate our dataset and measurements. A combination of exploratory and confirmatory factor analysis methods should be adopted to further test the results. The third section was an open-ended question to elicit the advantages and disadvantages of digital reading tools on computers for academic purposes from the participants' perspectives. Additional file 1: Appendix 1 is the full version of our questionnaire for this study.

Research procedures

After the questionnaire design, we posed the final version on an online survey platform (http://www.wjx.cn), which allowed us to distribute our questionnaire online through a hyperlink or a QR code. Regarding data collection, rapid convenient sampling was a popular method in research on technology acceptance modeling, especially when a large sample was required for structural equation modeling methods. Previous researchers recruited participants through convenient channels, such as the Internet, local newspaper, television, and institutional invitations (Raza et al., 2020; Stangier et al., 2021). Such datasets could still provide strong findings when validated through rigorous statistical approaches, such as normality, validity, and reliability tests. Following this research paradigm, we distributed our survey questionnaire through personal networks and public social media, especially with the hyperlink spread on WeChat groups. Group members were invited and could voluntarily participate in this survey without our further intervention and participant selection. The sampling method was similar to the previous literature that adopted, validated, and utilized such sampling data to test hypothesized models using structural equation modeling approaches (Wang et al., 2022b).

From 10 November 2022 to 28 February 2023, we collected valid data from 903 participants. The sample size could be considered nearly excellent since researchers viewed 500 as a very good population and 1,000 as excellent for factor analysis (Raza et al., 2020). All data were then exported in an xlsx file for further processing. Demographic information was first revealed. Then, we evaluated the reliability and validity of the questionnaire and tested the hypothesized model with IBM SPSS 26.0 and IBM AMOS 24.0. The qualitative data from our survey were filtered to remove answers that did not provide much information, such as "no further comment", "no idea", or blank answers. Other answers were analyzed regarding the advantages and disadvantages of digital academic reading tools on a computer with AntConc 3.5.7, a corpus analysis tool that could calculate the frequency list of word items in Chinese and English.

Statistical approaches

When the sample size reached our expected level and data collection was ended, we first excluded the records from the exported survey data in which the participants did not provide informed consent to the researchers. According to our setting, the survey would jump to the end directly if the participants signed "No" to the informed consent question. As this study would focus on higher-education students' technology acceptance of digital academic reading on computers, we also excluded records from teachers and workers. We then calculated the skewness and kurtosis for each item, which are common tests for the normality of distribution. Normality tests are significant since they help identify whether the dataset is so biased that it is not suitable for further statistical approaches and discussions. According to Kline (2015), when (1) the absolute value of skewness is greater than 3.000, or (2) the absolute value of kurtosis is greater than 10.000, the data is extremely skewed; otherwise, the distribution normality is acceptable. We used the "Tests for normality and outliers" function in AMOS to test the distribution of each item, which could prevent us from the risk of using a biased dataset collected from the convenient sampling methods.

Then, we tested the validity and reliability of the survey questions. We calculated the factor loadings and the internal consistency (Cronbach's α) with SPSS. We deleted items with factor loadings lower than 0.500 that could not demonstrate great validity and reliability (Pham et al., 2019). In the meantime, we used the "Validity and Reliability Test", a plug-in in AMOS to calculate the average variance extracted (AVE) and composite reliability (CR) for the covariates and test the discriminant validity according to the

Fornell-Larker method. The AVE and CR values of the other variables were calculated with a programmed tool according to statistical formulas for each value.

With validity and reliability assured, we would further examine the explanatory power of the hypothesized model and test the hypotheses with effect sizes and their statistical significance. Consistent with the previous literature, the explanatory or predictive power of the postulated model should be measured by the values of R^2 (Deng & Yu, 2023; Wang et al., 2022b; Wu & Chen, 2017). An R^2 value greater than 70% indicates that the model has a substantial explanatory power (Moore et al., 2013, p.138). The explanatory power value could be estimated by calculating "Squared Multiple Correlations" in AMOS. For hypothesis testing, effect sizes would demonstrate how one variable could influence the other, according to Larson-Hall and Plonsky (2015). In this study, we adopted two statistics to measure the effect sizes between different variables, i.e., Pearson correlation coefficients (r) and path coefficients (β). The former would be calculated when we adopted the Fornell-Larker method to evaluate the discriminant validity of the covariates. If $r > 0.500$, the correlations between the two covariates would be significant. We would use β calculated by AMOS in the path analysis of the hypothesized model. When $0 < |\beta| < 0.100$, the effect size of the path would be weak; $0.100 < |\beta| < 0.300$, $0.300 < |\beta| < 0.500$, and $0.500 < |\beta| < 1.000$ would indicate modest, moderate, and strong effect sizes, respectively (Zhang & Liu, 2022). If $\beta > 0$, the effect sizes were positive; otherwise, the path would demonstrate negative relations between variables.

Results

Descriptive statistic and normality test results

According to our survey data, Table 1 demonstrates participants' informed consent and demographic information. As we listed, 7 participants who selected "No" for the informed consent and 12 who identified as "Teachers and workers" had to be excluded from this survey. The total records passed the above filtration amounted to 884 valid records. When we distributed the questionnaire link, we noticed that due to our research areas and personal relationships, most participants who responded were learning social sciences, even if the sampling was random and covered participants from

Table 1 Demographic information of all participants

Item	Type	Frequency	Percentage
Informed consent response	Yes	896	99.24%
	No	7	0.76%
Participants who consented (N = 896)			
Gender	Female	784	86.92%
	Male	112	13.08%
Educational levels	Undergraduates	341	38.06%
	Master's students	522	58.26%
	Doctoral candidates	21	2.34%
	Teachers and workers	12	1.34%

multiple universities across China. As a consequence, we found that female participants took up a larger proportion, which was common in social science majors in China. Also, master's students responded to this survey more actively than undergraduates and doctoral candidates. The results might demonstrate their active interest in evaluating their use of digital reading tools on computers for academic purposes, while the undergraduates were not entirely familiar with academic or especially research work. Doctoral candidates responded less, probably due to the limited size of the eligible population at this level.

The measurements of all ten variables in the survey were tested regarding the normality of distribution. The 40 items were tested separately, and results demonstrated that for all items, the maximum absolute value of skewness was $1.056 < 3.000$, and the maximum absolute value of kurtosis was $2.520 < 10.000$. The results indicated that insignificant distribution skewness existed in the survey data for each item based on the critical values suggested in the previous section. The tests of variable normality should serve as the basis of further structural equation modeling approaches since the modeling adopted the maximum likelihood estimation method that assumed multi-normality (Kline, 2015). When the preconditions were tested for further structural equation modeling approaches, we further tested the reliability and validity of the survey data, followed by model fit assessment and path analyses. In order to enhance the validity, reliability, and model fit statistics, we deleted three items (one item from LPR, PU, and ATT, respectively), since their factor loadings were smaller than 0.500 in the preliminary statistical analysis. The following analyses will be based on the refined set of items to test our hypothesized model.

Structural equation model assessment

Exploratory factor analysis

Although the factors have been manipulated and fixed in the hypothesized model for this study, we first conducted an exploratory factor analysis to generate reliable interpretations of the proposed factors. As Kline suggests (2015), this could enhance the "interpretability of established factors in the unrestricted measurement model" (Zhang & Liu, 2022, p.14). We used SPSS to evaluate the suitability of the collected data for structural equation modeling. The suitability was evaluated with the Kaiser-Meyer-Okin (KMO) test and Bartlett's test of sphericity. The results showed that the KMO value was 0.958, and the sphericity was significant ($p < 0.001$). According to the critical values suggested by Taherdoost et al. (2022) and Zhang and Liu (2022), both tests indicated that the collected data could be used for structural equation modeling methods. We conducted an exploratory factor analysis in SPSS, setting the factor extraction method based on principal components and Eigenvalue greater than 1. When the number of components reached ten, 72.100% of the total variance could be accounted for, showing a powerful explanation by the set of factors in the hypothesized model.

Confirmatory factor analysis

We conducted a confirmatory factor analysis, extracting the components with the "Fixed number of factors" equal to ten, as we proposed in the hypothesized

Table 2 Results of factor loadings, reliability, and validity tests

Variable	Item	Loading	AVE	CR	Cronbach's α
Academic experience	AE1	0.7948	0.5900	0.8520	0.8480
	AE2	0.7789			
	AE3	0.8327			
	AE4	0.7459			
Ease of access	EA1	0.7371	0.5270	0.8160	0.8140
	EA2	0.6917			
	EA3	0.7458			
	EA4	0.5427			
Perceived ease for collaborative learning	PECL1	0.7285	0.6520	0.8820	0.8810
	PECL2	0.7838			
	PECL3	0.8109			
	PECL4	0.7436			
Lecturer's positive response	LPR2	0.7054	0.6070	0.8220	0.8210
	LPR3	0.7671			
	LPR4	0.7512			
Self-efficacy	SE1	0.6405	0.5390	0.8230	0.8180
	SE2	0.6522			
	SE3	0.6815			
	SE4	0.5860			
Expectations of academic achievement	EAA1	0.5660	0.5450	0.8270	0.8220
	EAA2	0.7754			
	EAA3	0.7903			
	EAA4	0.7051			
Perceived usefulness	PU1	0.7093	0.4376	0.6955	0.7180
	PU2	0.7359			
	PU3	0.5179			
Perceived ease of use	PEU1	0.6788	0.4244	0.7465	0.8570
	PEU2	0.6696			
	PEU3	0.6414			
	PEU4	0.6120			
Attitudes	ATT2	0.6096	0.4222	0.6859	0.8440
	ATT3	0.6295			
	ATT4	0.7063			
Intention to use	IT1	0.7503	0.5990	0.8565	0.8910
	IT2	0.7529			
	IT3	0.8000			
	IT4	0.7913			

Table 3 The matrix of discriminant validity test

	AE	EA	PECL	LPR	SE	EAA
AE	**0.768**					
EA	0.575***	**0.726**				
PECL	0.379***	0.582***	**0.808**			
LPR	0.325***	0.520***	0.582***	**0.779**		
SE	0.494***	0.732***	0.628***	0.611***	**0.734**	
EAA	0.390***	0.538***	0.510***	0.568***	0.624***	**0.738**

***Indicates statistical significance ($p < 0.001$). Square roots of AVEs are in bold on the diagonal line model. We also used the principal component and varimax methods for factor rotation. In the meantime, we calculated each item's AVE, CR, and Cronbach's α to test the validity and reliability. According to Pham et al. (2019) and Fornell and Larcker (1981), the convergent validity would be great if loading > 0.500, CR > 0.500, and AVE > 0.500. For some established sets of items that measured frequently investigated variables, Fornell and Larcker suggested that researchers could also accept AVE > 0.400 when CR > 0.600 (1981); this criterion has been widely adopted by recent publications (e.g., Tang et al., 2021; Hsu & Lin, 2022). Cronbach's α would indicate excellent (α ≥ 0.900), good (0.800 ≤ α < 0.900), or acceptable (0.700 ≤ α < 0.800) internal consistency (Hutcheson & Sofroniou, 1999). Table 2 shows the factor loadings, AVEs, CRs, and Cronbach's α values, indicating great validity and reliability.

The discriminant validity was ideal for our survey according to the Fornell-Larker method. As Table 3 indicates, the square roots on the diagonal line were greater than all other correlations in the corresponding columns and rows. The results indicated that the covariates could be significantly distinguished from one another. The Pearson correlations generated in this table also demonstrated to what extent the covariates were correlated. According to the widely adopted criteria, coefficients greater than 0.500 would indicate significant correlations between covariates. As such, we also identified significant correlations between these covariates, except that AE was not significantly correlated with PECL, LPR, SE, and EAA. As for the other correlations in this table, the coefficients reached a significant level. The highest positive correlation could be identified between EA and SE.

Model fit indices

The model fit was evaluated by AMOS using the collected data based on the following indices: χ^2 divided by degree of freedom (CMIN/DF), goodness-of-fit index (GFI), comparative fit index (CFI), root mean square residual (RMSEA), Tucker Lewis Index (TLI), and normed fit index (NFI). According to the recommended values for these indices (Cangur & Ercan, 2015; Wu & Chen, 2017), all indicators could support that the hypothesized model in this study had ideal model fit statistics (Table 4).

Therefore, this "Structural equation model assessment" section has examined the validity and reliability of the survey designs and the model fit indices of the postulated model in this study. The results indicated that the proposed model could explain the included exogenous variables' influences on the acceptance and use of digital academic reading tools on computers for higher-education students.

Table 4 Model fit indices and the recommended values

	CMIN/DF	GFI	CFI	RMSEA	TLI	NFI
Model fit indices	2.710	0.903	0.946	0.044	0.940	0.918
Recommended values	≤ 3.000	≥ 0.900	≥ 0.900	≤ 0.050	≥ 0.900	≥ 0.900

Structural equation modeling and hypothesis testing results

With validity, reliability, and model fit assured in the above sections, we further examined how the included exogenous variables could influence traditional variables in the Technology Acceptance Model to different degrees. Overall, the proposed model had substantial explanatory powers measured by R^2 for the outcome variables, i.e., PEU, PU, ATT, and IU. The postulated model in this study could explain the 64.70% variance of PEU, 68.20% of PU, 75.20% of ATT, and 84.20% of IU. According to the standardized estimation in AMOS, we analyzed the effect sizes of exogenous variables with the path coefficients, as suggested by Kline (2015). Table 5 lists the path coefficients, the significance of the effect sizes, and the hypothesis testing results of this study. The three largest effect sizes were found in the following paths: (1) ATT on IU, (2) SE on PEU, and (3) PEU on PU. Insignificant effect sizes were found in the following paths: (1) EA on PU, (2) PECL on PU, (3) PU on IU, (4) EA on IU, and (5) LPR on PEU. We will further discuss these exogenous variables and paths in Sect. "Discussion" regarding the significant roles of variables related to academic performances and research work for higher-education students.

Table 5 Path coefficients and the hypothesis testing results

No	Path	β	S.E	C.R	p	Hypothesis testing
H1	PEU → PU	0.527	0.053	10.02	***	Supported
H2	PEU → ATT	0.452	0.051	8.938	***	Supported
H3	PU → ATT	0.288	0.059	4.841	***	Supported
H4	PU → IU	− 0.036	0.057	− 0.632	0.528	Not supported
H5	ATT → IU	0.879	0.062	14.177	***	Supported
H6	LPR → ATT	0.262	0.036	7.194	***	Supported
H7	LPR → PU	0.236	0.046	5.167	***	Supported
H8	LPR → PEU	0.073	0.042	1.739	0.082	Not supported
H9	AE → ATT	− 0.122	0.026	− 4.682	***	Not supported
H10	EAA → PU	0.221	0.047	4.716	***	Supported
H11	EAA → IU	0.095	0.033	2.83	0.005**	Supported
H12	EA → PU	− 0.013	0.058	− 0.217	0.828	Not supported
H13	EA → IU	− 0.042	0.036	− 1.152	0.249	Not supported
H14	PECL → PU	0.02	0.045	0.455	0.649	Not supported
H15	PECL → PEU	0.183	0.042	4.346	***	Supported
H16	SE → PEU	0.718	0.062	11.55	***	Supported

***Indicates statistical significance at $p < 0.001$ level, and ** at $p < 0.01$ level

Table 6 Top eight advantages and disadvantages of digital academic reading tools on computers from the qualitative results in this study

Frequency	Advantage	Frequency	Disadvantage
307	Easy to use	301	Eye-tiring
105	Easy access to resources	81	Distracting
83	Easy to sort and retrieve	37	Requiring professional skills
73	Easy to carry and use anytime	34	Hard to take digital notes
63	Rich resources	59	Difficult to filter useful information
56	Easy to take notes	25	Lacking the sense of satisfaction
29	Efficient	19	Difficult access to resources
19	Economical	19	Preventing in-depth thinking

Qualitative results

We used AntConc to process the qualitative data from our survey regarding the advantages and disadvantages of digital academic reading tools on computers. Table 6 demonstrates the most frequently provided advantages and disadvantages after merging equivalent items in both Chinese and English. The most frequently mentioned advantages of digital academic reading on computers included ease of use, accessing to resources, sorting materials, and carrying the devices. In contrast, the most common disadvantages were causing eyesight problems, distraction, and technical difficulties.

Discussion

Paths in the traditional Technology Acceptance Model

The traditional Technology Acceptance Model, except for H4 in this study, can be extended to explain students' acceptance and use of digital reading tools on computers for academic purposes. Perceived ease of using digital academic reading tools on computers can significantly contribute to students' attitudes and perceived usefulness (H1 and H2). H3 reveals that students can perceive the benefits of digital reading tools on computers when they adopt these tools for academic purposes, which leads to positive attitudes. Like most educational research on technology acceptance models, students' attitudes can positively influence their intentions to use (e.g., Fussell & Truong, 2022). The results are consistent with technology acceptance research in a wide range of other educational technologies (Deng & Yu, 2023; Wang et al., 2022b). The testing results in this study further validate the traditional Technology Acceptance Model regarding its explanatory power for students' technology acceptance and use. Similar to investigations on other educational technologies, the traditional Technology Acceptance Model can largely explain how perceived usefulness, perceived ease of use, and attitudes can influence the intentions to use digital academic reading tools on computers (Luo et al., 2021). Although these concepts may demonstrate subtle distinctions when examined separately, they can form a model explaining technology acceptance and use in educational contexts to a considerably good extent. As such, our extension of the model to digital reading tools on computers for academic purposes can contribute to understanding the mechanism of technology acceptance and use with the Technology Acceptance Model, based on which external factors are introduced to specify this model.

However, not all paths in the Technology Acceptance Model are supported in the context of higher-education students' use of digital reading tools on computers for academic purposes. Perceived usefulness does not significantly predict students' intentions to use digital reading tools on computers for academic purposes. Similarly insignificant results have been found in Wang et al. (2022b) and Deng and Yu's (2023) modeling results for other educational technologies. A possible explanation to this phenomenon is that despite benefits regarding digital reading tools on computers for academic purposes, students' intentions to use these tools depend on whether they can easily use the tools. This is consistent with the significant role of students' digital literacy in determining their acceptance and use of such technologies (Mohammadyari & Singh, 2015). External factors other than perceived usefulness can determine the behavioral intention to use digital academic reading tools on computers for academic purposes. This finding encourages researchers to explore more external elements to enhance the explanatory and predictive power of the extended technology acceptance models. In the following section, we will elaborate on the external factors contributing to students' acceptance and use of these tools, with a special interest in factors related to academic performance and research work.

External contributors determining students' use of digital academic reading tools on computers

Lecturers' attitudes and responses have significant impacts on students' choices of digital academic reading tools. As indicated by H5 and H6, students may gain psychological support from the lecturer's positive response to using digital academic reading tools on computers (Hong et al., 2022). As we specify the contexts of this variable in our survey, students will likely consider these tools helpful to their academic achievements if lecturers recommend using the tools and stress their benefits. This is consistent with studies suggesting the role of teachers' attitudes toward digital learning tools (Raygan & Moradkhani, 2022) and their superior influences on students (Yu & Yu, 2019). However, the lecturer's positive response does not significantly enhance students perceived ease of using these tools (H6), which may suggest that a positive response without specific instructions on using these tools is not enough. Almogren (2022) identifies various factors influencing lecturers' attitudes toward digital blackboard using the Technology Acceptance Model and the Unified Theories of Acceptance and Use of Technology, suggesting their reaction as a compound outcome. This may also explain why the lecturer's positive response only has minor or insignificant effects on students' acceptance and use of digital academic reading tools on computers. Students may expect more from lecturers than solely psychological support. To enhance students' perceived ease of using these tools and the actual use, instructions on particular tools and accessing digital resources may also play a decisive role, as the help-seeking behavior investigated by Barrot et al. (2021).

Academic experience and expectations of academic achievements significantly impact students' acceptance and use of digital academic reading tools on computers (Leong et al., 2018; Levi et al., 2014). It is noticeable that academic experience negatively predicts students' acceptance and use of digital academic reading tools on computers. Participants reported their academic experience, but whether they relied on digital reading tools was not clarified. It is likely that participants with academic experience in using traditional media and academic resources, such as printed books and papers, are unwilling to switch to digital tools for academic purposes. In this sense, academic experience in this survey is highly associated to concepts like willingness for digital learning and "personal innovativeness" (Deng & Yu, 2023). In Deng & Yu's model, personal innovativeness positively predicts perceived ease of use, supporting the effects of e-learning willingness on technological readiness (2023). However, many participants in this study are master's students in social sciences who may have some academic experience during their undergraduate study that does not require much digitalization and following-up on the most updated academic resources online. They may stick to traditional printed materials and find difficulties in changing to a digital academic workflow. Additionally, alternative digital devices can undermine students' intentions to use digital academic reading tools on computers, such as tablets and mobile phones (Pinto et al., 2014). In contrast, the expectation is the inner impetus for pursuing high-ranking academic achievements that are more likely to be realized with digital tools and resources. The finding is consistent with previous studies, for example, Persada et al. (2022).

Gaining easy access to digital academic resources is not a significantly positive contributor to students' acceptance and use of digital academic reading tools on computers. The acceptance and use of digital academic reading tools on computers depend on the primary components related to the technologies, including digital reading programs or platforms for academic purposes and electronic resources. From the technological dimension, digital academic reading tools can be easily installed and contain multiple choices for personal preferences. In addition to the programs, institutional support may provide students with easy and cheap access to digital resources related to academic work (Eze et al., 2020). The two primary components can determine students' acceptance and use of digital academic reading tools. Previous studies suggest that the openness of resources is one of the significant benefits of digital reading (Haleem et al., 2022; Kuhn et al., 2022), about which findings in this study may provoke discussion. We investigated with the corresponding items about whether students could easily obtain access to digital academic resources. However, students do not always search for digital academic resources independently to use digital reading tools on computers. They may rely on institutional, lecturers', and peer students' support for digital resources. In this sense, students may not be prevented from accepting and using digital reading tools on computers even if they cannot obtain easy access. Alternative methods may also provide digital academic resources.

Students' perceived ease of using digital academic reading tools on computers for collaborative learning and self-efficacy can be significantly positive predictors of their perceived ease of use. This is consistent with previous studies suggesting that one of the primary benefits of digital reading is how users can easily share resources and work together through digital devices (Habibi et al., 2022; Haleem et al., 2022). However, the perceived ease of using them for collaborative learning does not positively predict students' perceived usefulness of these tools. Perceived ease for collaborative learning is a component of technological usefulness but may count as a relatively marginal one, even if many studies have emphasized the benefits of collaborative learning in academic work and research (Herrera-Pavo, 2021). In other words, digital reading tools bring other benefits, and facilitated collaborative learning is not always a necessary motivator for students to use digital academic reading tools on computers. Although the result is insignificant, this study intends to explore a specific aspect of technological usefulness by this variable. Other benefits may contribute to the perceived benefits of digital reading tools on computers for academic purposes, such as personalized recommendations of reading materials supported by artificial intelligence, enhanced virtual interactions between learners, and flexible or distributed learning styles (Haleem et al., 2022). Digital reading tools and resources are easy to use and share, but this advantage does not mean the necessary enhancement of learning effectiveness and the students' intentions to accept this learning strategy.

Conclusion

Major findings

This study adopts structural equation modeling methods to explore factors influencing higher-education students' acceptance and use of digital academic reading tools on computers. This study contributes to the following major findings: (1) The largest and most significant effect sizes are found in ATT on IU, SE on PEU, and PEU on PU; (2) four hypotheses adapted from the traditional Technology Acceptance Model are significantly supported, while PU cannot positively predict IU in this study; (3) LPR, EAA, PECL, and SE have significant impacts on the acceptance of digital academic reading tools on computers measured by some traditional variables in the Technology Acceptance Model to different degrees, except that LPR is not a significant predictor of PEU, and that PECL of PU ; (4) AE has a significantly negative impact on ATT; (5) EA is not a significantly positive predictor of PU and IU; (6) significant correlations are found in all pairings between EA, PECL, LPR, SE, and EAA and between AE and EA; (7) the qualitative data reveal the primary challenges of using digital academic reading tools are eyesight damaging, distraction, and technical difficulties; and (8) the primary advantages of these tools include their ease of use, accessing resources, and sorting materials.

Limitations

We have to acknowledge that this study is subjected to several limitations. First, participants in this study were primarily undergraduates and master's students, while participants at other educational levels were very limited in number or not invited to this study. Second, qualitative data were not emphasized in this study. We did not conduct many qualitative investigations but only added one open-ended question to our questionnaire, which might not sufficiently generate participants' subjective perceptions and experience related to using digital academic reading tools on computers. Third, concerns may occur regarding our sampling methods in this survey. As reported in Sect. "Descriptive statistic results and normality test", our participants included uneven proportions regarding genders and educational levels. However, the impacts could be restricted since the normality of the collected data was tested and supported, indicating that the dataset was not skewed or biased statistically.

Implications for future studies

The findings in this study have both theoretical and practical implications. Theoretically, we have incorporated specific factors of external support and particular aspects of perceived ease of use into the traditional Technology Acceptance Model. We extend the Technology Acceptance Model to investigate the acceptance and use in higher education contexts regarding digital reading tools on computers used for academic and research purposes from students' perspectives. The explanatory power of our extended Technology Acceptance Model has reached a substantial level, which can significantly contribute to explaining and predicting higher-education students' acceptance and use of digital academic reading tools on computers. Future studies may continue to investigate other contexts by exploring the influencing factors and enhance students' academic use of technologies and performances. Some other theoretical benefits of digital reading tools on computers, tablets, and mobile phones can also be further validated with structural equation modeling methods. This study contributes to structural equation model applications in educational research. Future studies can follow the research paradigm and methods provided in this article for exploring complex interrelationships between a set of factors.

Practically, this study may provide some suggestions for students and teachers in higher education regarding how to guide students' use of digital reading tools on computers for academic purposes. Although the benefits of digital reading tools are popular and acknowledged by both students and teachers to a large extent, students' perceived usefulness may not positively predict their intentions to use digital academic reading tools in higher education contexts. Researchers and instructors can conduct further investigations in pedagogical practice to explore students' challenges in using digital reading tools on computers for academic purposes. The lecturer's positive attitude may provide psychological support for students to use digital academic reading tools on computers, but the findings suggest that more concrete instructions may facilitate students' technology acceptance and use to a more significant level. Academic experience, expectations, and technological readiness may be associated. This may reveal possible reasons why students are challenged to swift to digital learning workflow. With the popularity of digital literacy research from both students' and teachers' perspectives, willingness for e-learning needs to be considered in current and future teaching practice. The findings also suggest that instructors combine digital reading tools with other pedagogical designs in addition to collaborative learning. Popular advantages of digital reading tools need further validation in teaching practice and academic research. The findings can also encourage technological developers and designers to overcome some challenges mentioned by our participants, which may enhance their perceived ease of use and usefulness of these digital reading tools through technological advancements.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s41239-023-00403-8.

Additional file 1. Appendix: Questionnaire Sample.

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Author contributions

The conceptualization was performed by YL and ZY. Material preparation, data collection and analysis were performed by YL. YL wrote the first draft of the manuscript, and YL and ZY revised and edited it. The processes of investigation and writing were supervised by ZY. All authors read and approved the final manuscript.

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Availability of data and materials

Related data supporting the findings will be accessible on reasonable requests from the corresponding author of this article.

Declarations

Competing interests

The authors declare that they have no competing interests.

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