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Determinants of AI-Powered Online Reading Adoption: An Integrated TAM-UTAUT Approach among University Students in Hubei, China

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Received: February 12, 2026. Revised: April 11, 2026. Accepted: April 19, 2026.

Abstract

Purpose: This study investigates the factors influencing students' behavioral intention and use behavior toward AI-powered online reading in Hubei, China, addressing the limited understanding of how AI-driven reading contexts extend beyond conventional e-learning adoption models, based on an integrated TAM and UTAUT framework. **Research design, data and methodology:** A quantitative approach was employed, with data collected from 500 undergraduate students across three universities in Hubei Province using non-probability sampling, including judgment sampling to select institutions and quota sampling to ensure proportional representation. A validated questionnaire was administered, and data were analyzed using confirmatory factor analysis and structural equation modeling to examine measurement validity and structural relationships. **Results:** The findings indicate that social influence, attitude, perceived usefulness, performance expectancy, and perceived ease of use significantly affect behavioral intention. Social influence shows the strongest effect, followed by attitude and perceived usefulness. Behavioral intention significantly predicts use behavior, confirming its mediating role. **Conclusions:** The results suggest that effective adoption of AI-powered online reading depends on strengthening social support, enhancing perceived academic benefits, and improving system usability. This study contributes by extending TAM-UTAUT to an AI-powered reading context and highlighting the role of social and affective factors beyond traditional models. Universities and platform developers should focus on integrating social interaction features and user-centered design to promote sustained student engagement.

Keywords: Artificial Intelligence, Online Reading, Behavioral Intention, Use Behavior, Undergraduate Student

JEL Classification Code: D83, I23, L86, M15, O33

1. Introduction

Education systems worldwide are increasingly shaped by artificial intelligence technologies. AI applications such as machine learning, natural language processing, and generative AI are transforming how knowledge is delivered, accessed, and personalized in academic settings (Wang et al., 2021). Online reading platforms have evolved from text-based tools into multimodal systems integrating audio, video, and interactive features (Sablić et al., 2021). In higher education, these platforms support flexible and personalized learning. University students, as digital natives, are familiar with mobile technologies, and their learning behaviors reflect fragmentation, personalization, and interactive engagement (Khamis, 2020; Ondáš et al., 2019).

AI-powered online reading platforms have expanded rapidly, offering functions such as intelligent recommendations, adaptive learning paths, and automated feedback (González-Calatayud et al., 2021). Platforms such as Himalaya and WeChat Reading enhance user experience through AI-generated narration, while systems like Lexia Core5 Reading adjust content based on learner ability (Khan & Mutawa, 2021; Liu et al., 2020). These developments create more adaptive learning environments.

Despite these advances, adoption remains uneven. Some users still prefer traditional reading formats or human narration (Ondáš et al., 2019). Although the Technology

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Acceptance Model and Unified Theory of Acceptance and Use of Technology are widely used to explain technology adoption, they are primarily developed in general information system contexts and emphasize utilitarian factors such as perceived usefulness and ease of use (Davis, 1989; Venkatesh et al., 2012). These models provide limited insight into AI-driven learning environments, where personalization and human-AI interaction may shape user behavior differently.

Existing models do not fully explain how cognitive evaluations interact with social influence and attitude in AI-powered learning contexts. In particular, social and affective factors may play a stronger role when users engage with intelligent systems, yet these mechanisms remain underexplored among Chinese university students.

Recent policy initiatives further highlight this need. National strategies emphasize integrating AI into education and promoting intelligent learning systems, which increases the relevance of studying student adoption behavior in this context.

In response, this study positions itself as a contextual extension of TAM and UTAUT in an AI-powered online reading setting. It examines how cognitive, social, and attitudinal factors jointly influence behavioral intention and use behavior, providing a more comprehensive understanding of adoption mechanisms.

This study contributes in three ways. First, it extends TAM and UTAUT to AI-powered online reading, offering a context-specific application. Second, it integrates cognitive and social-affective factors within a unified framework. Third, it provides empirical evidence from Chinese higher education, where AI adoption is increasing but remains underexplored.

2. Literature Review

2.1 Social Influence

Social influence refers to the degree to which an individual perceives that important others believe he or she should use a particular technology (Venkatesh et al., 2003). This construct originates from the subjective norm in the Theory of Reasoned Action and was later incorporated into the Unified Theory of Acceptance and Use of Technology (Fishbein & Ajzen, 1975; Venkatesh et al., 2012). It reflects how social pressure from peers, instructors, or significant others shapes an individual's intention to adopt a system.

Empirical research consistently demonstrates the impact of social influence on behavioral intention. In mobile commerce, social influence significantly predicts users' intention to adopt new services (Chong et al., 2012; Jaradat & Rababaa, 2013). Similar findings are reported in mobile banking adoption, where social norms positively affect willingness to use financial technologies (Yu, 2012). In educational settings, social influence also affects students' intention to adopt e-textbooks and digital learning platforms (Hsiao & Tang, 2014). However, these studies mainly examine conventional systems and assume passive user interaction. They provide limited insight into AI-driven environments, where system-generated content and human-like interaction may alter how social norms influence user decisions.

In the context of AI-powered online reading, university students may rely on peer recommendations, instructor encouragement, and digital trends when forming usage intentions. Examining social influence in this context therefore extends its role beyond traditional adoption settings.

H1: Social influence has a significant positive impact on behavioral intention.

2.2 Performance Expectancy

Performance expectancy refers to the degree to which an individual believes that using a technology will help achieve gains in task performance (Venkatesh et al., 2003). As a core construct of the Unified Theory of Acceptance and Use of Technology, it captures users' expectations regarding productivity, efficiency, and overall performance improvement associated with system use (Venkatesh et al., 2012). Unlike perceived usefulness, which focuses on task-specific utility, performance expectancy reflects broader anticipated performance outcomes in a given context.

Empirical evidence consistently confirms the significant influence of performance expectancy on behavioral intention. Studies in mobile banking and mobile payment adoption show that users' expectations of performance improvement strongly predict their intention to adopt new technologies (Martins et al., 2014; Slade et al., 2014). Similar findings are reported in mobile learning environments, where performance expectancy significantly influences students' intention to use digital learning systems (Fagan, 2019; Wang et al., 2009). However, these studies primarily interpret performance in terms of efficiency and productivity. In AI-powered environments, performance may also involve adaptive learning, personalized recommendations, and intelligent feedback, which are not fully captured in traditional models.

In the context of AI-powered online reading, university students are likely to evaluate whether the platform improves academic productivity, reading effectiveness, and learning outcomes. Thus, examining performance expectancy in this setting extends its application to more dynamic and adaptive learning systems.

H2: Performance expectancy has a significant impact on behavioral intention.

2.3 Perceived Ease of Use

Perceived ease of use refers to the degree to which an individual believes that using a system would be free of effort (Davis, 1989). As a central construct in the Technology Acceptance Model, it reflects users' perceptions of simplicity, clarity, and the amount of mental or physical effort required to use a technology (Davis et al., 1989). In educational settings, perceived ease of use describes students' beliefs that a digital learning platform is intuitive, easy to navigate, and not time-consuming (Hsiao & Tang, 2014).

Extensive empirical research supports the significant role of perceived ease of use in shaping behavioral intention. Studies on electronic books and digital reading platforms demonstrate that ease of use positively influences users' intention to adopt these technologies (Al-Suqri, 2014; Wu & Chen, 2017). Similar findings are reported in mobile reading applications and online learning systems, where perceived ease of use significantly predicts students' intention to use digital resources (Xiao et al., 2014; Zhou et al., 2015). The broader TAM literature consistently confirms that technologies perceived as easy to use are more likely to be accepted and adopted (Venkatesh, 2000; Venkatesh & Davis, 1996).

In the context of AI-powered online reading, students are more likely to adopt platforms that are user-friendly and require minimal learning effort. Therefore, perceived ease of use is expected to positively influence behavioral intention.

H3: Perceived ease of use has significant impact on behavioral intention.

2.4 Perceived Usefulness

Perceived usefulness refers to the degree to which an individual believes that using a particular system will enhance task performance (Davis, 1989). As a central construct of the Technology Acceptance Model, it reflects users' cognitive evaluation of the practical benefits gained from technology use. In educational contexts, perceived usefulness represents students' beliefs that a digital platform can facilitate learning, improve comprehension, and enhance academic outcomes (Davis, 1993; Hsiao & Tang, 2014). While performance expectancy captures broader anticipated performance gains, perceived usefulness focuses on the system's utility in supporting immediate academic tasks.

Extensive empirical research consistently confirms perceived usefulness as a primary determinant of behavioral intention. Foundational TAM studies demonstrate its strong and direct influence (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2003), and meta-analytic evidence supports its central role across technologies (Lee et al., 2003). In educational settings, students are more likely to adopt platforms they perceive as beneficial for learning (Elyazgi, 2018; Lai & Ulhas, 2012; Spies, 2017; Zhou et al., 2015). However, prior studies often treat usefulness as a static evaluation based on functional outcomes. In AI-powered systems, usefulness may evolve through personalized recommendations and real-time feedback, which introduces a more dynamic assessment process not fully captured in traditional models.

In the context of AI-powered online reading, students who perceive tangible learning advantages are more likely to form strong usage intentions. This study therefore re-examines perceived usefulness within an adaptive learning environment.

H4: Perceived usefulness has significant impact on behavioral intention.

2.5 Attitude

Attitude refers to an individual's overall positive or negative evaluation of performing a particular behavior (Ajzen, 1989). It represents a psychological tendency expressed through favorable or unfavorable judgments toward an object or activity (Eagly & Chaiken, 1993). In technology adoption research, attitude reflects users' evaluative assessment of using a specific system (Davis, 1989). A favorable attitude indicates a positive disposition toward system use, which may strengthen behavioral intention.

Although later extensions of the Technology Acceptance Model reduced the mediating role of attitude (Venkatesh, 2000), substantial empirical evidence reaffirms its direct influence, particularly in voluntary and consumer-oriented contexts. In digital learning environments, students' positive attitudes toward online platforms significantly predict their intention to use such systems (Moon & Kim, 2001; Shroff et al., 2011). Research in digital reading contexts further supports this relationship. Studies on online reading and e-book adoption demonstrate that attitude exerts a strong and significant effect on behavioral intention (Cakır & Solak, 2015; Faham & Asghari, 2019; Khanh & Gim, 2014; Letchumanan & Tarmizi, 2011; Wu & Chen, 2017). These findings indicate that affective evaluation plays a critical role in shaping technology adoption decisions.

In the context of AI-powered online reading, students who develop favorable feelings toward the platform are more likely to intend to use it. Therefore, the following hypothesis is proposed:

H5: Attitude has significant impact on behavioral intention.

2.6 Behavioral Intention

Behavioral intention refers to an individual's conscious plan or willingness to perform a specific future behavior (Ajzen, 1991; Benjangjaru & Vongurai, 2018). It reflects the subjective probability that a person will engage in a given action and represents the effort one intends to invest in performing that behavior (Fishbein, 1980; Homburg et al., 2005). In information systems research, behavioral intention is widely regarded as the most immediate and reliable predictor of actual use behavior (Venkatesh & Davis, 2000).

Extensive empirical research supports the strong link between behavioral intention and use behavior. The Unified Theory of Acceptance and Use of Technology confirms that intention significantly predicts actual system use (Venkatesh et al., 2003). In educational contexts, this relationship has been consistently validated. Studies on digital academic reading show that students' behavioral intention significantly determines their engagement with online reading resources (Chang et al., 2023). Similarly, research on digital textbooks and other educational technologies confirms that behavioral intention is a critical driver of actual usage among university students (Okocha, 2019; Wijaya et al., 2022). These findings align with broader evidence that students who form strong usage intentions are highly likely to translate those intentions into observable behavior (Nie, 2019).

In the context of AI-powered online reading, students who intend to use the platform are expected to translate this intention into observable use, provided that access and usability barriers are minimal.

H6: Behavioral Intention has significant impact on use behavior.

2.7 Use Behavior

Use behavior refers to the actual execution of system usage and represents the observable outcome of technology adoption. In contrast to behavioral or continuous use intention, which reflects an individual's expressed willingness to continue using a system, use behavior captures realized actions over time (Gupta & Kim, 2007; Limayem et al., 2003). Continuous use intention indicates a conscious decision to persist beyond the initial adoption phase (Hsiao & Tang, 2014), whereas use behavior reflects measurable engagement with the system.

To understand actual usage behavior, prior research identifies two primary dimensions: usage frequency and usage variety (Ram & Jung, 1989). Usage frequency refers to how often a product or system is used within a given period and reflects the intensity of engagement (Zaichkowsky, 1985). Usage variety, in contrast, captures the breadth of system utilization across different tasks or situations, regardless of how frequently it is used (Ram & Jung, 1989). This dual perspective, sometimes described as amount of use and utilization diversity, provides a comprehensive assessment of user engagement (Dutton et al., 1985). Scholars suggest that combining frequency and variety offers a more accurate representation of actual usage behavior (Foxall & Bhate, 1991).

In the context of AI-powered online reading, use behavior reflects students' frequency and diversity of platform engagement in their academic activities.

3. Research Methods and Materials

3.1 Research Framework

This study integrates constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) and the Technology Acceptance Model (TAM) (Davis, 1989) to develop the conceptual framework, as shown in Figure 1. This study integrates them to capture different but complementary aspects of technology adoption. UTAUT contributes performance expectancy and social influence as external drivers, while TAM provides perceived usefulness, perceived ease of use, and attitude as individual evaluations. Although perceived usefulness and performance expectancy are closely related, this study distinguishes them as task-specific benefits and overall performance gains.

The relationship between intention and behavior is supported by the Theory of Planned Behavior (Ajzen, 1991). Attitude is included to capture users' positive or negative feelings toward the system, which are important in AI-based environments where user experience extends beyond functional benefits. This integrated framework therefore provides a more comprehensive explanation of students' adoption behavior.

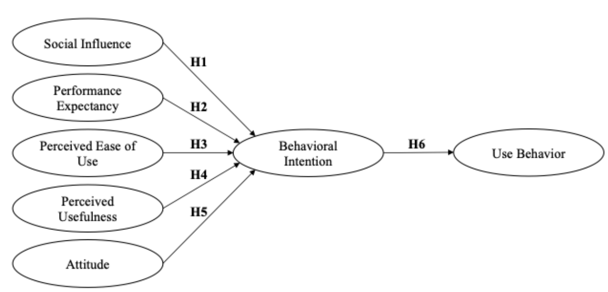

Figure 1: Conceptual Framework

3.2 Research Methodology

This study adopted a quantitative research design using non-probability sampling, specifically judgment sampling to select institutions and quota sampling to allocate respondents proportionally across universities. Data were collected through an online questionnaire distributed to undergraduate students from three universities in Hubei Province. The study aims to examine the factors influencing students' behavioral intention and actual use of AI-powered online reading platforms.

The questionnaire consisted of three sections. The first section included screening questions to ensure that respondents had prior experience using AI-powered online reading platforms. The second section measured the study variables using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The items were developed to assess the constructs corresponding to the six proposed hypotheses. The third section gathered demographic information, including gender, age, and academic year.

Before administering the main survey, a pilot test was conducted with 50 respondents to evaluate clarity, reliability, and content validity. The instrument was reviewed by subject experts, and the Item-Objective Congruence index confirmed the appropriateness of the measurement items. Reliability was assessed using Cronbach's alpha (Hartog & Verburg, 2004), and the results indicated acceptable internal consistency.

Participation in the study was voluntary. Respondents were informed of the study purpose, and anonymity and confidentiality were assured. No personally identifiable information was collected.

Following the pilot phase, the main survey yielded 500 valid responses. Data were analyzed using SPSS AMOS. Confirmatory factor analysis was conducted to evaluate convergent validity and measurement model fit. Structural equation modeling was then employed to test the hypothesized relationships among the variables.

3.3 Population and Sample Size

This study applied non-probability sampling techniques, specifically judgment sampling and quota sampling. Judgment sampling was used to select three universities in Hubei Province that represent major public higher education institutions. Quota sampling was then applied to ensure proportional representation of undergraduate students from each university based on their population size.

The total undergraduate population across the three universities was 3,458 students. Based on proportional allocation, a target sample size of 500 respondents was determined. Table 1 presents the population size and corresponding proportional sample size for each institution.

Table 1: Population and Proportional Sample Distribution of Undergraduate Students in Selected Universities

University	Undergraduate Population	Proportional Sample Size
Hubei University	860	124
Hubei Normal University	1,200	174
Central China Normal University	1,398	202
Total	**3,458**	**500**

Source: Population data obtained from the official websites of the three universities

Data collection was conducted from February to October 2024 through an online questionnaire platform. Only undergraduate students from the selected universities were eligible to participate, and screening questions were used to confirm their status. Administrative support was obtained from the deans of the three universities, who encouraged student participation. After data screening and validation, 500 valid responses were retained for analysis.

The final sample size meets recommended thresholds for structural equation modeling and ensures adequate representation of the target population.

4. Results and Discussion

4.1 Demographic Information

This study surveyed 500 undergraduate students from three universities in Hubei Province. Table 2 presents the demographic profile of the respondents.

Among the participants, 58 percent were female and 42 percent were male, indicating a relatively balanced gender distribution. In terms of age, nearly half of the respondents were between 18 and 19 years old, while the remaining participants were distributed across the 20 to 21 age group and above 22 years old. This reflects a typical undergraduate age structure.

Regarding institutional representation, the sample was proportionally distributed across the three universities, with comparable participation from each institution. The distribution aligns with the sampling design and supports the representativeness of the dataset for subsequent analysis.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Female	293	58.6
	Male	207	41.4
Age	18 to 19 years	247	49.4
	20 to 21 years	139	27.8
	22 years and above	114	22.8
University	Hubei University	124	24.8
	Hubei Normal	174	34.8

Demographic and General Data (N=500)		Frequency	Percentage
	University		
	Central China Normal University	202	40.4

Source: Created by the author

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis was conducted using SPSS AMOS to evaluate the measurement model. As shown in Table 3, all measurement items loaded significantly on their respective constructs. Factor loadings ranged from 0.713 to 0.930, exceeding recommended thresholds and supporting indicator reliability.

Internal consistency was confirmed, as Cronbach's alpha and composite reliability values for all constructs were above 0.70. Convergent validity was also supported because the average variance extracted values for each construct exceeded 0.50, as presented in Table 3.

Discriminant validity was assessed using the Fornell-Larcker criterion. As shown in Table 4, the square roots of the AVE for each construct were greater than the corresponding inter-construct correlations. This indicates that each construct is empirically distinct from the others.

The overall model fit was examined using multiple goodness-of-fit indices. The CFA results in Table 5 show that CMIN/df = 1.326, GFI = 0.944, AGFI = 0.931, NFI = 0.952, CFI = 0.988, TLI = 0.986, and RMSEA = 0.026. All indices meet recommended criteria, indicating that the measurement model demonstrates good fit and adequate construct validity.

Table 3: Confirmatory Factor Analysis (CFA), Composite Reliability (CR), and Average Variance Extracted (AVE) Results

Variable	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factor Loading	CR	AVE
Social Influence (SI)	Maduku (2016)	3	0.878	0.782-0.875	0.879	0.708
Performance Expectancy (PE)	Maduku (2016)	4	0.876	0.743-0.845	0.877	0.641
Perceived Ease of Use (PEOU)	Maduku (2016)	5	0.915	0.745-0.930	0.916	0.686
Perceived Usefulness (PU)	Elyazgi (2018)	5	0.900	0.714-0.891	0.901	0.647
Attitude (ATT)	Jiramahapoka and Loh (2019)	3	0.794	0.713-0.796	0.794	0.563
Behavioral Intention (BI)	Chang et al. (2015)	4	0.871	0.740-0.842	0.873	0.633
Use Behavior (UB)	Wijaya et al. (2022)	3	0.844	0.766-0.831	0.845	0.644

Note: CR = Composite Reliability, AVE = Average Variance Extracted

Table 4: Discriminant Validity

Variable	Factor Correlations						
	SI	PE	PEOU	PU	ATT	BI	UB
SI	**0.842**						
PE	0.330	**0.800**					
PEOU	0.318	0.301	**0.828**				
PU	0.357	0.309	0.314	**0.804**			
ATT	0.307	0.292	0.319	0.319	**0.750**		
BI	0.562	0.471	0.450	0.511	0.489	**0.796**	
UB	0.311	0.297	0.319	0.340	0.296	0.399	**0.803**

Note: The diagonally listed value is the AVE square roots of the variables

Table 5: Goodness of Fit

Index	Criterion	CFA Values	SEM Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1.326	2.492
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.944	0.877
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.931	0.853
NFI	≥ 0.80 (Wu & Wang, 2006)	0.952	0.905
CFI	≥ 0.80 (Bentler, 1990)	0.988	0.941
TLI	≥ 0.80 (Sharma et al., 2005)	0.986	0.935
RMSEA	< 0.08 (Pedroso et al., 2016)	0.026	0.055

Note: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

4.3 Structural Equation Model (SEM)

Following validation of the measurement model, structural equation modeling was performed to test the hypothesized relationships among the constructs.

The structural model fit indices are presented in Table 5. The ratio of chi-square to degrees of freedom was 2.492, which is within the acceptable range. Other fit indices also meet established criteria, including GFI = 0.877, AGFI = 0.853, NFI = 0.905, CFI = 0.941, TLI = 0.935, and RMSEA = 0.055. These results indicate that the structural model fits the data satisfactorily.

Overall, the acceptable goodness-of-fit results provide empirical support for proceeding with hypothesis testing.

4.4 Research Hypothesis Testing Result

Structural equation modeling was conducted to test the proposed hypotheses. As presented in Table 6 and illustrated in Figure 2, all structural paths are positive and statistically significant at the 0.05 level. The results indicate that the proposed model adequately explains students' behavioral intention and use behavior toward AI-powered online reading platforms.

Table 6: Hypothesis Testing Result

Hypothesis	Standardized path coefficients (β)	t-value	Test Result
H1: SI → BI	0.433	9.488*	Supported
H2: PE → BI	0.274	6.289*	Supported
H3: PEOU → BI	0.210	4.985*	Supported
H4: PU → BI	0.308	6.939*	Supported
H5: ATT → BI	0.324	6.774*	Supported
H6: BI → UB	0.424	7.680*	Supported

Note: *=p-value < 0.05

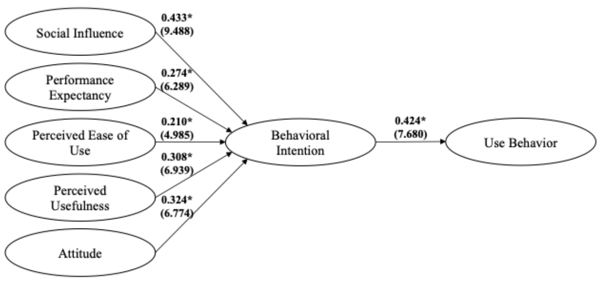

Figure 2: Path Diagram Results
Note: Solid lines report standardized coefficients with $p < 0.05$; t-values in parentheses.

H1 is supported. Social influence has a significant positive effect on behavioral intention ($\beta = 0.433$, $t = 9.488$, $p < 0.05$). This result indicates that peer influence and social norms play a strong role in shaping students' intention to adopt the platform.

H2 is supported. Performance expectancy significantly influences behavioral intention ($\beta = 0.274$, $t = 6.289$, $p < 0.05$). Students who believe that the platform enhances their academic performance are more likely to intend to use it.

H3 is supported. Perceived ease of use has a significant positive effect on behavioral intention ($\beta = 0.210$, $t = 4.985$, $p < 0.05$), suggesting that user-friendly systems strengthen adoption intention.

H4 is supported. Perceived usefulness significantly affects behavioral intention ($\beta = 0.308$, $t = 6.939$, $p < 0.05$). When students perceive clear learning benefits, their intention increases.

H5 is supported. Attitude positively influences behavioral intention ($\beta = 0.324$, $t = 6.774$, $p < 0.05$). A favorable evaluation of the platform strengthens adoption intention.

H6 is supported. Behavioral intention significantly affects use behavior ($\beta = 0.424$, $t = 7.680$, $p < 0.05$), confirming that stronger intention leads to higher actual usage.

5. Conclusions and Recommendation

5.1 Conclusions

This study examined the factors shaping undergraduate students' behavioral intention and use behavior toward AI-powered online reading platforms in Hubei, China. Building on TAM and UTAUT, six hypotheses were tested linking social influence, performance expectancy, perceived ease of use, perceived usefulness, and attitude to behavioral intention, and behavioral intention to use behavior. Data from 500 undergraduates were analyzed using confirmatory factor analysis and structural equation modeling.

The findings show that students' adoption of AI-powered online reading is influenced by both social and individual factors. The results show a shift in the relative importance of these factors. Social influence is the strongest predictor, which suggests that adoption in AI-based learning environments is strongly shaped by group norms and external opinions. This finding is consistent with prior UTAUT studies that highlight the role of social pressure in shaping behavioral intention (Jaradat & Rababaa, 2013; Venkatesh et al., 2003). Attitude and perceived usefulness also play important roles. This indicates that students evaluate AI-powered reading not only based on practical benefits, but also based on their overall learning experience. These results align with TAM research and digital reading studies that emphasize the importance of perceived usefulness and attitude (Davis, 1989; Faham & Asghari, 2019; Letchumanan & Tarmizi, 2011; Venkatesh & Davis, 2000).

Performance expectancy and perceived ease of use also influence intention. However, their weaker effects suggest that ease of use and performance alone may not be enough to explain adoption in more advanced systems. This extends previous findings that emphasize their importance in traditional technology contexts (Martins et al., 2014; Slade et al., 2014). Behavioral intention remains the key factor that links perceptions to actual use, which is consistent with established theory (Venkatesh et al., 2003).

These findings are consistent with TAM and UTAUT. However, this study shows that the role of these factors changes in AI contexts. Social and affective factors become more important than purely functional considerations. This suggests that traditional models may not fully explain user behavior in AI-based learning environments.

Overall, this study provides support for an integrated model of AI-powered online reading adoption in Chinese universities. It also improves current understanding by showing that adoption in AI environments is more socially influenced and experience-based than suggested in earlier models.

5.2 Recommendations

The findings of this study provide several practical implications for universities and developers of AI-powered online reading platforms. To improve clarity, these implications can be structured into three key areas: social engagement, functional value, and system usability.

First, strengthening social engagement is essential. Since social influence and attitude are strong predictors of behavioral intention, universities should create environments that encourage positive interaction with AI-based reading tools. Platforms should incorporate features such as peer sharing, discussion functions, and visible learning progress to enhance social visibility and motivation. Faculty support and classroom integration can further reinforce acceptance among students.

Second, enhancing functional value is critical. Perceived usefulness plays an important role in shaping intention. Developers should focus on features that directly support academic tasks. Tools such as automated summarization, intelligent annotation, and personalized recommendations can improve reading efficiency and learning outcomes. When these functions are embedded into regular study activities, students are more likely to recognize their value.

Third, improving system usability remains important. Performance expectancy and perceived ease of use indicate that students prefer systems that are simple and effective. Clear interface design, easy navigation, and low technical barriers can reduce effort and improve user experience. Providing basic guidance or adaptive support can help new users become familiar with the platform.

These findings suggest that successful adoption depends on the alignment of social support, perceived value, and system design. A balanced approach across these areas can strengthen both behavioral intention and actual use.

5.3 Limitation and Further Study

This study has several limitations. The sample was drawn from undergraduate students at three universities in Hubei Province, which may limit generalizability. Although quota sampling improved sample balance, the use of non-probability sampling limits representativeness and restricts broader population inference.

The cross-sectional design captures relationships at one point in time and does not support strong causal conclusions. The study also relied on self-reported data. This may introduce common method bias, as data were collected from a single source using the same method, which may affect the accuracy of the results. In addition, the framework focused on core technology acceptance constructs and did not include contextual factors such as privacy concerns or trust in AI systems.

Future research can expand the sample to other regions and educational levels. Using probability sampling methods would improve representativeness. Longitudinal or experimental designs may provide stronger causal evidence. Future studies may also use multi-source data or statistical controls to reduce common method bias and improve measurement accuracy.

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