An Analysis of Factors Influencing the Behavioral Intention to Use AI-Based Social Media Among Computer Science Undergraduates in Sichuan, China

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Abstract

Purpose: This study investigates the influence mechanisms of artificial intelligence (AI)-based social media on the behavioral intention of Chinese college students. **Research design, data and methodology:** A total of 480 computer science undergraduates from three provincial universities in Sichuan, China, were selected as research participants. Data were collected through a structured questionnaire. Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were applied to examine the interrelationships among perceived ease of use, perceived usefulness, attitude, social influence, information quality, facilitating conditions, and behavioral intention. **Results:** Convenience exhibited the strongest direct impact on behavioral intention ($\beta = 0.286$), followed by social influence ($\beta = 0.229$) and information quality ($\beta = 0.229$). Perceived ease of use significantly influenced both perceived usefulness ($\beta = 0.317$) and attitude ($\beta = 0.283$), while perceived usefulness ($\beta = 0.214$) and attitude ($\beta = 0.120$) had relatively weaker direct effects on behavioral intention. The model's overall explanatory power (R^2) was 20.2%, revealing a complex mediation mechanism. **Conclusions:** Social media platforms should optimize algorithm design to improve information quality and ease of use. Meanwhile, universities should strengthen AI ethics education and guide students to rationally use AI social media through courses and algorithm audit practices.

Keywords: Artificial Intelligence, Social Media, Technology Acceptance Model, Behavioral Intention

JEL Classification Code: A22, I23, L82, O30

1. Introduction

The integration of artificial intelligence (AI) into social media has revolutionized digital interaction, transforming platforms into intelligent ecosystems that enhance user experience through personalization, automation, and data-driven insights. AI-based social media leverages technologies such as machine learning, natural language processing, and computer vision to optimize content recommendations, automate moderation, and facilitate immersive interactions through chatbots and virtual assistants (Sadiku et al., 2021). In China, platforms such as WeChat, Weibo, and TikTok dominate daily communication, engaging hundreds of millions of active users including college students, who represent a highly involved demographic (China Youth Net, 2023). Despite its benefits such as personalized content delivery, efficient customer service, and targeted marketing, AI-driven social media raises critical concerns, including algorithmic bias, privacy

infringement, misinformation proliferation, and mental health implications (Sadiku et al., 2021). These challenges underscore the urgency of balancing technological innovation with ethical considerations, particularly for younger users who are both primary beneficiaries and vulnerable targets of these platforms.

Although existing studies emphasize the pervasive role of AI in reshaping social media dynamics, they often rely on qualitative assessments or focus on general populations. This leaves a gap in quantitative analyses targeting specific user groups, such as Chinese college students. Surveys show that over 80% of Chinese college students frequently use social media, primarily for social interaction, entertainment, and information sharing, with more than 50% spending over three hours daily on these platforms (China Youth Net, 2023). This research addresses persistent challenges such as data privacy violations, information overload, and compulsive usage patterns, highlighting the need for an

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evidence-based investigation of the determinants influencing behavioral engagement.

Integrating the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), this study analyzes the causal pathways connecting social influence (SI), information quality (IQ), facilitating conditions (FC), perceived usefulness (PU), perceived ease of use (PEOU), attitude (ATT), and behavioral intention (BI) among higher education students in Sichuan Province. Through systematic empirical validation, it elucidates the structural relationships and mechanistic interactions among these critical constructs in technology acceptance.

Adopting a quantitative approach, data were collected through structured questionnaires from 500 students across three universities, Sichuan University, Sichuan Normal University, and Sichuan University of Science and Engineering, using multi-stage and stratified sampling techniques. Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were applied to validate the theoretical constructs and examine seven proposed research propositions. This analytical framework enables rigorous verification of measurement models and provides empirical evidence for the hypothesized relationships among latent variables. The findings aim to identify key determinants of AI-based social media adoption, offering theoretical insights for refining acceptance models and practical strategies for platform developers to enhance user experience while mitigating associated risks. By addressing the intersection of technological innovation and ethical responsibility, this research contributes to the development of safer, more effective AI-integrated social media environments for educational and societal advancement.

2. Literature Review

2.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Davis (1989), is widely used to predict and explain individuals' acceptance of new technologies. Rooted in the Theory of Reasoned Action (Fishbein & Ajzen, 1975) and the Theory of Planned Behavior (Ajzen, 1991), TAM identifies two primary factors influencing technology adoption: perceived usefulness (PU) and perceived ease of use (PEOU). PU refers to the extent to which users believe a system enhances their task performance, while PEOU reflects the perceived effort required to use the system (Davis et al., 1989). Empirical studies have consistently validated TAM, confirming that both PU and PEOU significantly affect users' attitudes and behavioral intentions

(Taylor & Todd, 1995). In this study, TAM constructs of perceived ease of use, perceived usefulness, attitude, and behavioral intention form part of the conceptual framework to examine college students' acceptance of AI-based social media platforms.

2.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by Venkatesh et al. (2003), integrates elements from eight earlier models to explain users' technology adoption behavior. It highlights four core constructs: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). PE refers to perceived efficiency gains, EE to the ease of use, SI to the influence of social pressure, and FC to the availability of support and infrastructure. UTAUT has demonstrated strong explanatory power, accounting for up to 70% of the variance in behavioral intention (Venkatesh et al., 2012).

Originally designed for organizational settings, UTAUT has since been extended to various contexts, including education and social media. Its flexibility allows adaptation to different environments, making it valuable for understanding technology adoption beyond the workplace. In the social media domain, UTAUT is increasingly applied to assess users' willingness to adopt AI-driven features (Puriwat & Tripopsakul, 2021). In this study, social influence and facilitating conditions are adopted from the UTAUT model to explore their influence on students' behavioral intentions toward AI-based social media platforms.

2.3 Research Hypothesis and Relationship between Variables

2.3.1 Relationship between Perceived Ease of Use, Perceived Usefulness, and Attitude

Perceived ease of use (PEOU), a core construct in the Technology Acceptance Model (TAM), refers to the extent to which individuals believe that using a system requires minimal effort (Davis, 1989). Venkatesh and Davis (2000) emphasized that PEOU serves as a precursor to perceived usefulness (PU) and behavioral intention, as users are more inclined to adopt technologies they find intuitive. Empirical studies reinforce this relationship; for instance, Lin (2007) found that higher PEOU in social media platforms led to increased user engagement and satisfaction. Similarly, Dumpit and Fernandez (2017) confirmed PEOU's significance in early technology adoption, particularly within educational environments. Karahanna and Straub (1999) also highlighted its psychological influence, noting

that reduced cognitive load strengthens user motivation. Scott et al. (2016) further observed that users tend to favor systems that are easy to learn and expect functional benefits from them.

Building upon this prior research, the current study extends the application of PEOU to the context of AI-integrated social media platforms among Chinese university students, an area that has received limited empirical attention. By examining PEOU's influence on both perceived usefulness and users' attitudinal disposition, this study seeks to validate its role in shaping early adoption behavior in a digital environment increasingly driven by artificial intelligence. Accordingly, the following hypotheses are proposed:

H1: Perceived ease of use has a significant influence on perceived usefulness.

H3: Perceived ease of use has significant influence on attitude.

2.3.2 Relationship between Perceived Usefulness and Attitude

Perceived usefulness (PU), a foundational element of the Technology Acceptance Model (TAM), is defined as an individual's belief that using a particular system or technology will enhance their performance or productivity (Davis et al., 1989). Grover et al. (2019) expanded the construct by identifying two key dimensions: efficiency, assessing the system's ability to help users achieve objectives, and necessity and applicability, evaluating its advantages over alternative solutions. In various domains, PU has been conceptualized in diverse ways. For instance, Wu et al. (2017) viewed PU in mobile payment systems as users' overall assessment of service benefits, while Izuagbe et al. (2019) highlighted social media's usefulness in delivering problem-solving information. Al-Fraihat et al. (2020) emphasized PU as a critical factor in e-learning success, mediated by infrastructure and service quality. Likewise, Eveleth and Stone (2020) linked PU to satisfaction with mobile apps, and Moslehpour et al. (2018) confirmed its influence on online purchase intentions.

While previous studies have validated PU in contexts such as e-learning, mobile services, and digital commerce, few have specifically explored its impact within AI-driven social media environments among Chinese university students. This study extends the TAM framework by examining how students' perceptions of usefulness toward AI-based social media platforms influence their attitudinal disposition. By focusing on a technologically advanced and demographically relevant group, this research contributes to a more nuanced understanding of PU in emerging digital ecosystems. Accordingly, the following hypothesis is proposed:

H2: Perceived usefulness has a significant influence on attitude.

2.3.3 Relationship between Social Influence and Behavioral Intention

Social influence (SI) refers to how people's decisions are affected by the opinions or behaviors of others, such as peers, teachers, or family members (Kelman, 1958; Venkatesh et al., 2003). In past studies, SI has been shown to shape technology use, especially in school or work settings where people often follow group norms or expert recommendations (Decman, 2015; Lwoga & Komba, 2015). Tarhini et al. (2017) found this influence to be especially strong in cultures and environments where social conformity is valued.

This study builds on previous research by applying SI to the context of AI-based social media use among university students. Unlike structured learning or workplace systems, social media platforms are often used voluntarily and are highly influenced by peers, trends, and online communities. In such environments, social influence can play a major role in shaping users' behavioral intention (BI), that is, their willingness to adopt and continue using AI-driven platforms. This study investigates whether students are more likely to use these platforms when they see their friends or trusted sources doing the same. Hence, the following hypothesis is proposed:

H4: Social influence has a significant influence on behavioral intention.

2.3.4 Relationship between Attitude and Behavioral Intention

Attitude is how positively or negatively a person feels about using a particular technology (Ajzen & Fishbein, 1980). In the Technology Acceptance Model (TAM), attitude connects what people believe about a system such as how useful or easy it is, to whether they plan to use it (Davis et al., 1989). Research has shown that a positive attitude often leads to a higher intention to use a system. For example, Phang and Ming (2018) found that users with good feelings about social media reviews were more likely to make purchases. Similarly, Popy and Bappy (2020) found that attitude directly influenced users' behavior toward technology.

This study extends the role of attitude to the use of AI-based social media among students. These platforms use smart algorithms and personalized features, which can affect how users feel about them. A more positive attitude toward these platforms may lead to a stronger behavioral intention (BI) to use them regularly. By focusing on students' emotional and evaluative responses, this study explores whether attitude serves as a key driver of their engagement with intelligent social technologies. Therefore, the

following hypothesis is proposed:

H5: Attitude has a significant influence on behavioral intention.

2.3.5 Relationship between Information Quality and Behavioral Intention

Information quality (IQ) refers to how accurate, relevant, and timely the information is on a platform (Gorla et al., 2010). High-quality information helps users make better decisions and feel more confident in using a system. Prior research shows that good IQ leads to greater trust and engagement. For example, Park et al. (2007) and Hsu et al. (2013) found that accurate and useful content in online platforms improves users' attitudes and increases their intention to use them. Erkan and Evans (2016) also showed that IQ boosts information sharing and adoption.

This study builds on these findings by looking at IQ in the context of AI-based social media, where the content users see is often selected by algorithms. For students, receiving relevant, reliable, and up-to-date content can increase their behavioral intention (BI) to keep using the platform. This research explores whether perceived information quality influences students' willingness to continue engaging with AI-enhanced social media. Accordingly, the following hypothesis is proposed:

H6: Information quality has a significant influence on behavioral intention.

2.3.6 Relationship between Facilitating Conditions and Behavioral Intention

Facilitating conditions (FC) refer to the resources and support available to help people use a technology such as having internet access, digital devices, or technical help (Venkatesh et al., 2003). Studies have shown that when users have the right tools and support, they are more likely to adopt new technologies (Lwoga & Komba, 2015; Taylor & Todd, 1995). However, some researchers, like Cristina and Malini (2018), found that FC matters less when users already find the system easy to use. Still, for certain groups such as students with limited resources, FC remains a key factor.

This study extends previous research by applying FC to AI-based social media use among Chinese university students. It considers both basic resources (like internet access) and platform-related features (like usability and transparency). When students feel they have the support they need, their behavioral intention (BI) to use the platform is likely to increase. This study examines how the presence or absence of these conditions affects their engagement with AI-powered platforms. Based on this rationale, the following hypothesis is proposed:

H7: Facilitating conditions have a significant influence on behavioral intention.

3. Research Methods and Materials

3.1 Research Framework

This conceptual framework is based on TAM and UTAUT and combines three theoretical frameworks from existing research. Cortiñas et al. (2023) have proved the relevance of perceived usefulness, perceived ease of use, attitude, and behavioral intention. Alaydrus and Napitupulu (2022) found a correlation between information quality, facilitating conditions, and behavioral intention. Puriwat and Tripopsakul's (2021) empirical study revealed a significant correlation between social influence and behavioral intention in contexts of technology adoption. This finding aligns with existing literature identifying social factors as critical determinant of users' engagement intentions.

As illustrated in Figure 1, the proposed framework comprises seven key constructs, four independent dimensions (perceived ease of use, social influence, information quality, and facilitating conditions), two mediating components (perceived usefulness and attitude), and behavioral intention operating as the outcome variable.
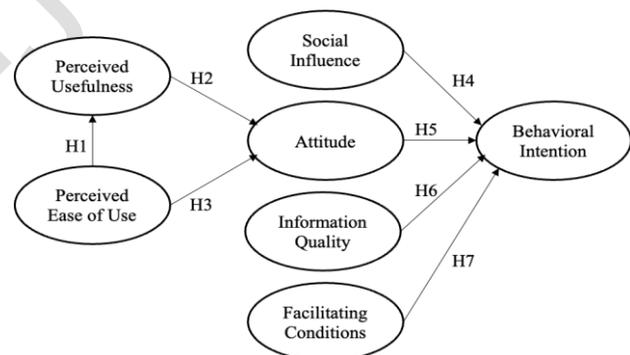

Figure 1: Conceptual Framework

3.2 Research Methodology

This study employed a quantitative research design to examine the factors influencing students' behavioral intention to use AI-based social media platforms. A quota sampling strategy was adopted to ensure proportional representation of undergraduate students across academic levels from three higher education institutions in Sichuan Province.

A standardized questionnaire was developed to measure the constructs in the proposed model, using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire assessed seven core dimensions: perceived usefulness, perceived ease of use, attitude, social influence, information quality, facilitating conditions, and

behavioral intention. To ensure content validity, an expert panel of three PhD-level scholars in social media research evaluated the questionnaire using the item-objective congruence (IOC) method. Based on their feedback, minor revisions were made to align the items with the research objectives. A pilot test with 30 undergraduate students was then conducted to assess the instrument's internal consistency. Cronbach's alpha coefficients for all constructs exceeded the recommended threshold of 0.70, confirming strong reliability.

During the data collection phase, 500 questionnaires were distributed across the three selected universities. After removing incomplete or invalid responses, 480 valid questionnaires were retained for analysis. Confirmatory Factor Analysis (CFA) was conducted to assess the validity of the measurement model. Once model fit was confirmed, Structural Equation Modeling (SEM) was employed to test the hypothesized relationships among the study variables.

All research procedures were approved by the relevant academic ethics committee. Informed consent was obtained from all participants before data collection, and confidentiality and anonymity were strictly maintained throughout the study to ensure ethical compliance.

3.3 Population and Sample Size

The research focuses on computer science students enrolled at three Sichuan provincial universities: Sichuan University (SU), Sichuan University of Science and Engineering (SUSE), and Sichuan Normal University (SNU). According to the sample size standard proposed by Hair et al. (2010) for the structural equation model (suggested range of 200-500 cases), 500 valid samples were systematically screened from 6,450 target groups through stratified quota sampling technology. The sampling process strictly follows the subject scale ratio and grade distribution characteristics to carry out quota control, and the final sample size not only meets the basic requirements of the SEM method for data size but also effectively ensures the structural representation of the research group.

3.4 Sampling Technique

This study employed a composite sampling strategy to systematically screen and select participants in multiple stages. In the first stage, a purposive sampling method was used to define the basic research group. A total of 6,450 undergraduate students majoring in computer science, each with at least six months of experience using social media, were identified from the three selected universities to form the initial sample pool.

In the second stage, 500 valid participants were accurately selected from this pool using a stratified quota

sampling method. This approach involved standardized screening procedures based on stratification variables such as the proportional scale of the student population and grade-level distribution. The sampling design meets the recommended sample size requirements for Structural Equation Modeling (SEM) and enhances the ecological validity of the study by applying clear inclusion criteria (i.e., a minimum of six months' social media usage) and structural control parameters (e.g., discipline and grade ratio). The distribution of the final sample is presented in Table 1.

Table 1: Sample Units and Sample Size

Universities	Population Size	Proportional Sample Size
Sichuan University (SU)	2,599	201
Sichuan University of Science and Engineering (SUSE)	2,025	157
Sichuan Normal University (SNU)	1,826	142
Total	**6,450**	**500**

Note: Constructed by the Author

4. Results and Discussion

4.1 Demographic Information

The demographic profile of the respondents is summarized in Table 2. Overall, the sample demonstrates a balanced and representative distribution, capturing diversity across gender, university affiliation, and academic year. This balanced composition enhances the reliability of subsequent analyses by ensuring that different student groups are adequately represented. Notably, the gender ratio reflects the current enrollment trends in computer science disciplines, while the distribution across the three universities aligns proportionally with their respective student populations. Furthermore, the distribution of academic years is evenly balanced, minimizing potential biases related to cohort differences. This comprehensive demographic structure strengthens the ecological validity of the research and provides a solid foundation for interpreting the results.

Table 2: Demographic Information

Demographic and General Data (N=480)		Frequency	Percentage
Gender	Male	297	61.9
	Female	183	38.1
University	SU	188	39.2
	SUSE	153	31.9
	SNU	139	28.9
Academic Year	Freshmen	117	24.4
	Sophomore	123	25.6
	Junior	121	25.2
	Senior	119	24.8

Note: Constructed by the Author

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) was conducted to validate the measurement model and assess the relationships between observed variables and their corresponding latent constructs, as proposed in the theoretical framework. All standardized factor loadings exceeded the acceptable threshold of 0.50, with each item loading significantly onto its respective construct. Additionally, the Composite Reliability (CR) for all constructs surpassed the recommended minimum of 0.70, indicating strong internal consistency. The Average Variance Extracted (AVE) for each latent variable was also above the 0.50 benchmark (Fornell & Larcker, 1981), demonstrating adequate convergent validity. These results confirm that the indicators used in the questionnaire reliably and validly represent the underlying theoretical constructs.

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
Perceived Ease of Use (PEOU)	Cortiñas et al. (2023)	4	0.910	0.789-0.837	0.883	0.654
Perceived Usefulness (PU)	Cortiñas et al. (2023)	4	0.871	0.718-0.810	0.857	0.600
Social Influence (SI)	Puriwat and Tripopsakul (2021)	4	0.944	0.779-0.835	0.887	0.663
Attitude (ATT)	Cortiñas et al. (2023)	5	0.909	0.641-0.896	0.892	0.627
Information Quality (IQ)	Alaydrus and Napitupulu (2022)	3	0.900	0.884-0.896	0.920	0.794
Facilitating Condition (FC)	Alaydrus and Napitupulu (2022)	3	0.917	0.804-0.823	0.853	0.660
Behavioral Intention (BI)	Cortiñas et al. (2023)	4	0.930	0.712-0.747	0.824	0.540

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

Following the assessment of item-level performance, overall model fit was evaluated using a set of absolute and incremental fit indices. As shown in Table 4, the model satisfied all commonly accepted fit criteria, including CMIN/DF, GFI, AGFI, RMSEA, CFI, NFI, and TLI. The strong model fit supports the appropriateness of the measurement model for further structural analysis.

Table 4: Goodness of Fit for Confirmatory Factor Analysis

Index	Criterion	Statistical Value
CMIN/DF	< 3.00 (Hair et al., 2006)	1.490
GFI	> 0.90 (Bagozzi & Yi, 1988)	0.938
AGFI	> 0.80 (Sica & Ghisi, 2007)	0.922
NFI	> 0.90 (Hair et al., 2006)	0.940
CFI	> 0.90 (Hair et al., 2006)	0.979
TLI	> 0.90 (Hair et al., 2006)	0.976
RMSEA	< 0.08 (Pedroso et al., 2016)	0.032

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

To evaluate discriminant validity, the square root of each construct's AVE was compared with the inter-construct correlation coefficients. As presented in Table 6, the diagonal values (representing the square roots of AVE) were greater than the corresponding off-diagonal correlation coefficients for all constructs. Moreover, none of the inter-construct correlations exceeded the critical value of 0.80. These results confirm that each construct is empirically distinct from the others in the model.

The CFA results demonstrate that the measurement model exhibits strong reliability, convergent validity, and discriminant validity, providing a solid foundation for subsequent structural equation modeling.

Table 5: Discriminant Validity

Variable	Factor Correlations						
	PEOU	PU	SI	ATT	IQ	FC	BI
PEOU	**0.809**						
PU	0.276	**0.775**					
SI	0.176	0.179	**0.814**				
ATT	0.247	0.280	0.095	**0.792**			
IQ	0.321	0.167	0.267	0.227	**0.891**		
FC	0.354	0.292	0.233	0.238	0.310	**0.812**	
BI	0.326	0.28	0.299	0.218	0.331	0.351	**0.735**

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

4.3 Structural Equation Model (SEM)

As shown in Table 6, the structural equation model (SEM) test results modified by AMOS 28 software show that key adaptation indicators such as CMIN/DF, GFI, AGFI, CFI, NFI, TLI, and RMSEA all meet the statistical standards (Hair et al., 2010; Kline, 2023). The structural equation modeling technique was used to verify the causal path of the theoretical hypothesis, evaluate the statistical significance of the linear relationship between the latent variables, and control the systematic error of the parameter estimation using the bias correction method (Byrne, 2010). The empirical results show that the model's overall fit meets the measurement requirements.

Table 6: Goodness of Fit for Structural Equation Modeling

Index	Criterion	Statistical Value
CMIN/DF	< 3.00 (Hair et al., 2006)	1.198
GFI	> 0.90 (Bagozzi & Yi, 1988)	0.911
AGFI	> 0.80 (Sica & Ghisi, 2007)	0.893
NFI	> 0.90 (Hair et al., 2006)	0.919
CFI	> 0.90 (Hair et al., 2006)	0.960
TLI	> 0.90 (Hair et al., 2006)	0.955
RMSEA	< 0.08 (Pedroso et al., 2016)	0.044

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

4.4 Research Hypothesis Testing Result

Table 7's results demonstrate that perceived ease of use exhibits the most substantial influence on perceived usefulness, supported by a significant standardized coefficient ($\beta = 0.553$, t = 4.550*). The second is the influence of facilitating condition on behavioral intention, $\beta=0.283$, t-value=4.098*. The effect of perceived usefulness on attitude, $\beta=0.214$, t-value=4.016*. The effect of perceived ease of use on attitude, $\beta=0.283$, t-value=5.356*. The influence of social influence on behavioral intention, $\beta=0.229$, t-value=4.456*. The effect of attitude on behavioral intention, $\beta=0.120$, t-value=2.422*. The effect of information quality on behavioral intention, $\beta=0.229$, t-value=4.554*.

Table 7: Hypothesis Testing Result

Hypothesis	Standardized path coefficients (β)	t-value	Test Result
H1: PEOU → PU	0.317	6.071*	Supported
H2: PU → ATT	0.214	4.016*	Supported
H3: PEOU → ATT	0.283	4.098*	Supported
H4: SI → BI	0.229	4.456*	Supported
H5: ATT → BI	0.120	2.422*	Supported
H6: IQ → BI	0.229	4.554*	Supported
H7: FC → BI	0.286	5.356*	Supported

Note: *=p-value<0.05

The structural equation modeling results (Table 7) reveal critical determinants of behavioral intention (BI) in AI-powered social media adoption among university students, demonstrating the following reconfigured relationships:

H1: Perceived ease of use (PEOU) of AI-driven interfaces significantly enhances perceived usefulness (PU) ($\beta = 0.317$, t-value = 6.071*). This aligns with Venkatesh et al. (2012) extended TAM framework, where algorithmic transparency in social media platforms amplifies users' utility perceptions through reduced cognitive friction. Al-Oraini's (2025) study explores the impact of AI chatbots on customer service and finds that perceived ease of use (PEOU) has a significant positive impact on perceived usefulness (PU). This suggests that when users think an AI interface is easy to use, they are more likely to think that the interface is useful. This is consistent with the hypothesis in this study.

H2: Perceived usefulness (PU) of AI-curated content directly shapes positive attitudes (ATT) ($\beta = 0.214$, t-value= 4.016*). Kim et al. (2024) explored the effects of perceived usefulness and perceived pleasure of artificial intelligence chatbots (AI-CAs) on user attitudes and usage intent. The results show that perceived usefulness has a significant positive impact on users' attitudes and usage intentions towards AI-CAs. This is consistent with the hypothesis of this study that the perceived usefulness of AI-curated content is enough to directly shape positive attitudes.

H3: PEOU to ATT pathway ($\beta = 0.283$, t-value= 4.098*) shows the influence of perceived usefulness on attitude strength. Davis et al. (1989) verified the positive impact of perceived ease of use (PEOU) on user attitude (ATT) by comparing the two theoretical models. They note that when users perceive a technology or system as easy to use, they have a more positive attitude toward that technology and are, therefore, more likely to accept and use it.

H4: Social influence (SI) from peer networks significantly predicts BI ($\beta = 0.229$, t-value= 4.456*). Venkatesh and Davis (2000) showed that When individuals perceive positive influences from a peer network, they are more likely to form positive behavioral intentions. In addition, research by Aral and Walker (2012) shows that individuals in social networks significantly influence each other's behavior through peer influence. Their research found that by identifying influential and susceptible members of the network, it is possible to better understand how behavior spreads within a social network. This is consistent with the hypothesis in this study that social influences from peer networks are significant predictors of behavioral intentions.

H5: This hypothesis states that attitude (ATT) has a significant but small effect on behavioral intention (BI) ($\beta = 0.120$, t-value= 2.422*). In their study, Jiang et al. (2022) explored the interaction between AI-powered chatbots and customers and found that users' positive attitudes toward chatbots significantly influenced their usage intentions, although this effect may be small. This finding is consistent with your hypothesis that attitude (ATT) has a significant but small effect on behavioral intention (BI).

H6: This hypothesis states that the Information Quality (IQ) of AI-generated content has a significant effect on Behavioral Intention (BI) ($\beta = 0.229$, t-value= 4.554*). Liu and Li (2011) studied the influence of information quality of mobile entertainment services on users' behavioral intention and found that information quality is a key factor affecting users' usage intention. This suggests that high-quality AI-generated content can significantly improve users' behavioral intentions, which is consistent with the hypothesis in this study.

H7: This hypothesis suggests that the Facilitating Conditions (FC) of AI literacy have the strongest predictive effect on Behavioral Intention (BI) ($\beta = 0.286$, t-value= 5.356*). A study by Ji et al. (2025) explored the impact of AI literacy on individual innovation behavior and found that facilitating conditions (such as the availability and supportive environment of AI literacy) significantly affected individuals' behavioral intentions. This suggests that

individuals are more likely to exhibit positive behavioral intentions when they believe that the facilitating conditions associated with AI literacy are sufficient.

The results of hypothesis testing highlight several critical factors influencing students' behavioral intention to use AI-based social media platforms. Facilitating conditions and perceived ease of use emerged as the strongest predictors, underscoring the importance of system accessibility and user-friendly design. Social influence and information quality also showed significant effects, indicating the combined role of peer dynamics and content credibility in shaping adoption behavior. Although attitude had a relatively modest influence, its significance reaffirms its mediating role in technology acceptance. These findings provide valuable insights for developing targeted strategies that enhance platform usability, improve information delivery, and strengthen institutional support, forming the basis for the study's practical recommendations.

5. Conclusions and Recommendation

5.1 Conclusions

This study investigated the key factors influencing students' behavioral intention to adopt AI-based social media platforms, focusing on computer science undergraduates from three public universities in Sichuan Province. Grounded in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), the proposed framework tested seven hypotheses involving perceived ease of use, perceived usefulness, attitude, social influence, information quality, facilitating conditions, and behavioral intention. A total of 480 valid responses were collected from students with at least six months of social media usage experience.

Using Confirmatory Factor Analysis (CFA), the study confirmed the measurement model's reliability and validity. Structural Equation Modeling (SEM) was then applied to examine the hypothesized relationships. The findings revealed that facilitating conditions had the strongest direct effect on behavioral intention, followed by social influence and information quality, all of which significantly predicted students' willingness to engage with AI-driven platforms. Additionally, perceived ease of use showed the strongest influence on perceived usefulness, reinforcing its foundational role in shaping users' cognitive evaluations. Both perceived ease of use and perceived usefulness significantly influenced attitude, although the magnitude of their effects on behavioral intention through this pathway was relatively modest.

The results highlight the importance of accessible infrastructure, credible information, intuitive platform design, and peer influence in fostering the adoption of AI-based social media in higher education contexts. These insights provide a basis for targeted recommendations aimed at improving AI platform usability, student support systems, and digital literacy education.

5.2 Recommendations

The integration of artificial intelligence (AI) algorithms into social media platforms presents both opportunities and challenges for university students. On one hand, these platforms facilitate more efficient access to information, enabling students to acquire, share, and disseminate content with greater ease. On the other hand, algorithmically driven recommendation systems such as those used by TikTok, may lead to cognitive narrowing, content echo chambers, and even problematic usage behaviors, including excessive screen time and platform addiction. This study proposed a comprehensive research framework and empirically analyzed the factors influencing students' behavioral intention toward AI-based social media. Based on the results, several recommendations are provided for universities, platform developers, individual users, and policymakers. These aim to optimize platform utility, mitigate cognitive bias, and promote responsible student engagement through multi-stakeholder collaboration.

For universities, curricular enhancements are essential to improve students' digital literacy. It is recommended that institutions incorporate AI-related modules into academic programs, particularly through a mandatory course titled "Artificial Intelligence and Social Computing." This course should cover three key dimensions: (1) algorithmic principles (e.g., collaborative filtering, neural networks), (2) content ecology and diversity management, and (3) ethical implications such as privacy risks and algorithmic bias. Practical components may include student engagement with open-source tools like IBM's AI Fairness 360 to visualize how algorithmic patterns influence information exposure. Additionally, interdisciplinary AI ethics committees should be formed to evaluate the impact of social media algorithms in academic settings, recommend bias mitigation tools, and host annual forums promoting transparency and responsible algorithmic governance.

For platform developers, it is essential to strike a balance between personalized recommendations and cognitive well-being. Developers are encouraged to implement hybrid recommendation systems that combine collaborative filtering with knowledge graph approaches, enabling a blend of familiar and educational content. Features such as a user-controlled "diversity slider" can give users the ability to adjust the ratio of personalized versus novel content. Other recommended features include cognitive safeguards such as periodic usage reset reminders, visual dashboards for

monitoring content diversity, and "exploration modes" that temporarily disable behavioral tracking to encourage discovery beyond habitual patterns.

For university students, increased awareness of algorithmic systems is crucial. Students should take proactive steps to diversify their digital content environments. Suggested practices include monthly content audits, engagement with academic-focused accounts, and the separation of professional and leisure social media profiles to prevent behavioral data cross-contamination. Developing critical content consumption habits such as cross-verifying viral content through academic databases and intentionally exploring interdisciplinary topics, can help reduce the risk of algorithm-induced cognitive narrowing.

For policymakers, regulatory and collaborative frameworks must be established to ensure the ethical deployment of AI in social media platforms. Transparent algorithmic labeling, akin to digital "nutrition labels", should be mandated for services targeting student users. Policymakers should promote partnerships between universities and platforms to co-develop academic recommendation systems, pilot open APIs for algorithmic auditing, and support publicly available libraries of bias mitigation tools and educational resources designed specifically for university populations.

By aligning technical development with educational objectives, these strategies can transform AI-based social media into a controlled, supportive tool for learning. Educators are encouraged to guide appropriate usage norms, developers to optimize for ethical engagement, and policymakers to enforce governance measures that ensure personalization enhances rather than limits students' intellectual growth and access to valuable knowledge.

5.3 Limitation and Further Study

This study presents two primary limitations that should be acknowledged. First, the sample is limited to undergraduate students from three public universities in Sichuan Province, which may constrain the generalizability of the findings. Broader regional representation could provide a more comprehensive understanding of students' behavioral intentions across diverse educational and cultural contexts. Second, the research framework focuses on seven core variables drawn from the TAM and UTAUT models, without incorporating other potentially relevant factors influencing AI-based social media adoption.

Future research can address these limitations in two ways. First, by expanding the sample to include multiple regions and a more diverse range of institutions, researchers can improve the external validity and universality of the findings. Second, future studies may consider integrating additional theoretical models such as the Theory of Planned Behavior (TPB) and the Theory of Reasoned Action (TRA), to construct a more comprehensive and multidimensional explanatory framework. This approach would not only deepen theoretical saturation but also provide richer insights into the psychological and contextual factors shaping technology acceptance among university students.

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