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Research Article

The role of social media use motivations in university students' adoption of AI-supported learning tools: The mediating effect of perceived usefulness

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ABSTRACT

This study aims to examine the impact of university students' motivations for social media use (information seeking, socialization, entertainment, and identity formation) on their intentions to use artificial intelligence (AI)-powered learning tools such as ChatGPT, Gemini, and Copilot. Designed within the framework of the technology acceptance model (TAM), the research addresses the mediating role of perceived utility and the moderating role of digital literacy. The study aims to contribute to the literature by understanding how social media habits evolve into academic technology adoption processes. This research, based on a sample of 370 university students, investigates the relationship between various social media motivations (social connection/FOMO, popularity/identity formation, appearance/impression management, and civic/advocacy) and behavioral intention (BI) to use AI learning tools. Perceived usefulness (PU) is included as a mediating variable in this relationship. Results from regression-based mediation analyses (PROCESS Model 4 equivalent) indicate that social media use motivations significantly predict both PU and BI. The indirect effect through PU was statistically significant (ab = 0.248, SE = 0.062, z = 3.988, p < .001), supporting a partial mediation model. Civic/advocacy motivations demonstrated the strongest relationship with PU and BI among subscales. These findings advance understanding of technology adoption in educational contexts and highlight the role of social media usage patterns in shaping AI tool adoption

Keywords: social media motivations, AI learning tools, perceived usefulness, behavioral intention, technology adoption, TAM, mediation

INTRODUCTION

In an era of accelerating digital transformation, higher education institutions are confronted with the profound impact of technological innovations on both teaching and learning processes. Among the most prominent manifestations of this transformation is the rapid integration of artificial intelligence (AI)-powered learning tools—such as ChatGPT, Gemini, and Microsoft Copilot, all grounded in large language models—into educational environments. These tools hold considerable promise in terms of facilitating access to information, delivering personalized learning experiences, and enhancing students' academic productivity (Rahman et al., 2025). A comprehensive understanding of the individual and contextual factors that shape the adoption of these technologies is therefore of critical importance for educational researchers and policymakers alike.

In the daily lives of university students, social media has evolved well beyond its original role as a platform for socialization and entertainment, now fulfilling functions such as information seeking, identity construction, and academic communication (Cuong et al., 2025). These usage patterns directly shape students' perceptions of and attitudes toward emerging technologies. The digital experience accumulated through social media platforms should thus be regarded as a potential source that influences individuals' expectations regarding AI tools, their assessments of the usefulness of such tools, and ultimately their intention to adopt them (Alkhawaja et al., 2022).

Technology adoption processes have been extensively examined in the literature through the lens of the technology acceptance model (TAM), originally developed by Davis (1989). TAM posits perceived usefulness (PU) and perceived ease of use as the primary determinants of individuals' intention to use a given technology (Alshammari & Babu, 2025; Liu & Ma, 2024). Although studies applying this model to AI-powered tools are increasingly prevalent, integrative frameworks that incorporate social media use motivations into the technology adoption process remain notably scarce—a gap that constitutes the central focus of the present study. Digital literacy, defined as individuals' capacity to use digital technologies effectively, critically, and safely, is similarly regarded as a potential moderating variable in the technology adoption process (Masli et al., 2025; Zhao et al., 2025). Digital competencies cultivated through social media experience may differentiate students' evaluations of PU and their intention to use AI learning tools (Yi et al., 2025). Accordingly, the inclusion of digital literacy as a moderating variable in the proposed model is expected to yield a more nuanced understanding of the relationships under investigation.

This study aims to examine the effect of social media use motivations on university students' intention to adopt AI-powered learning tools, with PU serving as a mediating variable. The findings are anticipated to contribute both to the theoretical literature on technology acceptance and to the development of evidence-based policy recommendations concerning the integration of AI in higher education.

Problem Statement

The integration of AI-powered learning tools into higher education settings has become an increasingly prominent concern for both researchers and educational institutions. Despite the substantial opportunities these tools offer, the factors governing students' adoption of such technologies remain insufficiently understood. Existing research has predominantly focused on variables such as PU (Alshammari & Babu, 2025), perceived ease of use (Toros et al., 2024), and institutional support (Jeilani & Abubakar, 2025); however, studies that directly address the relationship between social media use motivations and AI tool adoption remain considerably limited.

They use social media extensively at the beginning of university and exhibit various motivational patterns in their use. It is well known that different motivations, such as acquiring information, socializing, entertainment, and identity formation, differentiate their approaches to the new technologies they acquire (Buzeta et al., 2024; Kim & Lee, 2026). Nevertheless, how these motivations relate to students' intention to adopt AI tools, and what mediating role PU plays in this relationship, remains a fundamental research

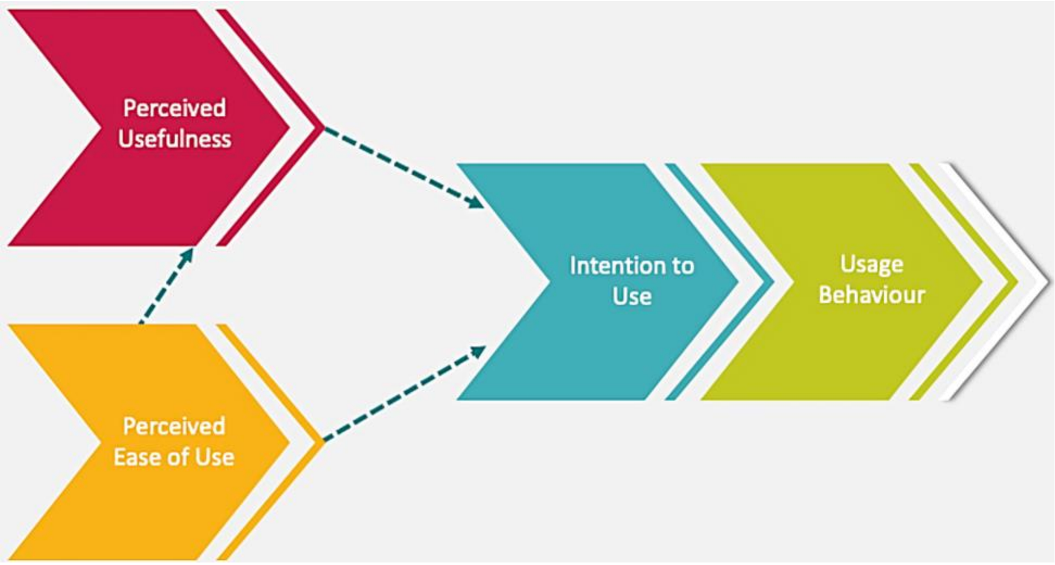

Figure 1. TAM model components (Davis, 1989)

problem yet to be adequately addressed. Furthermore, the extent to which differences in individuals' digital technology competencies moderate the motivation-intention relationship has yet to be clearly established. While some students are able to transfer the knowledge and skills acquired through social media to AI tools, those with lower levels of digital literacy appear to encounter greater difficulty in making this transition (Zhao et al., 2025). Determining how these dynamic influences research findings carries both theoretical and practical significance.

THEORETICAL FRAMEWORK

Technology Acceptance Model and Perceived Usefulness

TAM is one of the most established theoretical frameworks developed by Davis (1989) to explain the process through which individuals adopt information technologies. The model centers on two core constructs PU and perceived ease of use, and argues that these variables directly influence individuals' intention to use a technology (Liu & Ma, 2024). TAM has been widely applied in educational technology contexts, with its validity tested across diverse technological settings, including e-learning systems (Alkhawaja et al., 2022; Yan et al., 2024), AI-powered tools (Bawa et al., 2026), and social media platforms (Fan, 2023) (**Figure 1**).

PU is defined as an individual's belief that using a particular technology will enhance their job or learning performance, and it stands out as one of the strongest predictors of technology adoption intention (Alshammari & Babu, 2025). In the present study, PU is positioned as a mediating variable in the relationship between social media use motivations and the intention to adopt AI tools. This approach presupposes that students' social media experiences are a meaningful determinant of the extent to which they find AI tools useful, and that this perception subsequently exerts an indirect influence on their intention to use such tools.

Social Media Use and Artificial Intelligence-Powered Learning Tools

Social media platforms have become an inseparable component of contemporary university students' digital lives. Initially positioned merely as tools for socialization and entertainment, these platforms have over time assumed far broader functions encompassing information access, content creation, academic communication, and identity construction (Cuong et al., 2025). Viewed through the lens of uses and gratifications theory, students are seen to engage with social media actively and purposefully in order to satisfy specific needs (Sharif et al., 2021). This motivational diversity is conceptualized along dimensions of information seeking, socialization, entertainment, and identity formation, with each dimension argued to shape individuals' attitudes and behaviors toward technology in distinct ways (Buzeta et al., 2024). Indeed, studies in the literature demonstrate that intensive and motivationally diverse social media use enhances individuals' overall digital competence and cultivates a more receptive disposition toward new technologies (Alturki & Aldraiweesh, 2024).

AI-powered learning tools are claiming an increasingly prominent place in higher education environments. Built upon large language models, tools such as ChatGPT, Gemini, and Microsoft Copilot carry substantial potential to transform the learning experience through functions including guiding academic writing processes, simplifying complex concepts, supporting language acquisition, and providing students with immediate feedback (Liu & Ma, 2024; Rahman et al., 2025). One of the most noteworthy characteristics of these tools is their capacity to generate adaptive responses tailored to the individual user's needs and proficiency level—a feature that contributes to a personalized learning environment that diverges fundamentally from conventional instructional tools (Rahman et al., 2025). Low et al. (2025) emphasize that the rise of AI in higher education represents not merely a technological advancement but a paradigm shift giving rise to profound transformations in pedagogical understanding and institutional structures. Nevertheless, effective adoption of these tools remains contingent upon individual factors such as students' technological readiness, their perceptions of the tools, and their motivations for use (Bawa et al., 2026).

When examining how social media use relates to the adoption of AI tools, the digital experience obtained through social media may enhance individuals' capabilities to process, evaluate, and transfer knowledge to unfamiliar technological settings. This enhancement, in turn, positively shapes their perception of AI tools' usefulness (Badr et al., 2024; Li et al., 2026). Damerji and Salimi (2021) demonstrated that prior experience with and attitudes toward technology serve as critical determinants in the AI acceptance process. Everyday practices such as following news feeds on social media platforms, producing content, and interacting with algorithmic recommendation systems may lay the groundwork for the development of an intuitive understanding of how AI tools function (Zhao et al., 2025).

Research Gaps and the Importance of the Study

A review of the existing literature reveals that studies on AI tool adoption have focused predominantly on individual psychological variables such as PU, perceived ease of use, and self-efficacy (Alshammari & Babu, 2025; Bawa et al., 2026; Zhao et al., 2025), while research directly addressing the relationship between social media use and AI adoption remains limited. This gap gives rise to two important questions: first, do the digital practices developed through social media meaningfully predict PU toward AI tools? And second, which individual and contextual factors moderate this relationship?

Studies examining the relationship between social media motivations and technology adoption have been conducted largely within the context of e-learning platforms and conventional educational technologies (Badr et al., 2024; Fan, 2023). Although these studies indicate that social media use motivations can positively influence technology adoption intention, how the dynamics unique to AI tools take shape within this framework has yet to be clearly established. The distinctive characteristics inherent to the nature of AI including anthropomorphic interaction patterns, immediate feedback mechanisms, and adaptive learning support give rise to dynamics that set AI tool adoption apart from the adoption of conventional technologies (Park & Kim, 2023).

While studies examining PU as a mediating variable do exist (Damerji & Salimi, 2021; Yan et al., 2024), the vast majority of such research does not treat social media motivations as an independent variable. Consequently, the mediation model conceptualized as social media motivations → PU → AI adoption intention has not been tested—particularly within a university student sample. This gap constitutes the original theoretical contribution of the present study.

The primary aim of this study is to examine the effect of university students' social media use motivations on their intention to adopt AI-powered learning tools. In line with this overarching aim, the mediating role of PU is also addressed within the scope of the research. Against this background, the gaps identified in the existing literature give rise to the following four core research questions:

1. Which social media platforms and AI tools have university students been using, and for how long?
2. What level are university students' motivations for using social media, PU, and intention to use AI-powered learning tools?

Table 1. Demographic characteristics of participants (N = 370)

	Variable	Frequency (n)	Percentage (%)
Gender	Female	274	74.1
	Male	96	25.9
Age	18-20 years	343	92.7
	21-23 years	21	5.7
	24-26 years	4	1.1
	27+ years	2	0.5
Year of student	1st year	264	71.4
	2nd year	27	7.3
	3rd year	44	11.9
	4th year+	35	9.4
Field of academic discipline	Social sciences/humanities	164	44.3
	Natural sciences	146	39.5
	Engineering	37	10.0
	Health sciences	23	6.2

3. What variables influence students' social media use motivations, PU, and intention to use AI-powered learning tools?
4. Do social media use motivations significantly predict university students' intention to use AI-powered learning tools?
5. Does PU function as a mediating variable in this relationship?

METHOD

This study was conducted using a quantitative research framework that integrates both descriptive and correlational survey designs. The descriptive survey model is a quantitative approach intended to portray an existing situation in its natural form without manipulating any variables. Its primary aim is to systematically identify and present the characteristics, attitudes, views, and behaviors of individuals, groups, or phenomena, thereby providing a clear depiction of the current state (Störrle, 2017). In addition, the correlational survey design was employed to explore the relationships among two or more variables without any experimental intervention. This design focuses on identifying the direction and strength of associations between variables and understanding how they are related to one another (Creswell & Creswell, 2012).

Participants

The study sample consisted of 370 university students recruited through purposive sampling. In purposive sampling, participants are selected on the basis of specific criteria deemed relevant to the research objectives; accordingly, the target population was defined as undergraduate students actively enrolled at universities in Kazakhstan who had prior experience using social media platforms. The survey was distributed online and disseminated to the broadest possible student population across participating institutions; however, despite being sent to all eligible students, only 370 individuals completed and returned a valid response. An a priori power analysis indicated that at the observed total-effect $R^2 = .056$ ($f^2 = 0.056$), N = 370 provides statistical power exceeding .99 at $\alpha = .05$, confirming that the sample size is adequate to detect indirect effects of this magnitude.

The sample consisted of 274 female (74.1%) and 96 male (25.9%) students (**Table 1**). The majority of participants were aged 18-20 years (n = 343, 92.7%), followed by 21-23 years (n = 21, 5.7%), 24-26 years (n = 4, 1.1%), and 27 years and older (n = 2, 0.5%). Regarding year of student, 264 students (71.4%) were in their first year, 44 (11.9%) in their third year, 27 (7.3%) in their second year, and 35 (9.4%) in their fourth year or above. In terms of field of study, 164 participants (44.3%) were enrolled in social sciences/humanities, 146 (39.5%) in natural sciences, 37 (10.0%) in engineering, and 23 (6.2%) in health sciences.

Instruments

Three validated scales were administered to measure the study's primary constructs.

Perceived usefulness scale (PU). A 6-item scale adapted from Davis (1989) measured students' PU of AI-powered learning tools. Items were rated on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Example item: "Using AI-powered learning tools enables me to accomplish learning tasks more quickly." The scale demonstrated excellent internal consistency (Cronbach's α = .918). Items were adapted to replace "job performance" with "learning performance" to align with the educational context; all other wording was retained from the original scale.

Behavioral intention toward AI scale (BI). BI adapted from Chai et al. (2021) measured students' behavioral intention (BI) toward AI. A 4-item scale measured students' intention to use AI technologies in learning and daily life, rated on a 7-point Likert scale (1 = strongly disagree to 7 = strongly agree). Example item: "I plan to use GAI to help me learn and work now and in the future." Internal consistency was good (Cronbach's α = .873).

Motivations for social media use scale (MSMU). MSMU adapted from Rodgers et al. (2021) measured students' MSMU. A 15-item scale measured social media use motivations across four subscales:

(a) social connection/FOMO (items 1-2, α = .645),

(b) popularity/identity formation (items 3-6, α = .881),

(c) appearance/impression management (items 7-12, α = .891), and

(d) civic/advocacy motivations (items 13-15, α = .731).

Items were rated on a 5-point scale (1 = never to 5 = always). The total scale demonstrated excellent internal consistency (α = .927).

Procedure

Data were collected via an online Google Form survey distributed among university students. Participation was voluntary and anonymous. Informed consent was obtained from all participants prior to data collection. The survey was available in Russian to accommodate the participant population. Data were collected between December 2025 and February 2026, corresponding to the mid-semester and end-of-semester examination period of the 2025-2026 academic year at the participating institutions. All participants provided informed digital consent prior to completing the survey. Participation was entirely voluntary, anonymous, and no identifying data were retained. The study was conducted in accordance with the principles of the Declaration of Helsinki.

Data Analysis

Data were analyzed using SPSS 26 and Python with NumPy and SciPy libraries. The normality assumption was examined through skewness and kurtosis coefficients and it was understood that the normal distribution condition was met by seeing that the values were in the range of -2 and +2. For all scales, descriptive statistics and Cronbach's α values were computed. To identify differences between groups, independent samples t-test and ANOVA were employed. All figures were generated using Python 3.11 with the Matplotlib library (v3.7). All figure captions specify additional parameters where relevant. Pearson correlations were computed to examine bivariate relationships among study variables. Mediation analysis was conducted following the Baron and Kenny (1986) procedure and Hayes' (2017) PROCESS Model 4 logic, examining the indirect effect of social media use motivations on BI through PU. The Bias-corrected bootstrapped confidence intervals (BCa-CI, B = 5,000 resamples) were used to assess the significance of indirect effects, as this method is more robust than the Sobel test and does not assume normality of the product term (Hayes, 2017). The Sobel test is retained for supplementary comparison. All analyses were conducted with the complete sample (N = 370). Levene's test for homogeneity of variance was applied prior to all ANOVA comparisons.

RESULTS

Digital Tool and Social Media Usage Patterns

This section presents descriptive findings on participants' (N = 370) use of AI-powered learning tools, duration of use, and social media platform preferences. These characteristics provide important contextual information about the sample's digital engagement.

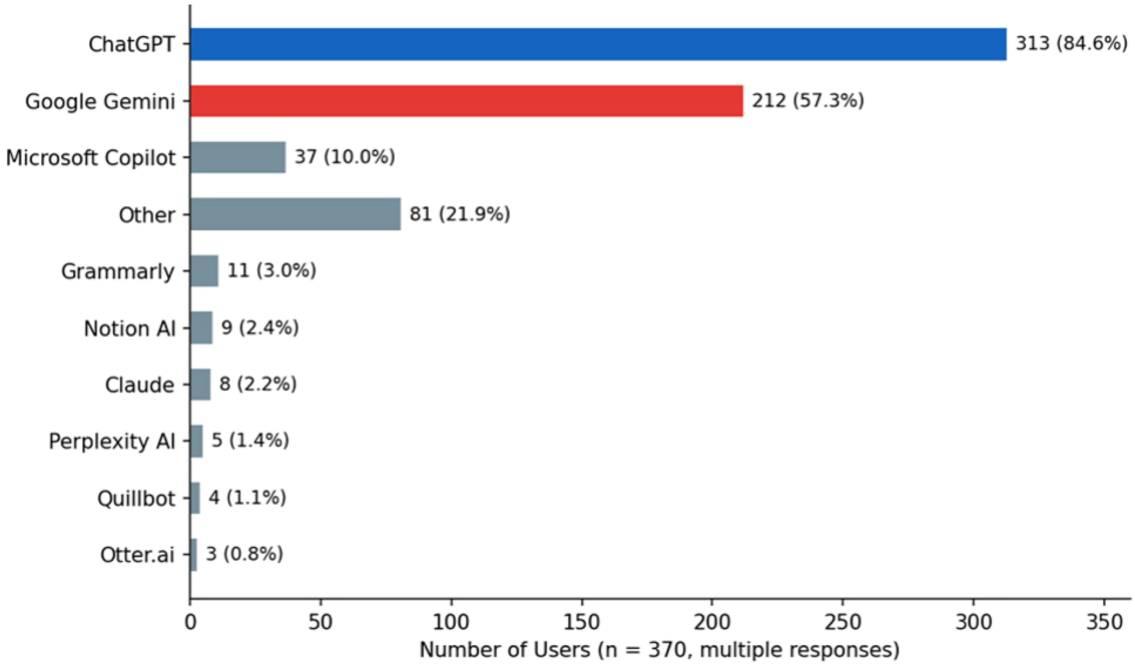

Figure 2. AI-powered learning tools used by participants (N = 370, multiple responses) (Source: Authors)

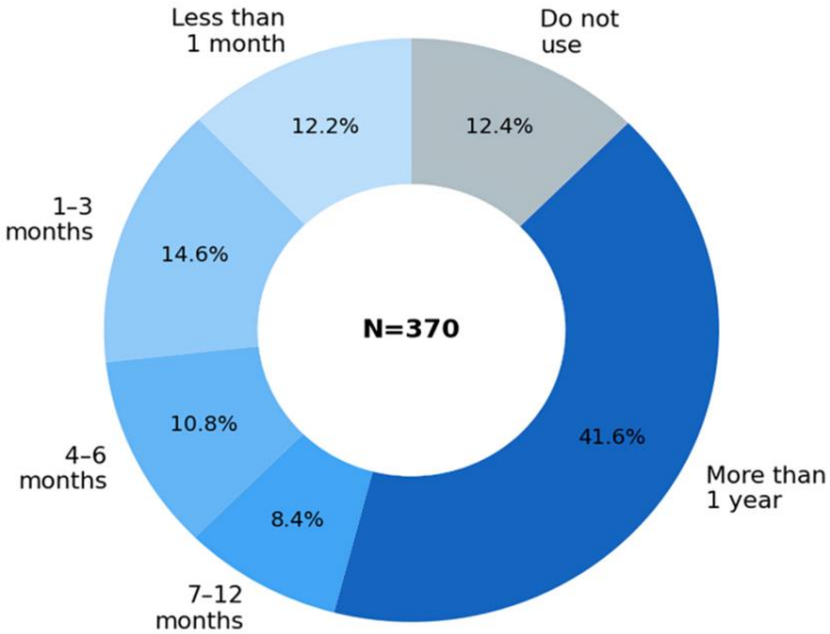

Figure 3. Duration of AI-powered learning tools used among participants (Source: Authors)

Artificial intelligence-powered learning tools

Participants were asked to indicate which AI-powered learning tools they currently use (multiple responses permitted). As shown in **Figure 2**, ChatGPT was by far the most widely used tool, reported by 313 participants (84.6%), followed by Google Gemini (n = 212, 57.3%) and unspecified other tools (n = 81, 21.9%). Microsoft Copilot was used by 37 participants (10.0%). Less commonly used tools included Grammarly (n = 11, 3.0%), Notion AI (n = 9, 2.4%), Claude (n = 8, 2.2%), Perplexity AI (n = 5, 1.4%), Quillbot (n = 4, 1.1%), and Otter.ai (n = 3, 0.8%). Thirty-five students (9.5%) reported not using any AI-powered learning tools.

Duration of artificial intelligence tool use

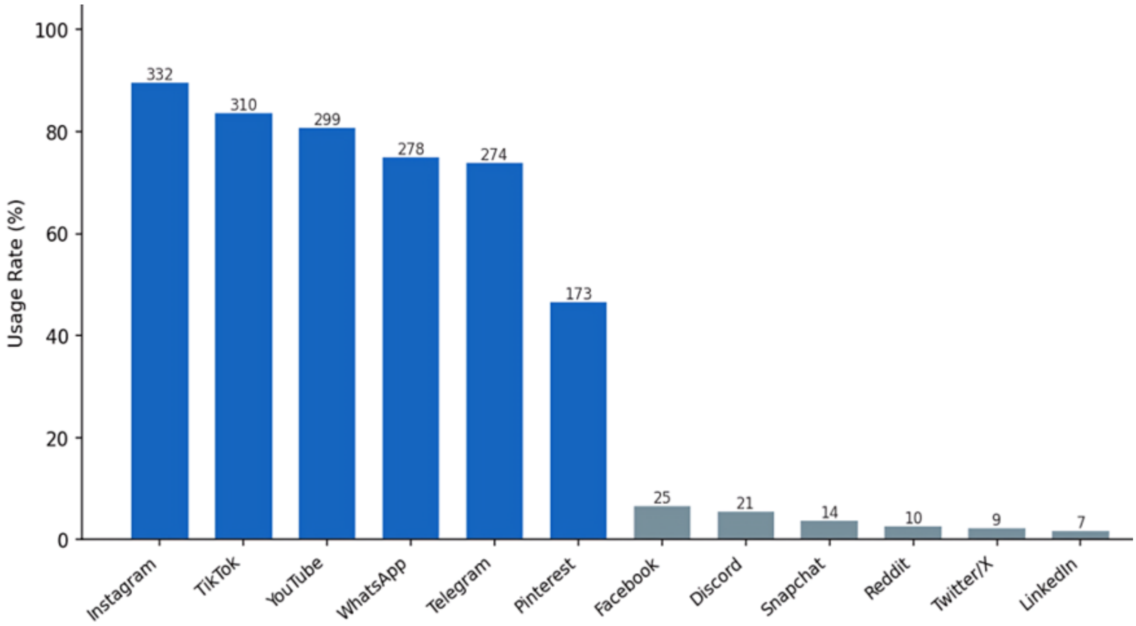

Figure 4. Social media platforms used by participants (N = 370, multiple responses) (Source: Authors)

Table 2. Descriptive statistics and reliability coefficients for study variables

Variable	n	M	SD	Minimum	Maximum	Cronbach's α
MSMU total	370	2.31	0.81	1.00	5.00	.927
FOMO/social connection	370	2.60	0.91	1.00	5.00	.645
Popularity/identity	370	2.21	0.97	1.00	5.00	.881
Appearance/impression	370	2.16	0.93	1.00	5.00	.891
Civic/advocacy	370	2.56	0.96	1.00	5.00	.731
PU	370	4.67	1.34	1.00	7.00	.918
BI	370	4.75	1.35	1.00	7.00	.873

Regarding the length of experience with AI learning tools, the most common response was more than 1 year (n = 154, 41.6%), indicating that a substantial portion of the sample had considerable experience with these tools. This was followed by 1-3 months (n = 54, 14.6%), less than 1 month (n = 45, 12.2%), 4-6 months (n = 40, 10.8%), and 7-12 months (n = 31, 8.4%). Forty-six participants (12.4%) reported not using AI learning tools, consistent with the tool usage data (**Figure 3**).

Social media platform usage

Participants indicated which social media platforms they use (multiple responses permitted). Instagram was the most widely used platform (n = 332, 89.7%), followed closely by TikTok (n = 310, 83.8%), YouTube (n = 299, 80.8%), WhatsApp (n = 278, 75.1%), and Telegram (n = 274, 74.1%). Pinterest was used by 173 participants (46.8%). Platforms with lower adoption rates included Facebook (n = 25, 6.8%), Discord (n = 21, 5.7%), Snapchat (n = 14, 3.8%), Reddit (n = 10, 2.7%), Twitter/X (n = 9, 2.4%), and LinkedIn (n = 7, 1.9%). These findings suggest that the sample primarily uses visual and messaging-oriented platforms (**Figure 4**).

Descriptive statistics and reliability

Table 2 presents the descriptive statistics and reliability coefficients for all study variables. The mean (M) score for PU was M = 4.67 (standard deviation [SD] = 1.34, scale range 1-7), and BI had a mean of M = 4.75 (SD = 1.35, scale range 1-7), both indicating moderate-to-high levels. The total social media use motivations score averaged M = 2.31 (SD = 0.81, scale range 1-5), suggesting that participants reported below-to-moderate motivation levels. Among the MSMU subscales, social connection/FOMO showed the highest mean (M = 2.60, SD = 0.91), followed by civic/advocacy (M = 2.56, SD = 0.96), popularity/identity (M = 2.21, SD = 0.97), and appearance/impression management (M = 2.16, SD = 0.93). With the exception of the FOMO subscale (α = .645), all reliability coefficients surpassed the acceptable threshold of .70. This lower alpha value for FOMO may be attributed to the limited number of items (k = 2). The MSMU items were measured on a 5-point scale

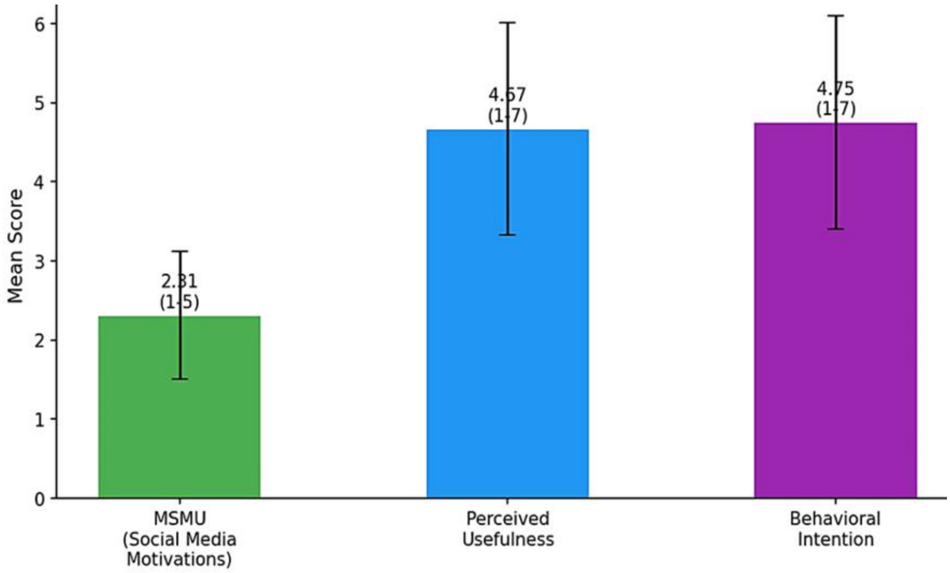

Figure 5. Mean scores of study variables (error bars represent ±1 SD) (Source: Authors)

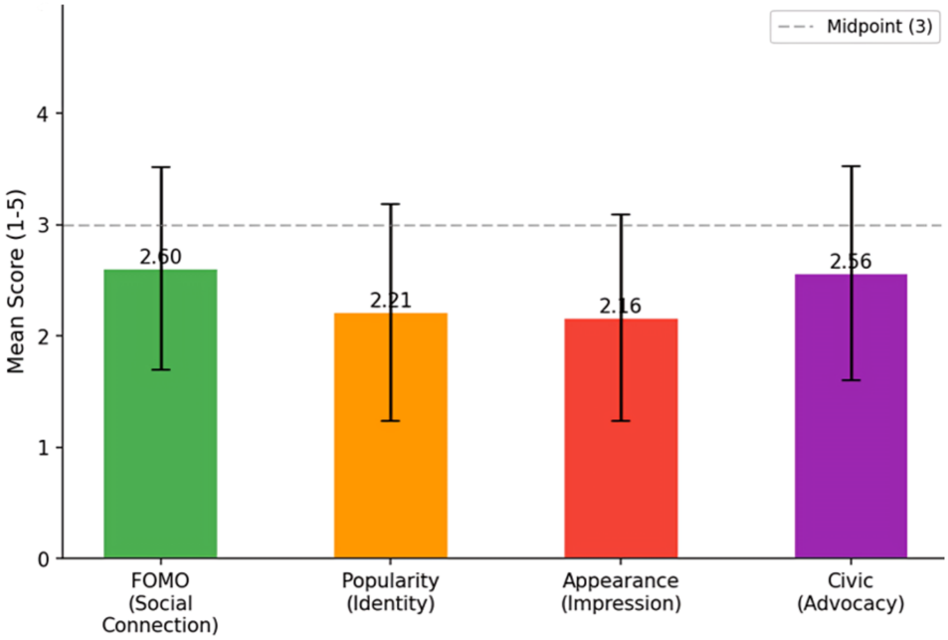

Figure 6. MSMU subscale mean scores (1-5 scale) (error bars represent ±1 SD & dashed line indicates scale midpoint) (Source: Authors)

ranging from 1 (never) to 5 (always). Meanwhile, the PU and BI items were rated on a 7-point scale from 1 (strongly disagree) to 7 (strongly agree). Note that α represents Cronbach's α reliability coefficient (**Figure 5** and **Figure 6**).

Group Difference Analyses

Gender differences in scale scores

Independent samples t-tests were conducted to examine whether female and male students differed significantly on the three primary study scales. Results indicated no statistically significant gender differences on any of the three scales (**Table 3** and **Figure 7**).

Female participants ($n = 274$) and male participants ($n = 96$) reported virtually identical mean scores on MSMU total (female: $M = 2.32$, $SD = 0.76$; male: $M = 2.30$, $SD = 0.94$; $t\ (368) = 0.180$, $p = .857$, $d = 0.02$), PU (female: $M = 4.68$, $SD = 1.34$; male: $M = 4.63$, $SD = 1.33$; $t\ (368) = 0.347$, $p = .729$, $d = 0.04$), and BI (female: $M =$

Table 3. Independent samples t-test results: Gender differences in scale scores

Scale	Female: M (SD)	Male: M (SD)	t	df	p	Cohen's d
MSMU total (1-5)	2.32 (0.76)	2.30 (0.94)	0.180	368	.857	0.02
PU (1-7)	4.68 (1.34)	4.63 (1.33)	0.347	368	.729	0.04
BI (1-7)	4.73 (1.36)	4.81 (1.32)	-0.477	368	.633	-0.06

Note. N = 370 (female n = 274, male n = 96); Two-tailed tests; & None of the differences reached statistical significance (p < .05)

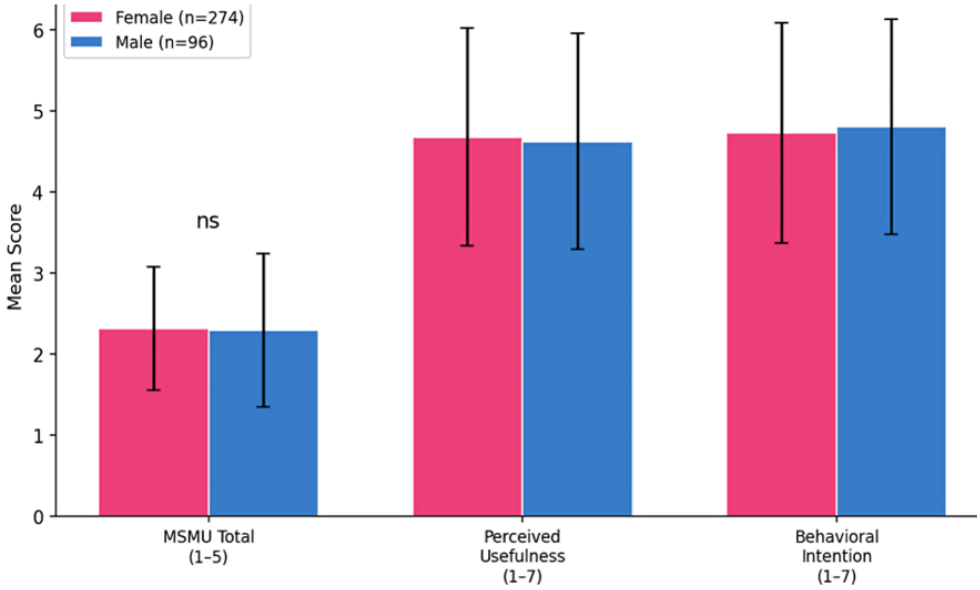

Figure 7. Scale mean scores by gender (error bars represent ±1 SD & ns = not significant) (Source: Authors)

Table 4. One-way ANOVA results: Year of study differences in scale scores

Scale	1st year: M (SD)	2nd year: M (SD)	3rd year: M (SD)	4th year+: M (SD)	F	p
MSMU total (1-5)	2.31 (0.81)	2.70 (0.79)	2.25 (0.80)	1.98 (0.58)	3.16	.025*
PU (1-7)	4.53 (1.38)	5.14 (1.24)	4.98 (1.08)	4.98 (1.37)	3.65	.013*
BI (1-7)	4.61 (1.41)	5.16 (1.06)	5.08 (1.07)	5.18 (1.31)	3.70	.012*

Note. N = 370 (1st year n = 264, 2nd year n = 27, 3rd year n = 44, 4th year+ n = 35); df = (3, 366); Levene's test confirmed homogeneity of variance for all three scales (MSMU: W = 0.850, p = .468; PU: W = 1.565, p = .198; BI: W = 2.211, p = .086), supporting the use of standard one-way ANOVA; & *p < .05

4.73, SD = 1.36; male: M = 4.81, SD = 1.32; t (368) = -0.477, p = .633, d = -0.06). All Cohen's d values indicated negligible effect sizes. These findings suggest that gender does not moderate relationships with social media motivations or AI tool adoption in this sample.

Year of study differences in scale scores

One-way ANOVAs were performed to determine whether students' year of study had an effect on their scale scores. In contrast to gender, year of study yielded statistically significant differences across all three scales (**Table 4** and **Figure 8**).

For MSMU total, a significant main effect was found, F (3, 366) = 3.160, p = .025. Post-hoc inspection of means suggests that second-year students reported the highest social media motivations (M = 2.70), while fourth-year and above students reported the lowest (M = 1.98). For PU, a significant effect was also observed, F (3, 366) = 3.654, p = .013, with second-year (M = 5.14) and fourth-year+ students (M = 4.98) reporting higher PU than first-year students (M = 4.53). Similarly, BI showed a significant year effect, F (3, 366) = 3.696, p = .012, with first-year students reporting notably lower intentions (M = 4.61) compared to upper-year students (range: M = 5.08-5.18).

Correlation analysis

Table 5 presents the Pearson correlation matrix for all study variables. BI was significantly and positively correlated with PU (r = .74, p < .001), MSMU total (r = .24, p < .001), social connection/FOMO (r = .30, p < .001), popularity/identity (r = .19, p < .001), appearance/impression management (r = .12, p < .05), and civic/advocacy

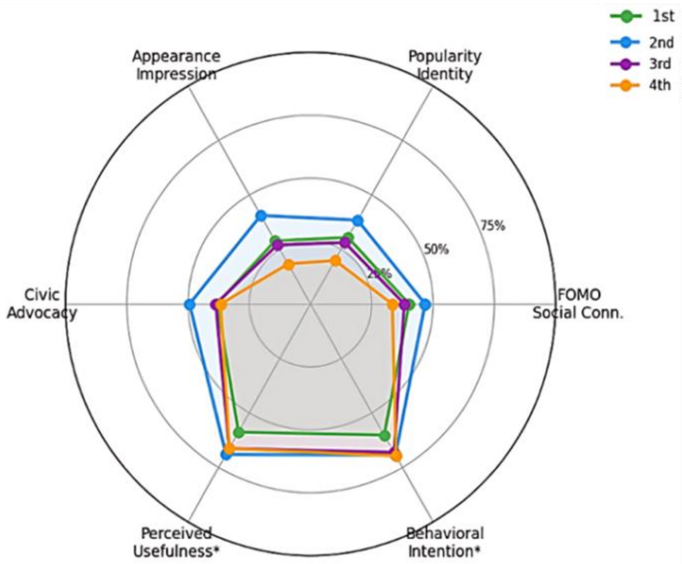

Figure 8. Radar charts of normalized scale scores by year of study (Source: Authors)

Table 5. Pearson correlation matrix for study variables

Variable	1	2	3	4	5	6
1. MSMU total	-					
2. FOMO/social connection	.72***	-				
3. Popularity/identity	.90***	.63***	-			
4. Appearance/impression	.94***	.59***	.80***	-		
5. Civic/advocacy	.72***	.42***	.48***	.59***	-	
6. PU	.21***	.22***	.14**	.12*	.32***	-
7. BI	.24***	.30***	.19***	.12*	.32***	.74***

Note. N = 370; *p < .05; **p < .01; ***p < .001; & MSMU total is presented in a separate first row; its high correlations with subscales (r = .72-.94) are partly mechanical as subscales are components of the total score

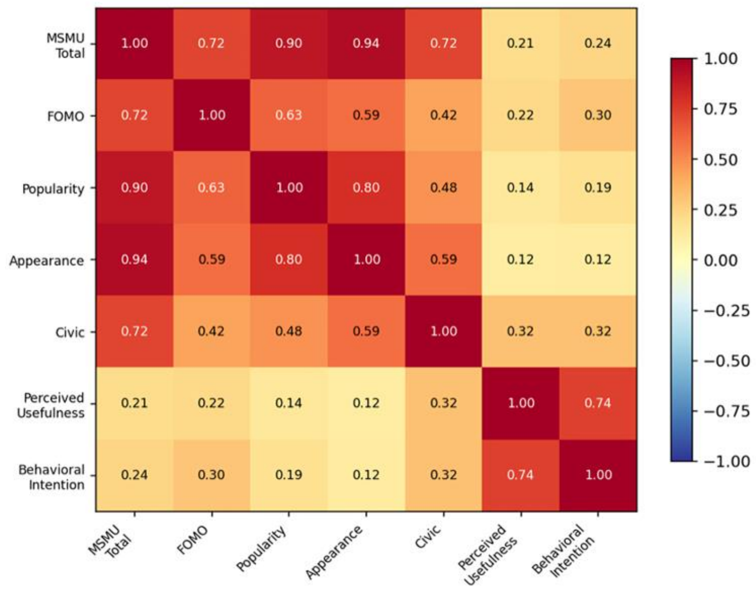

Figure 9. Correlation matrix heatmap of study variables (Source: Authors)

(r = .32, p < .001). PU was also significantly correlated with all MSMU subscales, with civic/advocacy showing the strongest association (r = .32, p < .001).

Figure 9 shows the correlation matrix heatmap of study variables.

Mediation analysis

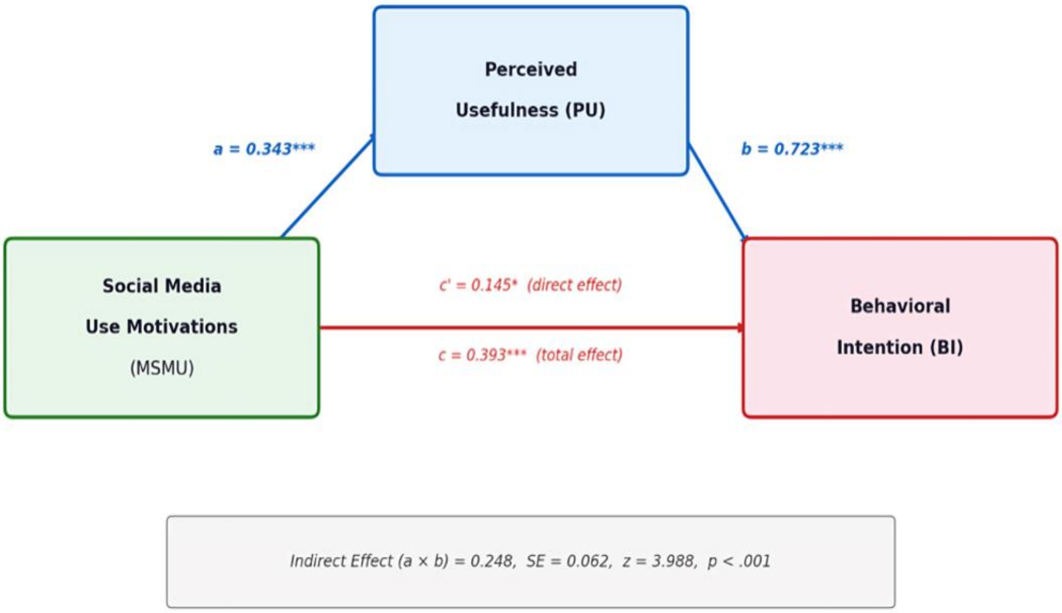

Figure 10. Mediation model: MSMU → PU → BI (standardized regression coefficients shown: c = total effect & c′ = direct effect) (Source: Authors)

Table 6. Mediation analysis results

Path	B	SE	t	p	R^2
Path a: MSMU → PU	0.343	0.084	4.069	< .001	.043
Path b: PU → BI (controlled)	0.723	0.036	20.017	< .001	
Path c′: MSMU → BI (direct)	0.145	0.060	2.430	.016	.549
Path c: MSMU → BI (total)	0.393	0.084	4.660	< .001	.056
Indirect effect (a × b)	0.248	0.062	z = 3.988	< .001	

Note. R^2 reported for equations & Indirect effect tested with Sobel z-test

Table 7. Subscale mediation analysis results

MSMU subscale	c (total)	a (->PU)	b (PU->BI)	c′ (direct)	ab (indirect)	z
FOMO/ social connection	.443***	.327***	.709***	.210***	.232***	4.280
Popularity/identity	.258***	.198**	.729***	.113*	.145**	2.772
Appearance/impression	.177*	.166*	.737***	.055	.122*	2.208
Civic/advocacy	.444***	.439***	.711***	.132*	.312***	6.054

Note. *p < .05; **p < .01; ***p < .001; All coefficients are unstandardized (B); Indirect effects (ab) tested with Sobel z-test; Indirect effects assessed via bias-corrected bootstrapped 95% CIs (BCa-CI, B = 5,000 resamples, seed = 42); SE and z values based on Sobel test (retained for comparison); & CIs excluding zero indicate statistically significant indirect effects

To test the mediating role of PU in the relationship between social media use motivations and BI, a regression-based mediation analysis was conducted following the PROCESS Model 4 approach (Hayes, 2017).

Figure 10 presents the conceptual mediation model with path coefficients.

Path analysis results are summarized in **Table 6**. The total effect of MSMU on BI was significant (path c: B = 0.393, standard error [SE] = 0.084, t = 4.660, $p < .001$, $R^2 = .056$). MSMU significantly predicted PU (path a: B = 0.343, SE = 0.084, t = 4.069, $p < .001$, $R^2 = .043$). PU significantly predicted BI after controlling for MSMU (path b: B = 0.723, SE = 0.036, t = 20.017, $p < .001$). The direct effect of MSMU on BI, after accounting for the mediator, remained significant but reduced (path c′: B = 0.145, SE = 0.060, t = 2.430, $p < .05$), indicating partial mediation. The indirect effect of MSMU on BI through PU was statistically significant. Bias-corrected bootstrapped confidence intervals based on 5,000 resamples confirmed the significance of the indirect effect (ab = 0.248, SE = 0.062, z = 3.988, $p < .001$, BCa 95% confidence interval [CI] [0.114, 0.384]). As the confidence interval excludes zero, the mediation hypothesis is supported (Hayes, 2017).

Table 7 presents mediation analysis results for each MSMU subscale. All four subscales showed significant total effects on BI. Bias-corrected bootstrapped confidence intervals (BCa, B = 5,000) were computed for each subscale indirect effect. All four CIs excluded zero, confirming the significance of each indirect pathway.

Table 8. Bootstrap results for indirect effects of MSMU on BI through PU

Predictor (X → M → Y)	ab	SE	z	p	BCa 95% CI LL	BCa 95% CI UL
MSMU total → PU → BI	0.248	0.062	3.988	< .001	0.114	0.384
FOMO/social connection → PU → BI	0.232	0.054	4.280	< .001	0.115	0.350
Popularity/identity → PU → BI	0.145	0.052	2.772	.006	0.040	0.255
Appearance/impression → PU → BI	0.122	0.055	2.208	.027	0.010	0.235
Civic/advocacy → PU → BI	0.312	0.052	6.054	< .001	0.203	0.429

Note. M: PU; Y: BI; *ab*: Indirect effect (product of paths a and b); SE: Standard error from Sobel test; *z*: Sobel z-statistic; BCa 95% CI: Bias-corrected and accelerated bootstrapped 95% CI based on 5,000 resamples; LL: Lower limit; UL: Upper limit; & All CIs exclude zero, confirming statistically significant indirect effects

Civic/advocacy motivations demonstrated the strongest indirect effect (ab = 0.312, SE = 0.052, z = 6.054, p < .001, BCa 95% CI [0.203, 0.429]), followed by FOMO/social connection (ab = 0.232, SE = 0.054, z = 4.280, p < .001, BCa 95% CI [0.115, 0.350]), popularity/identity (ab = 0.145, SE = 0.052, z = 2.772, p = .006, BCa 95% CI [0.040, 0.255]), and appearance/impression management (ab = 0.122, SE = 0.055, z = 2.208, p = .027, BCa 95% CI [0.010, 0.235]). Notably, the direct effect of appearance/impression management on BI became non-significant after controlling PU (c′ = 0.055, p = .287), suggesting full mediation for this subscale (**Table 8**).

DISCUSSION

The present study sought to examine how social media use motivations predict university students' BI to adopt AI-powered learning tools, with PU functioning as a mediating mechanism. The findings broadly support the proposed model and are consistent with the core tenets of the TAM. The total effect of social media use motivations on BI was statistically significant ($B = 0.393$, $p < .001$), and after introducing PU as a mediator, the indirect effect was also meaningful ($ab = 0.248$, $z = 3.988$, $p < .001$). These results extend the application of TAM to the domain of generative AI tools in higher education, demonstrating that PU continues to be a robust predictor of BI in this technologically evolving context. Prior applications of TAM to AI-assisted learning environments (Alshammari & Babu, 2025; Liu & Ma, 2024) similarly identified PU as a pivotal determinant of technology adoption intentions, corroborating the present findings. The exceptionally large PU → BI coefficient ($B = 0.723$, $\beta \approx .74$) warrants caution in interpretation. While this magnitude is consistent with prior TAM applications in educational technology contexts where PU and BI are theoretically proximate constructs (Alshammari & Babu, 2025; Venkatesh et al., 2003) it may also be partially inflated by common method variance (CMV). Both constructs were measured using 7-point Likert-format items administered within the same self-report survey at a single time point, a design condition known to artificially inflate correlations between attitudinally similar variables (Podsakoff et al., 2003). The absence of procedural remedies such as temporal separation of measurement occasions or the inclusion of a marker variable means that CMV cannot be ruled out as a contributing factor. Future research employing multi-wave or multi-source data collection designs would more precisely isolate the true predictive relationship between PU and BI in AI tool adoption contexts.

The partial mediation pattern whereby the direct effect of social media use motivations on BI remained significant even after controlling PU merits careful interpretation. A full mediating role of PU would have implied that social media motivations influence AI adoption exclusively through functional evaluations of the technology. Instead, the partial mediation indicates that certain aspects of social media motivation exert an independent influence on BI beyond the utility appraisal pathway. This is consistent with theoretical perspectives suggesting that motivational orientations have dispositional or habitual components that directly influence technology engagement, not necessarily requiring mediation through cognitive evaluation processes (Bawa et al., 2026; Venkatesh et al., 2003). It must be acknowledged, however, that a significant direct path does not unambiguously establish a true direct effect on omitted-mediator explanation remains plausible. Variables such as perceived ease of use, social influence, and digital self-efficacy were not included in the present model; their omission may account for part of the apparent direct path. Future studies with fuller TAM specifications are needed to test this possibility. In this sense, students who are intrinsically motivated to engage in digital environments, regardless of whether they perceive a given tool as useful, may still exhibit higher adoption intention simply by virtue of their broader digitally oriented identity.

Among the four MSMU subscales, civic and advocacy motivations demonstrated the strongest relationships with both PU (*B* = 0.439, $p < .001$) and BI, with the largest indirect effect (*ab* = 0.312, $z = 6.054$, $p < .001$). This finding suggests that students who use social media to connect with communities of shared interest, advocate for causes, and seek out socially relevant information are the most likely to perceive AI learning tools as functionally valuable (Alshammari & Babu, 2025). It should be noted, however, that the MSMU subscales exhibit substantial intercorrelations (r = .59-.94), which introduces multicollinearity when subscales are interpreted in isolation. These intercorrelations are partly mechanical subscales are components of the same total score and comparisons of subscale effect sizes should be regarded as directional rather than precise quantitative contrasts This pattern is consistent with information-utility theories of technology adoption: users who are motivated by information-seeking and collaborative knowledge production tend to evaluate productivity-enhancing tools more favorably (Badr et al., 2024; Cuong et al., 2025). The civic motivation dimension of social media use appears to cultivate a disposition toward tools that amplify one's capacity to access, organize, and communicate information precisely the competencies that generative AI tools such as ChatGPT are designed to support.

Social connection and FOMO motivations constituted the second strongest predictor of BI in the mediation model (*ab* = 0.232, $z = 4.280$, $p < .001$), and the direct effect also remained significant after controlling PU (*B* = 0.210, $p < .001$). Students driven by social connection motivations wanting to remain updated on peers' activities and avoiding social exclusion may be particularly receptive to adopting AI tools that are prominently discussed and normalized within their social networks. This interpretation supports the social influence mechanisms found in extended TAM models, in which both peer adoption norms and subjective social norms significantly speed up individual technology acceptance (Low et al., 2025; Venkatesh et al., 2003). In a university environment where AI tool usage is rapidly becoming a shared norm especially ChatGPT, reported by 84.6% of the present sample students with high social connection motivations may be further propelled toward adoption to maintain social synchrony with their peers.

Popularity and identity formation motivations also significantly predicted BI both directly and via PU, though with a smaller effect size (*ab* = 0.145, $z = 2.772$, $p = .006$). This finding suggests that students motivated to curate a positive self-image and expand their social visibility on digital platforms may perceive AI tools as instruments of academic enhancement that contribute to their projected identity as competent, technologically literate individuals. Prior work on digital self-presentation has shown that identity management motivations influence users' engagement with platforms and tools that afford reputation-building affordances (Alhabash & Ma, 2017; Sharif et al., 2021). Insofar as demonstrating proficiency with AI tools carries social currency in contemporary academic settings, popularity-driven students may be motivated to adopt them as part of an identity performance strategy rather than purely instrumental reasons.

A particularly noteworthy finding concerns the appearance and impression management subscale, for which the direct effect on BI became non-significant after controlling PU (*B* = 0.055, $p = .287$), while the indirect effect remained significant (*ab* = 0.122, $z = 2.208$, $p = .027$). This pattern is consistent with full mediation, suggesting that students motivated primarily by appearance-related social media use (e.g., assessing the attractiveness of their photos and comparing looks with peers) do not translate this motivation into AI tool adoption through any direct pathway—the effect is entirely channeled through PU. This implies that for this group, the adoption decision is purely functional: if and when they come to perceive AI tools as useful for their academic tasks, they will adopt them. The absence of a direct motivational link underscores the heterogeneity in motivational pathways and cautions against treating social media motivations as uniformly direct antecedents of technology adoption (Fan, 2023; Toros et al., 2024).

The supplementary analyses revealed that year of study produced statistically significant differences across all three primary scales. First-year students consistently reported lower PU and BI compared to second-, third-, and fourth-year students—a gradient that may reflect increasing academic demand and exposure to AI tools over the course of university study. Students with more than one year of AI tool experience constituted 41.6% of the sample, and this seasoned sub-group likely drives the higher PU scores observed among upper-year students. These findings echo prior research demonstrating that experience and self-efficacy are important moderators of PU within TAM-based models (Jeilani & Abubakar, 2025; Zhao et al., 2025). Practically, this pattern suggests that early-stage interventions aimed at building AI tool familiarity among first-year students could accelerate PU and adoption intention across the student population.

Contrary to some prior studies that have reported gender-based differences in technology acceptance (Damerji & Salimi, 2021), no significant gender differences emerged on any of the three scales in the present study (all $p > .05$, all $d < .10$). This null finding may partly reflect the homogeneity of the sample's platform ecology: the overwhelming majority of participants regardless of gender reported using Instagram (89.7%), TikTok (83.8%), and YouTube (80.8%), platforms characterized by visual, short-form content consumption and social sharing. When the digital landscape is relatively undifferentiated by gender, the motivational structures underpinning social media use—and by extension, AI tool adoption—may converge accordingly. This finding is consistent with more recent evidence from higher education technology adoption contexts indicating that gender gaps in technology acceptance are diminishing as digital access and socialization become increasingly universal among young adults (Aldraiweesh & Alturki, 2025; Rahman et al., 2025). Nonetheless, the disproportionate representation of female participants (74.1%) warrants caution in generalizing null gender findings. Nonetheless, the several caveats apply. First, with n = 96 male participants, the study had limited power to detect small gender effects (d < .20). The predominantly Kazakhstani, first-year composition may reflect a context where gender-based digital divides have narrowed considerably, and this conclusion may not generalize to other settings. Damerji and Salimi (2021) found significant gender differences in AI adoption within accounting education; their sample faced institutional pressure to adopt professional AI tools, whereas the present sample used generative AI for general academic purposes. This domain-specific difference may explain the divergence and underscores that null gender effects should not be universally assumed.

Limitations

Several limitations should be acknowledged when interpreting the present findings. First, the sample was predominantly female (74.1%) and composed largely of first-year students (71.4%) from Kazakhstani universities, which may restrict the generalizability of the results to more balanced or internationally diverse populations. In addition to this the cross-sectional survey design precludes causal inference; longitudinal designs would be better suited to establish the temporal ordering of motivations, PU, and BI. The social connection/FOMO subscale of the MSMU demonstrated relatively low internal consistency ($\alpha = .645$), which may have attenuated the estimated effects for this dimension and should be interpreted cautiously. The study did not include perceived ease of use, social influence, or digital literacy as control variables, all of which have been identified as relevant predictors in comparable technology adoption models (Alkhawaja et al., 2022; Yan et al., 2024), and their omission may constitute a source of confounding. Furthermore, all constructs were collected from a single respondent via a single online survey, raising the possibility of common method bias (CMB). Although procedural remedies were employed (anonymity, voluntary participation), statistical assessment of CMB or example, via Harman's single-factor test was not conducted and represents a limitation. Finally, BI was measured rather than actual usage behavior, and the gap between intention and behavior is well-documented in the technology acceptance literature.

CONCLUSIONS AND RECOMMENDATIONS

The present study provides empirical evidence that university students' motivations for using social media are meaningfully associated with their intention to adopt AI-powered learning tools, and that this relationship is partially mediated by PU. Grounded in the TAM and uses and gratifications theory, the findings demonstrate that social media motivations function as upstream antecedents of technology adoption not only through functional appraisal pathways but also through direct motivational processes. In particular, civic and advocacy motivations emerged as the strongest drivers in both direct and indirect pathways, underscoring the importance of information-oriented engagement dispositions for AI tool adoption in educational contexts.

For university educators and instructional designers, these findings suggest that AI tool integration initiatives are likely to be most effective when they are framed within the information-seeking and collaborative knowledge-building motivations that students already exhibit in their social media use. Rather than simply introducing AI tools as productivity utilities, pedagogical approaches that position generative AI as an instrument for civic engagement, critical inquiry, and knowledge advocacy may resonate more powerfully with students' existing motivational profiles. Training programs that connect AI tool competencies to students' social media literacies could further facilitate the transfer of motivation from familiar digital environments to emerging educational technologies (Alturki & Aldraiweesh, 2024).

At the institutional level, the significant year-of-study differences found in this study imply that targeted orientation and capacity-building support are particularly needed for first-year students, who reported meaningfully lower PU and BI than their senior counterparts. Institutions should consider embedding AI tool literacy workshops and structured exposure activities within first-year curricula rather than assuming students will organically develop favorable perceptions of these tools. Given that more than 41% of participants had been using AI tools for over a year, peer-learning and mentoring models—where experienced AI users guide newer students—could be an effective and low-cost intervention strategy. Such institutional scaffolding aligns with research demonstrating that perceived institutional support significantly elevates students' perceptions of AI learning tools (Jeilani & Abubakar, 2025; Zhao et al., 2025).

The absence of significant gender differences across all measured constructs is an encouraging finding from an equity perspective, suggesting that the motivational and cognitive mechanisms underlying AI tool adoption may be broadly similar across genders in this population. However, this finding should not lead to complacency. The female-dominated composition of the sample limits the strength of this conclusion, and future research with balanced gender samples is needed to confirm whether this parity holds across different educational and cultural contexts. Institutions should continue to monitor gender-disaggregated AI adoption data to detect any emerging disparities, particularly given documented gender gaps in STEM technology careers that may have roots in differential technology socialization during the university years (Park & Kim, 2023).

Future research should extend this work in several directions. First, longitudinal designs tracking the same students across academic years would clarify whether the year-of-study differences observed here reflect developmental changes in individual students or cohort effects. Second, including digital literacy and perceived ease of use as additional variables in the model would allow for a more comprehensive test of TAM within a uses and gratifications framework. Third, cross-national comparative studies are warranted to examine whether the motivational pathways identified here are specific to Central Asian university contexts or generalizable across different educational systems and platform cultures. Finally, the emergence of increasingly diverse AI tool ecosystems, including specialized tools such as Perplexity AI and discipline-specific applications, opens new questions about whether motivational predictors of adoption differ across tool types, user experience levels, and academic fields.

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Ethics declaration: This study was carried out in full compliance with the Declaration of Helsinki (WMA, 2024), the CIOMS International Ethical Guidelines (2016), and the ICMJE protection standards. Voluntary informed consent was obtained from all participants. The research adhered to COPE ethical standards throughout.

AI statement: The authors declare that no generative artificial intelligence tools were used in the conception, execution, or writing of this study.

Declaration of interest: The authors declared no competing interests.

Data availability: Data generated or analyzed during this study are available from the authors on request.

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