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RESEARCH ARTICLE OPEN ACCESS

USING THE AHP METHOD TO ASSESS THE IMPACT OF SOCIAL MEDIA ON STUDENT LEARNING MOTIVATION: A CASE STUDY OF A HIGH SCHOOL FOR GIFTED STUDENTS IN VNU

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ABSTRACT

This study examines how social media influences student learning motivation by identifying and prioritizing the factors that matter most in a high-school learning context. Using the Analytic Hierarchy Process (AHP), the research evaluates four main dimensions Content Exposure, Relationship Network, Algorithmic Personalization, and Learning Tools and 15 corresponding sub-factors through pairwise comparisons conducted by a panel of experts in education management, artificial intelligence, and student learning practice. The results show that Learning Tools is the most influential main factor, followed by Relationship Network, Algorithmic Personalization, and Content Exposure. At the sub-factor level, Reciprocity, Convenience of Breaking Down Lessons, Interaction Intensity, and Learning Management Support Features achieve the highest overall priorities. These findings indicate that social media enhances student learning motivation most effectively when it supports reciprocal interaction, manageable learning tasks, and a practical learning organization rather than passive exposure alone. The study contributes to the literature by offering a structured prioritization of motivational mechanisms within social media environments and provides practical implications for educators, school managers, and platform designers seeking to use digital platforms more effectively for learning support.

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INTRODUCTION

Social media has become a central part of adolescents' everyday lives and increasingly shapes how they communicate, access information, and participate in learning-related activities. Rather than functioning only as entertainment platforms, social media environments now operate as hybrid spaces where students search for knowledge, exchange ideas, follow educational creators, and engage with learning communities. Scholars have therefore noted that social media is transforming the boundaries between formal and informal learning, creating new opportunities for interaction, autonomy, and knowledge sharing (Boyd, 2014; Carr & Hayes, 2015; Greenhow &Lewin, 2016). In this context, understanding how specific features of social media shape student learning motivation has become an important issue for both educational research and practice. Learning motivation plays a decisive role in student engagement, persistence, and academic development. From the perspective of Self-Determination Theory, motivation is strengthened when learners experience autonomy, competence, and relatedness in the learning process (Ryan & Deci, 2000). Social media can potentially support these needs by allowing students to choose content, interact with peers and teachers, receive rapid feedback, and access materials in flexible formats. At the same time, social media does not influence motivation through a single pathway. Its effects may stem from content exposure, social interaction, algorithmic recommendations, and the availability of learning-support tools. Existing studies have discussed many of these dimensions separately, but there is still limited evidence on their relative importance within an integrated evaluative framework. To address this gap, the present study applies the Analytic Hierarchy Process (AHP) to assess the relative importance of the main factors through which social media affects student learning motivation. AHP is particularly suitable for this purpose because it enables complex multi-criteria problems to be decomposed into a structured hierarchy and weighted systematically through expert judgment (Saaty, 1987; Millet, 1998). Focusing on a case study of a high school for gifted students within VNU, the study develops a model consisting of four main dimensions and 15 sub-factors. By ranking these elements, the research seeks to clarify which aspects of social media are most important for motivating students to learn and to provide evidence-based implications for educators and educational managers.

LITERATURE REVIEW

Social media: Social media refers to digital platforms that allow users to create profiles, generate content, interact with others, and circulate messages in networked environments (Mayfield, 2008; Carr & Hayes, 2015). Beyond a technical infrastructure, social media constitutes a participatory communication space in which adolescents construct identity, maintain peer ties, and negotiate visibility, reputation, and belonging (Boyd, 2014). In educational settings, these affordances matter because platforms such as TikTok, YouTube, Facebook, and Instagram expose students to a constant mix of entertainment, peer interaction, and learning resources. Accordingly, social media should not be viewed solely as a leisure medium, but also as a socio-technical environment that can shape how students access information and engage with learning.

Student learning motivation: Learning can be understood as a relatively enduring change in knowledge, skills, or behavior resulting from experience and practice (Schunk, 2012). In the present study, the focus is not academic achievement itself, but learning motivation, namely, the willingness of students to invest attention, effort, and persistence in educational activities. Self-Determination Theory argues that motivation is stronger and more sustainable when the needs for autonomy, competence, and relatedness are supported (Ryan & Deci, 2000). This perspective is highly relevant to social media because digital platforms may simultaneously expand learners' choices, provide immediate feedback, and connect them with peers and wider communities.When these psychological needs are satisfied, students are more likely to show intrinsic interest, sustained participation, and self-directed engagement in learning. Conversely, when digital environments become distracting, socially isolating, or cognitively overwhelming, they may weaken motivational quality. The educational significance of social media, therefore, depends not merely on frequency of use but on whether its features support autonomy, competence, and meaningful social connection in the learning process.

Social media and student learning motivation: The relationship between social media and learning motivation is multidimensional. Prior research shows that social media can blur the boundary between formal and informal learning, enabling students to move between classroom content and self-initiated exploration (Greenhow &Lewin, 2016). From this perspective, social media may strengthen motivation when it makes learning more accessible, socially supported, and personally relevant. At the same time, its effects are not uniform; different platform features may activate different psychological mechanisms and lead to different motivational outcomes. To capture this complexity, the present study organizes the literature into four factor groups: content exposure, relationship network, algorithmic personalization, and learning tools. These dimensions reflect the idea that motivation on social media emerges not only from what students see, but also from how they interact with others, how content is filtered and recommended, and which digital affordances help them learn effectively.

Content exposure: Content exposure refers to the extent to which students encounter educationally relevant material through impressions, viewing duration, and micro-interactions such as likes, saves, or brief comments. Social media content is typically multimodal, combining text, sound, images, and video. Dual Coding Theory suggests that information is more likely to be remembered when verbal and non-verbal representations are processed together (Paivio, 2007). Similarly, multimedia learning research shows that appropriate combinations of words and images can improve comprehension by making abstract ideas more concrete and cognitively manageable (Mayer, 2002). However, passive exposure alone is unlikely to generate strong motivation. Sustained viewing duration may matter more than simple impressions because students need time and attention to process, connect, and retain information. Micro-interactions can also reinforce relevance by encouraging repeated contact with learning-related content. Thus, content exposure is expected to enhance learning motivation when it transforms social media from a stream of entertainment into a source of understandable, memorable, and educationally meaningful input.

Relationship network: Relationship network captures the social dimension of platform use, including interaction intensity, reciprocity, and multiplexity across peers, teachers, and wider learning communities. Social media does not merely deliver content; it embeds students in visible networks of feedback and participation. The need to belong is a fundamental human motive, and feelings of connectedness can strengthen persistence and engagement in academic activities (Baumeister& Leary, 1995). In educational settings, peer environments also shape behavior by establishing norms regarding effort, participation, and aspiration (Sacerdote, 2011). These mechanisms are especially salient on social media because feedback is immediate, public, and recurrent. Sherman et al. (2016) showed that peer endorsement cues such as "likes" influence adolescents' responses to online content, indicating that visible social approval can guide attention and behavior. In addition, Social Learning Theory suggests that individuals learn by observing models and the consequences attached to their behavior (Bandura, 1977). Reciprocal exchanges with peers, interactions with online teachers, and repeated participation in discussion groups may therefore increase learning motivation by reinforcing recognition, normalizing academic effort, and strengthening students' sense of belonging to a learning community.

Algorithmic personalization: Algorithmic personalization refers to the role of platform algorithms in selecting, prioritizing, and recommending content for individual users. Algorithms are not neutral channels; they actively shape visibility and relevance by sorting information according to behavioral signals and platform logics (Gillespie, 2014). For students, the learning value of social media depends partly on whether recommendation systems surface suitable educational content rather than distractions. When suggested content matches learners' interests, needs, or current level, social media can reduce search costs and increase the perceived relevance of learning materials. This logic is consistent with the literature on personalized learning, which emphasizes tailoring content and pathways to learner needs and progress (Pane et al., 2015). When content is well matched to skill level, students are more likely to feel competent and remain engaged; under such conditions, they may even experience flow, a state of deep concentration and intrinsic involvement in an activity (Csikszentmihalyi, 1990). Connectivist thinking also suggests that learning in digital environments depends on access to timely and relevant information across networks (Siemens, 2005). Accordingly, algorithmic systems may support learning motivation when they improve the accuracy, timeliness, and personal relevance of educational exposure.

Learning tools: Learning tools refer to the concrete affordances embedded in social media environments that help students study, practice, organize, and apply knowledge. These affordances include short-form lesson breakdowns, online community support, discussion functions, and learning-management features such as saving, replaying, bookmarking, or tracking progress. From a learning-sciences perspective, digital environments are most effective when tools help learners connect resources, contexts, and feedback in usable ways (Luckin, 2010). Social media can therefore function as a form of ubiquitous learning, enabling students to study beyond classroom boundaries and within everyday routines (Cope & Kalantzis, 2009). The motivational value of learning tools lies in their support for autonomy and manageable cognitive effort. Learner autonomy grows when students can choose resources, control pace, and revisit materials independently (Little, 1991). At the same time, breaking down content into smaller units may reduce cognitive overload and make learning tasks feel more achievable (Sweller, 1988). Informal and incidental learning research further suggests that students learn effectively when knowledge is embedded in self-directed exploration and authentic activity (Marsick& Watkins, 2001). Tools that allow learners to discuss, test, and apply ideas are also consistent with experiential learning principles that link knowledge acquisition to practice and reflection (Kolb, 1984). For this reason, the present study treats learning tools as a distinct driver of student learning motivation in social-media-based environments. Table 1 shows all the factors of social media's impact on student learning motivation.

Table 1. The factors of social media's impact on student learning motivation

Main factor	Sub-factor	Sources
Content exposure (F1)	Impressions (F11)	Paivio (2007); Mayer (2002)
	View Duration (F12)	
	Micro-interactions (F13)	
Relationship Network (F2)	Interaction Intensity (F21)	Baumeister and Leary (1995); Sacerdote (2011); Sherman et al. (2016); Bandura (1977)
	Reciprocity (F22)	
	Multiplexity (F23)	
Algorithm (F3)	Accuracy of suggested content (F31)	Gillespie (2014); Pane et al. (2015); Siemens (2005); Csikszentmihalyi (1990)
	Priority of lesson display (F32)	
	Dynamic lesson presentation (F33)	
	Personalization of the algorithm (F34)	
	Related smart suggestions (F35)	
Learning tools (F4)	Convenience of breaking down lessons (F41)	Luckin (2010); Cope and Kalantzis (2009); Little (1991); Kolb (1984); Marsick and Watkins (2001); Sweller (1988)
	Online community support (F42)	
	Connectivity and discussion (F43)	
	Learning management support features (F44)	

Sources: Authors

RESEARCH METHODS

This study applies a quantitative research design and uses the Analytic Hierarchy Process (AHP) to examine decision-making problems characterized by multiple evaluation criteria. Developed by Saaty (1987), AHP is widely recognized as a structured method for breaking down complex problems into hierarchical levels, allowing both quantitative evidence and expert judgment to be incorporated into the analysis. The method is based on pairwise comparisons and a standardized preference scale, which helps determine the relative importance of each factor in a coherent and transparent way. Millet (1998) emphasized that this comparative scale supports decision makers in combining logical analysis with professional experience in a systematic manner. The AHP procedure generates a set of priority weights for the criteria through the construction, aggregation, and normalization of comparison matrices. In this study, the implementation of AHP consists of five main stages.

Step 1: Identification of dimensions and criteria

The first stage involves identifying the main dimensions F_j(j = 1, ..., h) and the associated sub-criteria F_{jg} (g = 1, ..., n) from the literature review and the proposed model in Figure 1. These elements form the hierarchical structure used for the subsequent AHP analysis.

Step 2: Establishment of the expert panel

Next, a panel D_t of k experts is convened to review, validate, and compare the proposed dimensions and sub-criteria. Using a structured pairwise-comparison form, the experts evaluate the relative importance of the main factors and the sub-factors under each factor by applying a five-level importance scale: equal, moderate, strong, very strong, and extremely strong.

Step 3: Estimation of weights for the main criteria

Each expert t assigns a weight w_{jt} to criterion F_j, where j = 1, ..., h and t = 1, ..., k. The final weight of each main criterion is calculated as the mean of the experts' assessments, as shown in Equation (1):

$$w_j = (1/k) \otimes (w_{j1} \oplus w_{j2} \oplus \ldots \oplus w_{jk}) \quad (1)$$

Step 4: Estimation of weights for the sub-criteria

The same procedure is applied to the sub-criteria within each main factor. Let w_{jgt} denote the weight assigned by expert t to sub-criterion g under criterion j. The aggregated weight of each sub-criterion is then obtained as:

$$wjg = \left(\frac{1}{k}\right) \times (wjg1 + wjg2 + \cdots + wjgk) \quad (2)$$

Step 5: Calculation of the final priority score

The final score for each sub-criterion is obtained by multiplying the weight of the main criterion (w_j) by the local weight of the corresponding sub-criterion (w_{jg}):

$$Tjg = \left(\frac{1}{h}\right) Wj \times Wg, j = 1, \ldots h; g = 1, \ldots n) \quad (3)$$

This score reflects the overall contribution of each sub-criterion within the hierarchical evaluation framework and serves as the basis for ranking priorities in the decision-making process.

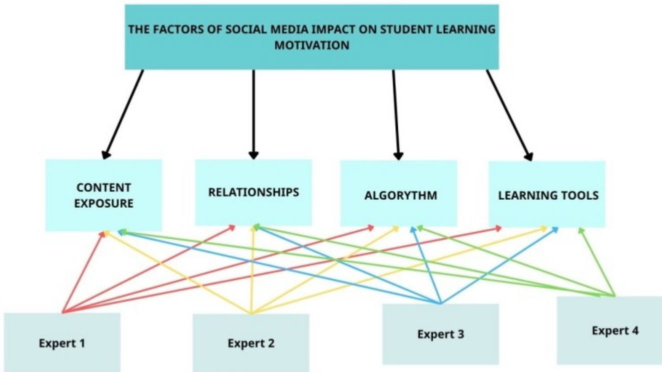

Figure 1. The research model proposal. ***Source: authors***

RESULTS AND DISCUSSION

The empirical results are based on the AHP assessments of four experts retained after the screening process. The panel combined expertise in education management, artificial intelligence, and student experience, thereby capturing both pedagogical and technological perspectives on how social media may shape student learning motivation. More specifically, the final panel included one scholar in education management, one AI specialist, and two high-achieving students from high schools in Hanoi. Their judgments were used to compare the relative importance of the factors and sub-factors presented in Figure 1 and Table 1.

Step 1: Identify evaluation criteria and directions

Based on the literature review and the model in Figure 1, the study evaluates four main factors affecting student learning motivation through social media: Content Exposure (F1), Relationship Network (F2), Algorithm (F3), and Learning Tools (F4). These four dimensions are operationalized through 15 sub-factors listed in Table 1, which together form the hierarchical structure for the AHP assessment.

Step 2: Establishing the expert panel

The expert panel consisted of four decision makers (D1-D4). After validating the framework, they performed pairwise comparisons for both the four main factors and the sub-factors nested within each factor.

Step 3: Determining the weight of the criteria

After the criteria had been finalized, the expert panel conducted pairwise comparisons among the four main factors. The resulting average weights, calculated using Equation (1), are reported in Table 2.

Table 2. Weighted values of criteria

	F1	F2	F3	F4	Total average	Weight ($w_{j=1;4}$)
F1	1.000	0.308	0.375	0.425	0.527	0.095
F2	3.750	1.000	2.000	0.458	1.802	0.324
F3	2.750	0.500	1.000	0.458	1.177	0.211
F4	2.750	2.250	2.250	1.000	2.063	0.370
					5.569	

Source: Analysis results from research data

Table 2 shows that Learning Tools (F4) receives the greatest weight (0.370), followed by Relationship Network (F2) at 0.324, Algorithm (F3) at 0.211, and Content Exposure (F1) at 0.095. This ranking indicates that, within this expert-based model, the strongest contribution of social media to student learning motivation is associated with the practical learning affordances of the platform, especially the ways in which social media helps students access, organize, and manage learning activities. Social interaction comes next, suggesting that reciprocity, interaction intensity, and peer exchange are also central to motivational dynamics. By contrast, simple exposure to content alone appears less influential than networking, algorithmic support, and learning tools.

Step 4: Derive the weights of the sub-criteria within each primary factor group

After the main-factor weights had been obtained, the expert panel compared the sub-factors within each main dimension. The resulting local weights, calculated using Equation (2), are presented in Table 3.

Within Content Exposure (F1), View Duration (F12) has the largest local weight (0.511), followed by Micro-interactions (F13) at 0.333 and Impressions (F11) at 0.156. This pattern suggests that sustained engagement with educational content is more important for learning motivation than merely seeing content or generating lightweight reactions. Within Relationship Network (F2), Reciprocity (F22) ranks first (0.523), followed by Interaction Intensity (F21) at 0.331 and Multiplexity (F23) at 0.146. The result implies that two-way exchange and mutual support are more motivational than the simple breadth of online ties. For Algorithm (F3), Dynamic Lesson Presentation (F33) records the highest local weight (0.412), followed by Personalization of the Algorithm (F34) at 0.236, Accuracy of Suggested Content (F31) at 0.160, Priority of Lesson Display (F32) at 0.117, and Related Smart Suggestions (F35) at 0.075. Hence, students' motivation appears to benefit most when social media presents learning materials in a dynamic and adaptive manner rather than through generic recommendation functions alone. Within Learning Tools (F4), Convenience of Breaking Down Lessons (F41) is the most important sub-factor (0.438), followed by Learning Management Support Features (F44) at 0.272, Connectivity and Discussion (F43) at 0.199, and Online Community Support (F42) at 0.091. This shows that the tool-like functionality of social media is particularly valuable when it makes learning tasks easier to digest and manage. Taken together, the local weights in Table 3 indicate that the most salient within-factor drivers are View Duration (F12), Reciprocity (F22), Dynamic Lesson Presentation (F33), and Convenience of Breaking Down Lessons (F41). Each of these sub-factors highlights a different mechanism through which social media can encourage learning motivation: attention retention, mutual exchange, adaptive presentation, and manageable learning design.

Table 3. Weighted values of sub-criteria across main evaluation factors

Content Exposure	F11	F12	F13			Total average	Weight (w_{jg})
F11	1.000	0.417	0.417			0.611	0.156
F12	2.500	1.000	2.500			2.000	0.511
F13	2.500	0.417	1.000			1.306	0.333
						3.917	
Relationship Network	F21	F22	F23			Total average	Weight (w_{jg})
F21	1.000	0.458	2.500			1.319	0.331
F22	2.250	1.000	3.000			2.083	0.523
F23	0.417	0.333	1.000			0.583	0.146
						3.986	
Algorithm	F31	F32	F33	F34	F35	Total average	Weight (w_{jg})
F31	1.000	1.833	0.246	0.500	2.167	1.149	0.160
F32	0.563	1.000	0.354	0.458	1.813	0.838	0.117
F33	4.250	3.000	1.000	2.250	4.250	2.950	0.412
F34	2.125	2.250	0.458	1.000	2.625	1.692	0.236
F35	0.483	0.575	0.246	0.392	1.000	0.539	0.075
						7.168	
Learning tools	F41	F42	F43	F44		Total average	Weight (w_{jg})
F41	1.000	4.000	2.750	2.250		2.500	0.438
F42	0.250	1.000	0.375	0.458		0.521	0.091
F43	0.375	2.750	1.000	0.417		1.135	0.199
F44	0.458	2.250	2.500	1.000		1.552	0.272
						5.708	

Source: Analysis results from research data

Table 4. Sub-criterion weight coefficients corresponding to each main criterion

Main factor	Average weight of main factor (w_j)	Sub-factor	Local weight of sub-factor (w_{jg})	Global weight (T_{jg})
F1	0.095	F11	0.156	0.015
	0.095	F12	0.511	0.048
	0.095	F13	0.333	0.032
F2	0.324	F21	0.331	0.107
	0.324	F22	0.523	0.169
	0.324	F23	0.146	0.047
F3	0.211	F31	0.160	0.034
	0.211	F32	0.117	0.025
	0.211	F33	0.412	0.087
	0.211	F34	0.236	0.050
	0.211	F35	0.075	0.016
F4	0.370	F41	0.438	0.162
	0.370	F42	0.091	0.034
	0.370	F43	0.199	0.074
	0.370	F44	0.272	0.101

Source: Analysis results from research data

These findings also suggest that student learning motivation is not driven by a single social-media feature. Rather, motivation emerges from the interaction between technological support and social exchange, with the strongest emphasis placed on features that help students participate actively and process learning materials effectively.

Step 5: Calculation of the final aggregated scores of criteria by factor group

Once the local weights had been established, the global scores for each sub-factor were calculated by multiplying the weight of the main factor by the local weight of the corresponding sub-factor, as specified in Equation (3). The results are reported in Table 4. Table 4 reports the global AHP scores for all sub-factors in the model. At the overall level, Reciprocity (F22 = 0.169) is the highest-ranked sub-factor in the entire model, followed closely by Convenience of Breaking Down Lessons (F41 = 0.162). The next most important elements are Interaction Intensity (F21 = 0.107) and Learning Management Support Features (F44 = 0.101). These results indicate that learning motivation is strengthened most when social media supports reciprocal interaction and turns learning content into smaller, more manageable units. A second tier of influences includes Dynamic Lesson Presentation (F33 = 0.087), Connectivity and Discussion (F43 = 0.074), and Personalization of the Algorithm (F34 = 0.050). These findings imply that students respond positively not only to interaction and tool support, but also to platform designs that present lessons vividly, enable discussion, and adapt content to individual needs. Moderate global effects are observed for View Duration (F12 = 0.048), Multiplexity (F23 = 0.047), Accuracy of Suggested Content (F31 = 0.034), Online Community Support (F42 = 0.034), and Micro-interactions (F13 = 0.032). While these elements remain relevant, their influence is weaker than that of reciprocity, structured learning support, and dynamic lesson delivery. The lowest-ranked sub-factors are Priority of Lesson Display (F32 = 0.025), Related Smart Suggestions (F35 = 0.016), and Impressions (F11 = 0.015). In substantive terms, this suggests that passive visibility alone is insufficient to sustain learning motivation unless it is accompanied by deeper engagement, social exchange, or concrete learning support.

Overall, the global ranking reinforces the pattern observed in Table 2: social media contributes to learning motivation most strongly when it functions as an interactive learning environment rather than merely as a channel for exposure. The findings therefore place greater emphasis on reciprocal participation, pedagogically useful tools, and adaptable presentation than on surface-level content reach. From an educational-management perspective, these results suggest that students are motivated less by the sheer abundance of social-media content and more by features that make learning participatory, reciprocal, and manageable. In other words, motivational value appears to arise when platforms support interaction, structure learning tasks, and help students navigate content efficiently. The weaker scores for impressions and smart suggestions should not be interpreted as meaning that these features are unimportant; rather, within the present AHP hierarchy, they play a supporting role relative to stronger motivational mechanisms. Their effectiveness may depend on whether they lead students into more sustained viewing, discussion, and learning-management activities. Taken together, the results identify Reciprocity (F22), Convenience of Breaking Down Lessons (F41), Interaction Intensity (F21), and Learning Management Support Features (F44) as the most influential drivers in the model, whereas Impressions (F11) and Related Smart Suggestions (F35) receive the lowest overall priorities.

CONCLUSION

This study examines how social media affects student learning motivation by applying the Analytic Hierarchy Process (AHP) to an expert-based evaluation model. Drawing on the framework in Figure 1 and Table 1, the analysis compares four main dimensions - Content Exposure, Relationship Network, Algorithm, and Learning Tools - and their 15 sub-factors. The results show that Learning Tools (F4) is the most influential main factor, followed by Relationship Network (F2), Algorithm (F3), and Content Exposure (F1). This pattern suggests that social media motivates students most effectively when it functions as a practical learning environment that helps them organize study tasks, access manageable learning units, and support their ongoing study process. Among the sub-factors, Reciprocity (F22) achieves the highest overall priority, followed by Convenience of Breaking Down Lessons (F41), Interaction Intensity (F21), and Learning Management Support Features (F44). These findings indicate that student motivation is especially strengthened by reciprocal communication, active interaction, and platform features that make learning more structured and actionable. Algorithm-related features also matter, especially Dynamic Lesson Presentation (F33) and Personalization of the Algorithm (F34). Their relative importance suggests that motivational benefits increase when learning materials are presented in adaptive, vivid, and user-relevant ways rather than through passive or generic recommendation alone. By contrast, the lowest-ranked elements are Impressions (F11), Related Smart Suggestions (F35), and Priority of Lesson Display (F32). This does not mean that these features are irrelevant, but it indicates that visibility by itself is not enough to sustain learning motivation without deeper engagement and meaningful pedagogical support.

From a theoretical perspective, the study contributes to the literature on social media and learning motivation by showing that the motivational impact of social media is multidimensional. The AHP approach makes it possible to distinguish between surface exposure effects and more substantive mechanisms related to interaction, personalization, and learning support. From a practical perspective, educators and school managers should pay greater attention to the design of social-media-based learning environments. Interventions that encourage reciprocal exchange, support discussion, segment lessons into smaller units, and provide learning-management functions are likely to be more effective than simply increasing students' exposure to educational content. This study is limited by its reliance on a small expert panel and by its focus on a specific educational context. Future research may extend the framework through larger student surveys, cross-school comparisons, or mixed-method designs that test whether the same ranking pattern holds across different learner groups and platforms. In conclusion, the study suggests that the motivational value of social media lies primarily in its capacity to support reciprocal interaction and usable learning tools. Social media appears most beneficial for student learning motivation when it helps students engage actively, manage learning tasks, and participate in meaningful exchanges rather than merely consume content.

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