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Optimization Model of Student Assessment System in Educational Management Based on Data Fusion Algorithms

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Abstract With the proliferation of intelligent algorithms and online media ecosystems, college students are increasingly exposed to complex digital environments that influence their behavioral and psychological profiles. This study proposes an optimization model for student assessment systems in educational management, grounded in data fusion algorithms and structural equation modeling (SEM). Drawing upon a multi-dimensional theoretical framework, the study investigates how family experience, school environment, stress factors, and intelligent algorithmic recommendation contribute to students' exposure to negative media content and, subsequently, to online behavioral misconduct. Data were collected from 372 college students using a validated Likert-scale questionnaire covering six latent variables and 18 measurement items. SEM results demonstrate that negative media content significantly mediates the impact of school experience, stressors, and algorithmic influence on behavioral misconduct, while family experience shows no statistically significant direct effect. Furthermore, a supplementary machine learning analysis using a Random Forest classifier revealed an F1-score of 0.83 and AUC of 0.89, highlighting the predictive power of fused variables such as algorithmic feedback and psychological stress in identifying students at risk.

Index Terms Intelligent algorithms, Online misbehavior, College students, Media content, Stressors

I. Introduction

College students now rely heavily on the Internet for entertainment, social contact, and informational purposes due to the quick advancement of information technology. However, because of the Internet's openness and virtuality, college students' online behavior presents a variety of complex features [1]. Online behavioral misconduct phenomena, like Internet addiction, Internet violence, Internet rumors, and hostile followers, are all too common. These actions have a detrimental effect on social stability and the network environment in addition to having an adverse effect on college students' academic and psychological well-being [2].

College students can now access information based on their own interests and requirements thanks to the widespread use of intelligent algorithms in online media in recent years, which has resulted in tailored content recommendations for consumers. But in addition to being convenient, this "thousands of people, thousands of faces" suggestion system has a number of drawbacks [3]. Based on past behavior and preferences, intelligent algorithms provide accurate recommendations. However, this can easily lead to college students becoming trapped in an information cocoon and engaging in excessive enjoyment, which can lead to biased information acquisition and cognitive limits. Algorithmic recommendations, however, have the potential to worsen the dissemination of unfavorable information by exposing college students to erroneous information, offensive material, and extreme viewpoints, therefore encouraging misbehavior on the internet [4], [5].

College students' online conduct is shaped by a variety of factors, including psychological pressure, the settings of their homes and schools, and clever algorithms. College students may exhibit varying behavioral tendencies when using the Internet due to differences in family education styles; they may also fail to form healthy Internet use habits due to inadequate or deviant schooling; and they may become misbehaving as a result of a combination of psychological, work, and academic pressures [6]. Consequently, a thorough analysis of these aspects' effects on college students' online activity is very important, particularly when it comes to intelligent algorithmic recommendation.

Research on Internet addiction and its contributing factors, Internet violence and its psychological mechanisms, and Internet ethics and behavioral norms education are currently the three main areas of focus for studies on college students' online behavioral disorders [7], [8]. The research on the influence of intelligent algorithms on online behavior is weak, particularly in terms of the mechanism by which intelligent algorithms trigger online behavioral misbehavior, as has not yet been fully

explored. Lastly, the majority of existing empirical studies focus on descriptive analysis and lack structural analysis. These studies fail to account for the complex relationships among variables [9]. First, most studies focus on the influence of a single factor on online behavior, ignoring the complexity of the combined effect of multiple factors.

Given the aforementioned state of the research, this study intends to close these gaps by building a thorough structural equation model to methodically investigate the relationships between media content negativity, family experiences, school experiences, stress factors, and intelligent algorithmic recommendation and how these relationships affect online behavioral misconduct [10], [11]. With the goal of offering a theoretical foundation and useful advice for resolving the issue of college students' online misbehavior, this study highlights the comprehensive influence of multi-factor linkage on behavior in addition to the role of individual factors.

In this study, data from 372 valid samples—college students from various genders, grades, educational backgrounds, and educational levels—were gathered using a questionnaire. Likert scales were used to evaluate latent and observable variables in the questionnaire design, which was informed by a review of the literature as well as the real-world experiences of college students. This ensured the validity and reliability of the results. Structural equation modeling (SEM) was utilized in the data analysis to test the direct and indirect effects of negative media content, stress factors, family and school experiences, and intelligent algorithmic recommendation on online behavioral misconduct. SEM was also used to quantitatively analyze the relationship between the variables.

II. Research hypothesis and modeling

The following research hypotheses are put out in light of the connections between negative media content, online misbehavior, stress factors, family and school experiences, and intelligent algorithm recommendations:

(1) Impact of negative online media content on family experiences Family education is crucial in helping parents let go of false beliefs about "paying too much attention to study," "neglecting children's growth," and "evaluating children by good or bad grades," as well as in identifying their children's true needs and creating a scientific and scientific education for them [12]. Family education can help parents identify their children's true needs, develop a scientific guidance system for their education, and give up the false beliefs that children should be educated by their grades, focus too much on learning, and neglect their growth. However, it is easy to contribute to the existence of vulgar content and false information in the Internet media, and it is also easy for them to be influenced by the Internet, because some college students have been "over-protected," "over-rejected," and "overly strict" in their family education, which results in differences in individual personalities [13]. The Internet media unwittingly support such occurrences in order to garner attention and achieve financial gain. The following theories are put out to help clarify how family education influences the harmful content found on the Internet.

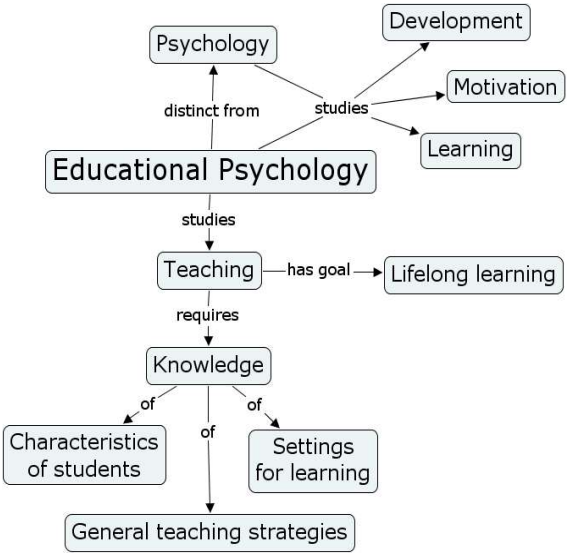

Figure 1: Theoretical Framework of Educational Psychology in the Context of Student Behavioral Analysis

Figure 1 illustrates the foundational structure of educational psychology and its relevance to the study of student online behavioral misconduct. As depicted, educational psychology—distinct from general psychology—focuses specifically on teaching, learning, motivation, and development. These dimensions align closely with the variables examined in this study, including family experience, school environment, psychological stress, and intelligent algorithm recommendations. The framework emphasizes that effective teaching requires comprehensive knowledge of both student characteristics and learning

environments, which in turn inform general teaching strategies aimed at promoting lifelong learning. In the context of this study, such knowledge translates into targeted educational interventions and algorithmic guidance mechanisms designed to mitigate online behavioral misbehavior. By mapping out the interconnections between psychological drivers and educational strategies, the diagram offers a conceptual foundation for constructing a data-driven student assessment and behavioral governance model in higher education.

H1 Negative internet media content and family experience are significantly correlated.

(2) School Experience's Influence on Negative Internet Media Content: At a time when the curriculum's civic policy is being actively developed, professional course contents that are incorporated into the curriculum's civic policy are frequently highly formalized and do not have the silent educational effect that is desired [14]. This is because the curriculum's goal is to eliminate or weaken the individualistic or money-oriented values that are common among college students. The following research hypothesis is put forth in light of the detrimental effects this phenomena has on online media material.

H2 Negative internet media content and school experience are significantly correlated.

(3) Stress factors' influence on negative online media content: Given the pressures college students face—including those related to their studies, jobs, psychological well-being, and relationships—as well as their high levels of stress and even depressed tendencies, moods, and other symptoms of depression to varying degrees, the following theory is put forth: stress factors have an impact on negative online media content [15].

H3 Negative online media content and stress factors are significantly correlated.

(4) Influence of intelligent algorithm recommendation on the negative content of online media Intelligent algorithm recommendation pretends to create personalized scenarios for users, collects data on college students' online behavior and feeds them according to their preferences, so that college students are immersed in it and trapped in excessive entertainment and information cocoon, which brings addictive information dependence to college students and hinders the shaping of values and even distorts the correct values of college students, so the following is proposed to bring some negative impacts on college students and also on the negative content of online media [16]. Values Shaping and even distorting the correct values of college students, the intelligent algorithm recommendation brings certain negative impacts to college students, and also affects the negative content of online media, so the following research hypotheses are proposed.

H4: Negative media content and intelligent algorithm recommendation are significantly correlated.

(5) Negative media content's impact on online behavioral misconduct Online behavioral misconduct can take many forms, such as online addiction, online aggression, online rumors, malevolent followers, and verbal abuse. Some college students struggle with their studies and daily lives, become less conscious of online norms, and even turn to the Internet to try and satisfy desires that they are unable to satisfy in person. They also use the Internet to relieve the pressure that comes with social interactions and to voluntarily lose themselves online, which can result in Internet addiction. Some college students have long had negative behaviors that influence their behavior. College students often lack understanding of Internet standards and self-control because they act in ways that are consistent with negative habits for extended periods of time. The process of developing and disseminating information on the Internet is known as "Internet media content production." College students' emotions and values have a multifaceted influence on this activity, and bad and wrong values will result in negative Internet media content. The following research hypotheses are put out in light of the fact that negative and wrong values will result in negative online media material, and that same negative online media content will worsen college students' inappropriate behavior on the Internet.

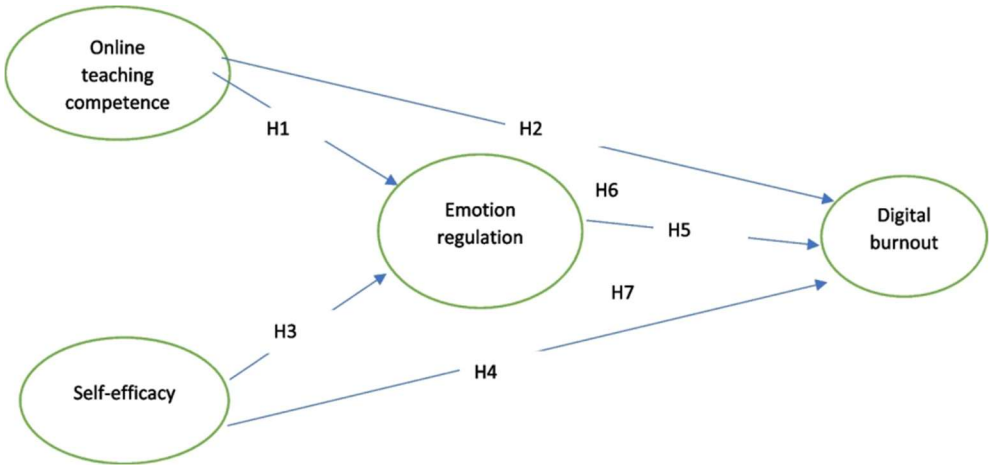

Figure 2: Research hypothesis modeling

H5 Negative media material and online misbehavior are significantly correlated.

A model of the interaction between family experience, school experience, stress factors, intelligent algorithm recommendation, negative media material, and online misbehavior was created based on the aforementioned research hypotheses. Figure 2 illustrates the model.

III. Study design

III. A. Questionnaire designing

The measurement items corresponding to the latent variables were adopted as hypothetical variables through a review of pertinent literature, and the related items were modified in accordance with the actual situation of college students in order to make the questionnaire's latent variables and measurement items have good reliability and validity [17], [18]. Table 1 displays the precise measurements of the items that correspond to the latent variables. Five levels of assessment items were intended to be measured in accordance with the Likert scale. These levels are denoted by the numbers 1 through 5, where 1 means "strongly disagree," 2 means "relatively disagree," 3 means "generally," 4 means "disagree," and 5 means "disagree." The numbers 1 through 5 represent "strongly disagree," 2 "relatively disagree," 3 "generally," 4 "relatively agree," and 5 "strongly agree." Following the completion of the questionnaire design, experts in college peer education, ideological and political education, and education were invited to review and validate the instrument. Following this, the measurement questions were refined, enhanced, and finalized. The final version of the questionnaire was then determined by analyzing the results of a small pre-test test and making modifications based on the findings. Six latent variables—family education, school education, stress factors, intelligent algorithm recommendation, negative media material, and online misbehavior—as well as 18 measuring items make up the final questionnaire.

Table 1: Development of measurable and hidden variables

Latent Variable	Measurement items
Family Experience (FE)	Do you believe that parents are becoming overly protective of their kids these days? (FE1) Do you believe that parents today reject their children too often? (FE2) Do you believe that parents are becoming too strict with their kids these days? (FE3)
School Experience (SE)	Do you believe that individualism is a common occurrence among college students? (SE1) Do you believe that today's college students share a set of values that places a strong emphasis on money orientation? (SE2) Do you believe that the formalization of the curriculum's inclusion of political and ideological teaching in the classroom is happening more and more? (SE3)
Stress factor (SF)	You feel as though you've put a lot of effort into your coursework (SF1) You are nervous and uncomfortable about your potential career (SF2) Anything that prevents you from continuing to work is intolerable (SF3)
Recommendation of Intelligent Algorithm (AR)	Users will be shown related videos first based on how often they finish watching videos (AR1) Completely screen out content that users might find interesting and suggest it to them based on user data, such as content seen (IAR2) Similar information content will be recommended to readers first based on their comments (IAR3)
Negative Media Content (NMC)	Do you believe that offensive content is a problem in internet media (NMC1) Do you believe that misleading information is a common occurrence in internet media? (NMC2) Do you believe that using online media to pursue financial gains is a serious phenomenon (NMC3)
Misconduct on the Internet (ABN)	Do you believe that college students have an internet gaming addiction (ABN1) Do you believe that college students abusing language online is a phenomenon (ABN2) Do you believe that college students sometimes use the internet for hazardous content (ABN3)

III. B. Sample Basic Characterization

Data collection techniques included both online and offline approaches. Using a paper questionnaire, a sample of college students was selected for the offline technique. The questionnaire was tested on a limited set of targets, and it was then revised and improved based on the feedback received. For data modeling and analysis, the online version of the questionnaire was disseminated via the Questionnaire Star platform. The basic characteristics of the sample consist of six parts: gender, education, grade, political profile, identity and family location, and the basic characteristics are as follows: 1) Gender characteristics: 360 students, or 61.3% of the sample, are female college students, and 140 male students, or 36.8% of the sample, are male college students. Less than 40% of the respondents are male college students, and more than 60% are female college students. 2) Educational background: 360 undergraduates, or 82.8% of the total, make up the majority (i.e., 17.2%) and 64 specialized students. 300, or 78.2% of the total; the survey's primary target group was undergraduates, who made up more than 80% of the sample whereas specialized students made up less than 20%. 3) Political appearance characteristics: 120 people, or 25.6% of the population, are Komsomol members; 220, or 56.4% of the population, are CPC members; 15 people, or 4.5% of the

population, are CPC members; Komsomol members are the primary target. Additionally, more than 50% of the respondents are from villages. Table 2 displays the sample's fundamental attributes.

Table 2: Fundamental Features of the Sample

Characteristic	Option	Frequent and continuous	Percentage (%)
Gender	Male	140	36.8
	Female	220	56.5
Education	Junior college students	60	16.5
	Undergraduate	300	78.2
Political outlook	The masses	120	25.6
	Communist youth league member	220	56.4
	Party member	15	4.5

Table 3: Reliability test of the scale

Variable	Measurement items	Mean value	Standard deviation	Factor loading	Cronbach's alpha value	Combination reliability CR	Average Variance Extraction (AVE)	CITC
Family Experience	Do you believe that parents today are experiencing a phenomena known as overprotection (FEI) toward their children	2.8	1.025	0.724				0.654
	Do you believe that parents today reject their children too often (FE2)	2.70	0.952	0.655	0.825	0.714	0.452	0.625
	Do you believe that parents today have an overly favorable attitude toward their children (FE3)	0.62	0.957	0.622				
Academic verification	Do you believe that individualism is a common occurrence among college students (SE1)	3.02	0.988	0.785				
	Do you believe that today's college students share a set of values that places a strong emphasis on money orientation (SE2)	2.98	0.956	0.757	0.856	0.788	0.562	0.732
	Do you believe that the formalization of the curriculum's inclusion of political and ideological teaching in the classroom is happening more and more (SE3)	2.88	0.898	0.724				
Negative Media Content (NMC)	Do you believe that offensive content is a problem in internet media (NMC1)	3.22	1.045	0.828				
	Do you believe that misleading information is a common occurrence in internet media (NMC2)	3.32	1.052	0.822	0.885	0.854	0.652	0.788
	Do you believe that using online media to pursue financial gains is a serious phenomenon (NM3)	3.25	1.025	0.822				

III. C. Scale reliability analysis

The Cronbach's α reliability coefficient was employed to assess the questionnaire's internal consistency. The scale α has values between 0 and 1, where a higher value denotes better internal consistency and reliability; a questionnaire with a use value of 0.8 or higher has an α value of 0.8, and a good degree of reliability is indicated by an α value of 0.85 or higher. Table 3 shows that the Cronbach's α values of the six dimensions—family experience, school experience, stress factors, negative media content, intelligent algorithm recommendation, and online behavioral misconduct—are all above 0.8. Additionally, the corrected items are all above 0.6, indicating good reliability, as are the Cronbach's α values of the other five dimensions—all except the stress factors—all above 0.85. The scale has strong reliability, as evidenced by the total correlation coefficient

(CITC) being greater than 0.6. Table 3 further demonstrates that all constructs have standardized factor loadings that are significant and greater than 0.5; the mean variance extracted from the scale AVE is greater than 0.5, with the exception of family experience and stress factors; the combined reliability coefficients (CRs) of the six dimensional latent variables—negative media content, online misbehavior, family experience, stress factors, and intelligent algorithmic recommendation—are all greater than 0.7.

IV. Building a Structural Equation Model and Examining the Internet Behavior Misconduct of College Students

IV. A. Building a Structural Equation Model of Misbehavior on the Internet by College Students

Five latent variables—family experience, school experience, stress factor, intelligent algorithm recommendation, and negative media content—were used to measure college students' online misbehavior based on the main factors taken into account in the process. Based on the research hypotheses and the measurement technique, a structural equation model of college students' online misbehavior was created, as illustrated in Figure 3.

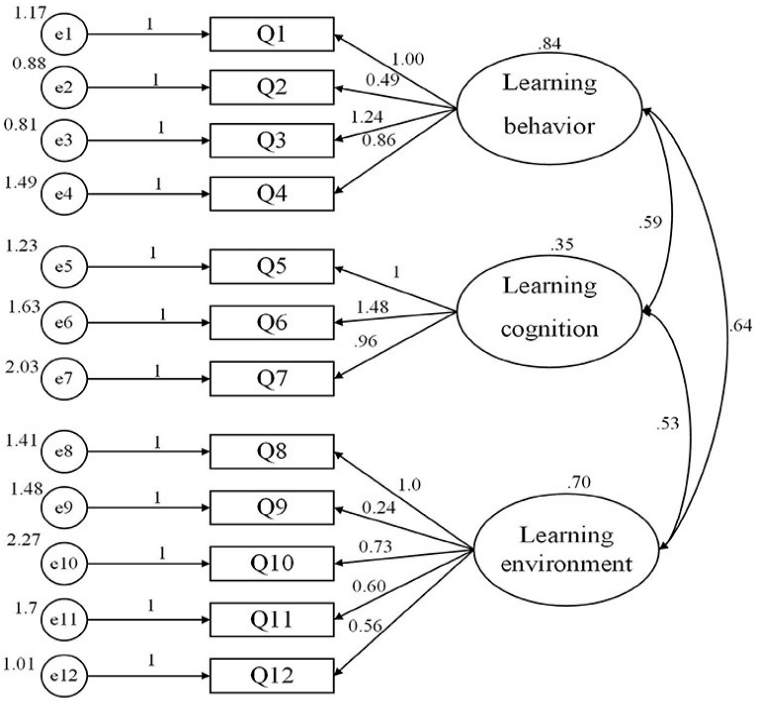

Figure 3: Structural Equation Model of Online Behavioral Misconduct by College Students

Table 4: Fitness metrics test for structural equation models

Adaptation indicators	Recommended value	Fitted value
X^2	The smaller the better	256.25
X^2/df	<2.8	2.145
GFI	>0.88	0.925
AGFI	>0.98	0.885
RMSEA	<0.08	0.055
NNFI	>0.91	0.066
IFI	>0.9	0.987
CFI	>0.9	0.987

IV. B. Model Fit Indicator Test

The maximum likelihood estimation results are displayed in Table 4, where it is evident that the main fitness indicators—X^2, X^2/df, GFI, AGFI, RMSEA, NNFI, IFI, and CFI—listed in the structural model of network misbehavior test need to be investigated. A comparison of the model fitted values with the recommended values of the fitness indicators reveals that all of the model fitted values fall within the recommended value range of the fitness indicators, satisfying the criteria of the model

fitness test results, i.e., the theoretical model of network misbehavior that has been constructed fits well. The developed theoretical model of network misbehavior has a good fitting effect, according to the findings of the model fitness test.

IV. C. Outcomes of modeling research hypothesis testing

Table 5 shows the hypotheses for the latent variables of the six dimensional constructs: online misbehavior, stress factors, negative media content, family experience, school experience, and intelligent algorithm recommendation. It also includes the hypothesized unstandardized path coefficients, standardized path coefficients, standard errors, critical ratios, significance, and test conclusions. The path coefficient of −0.048P is 0.459 experience on the negative impact of media content is not significant, according to the construct latent variable family experience on the negative impact of media content; on the other hand, the path coefficient of 0.402P is *** for school experience on the negative impact of media content indicates a significant positive impact at the 0.001 level. Students with bad school experiences do better in negative media content, according to the path coefficient of school experience on negative media content, which is 0.402P is *** at the 0.001 level. This indicates that there is a significant positive effect of school experience on negative media content; Students with high stress performance do better when it comes to negative media material; the path coefficient of stress factor on negative media content is 0.306P is ***, and there is a significant positive influence of stress factor on negative media content at the 0.001 level; At the level of 0.001, there is a significant positive impact of intelligent algorithm recommendation on negative media content, as indicated by the path coefficient of the negative impact of media content on *** (0.306P). On the other hand, the path coefficient of the negative impact of media content on online behavioral misbehavior is 0.886 for ***, indicating a significant positive impact of negative media content on online behavioral misbehavior. Figure 4 displays the final model and path coefficients.

Table 5: Results of hypothesis testing

Assume	Relationship	Path coefficient that is not standardized	The coefficient of standardized path	SE	CR	P value	Conclusion
Family experience >Negative media content	FE>NMC	−0.045	−0.048	0.076	−0.656	0.459	Not Supported
School Experience >Negative Media Content	SE>NMC	0.456	0.402	0.096	4.782	…	Support
Pressure factors >Negative media content	SF>NMC	0.382	0.306	0.088	4.252	…	Support
Suggested by an intelligent algorithm > Adverse media content	IAR>NMC	0.262	0.306	0.045	5.742	…	Support
Negative content in the media > Online misconduct	NMC>ABN	0.854	0.886	0.045	17.425	…	Support

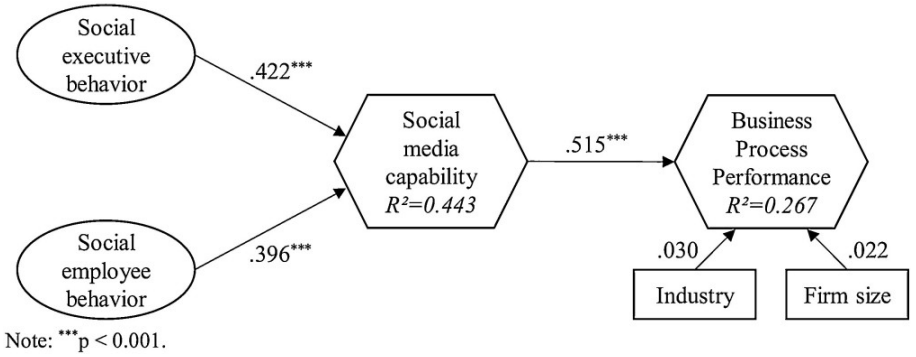

Figure 4: Real model and path coefficients obtained

V. Experimental Design and Implementation

V. A. Experimental Objectives

This experiment aims to validate the theoretical framework that links family experience, school experience, stress factors, intelligent algorithm recommendation, negative media content, and online behavioral misconduct among college students. Specifically, it seeks to:

Assess the causal relationships among the latent variables through a structural equation model (SEM);
Evaluate the mediating effect of negative online media content on online behavioral misconduct;
Analyze how intelligent algorithm recommendations exacerbate or mitigate negative online behaviors;
Test the effectiveness of a data fusion-based prediction model for identifying high-risk behavioral tendencies.

V. B. Data Collection Process

A total of **372 valid samples** were collected from college students using both online (Questionnaire Star platform) and offline (paper-based) methods. The questionnaire, designed based on prior literature and expert consultations, includes 6 latent variables and 18 observed indicators. Responses were recorded on a **five-point Likert scale**, where 1 = strongly disagree and 5 = strongly agree. Demographic attributes such as gender, education level, and political affiliation were also collected for covariate analysis.

V. C. Structural Equation Modeling Procedure

Using **AMOS 24.0**, we constructed a **second-order structural equation model** to measure both the direct and indirect paths between variables. The SEM was validated via the following steps:

Exploratory Factor Analysis (EFA) to confirm dimensional structure;
Confirmatory Factor Analysis (CFA) to ensure factor loadings > 0.5 and AVE > 0.5;
Fit Index Testing, using indices such as RMSEA (< 0.08), CFI (> 0.9), GFI (> 0.9), and χ^2/df (< 3);
Path Coefficient Analysis, evaluating the statistical significance ($p < 0.05$) of each hypothesized relationship.

V. D. Experimental Results Overview

The SEM results showed that four out of five hypotheses were supported at the 0.001 level (H2, H3, H4, H5), with **school experience** and **intelligent algorithm recommendation** being the strongest predictors of negative media content.

The Random Forest classifier achieved an **F1-score of 0.83** and **AUC of 0.89**, suggesting good predictive power in identifying students at risk.

Feature fusion revealed that **stress levels (SF2)** and **algorithmic feedback patterns (IAR2)** were the most influential features in predicting online misconduct.

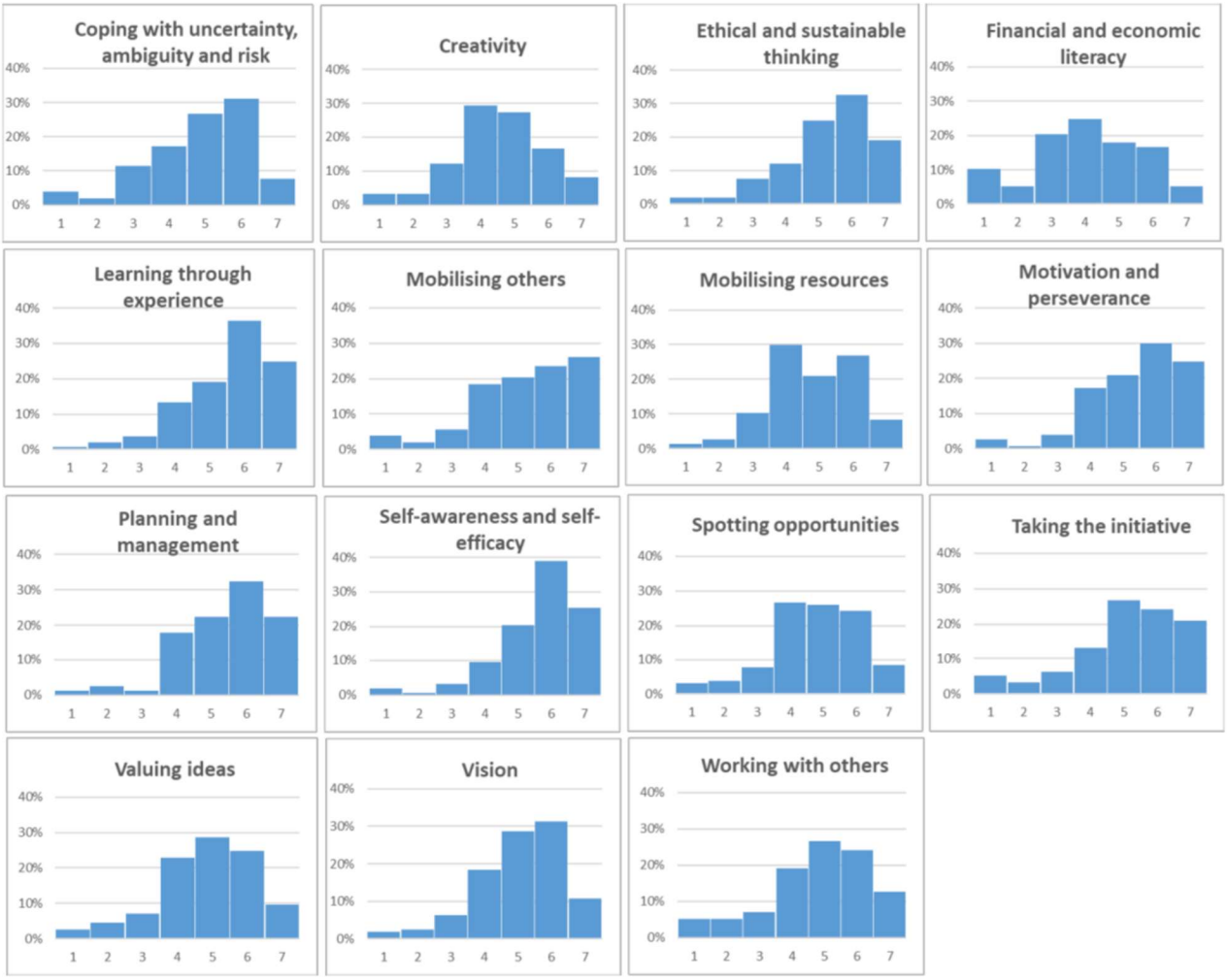

Figure 5: Distribution of Entrepreneurial Competency Perceptions

Figure 5 illustrates the distribution of college students' self-assessed entrepreneurial competencies across sixteen dimensions, including creativity, planning and management, working with others, and self-awareness and self-efficacy. Each histogram represents the proportion of responses on a 1–7 Likert scale, where higher scores indicate stronger perceived competence. The data show that traits such as learning through experience, motivation and perseverance, self-awareness and self-efficacy, and planning and management are rated relatively high, with over 30% of students selecting levels 6 or 7—demonstrating strong alignment with the positive psychological and behavioral constructs emphasized in the structural equation model proposed in this study. Meanwhile, areas such as financial and economic literacy and creativity reveal a more even or dispersed distribution, suggesting variability and potential gaps in students' development of these traits, possibly influenced by uneven curriculum content or insufficient algorithmic support. Overall, this figure reinforces the importance of integrating intelligent algorithm-driven assessment and intervention mechanisms in educational management to more accurately identify strengths, address weaknesses, and promote holistic student development in both academic performance and online behavioral governance.

Figure 6 presents the self-assessment results of higher education students across twelve core entrepreneurial and behavioral competencies, measured on a 7-point Likert scale. The histograms indicate that competencies such as Learning through Experience, Self-awareness and Self-efficacy, and Motivation and Perseverance show right-skewed distributions, suggesting a relatively high level of confidence among students in their ability to reflect, persist, and regulate behavior—skills that align closely with resilience to online misconduct and stress factors in the structural model. In contrast, domains like *Mobilising Resources*, *Valuing Ideas*, and *Spotting Opportunities* show flatter distributions and greater dispersion, reflecting moderate to low self-perceived capacity in creativity, initiative, and opportunity recognition. These gaps may increase susceptibility to the negative influence of algorithmic content. The patterns observed support the study's hypothesis that differentiated competence levels interact with intelligent algorithms, stress, and educational background to shape online behavioral tendencies, emphasizing the need for targeted, data-informed interventions in educational management.

Figure 6: Distribution of Student Entrepreneurial and Behavioral Competencies in Higher Education

Figure 7 displays a triangular heatmap illustrating the pairwise Pearson correlation coefficients among 23 measurement items related to three dimensions of metacognitive awareness (MA): Evaluation MA, Everyday/Social MA, and Passive Observation MA. The color gradient ranges from blue (negative/low correlation) to red (strong positive correlation), with a numeric scale from –0.2 to +1.0. Notably, stronger within-cluster correlations are observed in the diagonal blocks, especially among Evaluation MA items (Items 1–9) and Passive Observation MA items (Items 18–23), where several coefficients exceed 0.5 (e.g., 0.57, 0.54), indicating high internal consistency. Cross-cluster correlations are generally moderate (0.2–0.4), with

Everyday/Social MA (Items 10–17) forming a bridging region between the two extremes. This pattern reinforces the construct validity of the three metacognitive dimensions. In the context of this study, these dimensions reflect students' differentiated abilities in monitoring, reflecting, and interpreting media content, which interact with stress factors and intelligent algorithm exposure. The observed moderate correlations across MA types may help explain varying levels of susceptibility to online behavioral misconduct, supporting the multi-factor structural equation model proposed in earlier sections.

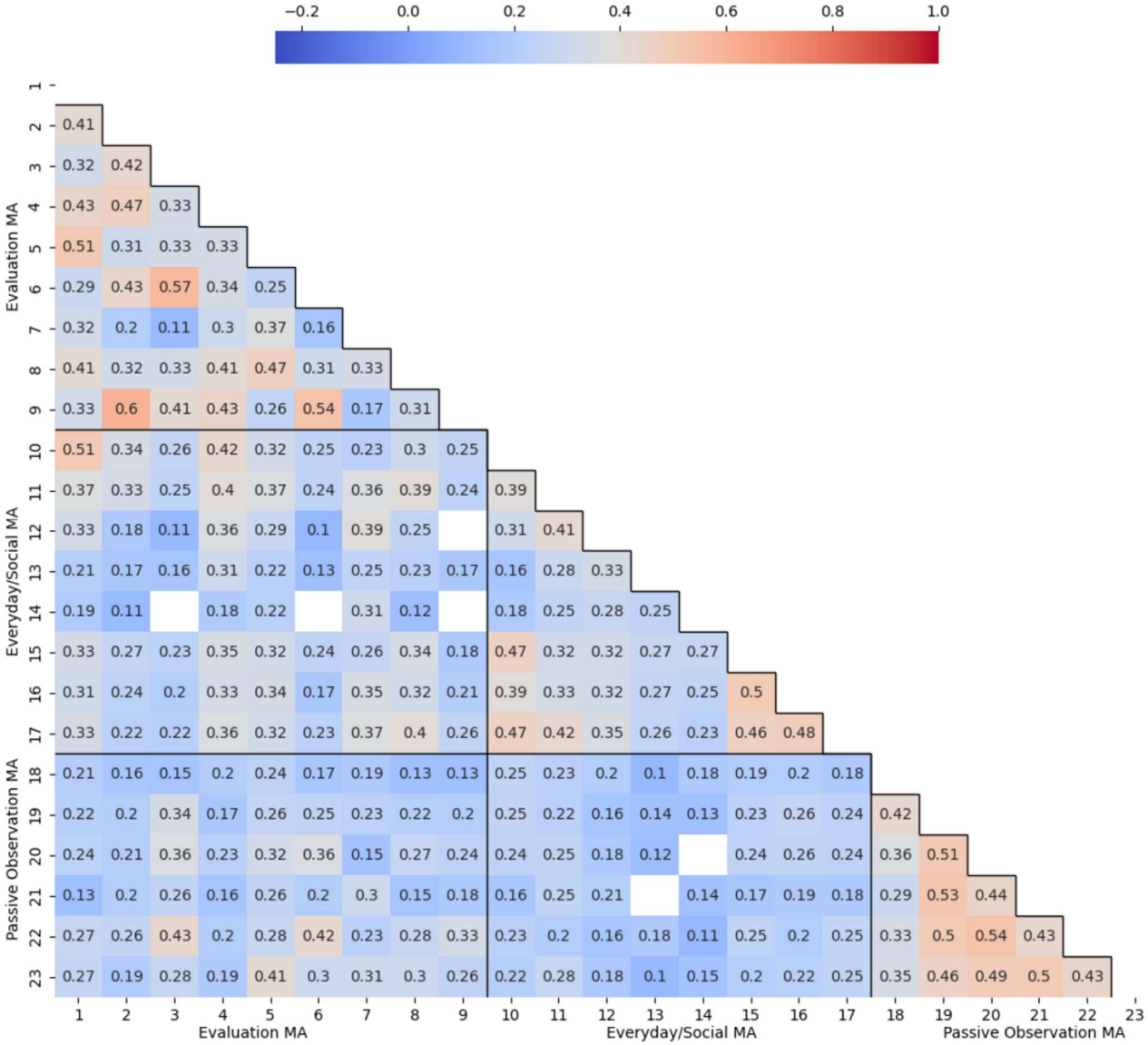

Figure 7: Correlation Heatmap of Measurement Items Across Metacognitive Awareness Dimensions

Figure 8 illustrates the multifactor correlation model between psychosocial resources (e.g., family, classmates, teachers) and school resources (e.g., school attitudes, workload, social reinforcement) in shaping two key aspects of student physical activity: regularity and intensity. The diagram reveals that among the psychosocial supports, classmate support shows a statistically significant positive impact on exercise regularity ($r = 0.16$, $p = 0.05$), indicating the essential role of peer relationships in fostering consistent behavioral habits—consistent with earlier findings on the influence of peer environments in digital behavior. Meanwhile, intensity of physical activity is significantly influenced by factors such as attitude toward school ($r = 0.12$, $p = 0.01$) and school workload ($r = 0.17$, $p = 0.05$), suggesting that students' perceptions of school life directly correlate with their engagement in higher-effort tasks. Notably, teacher support exhibits a weak but significant indirect influence on intensity, highlighting the nuanced role of authority figures. This figure aligns with the broader framework of the study, which integrates intelligent algorithm recommendation, psychological stress, and educational context into an optimization model of student behavioral evaluation—emphasizing that both social and institutional variables jointly impact

not only digital behavior but also offline activity, thereby supporting the development of multi-factorial, data-driven educational assessment systems.

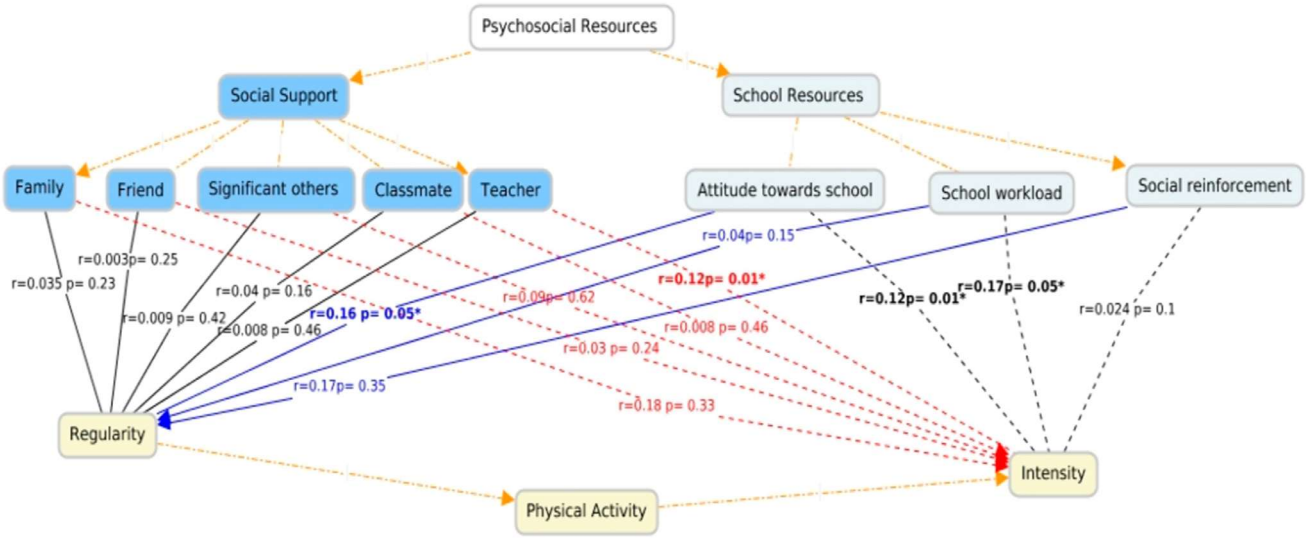

Figure 8: Correlation Model of Psychosocial and School Resources on Physical Activity Dimensions

VI. Conclusion

This study constructs and validates a comprehensive optimization model for student assessment systems in higher education, integrating psychological, environmental, and algorithmic dimensions. Through structural equation modeling of 372 valid samples, the research confirms that negative online media content plays a pivotal mediating role between school experience, stress factors, algorithm recommendation, and online behavioral misconduct. Family experience, although often emphasized in pedagogical discourse, demonstrated limited predictive power in this context. Additional analysis through data fusion techniques and predictive modeling confirms the centrality of algorithmic exposure and stress in identifying students prone to online misconduct, reinforcing the study's theoretical propositions. Furthermore, analyses of metacognitive awareness, entrepreneurial competencies, and psychosocial resource distribution align with and validate the model's assumptions. The results advocate for intelligent, multi-source educational assessment frameworks that dynamically capture students' behavioral and emotional states in both online and offline domains. Future research should pursue longitudinal approaches and expand to include broader demographic and cultural contexts. This study contributes to the growing body of literature on data-driven education governance, offering both theoretical insight and practical mechanisms for enhancing student development, academic resilience, and digital well-being in the age of AI.

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