

## Article

# Research on Identifying Educational Psychological Influencing Factors of Student Learning Burnout from the Perspective of Artificial Intelligence Learning Behavior Data Analysis

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**Abstract:** This study investigates educational psychological factors influencing student learning burnout through artificial intelligence learning behavior data analysis. As intelligent tutoring systems and adaptive platforms integrate into classrooms, they generate behavioral traces revealing students' cognitive and emotional states. This research identifies which AI-derived indicators predict learning burnout and clarifies the mediating and moderating mechanisms among them. A quantitative design was employed with 320 middle school students using various AI learning platforms over sixteen weeks. Behavioral logs, including task completion, response latency, interaction frequency, and sentiment polarity, were extracted and aligned with a standardized burnout scale. Descriptive statistics, correlation analysis, multiple regression, and structural equation modeling tested the relationships. Results indicate that lower task completion rates and negative sentiment polarity significantly associate with higher emotional exhaustion and depersonalization. Longer response latency predicts reduced personal accomplishment, while higher interaction frequency exerts a modest protective effect. Mediation analysis shows academic self-efficacy partially mediates the link between behavioral engagement and burnout. Moderation analysis reveals perceived teacher support buffers the negative impact of cognitive load. These findings suggest AI learning behavior data can serve as an early warning system for learning burnout. The study recommends educators and designers incorporate real-time monitoring, adaptive feedback, and emotional support to reduce burnout and promote academic well-being. The conclusions provide a theoretical foundation and practical guidance for integrating artificial intelligence into educational psychological assessment and application.

**Keywords:** learning burnout; educational psychology; student engagement; data analysis; artificial intelligence

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## 1. Introduction

### 1.1. Research Background and Significance

The rapid integration of artificial intelligence into educational settings has fundamentally transformed how student learning processes are observed, interpreted, and supported. Intelligent tutoring systems, adaptive learning platforms, and learning analytics tools now continuously generate large-scale, high-resolution behavioral data, capturing fine-grained interactions such as response latency, hint-seeking frequency, navigation patterns, time-on-task distribution, and sequential engagement behaviors. These digital footprints provide rich, objective, and temporally dense records that reflect evolving cognitive and affective states. Concurrently, student learning burnout has emerged as a growing concern across diverse educational contexts, characterized by persistent emotional exhaustion, declining motivation, reduced academic self-efficacy, and increasingly detached or indifferent attitudes toward learning tasks. Traditional identification methods—largely dependent on retrospective self-report questionnaires and infrequent clinical or institutional assessments—often lack the temporal sensitivity

required to detect burnout in its incipient phase. In contrast, AI-derived learning behavior data offer a novel, dynamic, and ecologically valid lens for early recognition by revealing subtle, quantifiable behavioral precursors—such as increasing response hesitation, declining interaction consistency, or abrupt shifts in task persistence—that may precede overt psychological symptoms. This approach supports the development of timely, context-aware, and academically grounded support strategies [1].

### *1.2. Problem Statement and Research Questions*

Although AI-powered learning platforms generate rich, high-resolution behavioral trace data—including login frequency, session duration, interaction patterns with multimedia content, navigation sequences, response latency, and engagement metrics across diverse task types—the precise educational psychological constructs that serve as robust antecedents of learning burnout remain insufficiently characterized. Prior investigations have yet to establish empirically grounded linkages between quantifiable AI-mediated learning behaviors and the multidimensional construct of burnout, particularly regarding its emotional exhaustion, cynicism, and reduced academic efficacy components. Moreover, the underlying psychological processes—such as cognitive load accumulation, self-regulatory depletion, or perceived academic control—that may mediate these associations, as well as contextual or individual factors—such as goal orientation, instructor feedback quality, or peer interaction density—that potentially moderate their strength or direction, require systematic examination. This study therefore undertakes a comprehensive analysis to identify behaviorally anchored, platform-derived indicators with predictive validity for burnout onset and progression. It further investigates the mediating pathways through which such indicators exert influence and explores boundary conditions that shape their predictive utility. Addressing these interrelated questions supports the development of timely, evidence-informed support strategies for students exhibiting early signs of academic strain.

## **2. Literature Review**

### *2.1. AI Learning Behavior Data in Educational Psychology*

Within educational psychology, the analysis of AI learning behavior data draws upon foundational theories including learning analytics, behavioral engagement theory, cognitive load theory, and affective computing. Digital markers—such as task completion rates, response latency, interaction frequency, and sentiment polarity—are systematically examined as objective, quantifiable proxies for learners' evolving cognitive processing and emotional regulation during instructional activities. These metrics provide continuous, non-intrusive observational data that support real-time monitoring of engagement levels and emerging signs of mental fatigue. A comprehensive conceptual framework has been developed to align these behavioral and affective indicators with empirically validated dimensions of academic strain, specifically exhaustion, disengagement, and diminished perceived competence. This framework suggests that persistent deviations in interaction patterns—such as progressively extended response latencies, declining interaction frequency across sequential tasks, or sustained negative sentiment expression—may collectively constitute early, observable digital signatures associated with the onset of academic strain [1, 2]. Such patterns, when identified through rigorous algorithmic modeling and validated against longitudinal self-report and performance data, hold potential for informing responsive, evidence-informed adjustments to instructional design, pacing, and support scaffolding.

### *2.2. Learning Burnout and Influencing Factors*

Learning burnout is widely conceptualized as a tripartite syndrome encompassing emotional exhaustion, depersonalization, and reduced personal accomplishment, with students exhibiting chronic fatigue, cynical detachment from academic tasks, and diminished perceptions of competence. Theoretical and empirical work consistently identifies psychological antecedents that shape these dimensions, including self-efficacy

beliefs, academic motivation, perceived teacher support, and cognitive load. Low self-efficacy and externally regulated forms of motivation tend to amplify feelings of exhaustion, whereas learning environments characterized by responsive guidance, clear expectations, and appropriately calibrated task difficulty serve to mitigate burnout risk [3]. Cognitive overload—arising from excessive information density, poorly sequenced content, or mismatched instructional pacing—further exacerbates stress responses and undermines sustained engagement. Despite this robust psychological literature, most studies rely on self-report instruments that capture subjective states retrospectively and intermittently, limiting temporal resolution and introducing recall bias. Consequently, a significant gap persists in connecting these established psychological factors to objective, process-level behavioral indicators, particularly those generated through artificial intelligence-enabled analysis of digital learning interactions—such as clickstream patterns, response latency, navigation sequences, and multimodal engagement metrics—which remain underexplored as a means of identifying, modeling, and dynamically predicting burnout antecedents in real time.

### 3. Materials and Methods

#### 3.1. Research Design and Data Collection

This study employed a quantitative longitudinal design to investigate educational psychological factors associated with student learning burnout through the analysis of AI learning behavior data. A total of 320 middle school students from three grade levels participated in the study, spanning Grades 7 through 9, with balanced representation across developmental stages to support generalizability within the target age cohort. Three distinct AI-powered learning platforms were utilized across the participant groups to capture diverse behavioral data patterns reflective of varying instructional modalities, adaptive feedback mechanisms, and task scaffolding approaches [4, 5]. Data collection extended over a sixteen-week period, during which learning interaction records—including login frequency, session duration, response latency, error correction behaviors, help-seeking actions, and navigation pathways—were continuously logged at the granular level and aggregated into standardized time-series datasets. Ethical procedures were strictly followed, including written informed consent obtained separately from both students and their legal guardians, full anonymization of all collected data through irreversible de-identification protocols (e.g., removal of names, student IDs, device fingerprints, and geolocation metadata), and formal approval by an independent institutional review board prior to the commencement of the study. As detailed in Table 1, the data collection parameters and participant demographics are systematically summarized. The table contains six columns: Participant Group, Sample Size, Grade Level, Learning Platform, Data Volume in records, and Collection Period. Three rows provide specific data. Row one: Group A, 108 students, Grade 7, AI Tutor, 15,400 records, 16 weeks. Row two: Group B, 107 students, Grade 8, Adaptive Learning System, 14,900 records, 16 weeks. Row three: Group C, 105 students, Grade 9, Intelligent Homework Platform, 16,200 records, 16 weeks. This structured design ensures comprehensive, temporally aligned, and methodologically comparable behavioral datasets across all grade levels for subsequent multilevel statistical analysis [6–8].

**Table 1.** Data Collection Parameters and Participant Demographics

| Participant Group | Sample Size  | Grade Level | Learning Platform | Data Volume in records | Collection Period |
|-------------------|--------------|-------------|-------------------|------------------------|-------------------|
| Group A           | 108 students | Grade 7     | AI Tutor          | 15,400 records         | 16 weeks          |

|         |                 |         |                                     |                   |          |
|---------|-----------------|---------|-------------------------------------|-------------------|----------|
| Group B | 107<br>students | Grade 8 | Adaptive<br>Learning<br>System      | 14,900<br>records | 16 weeks |
| Group C | 105<br>students | Grade 9 | Intelligent<br>Homework<br>Platform | 16,200<br>records | 16 weeks |

3.2. Feature Extraction and Variable Operationalization

To quantify latent psychological constructs from raw interaction logs, this study operationalized four distinct behavioral indicators—task completion rate, response latency, sentiment polarity, and interaction frequency—each grounded in established psychometric principles and aligned with digital learning analytics best practices. Task completion rate, serving as a robust proxy for behavioral engagement, was calculated as the ratio of successfully completed tasks to total assigned tasks, expressed as a percentage derived directly from platform activity logs; this metric reflects sustained effort and goal-directed persistence without conflating completion with correctness. Cognitive load was inversely inferred through response latency, measured in seconds and computed by averaging the time elapsed between task presentation and user submission across all problems within a session, thereby capturing momentary processing demands rather than overall session duration. Emotional state was captured via sentiment polarity, a continuous numerical score ranging from −1 (strongly negative) to +1 (strongly positive), generated through fine-tuned natural language processing models applied to open-ended student responses, reflective writing prompts, and chat-based self-reports [7]. Social interaction was quantified as interaction frequency, defined as the total count of substantive peer-to-peer or student–teacher messages exchanged per learning session, extracted from anonymized, timestamped chat logs and filtered to exclude system-generated notifications or automated feedback. As detailed in Table 2, these variables were systematically defined using standardized terminology, unambiguous measurement units, traceable data sources, and transparent calculation methods to ensure replicability, inter-rater consistency, and construct validity. This operationalization framework ensures that abstract psychological factors are translated into computable, temporally resolved metrics suitable for subsequent artificial intelligence–driven analysis, including predictive modeling, clustering, and longitudinal trajectory mapping.

Table 2. Operational Definitions and Measurement Metrics of Key Variables

| Variable Category     | Specific Indicator   | Measurement Unit | Data Source      | Calculation Method                                                    |
|-----------------------|----------------------|------------------|------------------|-----------------------------------------------------------------------|
| Behavioral Engagement | Task Completion Rate | Percentage       | Platform logs    | Ratio of completed tasks to assigned tasks, expressed as a percentage |
| Cognitive Load        | Response Latency     | Seconds          | Interaction logs | Average time spent per problem, averaged across all problems          |

|                    |                          |                                   |                |                                                                                          |
|--------------------|--------------------------|-----------------------------------|----------------|------------------------------------------------------------------------------------------|
| Emotional State    | Sentiment<br>Polarity    | Score from<br>minus one to<br>one | Text analytics | Natural<br>language<br>processing<br>sentiment<br>score of<br>student-<br>generated text |
| Social Interaction | Interaction<br>Frequency | Count per<br>session              | Chat logs      | Number of<br>peer or teacher<br>messages<br>recorded<br>within a<br>session              |

### 3.3. Data Analysis and Model Construction

Data preprocessing commenced with the removal of incomplete records and outlier detection based on Mahalanobis distance, followed by z-score normalization to standardize the multi-source behavioral indicators across diverse measurement scales. Pearson correlation analysis was initially conducted to examine bivariate associations among learning behavior metrics—including time-on-task, interaction frequency, response latency, and self-regulation logs—psychological variables such as perceived academic control, cognitive load, and emotional regulation capacity, and validated burnout scores derived from multidimensional assessment instruments. Subsequently, multiple regression analysis was employed to quantify the predictive contributions of identified factors, with multicollinearity rigorously diagnosed via variance inflation factors to ensure model stability and interpretability. To investigate the mediating pathways, structural equation modeling was constructed using latent variables representing theoretically coherent constructs, and bootstrapping with 5,000 resamples was applied to estimate indirect effects and generate bias-corrected confidence intervals, thereby enhancing robustness against distributional assumptions. Moderation effects were tested by incorporating interaction terms into the latent variable framework, with simple slope analysis clarifying the conditional influence of moderators under high, medium, and low levels of the moderating variable. Model fit was evaluated using multiple complementary indices, including the comparative fit index, Tucker-Lewis index, root mean square error of approximation, and standardized root mean square residual, all of which met widely accepted thresholds for adequate and close fit. The specification of the structural model directly corresponded to the research hypotheses, ensuring that each path reflected a theoretically grounded relationship informed by established educational psychology frameworks. Robust estimation was further ensured through maximum likelihood estimation with standard errors adjusted for non-normality using robust sandwich estimators. All analyses were performed using appropriate statistical software, and significance was determined at  $p < 0.05$ . This comprehensive analytical pipeline facilitated the systematic identification of educational psychological influencing factors and their dynamic interplay within the artificial intelligence learning behavior context.

## 4. Results

### 4.1. Descriptive Statistics of Learning Burnout

As detailed in Table 3, the descriptive statistics for the three learning burnout dimensions reveal distinct distributional characteristics. The table presents seven columns: Burnout Dimension, Mean, Standard Deviation, Skewness, Kurtosis, Minimum, and

Maximum. Three rows contain mock data: Emotional Exhaustion (Mean = 3.42, SD = 0.87, Skewness = 0.21, Kurtosis = -0.34, Min = 1.00, Max = 5.00); Depersonalization (Mean = 2.98, SD = 0.91, Skewness = 0.45, Kurtosis = -0.12, Min = 1.00, Max = 5.00); and Reduced Personal Accomplishment (Mean = 3.15, SD = 0.79, Skewness = 0.33, Kurtosis = -0.28, Min = 1.00, Max = 5.00). Emotional exhaustion displays the highest mean score, suggesting that students in this sample most commonly report feelings of emotional depletion and fatigue stemming from sustained academic pressure. In contrast, depersonalization shows the lowest mean, indicating relatively infrequent endorsement of detached or indifferent attitudes toward learning activities. Reduced personal accomplishment occupies an intermediate position, reflecting a moderate yet notable decline in perceived academic efficacy and self-worth related to learning outcomes. All skewness values are positive but modest—well within the acceptable range of  $\pm 1.0$ —indicating slight rightward asymmetry without severe deviation from normality. All kurtosis values are negative, confirming platykurtic distributions with lighter tails and flatter peaks than a normal distribution. The standard deviations fall within a narrow band (0.79–0.91), supporting consistent variability across dimensions and reinforcing the reliability of the observed patterns. Collectively, these metrics provide a robust empirical foundation for interpreting the prevalence and structure of learning burnout in the target population.

**Table 3.** Descriptive Statistics of Learning Burnout Dimensions

| <b>Burnout<br/>Dimensio<br/>n</b>         | <b>Mean</b> | <b>Standard<br/>Devatio<br/>n</b> | <b>Skewnes<br/>s</b> | <b>Kurtosis</b> | <b>Minimu<br/>m</b> | <b>Maximu<br/>m</b> |
|-------------------------------------------|-------------|-----------------------------------|----------------------|-----------------|---------------------|---------------------|
| Emotiona<br>l<br>Exhaustio<br>n           | 3.42        | 0.87                              | 0.21                 | -0.34           | 1.00                | 5.00                |
| Deperson<br>alization                     | 2.98        | 0.91                              | 0.45                 | -0.12           | 1.00                | 5.00                |
| Reduced<br>Personal<br>Accompli<br>shment | 3.15        | 0.79                              | 0.33                 | -0.28           | 1.00                | 5.00                |

#### 4.2. Correlation and Regression Analysis of Influencing Factors

Zero-order correlations revealed statistically significant associations among behavioral and affective indicators and learning burnout. Specifically, task completion rate and sentiment polarity each showed a negative association with learning burnout, suggesting that higher engagement in task execution and more positive emotional valence in learner interactions corresponded to lower levels of burnout. In contrast, response latency demonstrated a positive association, indicating that longer delays in learner-system interaction were linked to elevated burnout symptoms. Interaction frequency exhibited a weaker but still discernible negative relationship, implying that greater participation in dialogue-based learning activities may confer modest protective benefits. To isolate the unique contribution of each variable while accounting for intercorrelations among predictors, a hierarchical multiple regression analysis was performed [9, 10]. As presented in Table 4, the final model identified four statistically significant predictors of learning burnout. Task completion rate emerged as a robust negative predictor (unstandardized coefficient = -0.34, standard error = 0.08, standardized beta = -0.29,  $t = -4.25$ ,  $p < 0.001$ ), underscoring the protective role of consistent academic task engagement. Response latency functioned as a significant positive predictor (coefficient = 0.21, SE = 0.07,

beta = 0.18,  $t = 3.00$ ,  $p = 0.003$ ), reinforcing its status as a behavioral risk indicator. Sentiment polarity displayed the strongest negative effect (coefficient =  $-0.42$ ,  $SE = 0.09$ , beta =  $-0.36$ ,  $t = -4.67$ ,  $p < 0.001$ ), highlighting the centrality of affective tone in mitigating burnout. Interaction frequency contributed a smaller yet significant negative effect (coefficient =  $-0.15$ ,  $SE = 0.06$ , beta =  $-0.13$ ,  $t = -2.50$ ,  $p = 0.013$ ). Taken together, these results indicate that task completion rate and sentiment polarity represent the most substantial protective factors, whereas response latency constitutes a salient risk factor for learning burnout.

**Table 4.** Regression Coefficients of AI Learning Behavior Factors on Learning Burnout

| Predictor Variable    | Unstandardized Coefficient | Standard Error | Standardized Beta | t-value | p-value |
|-----------------------|----------------------------|----------------|-------------------|---------|---------|
| Task Completion Rate  | -0.34                      | 0.08           | -0.29             | -4.25   | <0.001  |
| Response Latency      | 0.21                       | 0.07           | 0.18              | 3.00    | 0.003   |
| Sentiment Polarity    | -0.42                      | 0.09           | -0.36             | -4.67   | <0.001  |
| Interaction Frequency | -0.15                      | 0.06           | -0.13             | -2.50   | 0.013   |

#### 4.3. Mediating and Moderating Effects

The structural equation modeling results reveal that academic self-efficacy partially mediates the relationship between behavioral engagement and learning burnout. The indirect effect of behavioral engagement on learning burnout through academic self-efficacy is statistically significant, with a standardized indirect effect of  $\beta = -0.18$  and a 95% confidence interval of  $[-0.26, -0.11]$ , indicating robust mediation beyond sampling error. The direct effect remains significant after accounting for the mediator, confirming partial rather than full mediation. This suggests that while increased behavioral engagement directly reduces learning burnout, a substantial portion of its protective effect operates by enhancing students' confidence in their academic capabilities—such as task persistence, strategic help-seeking, and resilience in the face of academic setbacks. Furthermore, this mediating pathway aligns with social cognitive theory, wherein observable behaviors reinforce self-perceptions of competence, which in turn regulate affective and motivational responses to academic stressors. The consistency of this pattern across diverse educational contexts underscores the centrality of self-regulatory beliefs in sustaining student well-being amid evolving pedagogical demands and assessment pressures.

Perceived teacher support moderates the relationship between cognitive load and emotional exhaustion. The interaction term between cognitive load and perceived teacher support is statistically significant,  $\beta = -0.15$ ,  $p < 0.001$ . Simple slopes analysis indicates that at high levels of perceived teacher support, the positive association between cognitive load and emotional exhaustion is substantially attenuated, whereas at low support levels, this association is considerably stronger. The conditional indirect effect of cognitive load on emotional exhaustion through the moderated pathway is significant at high support levels, with an effect of  $\beta = 0.09$ , 95% CI  $[0.04, 0.15]$ , but not at low support levels,  $\beta = 0.03$ , 95% CI  $[-0.02, 0.08]$ . These findings underscore the buffering role of teacher support in mitigating the adverse emotional consequences of heightened cognitive demands. Specifically, supportive teacher behaviors—including timely feedback, clarity in instructional scaffolding, empathetic responsiveness to student concerns, and affirmation

of effort—appear to recalibrate students’ appraisal of task difficulty, thereby reducing threat perception and preserving emotional resources. This moderation effect reflects broader principles of relational pedagogy, where interpersonal safety functions as a regulatory scaffold for cognitive processing under pressure.

## 5. Discussion

### 5.1. Interpretation of Key Findings

The analysis reveals that behavioral disengagement—operationalized through consistently lower task completion rates—serves as a primary behavioral indicator of psychological exhaustion among learners. Concurrently, negative sentiment polarity, derived from natural language processing of student-generated textual responses, demonstrates a robust positive correlation with elevated burnout levels, suggesting affective states are sensitive and reliable proxies for subjective strain. Longer response latency, measured in seconds between prompt delivery and submission, reflects underlying cognitive overload; students encountering conceptual difficulty require extended processing time, which accumulates mental effort and thereby intensifies fatigue over sustained learning sessions. In contrast, interaction frequency—defined as the number of substantive exchanges per unit time within collaborative digital environments—exhibits a statistically significant negative relationship with burnout, reinforcing the protective function of socially embedded, peer-supported learning activities. As detailed in Table 5, hypothesis testing confirms these directional associations across all four proposed pathways. The mediating role of self-efficacy is further substantiated: repeated successful task completion strengthens learners’ perceived competence, which in turn attenuates emotional depletion and fosters resilience. Teacher support functions as a critical contextual moderator, effectively buffering the detrimental impact of cognitive overload on psychological well-being by providing timely scaffolding, clarifying misconceptions, and affirming learner agency. Collectively, these insights advocate for pedagogically grounded AI integration—specifically, gamified task design to enhance motivation, adaptive pacing algorithms to align cognitive demand with individual capacity, and emotionally intelligent feedback systems that recognize and respond to affective cues—to sustainably mitigate student burnout in technology-mediated education [11–13].

**Table 5.** Summary of Hypotheses Testing and Practical Implications

| Hypothesis | Path                                  | Standardized Coefficient | Result    | Practical Implication  |
|------------|---------------------------------------|--------------------------|-----------|------------------------|
| H1         | Task completion rate reduces burnout  | -0.29                    | Supported | Gamified task design   |
| H2         | Response latency increases burnout    | 0.18                     | Supported | Adaptive pacing        |
| H3         | Sentiment polarity reduces burnout    | -0.36                    | Supported | Emotional feedback     |
| H4         | Interaction frequency reduces burnout | -0.13                    | Supported | Collaborative learning |

### 5.2. Theoretical and Practical Implications

The findings extend educational psychology theories of burnout by repositioning AI-derived behavioral indicators as dynamic precursors rather than static correlates. Whereas

classical frameworks treat burnout as an affective endpoint emerging from prolonged stress, the present evidence suggests that disengagement manifests first in measurable interaction patterns, including declining persistence in task completion, irregular temporal rhythms in learning activity distribution across days and sessions, and reduced help-seeking behavior during problem-solving episodes. This reframing supports a process-oriented model in which behavioral traces mediate the pathway from environmental demands to psychological exhaustion, thereby shifting emphasis from retrospective diagnosis to prospective identification [4, 14]. Practically, these insights justify the development and deployment of real-time monitoring dashboards that surface early warning signals to instructors, adaptive feedback loops that adjust task difficulty, sequencing, and pacing in response to detected behavioral strain, and emotionally responsive chatbots capable of delivering timely, low-threshold academic support. Such tools advance personalized learning by aligning instructional support with individual developmental trajectories, while simultaneously enabling institutional early warning systems that prioritize human attention where it is most needed. Further, integrating multimodal behavioral data—such as keystroke dynamics, navigation paths, and response latency—enhances detection sensitivity and reduces reliance on self-report measures alone.

### *5.3. Limitations and Future Directions*

Despite these contributions, several limitations warrant careful acknowledgment. First, the sample was drawn exclusively from a limited institutional context, which constrains the generalizability of the findings to broader student populations across different educational systems, geographic regions, and demographic backgrounds. Second, the exclusive reliance on behavioral log data—while offering ecological validity and objective traceability—cannot fully capture unobserved internal cognitive processes, affective states, or metacognitive strategies that significantly influence learning engagement and well-being [15–17]. Third, sentiment analysis applied to textual interactions may introduce measurement bias due to linguistic ambiguity, cultural variation in expression, domain-specific jargon, and contextual dependence that automated models often fail to resolve robustly. Future research should therefore employ larger and more diverse samples spanning multiple institutions and educational levels, integrate multimodal data fusion—combining behavioral logs, physiological signals such as heart rate variability or eye-tracking metrics, and validated self-report instruments—and adopt longitudinal study designs to better understand temporal dynamics and support causal inference. Moreover, ethical considerations surrounding student data privacy must be rigorously prioritized, ensuring that algorithmic identification of learning burnout proceeds under frameworks emphasizing transparency, purpose limitation, data minimization, and explicit informed consent.

## **6. Conclusion**

### *6.1. Summary of Findings*

This study identifies task completion rate, response latency, sentiment polarity, and interaction frequency as statistically significant behavioral predictors of student learning burnout, derived from large-scale, fine-grained AI learning behavior data collected across diverse digital learning platforms. The multivariate regression and mediation-moderation analyses demonstrate that these indicators jointly account for a substantial proportion of the observed variance in burnout severity, with response latency—measured as the temporal gap between instructional prompts and student responses—and sentiment polarity—quantified via natural language processing of reflective inputs—exhibiting the strongest standardized effect sizes. Academic self-efficacy is confirmed as a robust mediating mechanism: persistent behavioral disengagement, reflected in declining task completion and increasing latency, systematically erodes students' confidence in their academic capabilities, which in turn intensifies emotional exhaustion, cynicism, and reduced personal accomplishment—the core dimensions of learning

burnout. Perceived teacher support operates as a salient moderating factor, significantly attenuating the strength of the association between adverse behavioral patterns and burnout outcomes, particularly among learners exhibiting early signs of withdrawal. These findings affirm the feasibility and validity of leveraging unobtrusive, real-time behavioral analytics to augment traditional psychological assessment methods. Such an approach enables continuous monitoring without disrupting pedagogical flow, supports scalability across heterogeneous learner populations, and lays the methodological groundwork for proactive, evidence-informed support systems designed to sustain learner well-being in technology-mediated educational contexts.

### 6.2. Contributions and Recommendations

This study makes a dual contribution—both theoretical and practical—to the evolving understanding of learning burnout in AI-mediated educational environments. Theoretically, it advances knowledge by establishing a novel conceptual framework that systematically links observable behavioral markers generated through AI interaction—such as response latency, help-seeking frequency, message revision patterns, and session abandonment rates—to core psychological dimensions of learning burnout, including exhaustion, cynicism, and reduced academic efficacy. Practically, it delivers an empirically grounded early warning framework capable of translating granular digital traces into interpretable, time-sensitive indicators of emerging distress. As a result, educators are advised to integrate real-time behavioral dashboards into instructional workflows, enabling timely, evidence-informed interventions before burnout escalates. System designers are encouraged to embed adaptive emotional feedback mechanisms—such as context-aware encouragement, calibrated pacing adjustments, and reflective prompts—that actively support self-regulation and psychological resilience. Institutions, meanwhile, bear responsibility for developing comprehensive ethical governance structures, including transparent data consent protocols, strict purpose limitation for predictive analytics, and independent oversight mechanisms to ensure equitable, privacy-preserving implementation.

### 6.3. Concluding Remarks

Artificial intelligence presents a paradigm-shifting opportunity to detect, interpret, and proactively address learning burnout by analyzing nuanced patterns in student behavioral data—such as engagement duration, interaction frequency, response latency, navigation pathways, and affective cues captured via multimodal interfaces. Realizing these potential demands rigorous, ethically grounded development frameworks that prioritize student autonomy, transparency, and psychological safety. Sustained interdisciplinary collaboration is essential—not only among educational psychologists, data scientists, and learning platform developers, but also with instructional designers, ethicists, and student stakeholders—to co-design interventions that are pedagogically sound, technically robust, and human-centered. Such integration ensures that technological innovation serves authentic educational well-being rather than merely optimizing for metrics or efficiency.

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