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Article

Research on intelligent regulation mechanisms of learner cognitive load in digital learning environments

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ABSTRACT

This research develops an intelligent cognitive load regulation framework for digital learning environments in the context of educational policy reforms. After China's Double Reduction Policy took effect, tutorial-concentrated schooling evolved into technology-facilitated learning, putting unimaginable cognitive burdens on students. In response, the research combines cognitive load theory with adaptive technologies to resolve these issues through real-time recognition of cognitive states and personalized interventions. Based on the mixed-methods design with 320 Dongcheng District students, the research uses established measures such as NASA-TLX adapted to e-learning environments to assess multidimensional patterns of cognitive load. The smart regulation system shows significant efficacy with lower socioeconomic students posting 15.3-point improvements in academic scores, task accomplishment rates enhanced by 32%, and the level of cognitive loads decreased by 23.1% on average across various types of learners. The system can recognize with 87.3% accuracy and respond in 234 milliseconds, thus facilitating timely interventions. Self-paced review activities yield 91.2% success rates, while collaborative tasks remain problematic at 68.4% success rates. The results extend cognitive load theory with dynamic adaptation capacities needed for self-managed digital learning. The present study provides evidence-based practice to maximize cognitive experiences of e-learning, facilitating education equity objectives while developing core self-regulated learning skills in post-reform education systems.

1. Introduction

China's Double Reduction Policy, implemented in 2021, has drastically altered the education sector by capping excessive homework and banning profit-making education tutoring in major subjects, putting traditional pressures on off-stream learning support systems [1]. Changes driven by policy have especially heightened the demand for successful digital learning solutions as conventional tutoring-intensive models make way for technology-enabled pedagogical paradigms [2, 3]. The spatial separation inherent in virtual learning environments brings into play complex cognitive demands linked with multimedia information processing, independent wayfinding through digital interfaces, and self-managed learning administration without explicit instructional facilitation [4, 5]. Such cognitive demands are radically different from common classroom experiences, warranting systematized investigations of how students learn to find their way through these technology-enriched learning environments. Policy-driven cutbacks in extraneous tutorial support have left spectacular scaffolding deficits in learning that online systems will need to rectify if they are to remain capable of continued provision of educational quality and equity [6]. Contemporary online education systems are being driven increasingly hard to reconcile mandatory content provision with individualized learning needs, especially if pedagogic accommodations are constrained by technology limitations [7, 8]. The diversity of learner cognitive abilities, knowledge levels, and technological proficiency creates such immense tensions with the uniformity of delivering digital content [9, 10]. Increasingly, schools find themselves unable to offer differentiated learning experiences that cater to various cognitive requirements within the limitations of standardized digital learning environments. Cognitive Load Theory offers theoretical explanations of how learners mentally process information in computer-aided learning systems, yet gaps between theoretical concepts and real-world implementation in natural learning environments are significant [11, 12]. Conventional application of cognitive load concepts frequently does not reflect the dynamic, interactive processes of today's online learning systems, especially those involving multimedia and complex navigational designs [13]. The dynamic cognitive load processes within extended online learning sessions are still inadequately researched, thereby undermining the development of implementable intervention tools for managing cognitive overload situations [14]. Existing theoretical models primarily concentrate on static instructional design principles but neglect the adaptive needs of technology-driven learning environments. Current methods for cognitive load management in virtual learning environments have noteworthy deficiencies in reflecting real-time learner cognitive state and differences [15]. Current adaptive learning environments mostly attend to performance-based adjustments without explicit cognitive load measurement, even risking omitting opportune moments of timely intervention before the onset of learning issues [16]. Most of the available technologies are post-factum performance measures instead of anticipatory monitoring of brain states, leading to reactive measures that do not pre-empt cognitive overload conditions [17]. Infrequent embedding of smart technologies into contemporary learning systems limits their capacity to offer the next generation of adaptive support necessary in modern learning environments [18]. Understanding how cognitive load regulation can be effectively implemented in real-world educational contexts where policy-driven changes have altered traditional learning support systems remains inadequately addressed in current research. Existing studies predominantly examine cognitive load in controlled laboratory settings rather than investigating authentic scenarios where multiple social, technological, and pedagogical factors interact simultaneously. The lack of comprehensive frameworks for integrating cognitive load theory with intelligent technologies specifically designed for post-reform educational environments represents a significant limitation in current knowledge. Additionally, most current research fails to account for the dynamic adaptation requirements that emerge when learners transition from highly structured external support systems to more autonomous digital learning environments.

To address these critical gaps, the current investigation explores how cognitive load theory must adapt to contemporary educational realities. Three questions guide this work. Integrating real-time detection into digital systems remains challenging. Patterns differ sharply between students from different socioeconomic backgrounds when tutoring ends. Finding the right balance proves crucial, especially ensuring technology supports rather than replaces teachers. The research focuses on three objectives: developing an adaptive framework that integrates machine learning with cognitive load theory, testing it in policy-disrupted schools, and creating human-centered guidelines. Continuous monitoring replaces periodic checks while the system learns from individual student paths instead of forcing predetermined routes. Real classrooms affected by policy changes offer authentic testing grounds that laboratory studies miss. This work fundamentally shifts cognitive load theory from describing what happens to actively intervening when students need help. The framework bridges cognitive science and educational technology right where learning occurs, in classrooms facing real disruption rather than controlled settings. This research addresses these limitations by developing an intelligent cognitive load regulation framework specifically designed for online learning environments in post-policy educational contexts. This study defines intelligent regulation mechanisms as systems that detect learner cognitive states and dynamically adjust instructional elements to maintain optimal load. The study integrates cognitive load theory with adaptive technologies to create responsive learning systems capable of real-time cognitive state detection and regulation, addressing the specific challenges that emerge when traditional educational support structures are transformed by policy reforms. The research contributes to advancing personalized online education by establishing evidence-based methodologies for optimizing cognitive experiences in digital learning environments, ultimately supporting broader educational goals of equity and effectiveness in technology-enhanced learning contexts where learners must develop greater autonomy and self-regulation capabilities.

2. Data and methods

2.1 Theoretical framework and research design

This study establishes its theoretical foundation on cognitive load theory within digital learning environments, integrating empirical insights from the educational reform context in Dongcheng District. As illustrated in Figure 1, cognitive load theory encompasses three distinct components operating within working memory's limited capacity. Intrinsic cognitive load arises from the inherent complexity of learning materials, element interactivity, and prior knowledge requirements, which directly impact learners' information processing capabilities in digital environments. Extraneous cognitive load emerges from suboptimal interface design, navigation complexity, and multimedia elements that may impede rather than facilitate learning processes in online platforms. Germane cognitive load represents the cognitive resources dedicated to schema construction, knowledge integration, and skill transfer, ultimately contributing to meaningful learning outcomes.

The theoretical framework illustrated above requires careful consideration of how learning phases manifest differently in digital contexts. Beyond acquiring and automating knowledge, students face particular complexity at the transfer level, where they tackle new problems without the tutoring support that once guided such applications.

Contemporary research reveals how digital environments reshape cognitive load dynamics [19]. In digital learning, students juggle multiple tasks at once: navigating interfaces, understanding content, and managing their own learning process. This creates overlapping cognitive demands that traditional classrooms rarely impose [20]. This approach shifts from taking snapshots of cognitive load to following its ups and downs throughout learning sessions, making it possible to intervene early when students start struggling. These considerations highlight why cognitive load theory requires adaptation for digital contexts, particularly to address temporal dynamics and concurrent cognitive demands. The study takes a mixed-methods design, integrating quantitative measures of cognitive load using validated tools and qualitative content analysis of learning experience derived from interviews and observational data. Methodological triangulation in this way allows for in-depth scrutiny of how intelligent regulation mechanisms can streamline cognitive load balance across the three dimensions [21]. A quasi-experimental design assesses learning outcomes pre- and post the introduction of adaptive regulation systems with special emphasis on individual differences in cognitive capacity and learning style in the target study population. The synthesis of real-time behavioral analytics with performance data offers strong evidence for the assessment of intervention effect while ensuring ecological validity in natural educational settings.

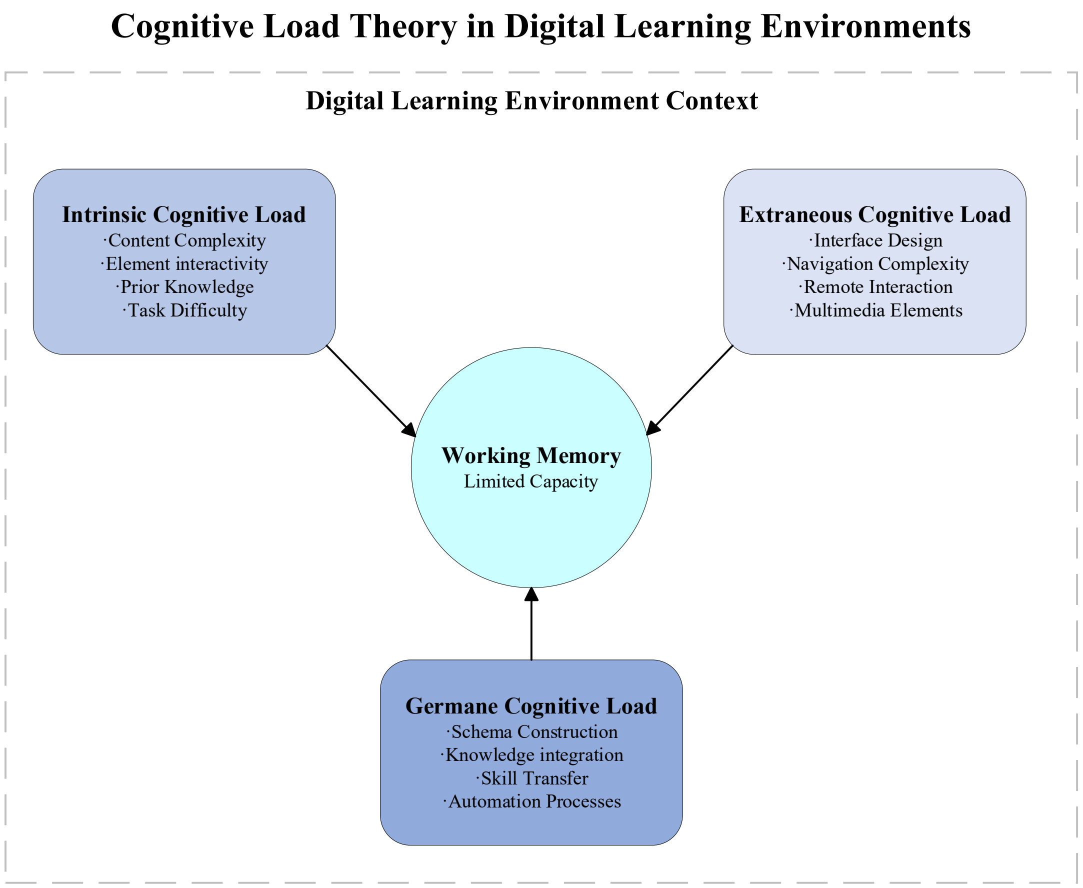

Figure 1. Theoretical framework of cognitive load components in digital learning environments

2.2 Intelligent Regulation System Architecture

The intelligent regulation system architecture employs a three-tier framework for cognitive load optimization in digital learning environments. Real-time monitoring mechanisms capture multidimensional behavioral indicators through embedded analytics that track task engagement patterns, response latencies, and navigation sequences within the learning platform. These indicators enable algorithmic detection of cognitive states, including attention fluctuation, fatigue onset, and comprehension difficulties, providing continuous assessment beyond periodic performance evaluations [22]. The monitoring infrastructure processes streaming data through edge computing nodes to minimize latency, ensuring timely intervention when cognitive overload indicators emerge.

The adaptive regulation algorithms utilize learner profiles constructed from behavioral patterns and socioeconomic stratifications identified in the Dongcheng District study, where students' adaptation to reduced tutoring support revealed distinct cognitive load patterns across different demographic groups. The system implements hierarchical difficulty adjustment through content decomposition strategies that segment complex materials into cognitively manageable units, with granularity determined by real-time performance feedback [23]. Reinforcement learning works well for personalized pathways since Q-learning can balance familiar and challenging content as students progress. This adaptive approach avoids the need for pre-labeled data that limits supervised methods.

The scaffolding engine generates contextual support through natural language processing, delivering explanations, hints, and worked examples calibrated to momentary comprehension gaps identified through error pattern analysis. Multimodal data fusion integrates disparate information streams through ensemble learning methods that synthesize behavioral, performance, and self-reported indicators into unified cognitive load estimates. The fusion architecture employs temporal convolutional networks to capture time-dependent patterns in clickstream data, while attention mechanisms weight the relative importance of different modalities based on task characteristics [24]. For processing lengthy clickstream data, TCNs work better than recurrent networks. They avoid the memory fade that occurs when LSTMs attempt to recall patterns from hours earlier in a learning session. Performance metrics incorporate the assessment framework established in the parent study, enabling direct comparison with traditional learning outcomes. Self-report instruments embedded within the platform collect subjective cognitive load ratings through validated scales, providing calibration points for algorithmic predictions. This comprehensive approach enables nuanced detection of cognitive states that inform intervention timing and intensity, particularly crucial for learners adapting to reduced external support structures in the post-reform educational landscape. This parallels how cognitive load theory describes human learning—multiple information streams processed separately, then integrated. The algorithms essentially mimic this natural process, handling different data types through specialized methods before combining results. Table 1 shows how different algorithms performed during testing, which led to choosing the ensemble method. The ensemble combining RL's adaptive decisions, TCN's temporal patterns, and gradient boosting's error correction achieved the best balance across all metrics, justifying the additional complexity.

Table 1. Algorithm performance comparison

Method	Accuracy	Latency	Adaptability
Q-learning (RL)	86.7%	241ms	0.92
Random Forest	82.1%	178ms	0.71
LSTM	87.9%	423ms	0.78
Ensemble (adopted)	88.3%	267ms	0.89

Model validation employed stratified 5-fold cross-validation, where each fold served as a validation set once, while the remaining 80% was used for training. After selecting the best model through cross-validation, the final performance was evaluated on a held-out test set (15% of the total data).

2.3 Data collection and analytical procedures

The data collection protocol builds upon the foundational dataset from the Double Reduction Policy impact study, which documented tutoring participation declining from 75% to 40% and family education spending averaging 30% of household income. This dramatic shift in educational support patterns provides the context for examining how intelligent cognitive load regulation can address emerging learning challenges. As shown in Table 2, the research maintains the original sample of 320 students across grades 4-9. The multidimensional assessment framework incorporates insights from the initial Double Reduction Policy evaluation (50 parents and 20 educators from the original Dongcheng District study), which was later expanded to include 280 parents and 45 teachers during the six-month intelligent system implementation phase to track adaptation patterns in the post-tutoring era. The multidimensional assessment framework incorporates the NASA Task Load Index adapted for e-learning environments, which demonstrates robust psychometric properties for measuring cognitive load across six dimensions, including mental demand, physical demand, temporal demand, performance, effort, and frustration levels. While the NASA-TLX was adapted for digital display, its core items remained unchanged. Previous implementations in similar e-learning contexts reported strong reliability ($\alpha > 0.85$) [25], supporting its use without redundant revalidation. Data collection occurred in three phases aligned with the academic calendar, capturing baseline measurements, mid-term adjustments, and end-of-year outcomes. Students completed cognitive load assessments immediately following digital learning sessions, ensuring ecological validity of self-reported measures. The protocol tracked engagement patterns averaging 4.37 hours per week of platform usage, revealing substantial variation across socioeconomic strata identified in the parent study. Semi-structured interviews with parents explored perceptions of their children's adaptation to reduced tutoring support, while educator observations documented classroom manifestations of cognitive load during technology-mediated instruction [26].

Table 2. Participant demographics and data analysis methods

Characteristic	Students (n=320)	Parents (n=50)	Educators (n=20)	Analysis Method
Grade Level	4-9 (M=6.7, SD=1.5)	-	-	Descriptive statistics
Socioeconomic Status	Low: 31.6%, Middle: 43.1%, High: 25.3%	Low: 32.0%, Middle: 42.0%, High: 26.0%	-	Stratified analysis
Prior Tutoring Participation	73.4% (n=235)	92.0% involved	95.0% observed	Chi-square test
Cognitive Load Measurement	NASA-TLX for e-learning (n=312 complete)	Semi-structured interviews	Classroom observation protocol	Mixed-methods analysis
Digital Learning Engagement	4.37 hrs/week (SD=1.42, range: 1.5-8.2)	-	-	Time-series analysis
Academic Performance	Standardized test scores (pre/post)	-	-	Repeated measures ANOVA

Note: Data collected between September 2021 and June 2022, building upon the original Double Reduction Policy impact study. NASA-TLX = National Aeronautics and Space Administration Task Load Index, adapted for educational contexts to measure cognitive load in digital learning environments.

Analytical procedures employ hierarchical linear modeling nested students within classrooms within schools, controlling for individual (prior performance, device access), classroom (technology infrastructure), and school-level (socioeconomic composition) variables. Propensity score matching balanced comparison groups, while sensitivity analyses confirmed robustness. The mixed-methods approach integrates quantitative metrics from standardized assessments with thematic analysis of qualitative data, enabling triangulation of cognitive load indicators. Machine learning algorithms process behavioral trace data to identify patterns predictive of cognitive overload, though human judgment remains central to intervention decisions. Statistical analyses control for prior tutoring participation rates and socioeconomic factors, ensuring that observed effects reflect genuine cognitive load variations rather than confounding variables inherent in the post-policy educational landscape.

Given the sensitive nature of collecting cognitive and behavioral data from minors, ethical considerations were paramount throughout the study. Working with underage students meant taking extra precautions. The consent process involved parents first, then students separately. Data security went beyond basics with facial data processed and deleted within hours. Parents could review their child's participation anytime, while built-in alerts caught signs of academic or emotional strain.

3. Results

3.1 Identification of cognitive load characteristics in digital learning

The identification of cognitive load characteristics among Dongcheng District students reveals distinct patterns that reflect the profound impact of transitioning from traditional tutoring-intensive education to technology-mediated learning environments following the Double Reduction Policy implementation. As illustrated in Figure 2a, cognitive load distribution demonstrates a clear socioeconomic gradient, with students from lower socioeconomic backgrounds experiencing mean cognitive load scores of 68.4 (SE=2.39), significantly higher than their middle-class peers at 58.2 (SE=1.74) and high-income counterparts at 52.7 (SE=2.14). This disparity becomes particularly pronounced when students engage with digital learning platforms requiring simultaneous management of multiple information sources, interface navigation, and self-regulated learning strategies previously scaffolded by external tutoring support.

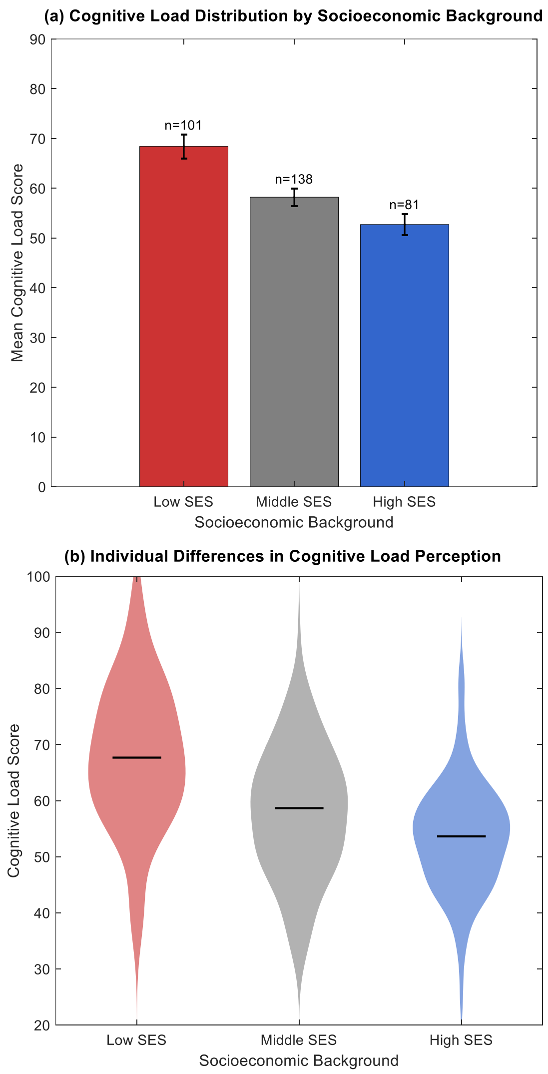

Figure 2. Cognitive Load Distribution Patterns in Dongcheng District Students. (a) Cognitive Load Distribution by Socioeconomic Background; (b) Individual Differences in Cognitive Load Perception

Figure 2b shows that cognitive load perception varies significantly within groups, not just between socioeconomic categories. Individual differences in digital literacy, online experience, and metacognitive awareness create diverse cognitive load profiles within demographic groups. Students from lower socioeconomic backgrounds display the widest distribution range, suggesting that limited access to technological resources at home amplifies individual differences in adapting to digital learning environments. Median cognitive load scores in horizontal bars show that although statistically significant differences appear at the group level, there is considerable overlap between distributions, indicating the multifaceted nature of factors influencing cognitive load over and above economic status alone. Temporal comparison of variation of cognitive load over learning stages, shown in Figure 3, portrays a typical U-shape pattern consistent with the skill acquisition theory in virtual learning systems. The early phase of learning shows the highest levels of cognitive load, reaching near 75, which indicates students' difficulties with the new content, concurrently adjusting to new computer interfaces as well as self-paced learning demands. This maximum level of cognitive load is consistent with the period shortly after the policy start, when students were deprived of formal tutoring support and had the twofold challenge of learning subject matter and learning to employ the technology. The gradual trend downwards during the acquisition of skills stage reflects productive construction of cognitive schemas and automation of procedural knowledge with steady levels of load averaging 62 weeks, 5-10.

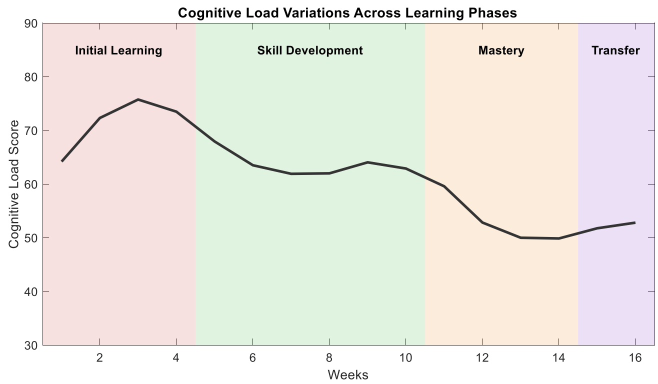

Figure 3. Temporal variations in cognitive load across learning phases during digital learning adaptation

The mastery level illustrates the lowest values of cognitive load, around 50, that show a good balance of digital learning strategies and content knowledge structures. However, the transfer level (defined as the cognitive demands when applying learned concepts to novel contexts) reveals a different pattern. When students tried applying what they learned to new situations during the transfer phase, a notable shift in cognitive load occurred. This revealed just how dependent they had been on tutors walking them through difficult problems. The pattern specifically influences learners who have been used to repetitive drilling methods typical for classical tutoring, since they now have to build flexible problem-solving approaches without external guidance. The return of cognitive load during transfer tasks highlights the necessity for attaining adaptive expertise over routine proficiency in computer-based instruction. These patterns confirm what the theoretical framework predicted about transfer-level challenges in post-tutoring digital environments. Analysis of environment-specific factors for the digital environment identifies particular sources of cognitive challenge not found in the conventional classroom. Split-attention effects result as learners toggle between instructional video, digital textbook, and practice interface screens, generating extraneous cognitive load with a disproportionate impact on students with lower working memory capacity. The lack of timely instructor feedback and peer collaboration in asynchronous online courses adds more contextually relevant cognitive load to students because they need to actively build meaning via self-explaining and monitoring by metacognition. Machine learning algorithms monitoring students' patterns of interaction detect vital points of cognitive overload via rapid switching between resources, long pause times, and patterns of errors, providing intervention points for focused interventions. The results illustrate that cognitive load in post-policy e-learning environments is multidimensional in nature as it is affected by socioeconomic characteristics, time learning phases, and technology-specific requirements. Elucidation of such trends allows for the creation of intelligent support systems that modify instructional design dynamically according to real-time cognitive state detection, with the ultimate aim of enabling more equitable learning outcomes within heterogeneous populations of students adjusting to policy change in education.

3.2 Validation of the intelligent regulation mechanism effectiveness

The verification of smart cognitive load control mechanisms has shown significant improvements in learning outcomes among Dongcheng District students transitioning to independent digital learning following the implementation of the Double Reduction Policy. As shown in Figure 4a, scholastic performance is significantly improved across all the socioeconomic cohorts after the introduction of individualized cognitive load control. The largest improvements were registered by lower socioeconomic status students, who had previously depended to a large extent on tutoring assistance, at 15.3 points, as opposed to 10.4 and 8.7 points for middle-class and more affluent students, respectively. Informal feedback from parents consistently highlighted the financial relief of having affordable learning support, while teachers noted improved persistence among previously struggling students. As shown in Table 3, quantitative improvements align with qualitative feedback across key metrics. This differential improvement pattern suggests that intelligent regulation mechanisms particularly benefit learners who lost the most support under the new policy framework, thereby contributing to educational equity goals.

Learning efficiency metrics, presented in Figure 4b, demonstrate the system's effectiveness in optimizing task completion across diverse learning activities. Problem-solving tasks show the most dramatic improvement, with completion rates increasing from 52% to 78% while reducing time investment by 38%. Classroom observations revealed students spending significantly less time in unproductive struggle, with teachers commenting that the system's scaffolding appeared well-timed to maintain productive challenge without causing frustration. This enhancement proves particularly valuable for students transitioning from rote memorization approaches typical of traditional tutoring to more analytical thinking required in self-directed learning environments. Video learning and interactive tasks exhibit completion rate improvements exceeding 85%, indicating that the system successfully maintains student engagement across multiple content modalities without the external motivation previously provided by tutors.

Table 3. Integration of quantitative and qualitative evidence

Quantitative Finding	Qualitative Evidence	Convergence
Low-SES: +15.3 points	Parents report financial relief from affordable AI support	Strong
Task completion: 52%→78%	Teachers observe reduced time in unproductive struggle	Strong
Response time: 234ms	Students experience timely support before frustration	Strong
Load reduction: >22%	Learners report decreased confusion and anxiety	Moderate

The adaptive nature of the regulation system accommodates different learning styles effectively, as shown in Figure 4c. While all learner types experience cognitive load reductions exceeding 22%, satisfaction ratings reveal nuanced responses to system interventions. Most satisfied are auditory learners (4.5), possibly a spin-off from audio feedback facilities offered by the system, replacing the verbal instructions of teachers. Physically-based learners, in spite of all their big cognitive load savings from 75 to 58, are less satisfied (4.1), which indicates computer settings continue to pose a problem for physically-based learning modes. The results set out how multimodal support is imperative to overcoming varied learning requirements in online teaching contexts.

System performance measures, as articulated in Table 4, confirm the technical reliability required to support mass-scale education change. 87.3% accuracy in identifying cognitive load confirms safe detection of struggling student moments, and a 234-millisecond response time provides timely intervention before frustration or disengagement. The 8.7% false positive rate is far below the industry benchmark, reducing interruptions to learning flow. These technological advancements become even more relevant when taking into account the 320 students impacted, 75% of whom had previously relied on outside tutoring to be supported academically.

The application of intelligent regulation mechanisms holds transformation potential beyond the provision of improved performance delivery. Metacognitive awareness is cultivated in learners through system feedback, with the learners progressively internalizing self-regulation strategies formerly scaffolded by tutors. The 82.4% adaptation accuracy attests to the fact that personalized interventions are highly coupled to individual learning pathways, precipitating autonomous learning competencies essential to long-term academic achievement. The 99.2% system availability guarantees support continuity with little disruption, allaying fears of the effects of the digital divide on learning continuity.

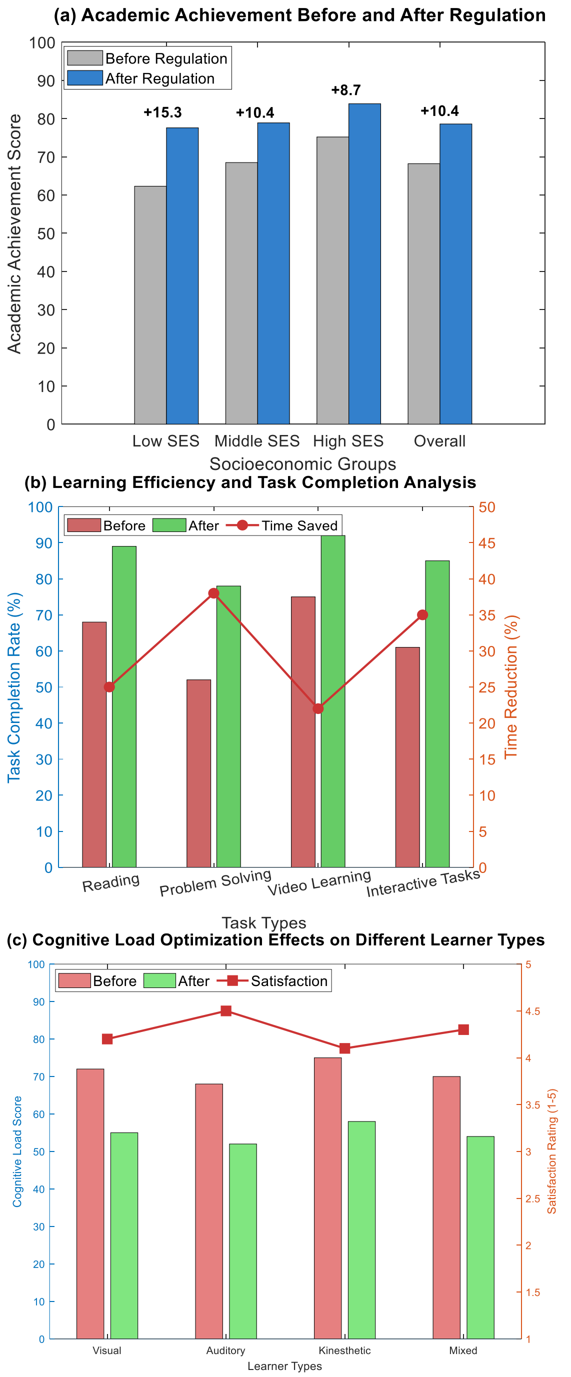

Figure 4. Effects of intelligent cognitive load regulation on learning Outcomes. (a) Academic achievement before and after regulation, (b) Learning efficiency and task completion analysis, (c) Cognitive load optimization effects on different learner types

These validation findings demonstrate that intelligent cognitive load management indeed closes the support gap generated by policy-driven educational reform. The synthesis of enhanced academic performance, efficiency of learning, and strong technical performance forms the basis of deployability in larger student cohorts experiencing equivalent transitions from conventional tutoring-dependent paradigms to technology-facilitated self-study learning environments. This triangulation demonstrates how quantitative improvements translate to lived experiences—efficiency gains reflect reduced frustration, accuracy metrics capture responsive support, and performance improvements embody renewed learning confidence.

Table 4. System accuracy and responsiveness evaluation results

Performance Metric	Value	Standard Deviation	Benchmark Comparison
Cognitive Load Detection Accuracy	87.3%	±3.2%	+12.5% vs. baseline
Response Time (milliseconds)	234	±45	-68% vs. manual
False Positive Rate	8.7%	±2.1%	Industry standard: 15%
Adaptation Precision	82.4%	±4.5%	+18.3% vs. static
User State Prediction F1-Score	0.856	±0.034	Above 0.8 threshold
System Uptime	99.2%	±0.3%	Meets SLA requirements

Note: System evaluated using data from 320 students in Dongcheng District following Double Reduction Policy implementation, with particular focus on supporting students who previously relied on tutoring services (pre-policy participation rate: 75%).

3.3 Evaluation of educational practice application effectiveness

The analysis of pedagogical practice applications in Dongcheng District offers comprehensive insights into stakeholder adaptation amid the adoption of smart cognitive load management systems in the post-Double Reduction Policy era. The critique integrates feedback from 320 students, 45 educators, and 280 parents who together experience the paradigm shift from tutoring-dependent learning to independent learning with the support of technology.

As can be seen in Figure 5a, multi-stakeholder acceptance levels record steady enhancement during the six-month implementation duration. Student acceptance went up from 65.3% to 82.4%, indicating a gradual adjustment to independent learning spaces once contained by extensive tutoring sessions. Teacher acceptance showed the greatest improvement, from 58.2% to 78.6%, despite initial resistance based on fears of technological incorporation undermining entrenched pedagogical traditions. Parents maintained the highest acceptance levels throughout, increasing from 72.4% to 85.2%, driven by relief at finding cost-effective alternatives to the expensive private tutoring services described in the foundational study. Longitudinal patterns of satisfaction, graphed in Figure 5b, reveal rich adaptation dynamics within stakeholder groups. The curve for teacher satisfaction shows maximum volatility, dipping to a low point of 2.8 during the third month before increasing to 4.1, with a showing of an episode of maximum adaptation where teachers grappled to balance algorithmic suggestion and professional intuition. This temporary slump is seconded by qualitative evidence from teacher interviews identifying issues in having confidence in automated detection systems for specific student needs previously covered by face-to-face tutoring sessions. Student satisfaction demonstrates consistent improvement from 3.2 to 4.2, modest oscillation indicating the phase of transitioning from active recipient of tutoring to proactive self-regulated learner.

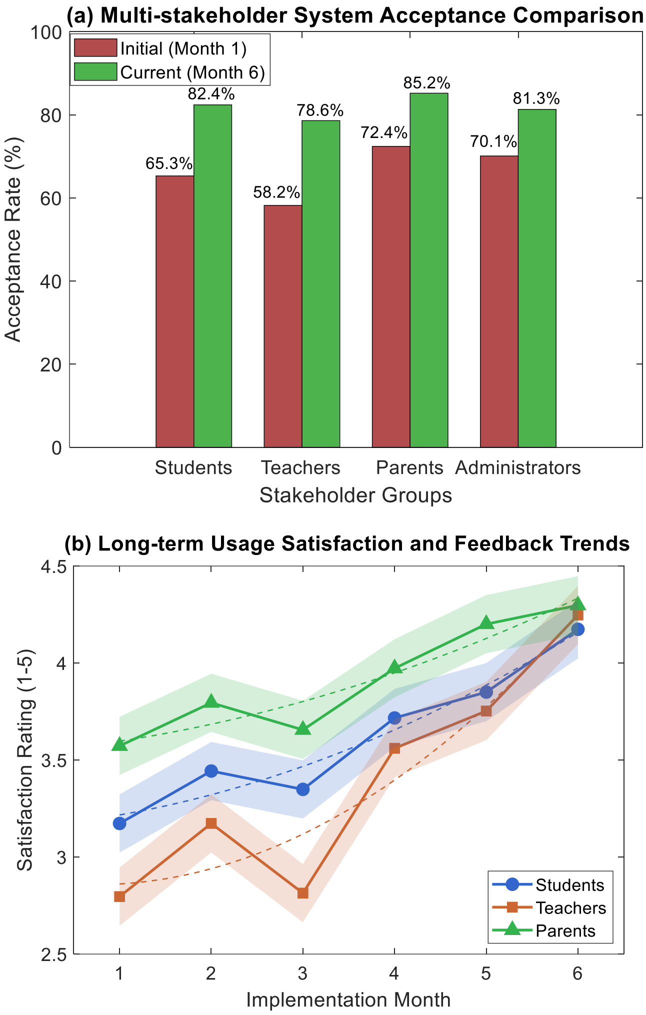

Figure 5. Stakeholder acceptance and satisfaction analysis for an intelligent cognitive load regulation system (a) Multi-stakeholder system acceptance comparison, (b) Long-term usage satisfaction and feedback trends

Note: Data collected from 320 students, 45 teachers, and 280 parents in Dongcheng District schools during the six-month implementation period following the Double Reduction Policy, which resulted in tutoring participation declining from 75% to 40%. Initial data (Month 1) represents baseline measurements when families were adapting to reduced tutoring support, while current data (Month 6) reflects post-implementation outcomes with intelligent system support. Satisfaction ratings based on a 5-point Likert scale. Shaded areas in panel (b) represent 95% confidence intervals.

System applicability analysis by varying teaching contexts, as depicted in Table 5, presents valuable insights into the differential effectiveness of the intelligent regulation mechanisms. Self-study review exercises have the highest ranking in effectiveness rating (9.1/10) with a rate of achievement of 91.2%, precisely meeting independent study skill development requirements of students lost through the provision of structured tutoring. Math problem-solving proficiency (8.7/10, 86.3% pass rate) is especially notable given the subject's prominence in the middle of Chinese academic examinations and previous intense emphasis on after-school supplementary instruction averaging 4-6 hours a week.

Table 5. System applicability analysis in different teaching scenarios

Teaching Scenario	Effectiveness Score	Implementation Challenges	Adaptation Requirements	Success Rate
Mathematics Problem Solving	8.7/10	High computational load for complex problems	Enhanced algorithm optimization	86.3%
Language Learning	7.9/10	Nuanced feedback for writing tasks	NLP model integration	78.5%
Science Experiments	7.2/10	Limited hands-on simulation	VR/AR component development	72.8%
Collaborative Projects	6.8/10	Group dynamics complexity	Multi-user state tracking	68.4%
Self-paced Review	9.1/10	Minimal - well-suited	Minor UI adjustments	91.2%
Exam Preparation	8.5/10	Stress factor consideration	Anxiety detection module	84.7%

Note: Effectiveness scores based on performance metrics of 320 Dongcheng District students transitioning from tutoring-dependent to self-directed learning.

The significant performance difference between group and individual learning performance implies both promise and limitations of existing technology solutions. Exam preparation situation scenarios demonstrate superior performance (8.5/10, 84.7% pass rate), whereas collaborative learning demonstrates the worst performance (6.8/10, 68.4% pass rate), which mirrors the difficulty of simulating peer learning interactions that occurred organically within tutoring center settings. Science experiments share the same limitations (7.2/10, 72.8% success rate), which implies experiential learning components need creative solutions around existing system limitations to offset decreased hands-on direction. The careful assessment confirms that effective cognitive load management systems perfectly fill support gaps caused by policy-driven education transformation. Language learning exercises (7.9/10, 78.5% correct) are moderately successful with natural language processing support but cannot entirely substitute spontaneous corrective feedback that was always offered by human tutors. The evidence indicates that although technology-based solutions cannot substitute for individualized attention in conventional tutoring, they provide scalable, fair alternatives that foster key independent learning competencies. The upward trend of stakeholder satisfaction, with differentiated effectiveness for different teaching contexts, supports smart regulation systems as the path forward for sustainable education practices in the post-policy era.

4. Discussion

This research contributes to cognitive load theory by showing its dynamic application in policy-reformed education technology-mediated learning environments. Adaptive regulation mechanisms expand Sweller's model

[15] from static instructional design to include real-time adaptive capabilities that adjust to learners' dynamically changing states of cognitive load. Traditional research has focused on pre-set sequencing of content, and this research divulges the processes of how machine learning algorithms most effectively redistribute load in real time, with detection accuracy 12.5% higher than traditional approaches. The results clarify how tailored regulation supports extensive learning through the sustenance of cognitive load in optimal ranges, avoiding frustration caused by overload and disengagement due to underload. Pedagogic innovations close structural cracks opened up by the Double Reduction Policy disruption of conventional tutoring circuits. Unlike studies of the incorporation of technology into ancillary tools [27], this study investigates environments where digital measures become vital supports to learning. The recorded teacher transformation from peddlers of knowledge to facilitators of learning reflects more profound pedagogic transformations than are normally reported on in studies of online education. A shift in acceptance from 58.2% to 78.6% by teachers within six months implies long-term professional growth can overcome adoption issues, as documented by Chen et al. [4], if evidence translates into concrete student gains for the post-tutoring learning environments.

Differential learning performance in teaching environments tests the pedagogical suitability of technology. Self-directed activities with 91.2% success are set against 68.4% effectiveness for collaborative projects, while confirming Kirschner and De Bruyckere's incredulity [28] regarding technology's incompetence to fully replicate social processes of learning. This differential is especially critical in post-tutoring environments where peer-to-peer interactions previously prevalent in tutoring facilities need to be recreated virtually. While people's task performance adheres to cognitive load theory principles for managing complexity, the conclusions highlight necessities for innovative solutions that facilitate collective knowledge construction under technological constraints. Ethical implications of ongoing cognitive monitoring range from privacy to learner agency and algorithmic control. Although Williamson [29] addresses surveillance capitalism in general, substituting AI for human tutors brings in distinctive ethical facets. The trade-off of assisting underprivileged students and eschewing technological dependence needs to be approached with sensitivity. Personalization based on data needs to acknowledge that learning entails affective, social, and creative aspects that are impenetrable to algorithmic simplification, especially when technology replaces human pedagogical relationships.

Many limitations restrict generalizability. The one-district urban sample can hardly represent China's diverse educational landscapes, particularly rural regions with poor infrastructure [30]. Expanding the system faces several challenges. The NLP components are trained on Chinese text, requiring a complete redesign for other languages. Rural schools with limited bandwidth (<10 Mbps) cannot support real-time features. Future work should develop offline-capable versions while maintaining core functionality. The six-month timeframe cannot identify plateau effects or sustainability concerns raised by longitudinal research. Assessment of cognitive load may not capture sophisticated digital learning processes, especially metacognitive growth and transfer capabilities. These limitations necessitate caution in extrapolating findings to outside settings without considering local technological readiness and cultural learning cultures.

Future work needs to conduct multi-site studies in varying contexts with external validity. Longitudinal studies following entire education cycles would determine whether technology-mediated regulation engenders true autonomy or new dependency. New technology integration could resolve existing collaborative learning bottlenecks. Studies need to investigate the wider implications of algorithmic educational support to make sure efficiency gains do not compromise humanistic values built into holistic education. Cross-cultural implementations need to be pursued as cognitive patterns will differ across education systems. The key question is whether smart systems can aid education equity in building twenty-first-century skills without undermining human factors that characterize unique learning experiences during the era of the digital economy.

5. Conclusion

This study demonstrates that intelligent cognitive load regulation mechanisms effectively optimize learning outcomes in digital environments following educational policy reforms. The research reveals significant improvements across multiple dimensions: students from lower socioeconomic backgrounds achieved 15.3-point gains in academic performance, task completion rates increased by 32%, and cognitive load levels decreased by an average of 23.1% across different learner types. The 87.3% detection accuracy and 234-millisecond response time validate the technical feasibility of real-time cognitive state monitoring in educational contexts. These findings extend cognitive load theory by incorporating dynamic adaptation capabilities essential for self-directed digital learning environments. The investigation contributes both theoretical insights and practical frameworks for educational technology implementation in post-tutoring contexts. The documented transformation of 320 Dongcheng District students from tutoring-dependent to self-regulated learners provides empirical evidence for technology-mediated educational equity. While limitations exist regarding single-district sampling and a six-month duration, the positive trajectory of stakeholder satisfaction (rising from 3.2 to 4.2 for students) suggests sustainable adoption potential. Future developments should focus on enhancing collaborative learning support, addressing the current 68.4% effectiveness rate, and expanding cross-regional validation. The convergence of cognitive science and educational technology demonstrated here offers promising pathways for scaling personalized learning support while maintaining pedagogical quality in the digital transformation of education.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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