REAL-TIME MONITORING OF COGNITIVE COLLAPSE IN GEOMETRIC REASONING: AN ANALYSIS OF BEHAVIORAL MICROMETRICS

Khakimov Utkirbek Ilxomjon ugli[1]
Azimov Akmaljon Axmadjon ugli[1]
Obidova Rayhona Axmadjon qizi[1]
[1]*Namangan State Pedagogical Institute, Uzbekistan*

DOI: **https://doi.org/10.5281/zenodo.20215184**

Abstract. *This study examines the trends of cognitive decline and task abandonment during geometric problem-solving. It introduces the concept of Geometric Reasoning Collapse (GRC)—a state where a student transitions from a systematic logical approach to disorganized, purposeless attempts. Leveraging telemetric data from 47,840 sessions in the GeoGebra environment, a lightweight AI model was developed to identify GRC with 84.3% accuracy, approximately 4 minutes before complete task cessation. Experimental trials involving 312 students in Uzbekistan demonstrated a 41% reduction in task abandonment and a 52% decrease in geometry-related anxiety.*

Keywords: *geometric reasoning collapse, behavioral micrometric analysis, AI early-warning system, GeoGebra, cognitive monitoring, geometry education, real-time prediction, cognitive stagnation, productive failure theory.*

Annotatsiya: *Ko'pchilik ta'limdagi sun'iy intellekt tadqiqotlari "SI o'quvchilarga o'rganishga qanday yordam beradi?" degan savolga javob izlaydi. Ushbu maqola boshqacha savol qo'yadi: "SI o'quvchining geometrik tafakkuri buzila boshlaganini — o'zi sezmasidan oldin — aniqlay oladimi?" Biz Geometrik fikrlash buzulishi (GRC) kontseptsiyasini kiritamiz — bu o'quvchining masala yechish yo'nalishi tizimli mantiqiy taraqqiyotdan tartibsiz sinov-xatoga o'tishi bilan tavsiflanadigan o'lchov mumkin bo'lgan kognitiv holat. GeoGebra muhitidagi o'quvchi xatti-harakatlarining mikrometrikalarini tahlil qilish (BMA) orqali biz GRC boshlanishini kuzatilishi mumkin bo'lgan passivlikdan 4 daqiqa oldin 84,3% aniqlik bilan bashorat qiluvchi yengil AI modeli ishlab chiqdik. O'zbekistonda 7–11-sinf o'quvchilarining 312 nafarida sinovdan o'tkazilgan model o'qituvchilarga proaktiv aralashish imkonini berdi — topshiriqni tark etish ko'rsatkichini 41% ga kamaytirdi va isbotlashni yakunlash ko'rsatkichini 52 % ga oshirdi.*

Kalit so'zlar: *geometrik mulohaza yuritish kollapsi, xulq-atvor mikrometrikalari tahlili, SI erta ogohlantirish tizimi, GeoGebra, kognitiv monitoring, geometriya ta'limi, real vaqt rejimida bashorat qilish, kognitiv turg'unlik, samarali muvaffaqiyatsizlik nazariyasi.*

Аннотация: *В данном исследованиианализируются тенденции когнитивного снижения и отказа от выполнения заданий в процессе решения задач по геометрии. Вводится понятие «Коллапса геометрического мышления» (GRC) — состояния, при котором учащийся переходит от систематического логического подхода к беспорядочным и бесцельным попыткам. На основе телеметрических данных 47 840 сеансов в среде GeoGebra разработана ресурсоэффективная модель ИИ, способная идентифицировать состояние GRC с точностью 84,3% приблизительно за 4 минуты до полного прекращения работы. Эксперимент с участием 312 учащихся в Узбекистане позволил снизить показатель отказа от заданий на 41%, а уровень геометрической тревожности — на 52%.*

Ключевые слова: *коллапс геометрического мышления, анализ поведенческих микрометрик, система раннего предупреждения ИИ, GeoGebra, когнитивный мониторинг, обучение геометрии, прогнозирование в реальном времени, когнитивный тупик, продуктивная неудача*

I. Introduction: The Problem of Detecting Cognitive Crisis

In geometry lessons, it is common to observe a student abruptly transition from active engagement to a state of cognitive stagnation. Teachers typically only notice this when the student puts down their pen or becomes visibly distracted. However, from a cognitive perspective, the process of "task abandonment" begins much earlier. Most current AI research in education focuses on *what* students are learning—adaptive content delivery, automated feedback, and predicting academic failure based on summative test scores. This literature often overlooks the exact moment learning ceases—not in a final grade, but during the real-time problem-solving process.

This study utilizes Artificial Intelligence to identify the initial moments when the thinking process begins to break down (collapse). The research makes three primary contributions:

1. **Formal Definition:** It defines and operationalizes Geometric Reasoning Collapse (GRC) as a measurable cognitive phenomenon.

2. **Micrometric Correlation:** It demonstrates that GRC is preceded by identifiable behavioral micrometrics in digital learning environments.

3. **Proactive AI Model:** It presents an AI model that detects these micrometrics in real-time and alerts the teacher before task abandonment becomes irreversible.

II. Theoretical Framework and Methodology

Geometric proofs place immense demands on working memory [1]. While the Van Hiele model identifies distinct stages in geometric understanding [2], it does not address the cognitive processes that occur when a student encounters a problem slightly beyond their current developmental threshold. Kapur’s (2016) theory of "productive failure" suggests that structured cognitive struggle deepens learning [3]. However, there is an unproductive counterpart—which we term "**unproductive collapse**"—where the gap between task demand and student ability is too wide for self-recovery. In this state, further struggle does not enhance learning; it erodes motivation and amplifies math anxiety.

The empirical basis and methodological approach of the study are as follows:

- **Database:** The study was conducted during the 2024–2025 academic year with 312 students (grades 7–11) from 6 schools in the Namangan region. All sessions took place in GeoGebra Classic 6, configured to record behavioral telemetry at 500 ms intervals.
- **Data Volume:** 47,840 unique student-problem sessions were collected, totaling 2,340 hours of interaction data. Each session was evaluated by two independent experts for GRC events ($\kappa = 0.81$).
- **Feature Analysis:** 23 behavioral metrics were analyzed, including inter-step intervals, repetitive undo-redo cycles, cursor trajectory, and click pressure variability.
- **Algorithm:** Data was processed using the **XGBoost** gradient boosting classifier. The model was trained with a 70/15/15 split and outputs a GRC probability score every 30 seconds.

GRC Operational Definition: The point where a student's trajectory shifts from **Structured Logical Trajectory (SLT) to Random Exploration Pattern (REP).**

- **SLT** is characterized by purposeful construction steps and hypothesis-testing cycles.
- **REP** is characterized by directionless or contradictory steps, repetitive identical actions without modification, and exponentially increasing step intervals.

III. Analysis

Research indicates that GRC typically manifests at the 7.3-minute mark of an average 20-minute task. GRC events were identified in 61.4% of all problem-solving sessions, and 78% of task abandonments occurred immediately following a GRC event—confirming that GRC is a cognitive precursor to failure.

Table 1. Behavioral Micrometric Feature Categories

Category	Key Features	GRC Signal
Temporal	Inter-action interval, acceleration/deceleration of steps, idle periods	Intervals increase >200% within 90 seconds
Repetitive	Undo-redo cycles, construction-deletion loops, identical tool reselection	≥3 identical cycles without modification
Directional	Step entropy score, geometric distance to solution, regression index	Entropy > 0.7 for 5+ consecutive steps
Affective Proxy	Click pressure variance, navigation speed collapse, off-task cursor drift	≥2 simultaneous signals active

One of the most significant findings is the **4.1-minute "Golden Window"**—the time difference between the AI's GRC alert and the student’s observable passivity. When teachers intervened within this window by asking a guiding question, the collapse was averted in **69% of cases**.

IV. Results

4.1. GRC Prevalence and Timing. GRC events were identified in 61.4% of all problem-solving sessions, with a mean onset time of 7.3 minutes into a 20-minute geometry task. Critically, 78% of GRC events preceded task abandonment — confirming that GRC is not merely correlated with failure but is its cognitive precursor.

Table 2. GRC-PE Performance and Intervention Outcomes

Metric	Without GRC-PE	With GRC-PE
GRC detection accuracy	N/A (teacher intuition)	**84.3%**
Mean alert lead time before abandonment	N/A	**4.1 minutes**
Task abandonment rate	48.6%	**28.7% (↓41%)**
Proof completion rate	34.2%	**45.5% (↑33%)**
Teacher intervention timeliness	23% within 3 min	**79% within 3 min**
Student-reported geometric anxiety (post)	High: 44%	**High: 21% (↓52%)**

4.2. The 4-Minute Window. Perhaps the most educationally significant finding was the consistent 4.1-minute gap between GRC-PE alert and observable disengagement. This window is not trivial: in a 45-minute lesson, 4 minutes represents a meaningful intervention opportunity. Teachers who received GRC-PE alerts and intervened within this window reversed the collapse trajectory in 69% of cases — typically with a single targeted question or hint that reoriented the student's reasoning pathway.

4.3. Grade-Level Variation. GRC frequency showed a non-linear relationship with grade level: 7th grade (73.2% session prevalence), 8th grade (68.9%), 9th grade (81.4%), 10th grade (54.1%), 11th grade (47.8%). The spike at Grade 9 corresponds to the introduction of coordinate geometry and trigonometric proofs — a curriculum transition point that presents acute cognitive load challenges. This finding suggests Grade 9 as the highest-priority deployment target for GRC-PE systems.

V. Discussion: Rethinking AI's Role in Geometry Education

The prevailing paradigm positions AI in education as a content optimization system — delivering the right material to the right student at the right time. Our findings suggest a complementary and arguably more urgent role: AI as a real-time monitor of the cognitive processes that determine whether content delivery is even possible.

A student in GRC cannot benefit from adaptive content, personalized hints, or scaffolded problems — because they have already exited the cognitive state required for learning. The intervention must precede the content. This sequencing insight has practical design implications: AI systems in geometry education should prioritize cognitive state monitoring as a prerequisite to content recommendation, not as an afterthought.

The 52% reduction in self-reported geometric anxiety is a finding that warrants particular attention. Geometry anxiety — distinct from general mathematics anxiety — is a documented barrier to long-term STEM engagement [6]. If proactive AI-mediated intervention can interrupt the anxiety-reinforcing cycle of repeated collapse and failure, the implications extend well beyond geometry classrooms.

VI. Conclusion

This paper introduces Geometric Reasoning Collapse as a formally defined, empirically measurable, and predictably detectable cognitive event. The GRC Prediction Engine demonstrates that AI systems can identify the precursors of student cognitive breakdown with sufficient accuracy and lead time to enable meaningful teacher intervention. Deployed in classrooms across Namangan region, GRC-PE reduced task abandonment by 41%, improved proof completion by 33%, and halved the prevalence of geometric anxiety.

We propose that the next frontier for AI in mathematics education is not smarter content delivery — it is smarter cognitive surveillance: systems that watch not what students are learning, but how their thinking is moving, and that sound the alarm before the thinking stops entirely. In a discipline as cognitively demanding as geometry, the ability to catch a student at the edge of collapse may be worth more than any adaptive curriculum the field has yet produced.

References

[1] Pekrun, R., Goetz, T., Titz, W., & Perry, R. P. (2002). Academic emotions in students' self-regulated learning and achievement. Educational Psychologist, 37(2), 91–105.

[2] Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. Cognitive Science, 12(2), 257–285.

[3] Van Hiele, P. M. (1986). Structure and insight: A theory of mathematics education. Academic Press.

[4] Kapur, M. (2016). Examining productive failure, productive success, unproductive failure, and unproductive success in learning. Educational Psychologist, 51(2), 289–299.

[5] D'Mello, S., & Graesser, A. (2012). Dynamics of affective states during complex learning. Learning and Instruction, 22(2), 145–157.

[6] Hembree, R. (1990). The nature, effects, and relief of mathematics anxiety. Journal for Research in Mathematics Education, 21(1), 33–46.

[7] Boaler, J. (2022). Mathematical mindsets: Unleashing students' potential through creative mathematics. John Wiley & Sons.

[8] Jonassen, D. H. (2010). Learning to solve problems: A handbook for designing problem-solving learning environments. Routledge.

[9] UNESCO. (2024). AI Competency Framework for Teachers. Paris: UNESCO. ISBN 978-92-3-100707-1.

[10] Sangwin, C. (2007). A brief review of GeoGebra: Dynamic mathematics. MSOR Connections, 7(2), 36–38.