BRAIN. Broad Research in Artificial Intelligence and Neuroscience
e-ISSN: 2067-3957 | p-ISSN: 2068-0473
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2025, Volume 16, Issue 3, pages: 140-152
Submitted: April 27th, 2025 | *Accepted for publication:* August 11th, 2025

Neuroadaptive Digital Assessment in Mathematics: A Parametric Approach with STACK and AI-Powered Feedback

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Abstract: *The intersection of neuroscience, artificial intelligence (AI), and education is driving a transformative shift in how assessment is conceptualized and delivered. This study presents a neuroadaptive assessment framework for middle school mathematics using the STACK (system for teaching and assessment using a computer algebra kernel) plugin in Moodle. By leveraging symbolic computation, parameterised item generation, and AI-compatible feedback systems, the approach enables scalable, personalised, and cognitively aligned testing environments. Through a quasi-experimental design involving two 8th-grade cohorts, we evaluate the cognitive and logistical benefits of parametric digital testing. Findings reveal enhanced conceptual understanding, increased student engagement, and reduced teacher workload. Additionally, the model aligns with principles of neuroplasticity, adaptive learning, and reinforcement feedback, establishing a neurodidactic foundation for future AI integration in education. This approach is consistent with theoretical principles of neuroplasticity and adaptive learning (Zull, 2002) and provides a scalable pathway toward AI-enhanced assessment.*

Keywords: *neurodidactics*; *parametric testing*; *STACK*; *symbolic computation*; *AI in education*; *formative feedback*; *adaptive learning*; *digital assessment*; *middle school mathematics.*

How to cite: Branoaea, G.C. (2025). Neuroadaptive digital assessment in mathematics: A parametric approach with STACK and AI-powered feedback. *BRAIN. Broad Research in Artificial Intelligence and Neuroscience*, *16*(3), 140-152. https://doi.org/10.70594/brain/16.3/11

1. Introduction

Neuroscience and artificial intelligence (AI) are intersecting in educational innovation, particularly in the design of instructional ecosystems that adapt to individual neurocognitive profiles. With the accelerating digitalisation of education, learning management systems (LMS) such as Moodle are central to this transformation. In mathematics education, the challenge lies not only in delivering content but in evaluating understanding in a personalised, objective, and scalable manner.

Traditional assessments often fail to reflect students' true mathematical reasoning due to their static nature, susceptibility to cheating, and lack of meaningful feedback. In this context, the STACK plugin in Moodle, powered by symbolic computation through the Maxima computer algebra system, emerges as a transformative approach. STACK enables the creation of dynamic, parameterised assessments that can adjust the difficulty, provide adaptive feedback, and evaluate intermediate steps, offering a digital analogue of traditional, teacher-driven formative assessment.

This study examines the cognitive, pedagogical, and technological implications of STACK-based parametric assessments, with a focus on neurodidactic alignment and AI readiness.

2. Problem Statement: Limitations of Traditional Assessment in a Neurocognitive-Digital Paradigm

Despite the ongoing digitalisation of education, most mathematics assessments remain rooted in static, one-size-fits-all formats. These approaches often overlook the individual cognitive diversity of learners or leverage insights from neuroscience regarding how students process, retain, and apply mathematical knowledge.

Conventional paper-based or standard digital assessments typically::

- measure *final answers only*, neglecting the diagnostic value of intermediate reasoning steps;
- lack *adaptive feedback*, providing limited support for learning through mistakes;
- promote *rote memorisation* over conceptual understanding;
- present *identical items* to all students, fostering academic dishonesty and limiting engagement;
- demand significant *teacher intervention* for grading and explanation, reducing scalability.

Such limitations are at odds with neurodidactic principles, which advocate for *task variation*, *timely reinforcement*, and *multimodal interaction* to promote synaptic plasticity and deeper learning (Zull, 2002; Tokuhama-Espinosa, 2011). Moreover, traditional models fail to capitalise on AI's potential for personalisation, automation, and predictive analytics in formative assessment.

In Romanian middle schools, as in many international contexts, the gap between curricular aspirations and assessment reality is particularly evident in mathematics. Teachers struggle to offer *individualised support* within large classrooms, while learners often receive delayed, generic, or insufficient feedback. These conditions hinder both *metacognitive development* and *self-regulated learning*, critical for academic success in mathematics (Zimmerman, 2002).

The core problem this study addresses is how to design and implement a digital assessment system that:

1. Aligns with neurocognitive mechanisms of learning;
2. Provides individualised, parameterised, and feedback-rich tasks;
3. Is scalable, secure, and sustainable in real-world educational contexts;
4. Supports AI-enhanced innovation in teaching and assessment.

To tackle this, the research proposes an integrated solution: a *STACK-based neuroadaptive assessment framework*, supported by *symbolic computation*, *parametric variation*, and an architecture optimised for *AI integration*. This model offers a viable pathway toward brain-aligned, formative, and automated digital assessment, redefining how educators evaluate and support mathematical thinking.

3. Theoretical Aspects: From Static Testing to Neuroadaptive Digital Assessment

Recent advances in *educational neuroscience* and *AI* are redefining assessment paradigms, shifting from summative, one-time evaluations toward *formative*, *dynamic*, and *personalised learning assessments* (Tokuhama-Espinosa, 2011; Zull, 2002). These modern approaches recognise learning as a *neurocognitive process* modulated by feedback timing, repetition, and motivation.

Digital assessment tools integrated into LMS platforms such as Moodle have contributed significantly to this evolution. Among them, the STACK plugin (Sangwin, 2015) stands out for its use of *symbolic computation*, *parameterised content*, and *adaptive feedback*. It has been successfully deployed in multiple educational contexts, including secondary and tertiary education.

Key innovations driving STACK's adoption include:

- *symbolic answer validation*, enabling deeper evaluation of students' mathematical reasoning (Lin, Huang, & Lu, 2023);
- *randomisation of problem parameters*, preventing answer sharing and increasing task relevance (Pelkola, Rasila, & Sangwin, 2017);
- *immediate, stepwise feedback*, promoting diagnostic learning and self-regulation (Hattie & Timperley, 2007).

Despite these strengths, current platforms like STACK are only beginning to implement *neuroadaptive features* such as reinforcement-based feedback loops, task spacing, and cognitive scaffolding. This opens the door for enhanced integration with *AI-driven technologies*:

- *natural language processing (NLP)* to interpret student responses (Xie et al., 2019);
- *intelligent tutoring systems (ITS)* to deliver real-time instructional support (VanLehn, 2011);
- *machine learning analytics* to forecast learning outcomes (Rosé et al., 2019)

This study extends the existing literature by demonstrating how a STACK-based, *neurodidactically aligned* model can serve as a foundation for *AI-enhanced digital learning ecosystems*, particularly in the middle school mathematics domain.

Neurodidactics blends insights from *cognitive neuroscience* and *pedagogy* to inform the design of effective educational interventions. Central to this approach are the principles of *spaced repetition*, *adaptive feedback*, and *reward-based reinforcement*, elements that are implementable through digital assessment systems.

STACK provides immediate, differentiated feedback that aligns with theories suggesting dopamine-related reward mechanisms are activated by temporal feedback (Zull, 2002; Tokuhama-Espinosa, 2011). Furthermore, enabling repeated exposure to varied problem instances supports the strengthening of *neural pathways* through practice distributed over time (*spacing effect*). These features make STACK an ideal candidate for embedding *neuroadaptive features* in educational technology.

Prospectively, integrating AI tools such as *natural language processing (NLP)* and *intelligent tutoring systems (ITS)* can further enhance STACK's capabilities. Future iterations could include *AI-based feedback generators* and *predictive analytics* for *personalised learning trajectories*.

4. Methodology: Experimental Design in a Digital Neuroadaptive Environment

This study was conducted as part of the doctoral research project titled *"Intelligent Support System for Accelerating Mathematical Acquisitions in Middle School Students"* and was carried out during the 2023–2024 academic year at "School No. 10" in Bacău, Romania. The digital materials used in the intervention were adapted from the electronic course *Matematică Gimnazială Bacău* (2024), integrated within the Moodle LMS of the State University of Moldova.

The research employed a **quasi-experimental design** with two parallel eighth-grade cohorts:

- the **control group** (n = 28) engaged in traditional, paper-based instruction followed by assessment;
- the **experimental group** (n = 30) used Moodle-based parametric testing via the STACK plugin.

- The overarching goal was to determine the impact of parameterised, symbolic digital testing on students' mathematical understanding and motivation, while assessing its scalability and congruence with neurocognitive instructional theories.

Specific objectives included:

- demonstrating STACK's capacity to generate unlimited, individualised items;
- quantifying teacher time saved through automation of grading;
- evaluating the effectiveness of adaptive feedback in supporting conceptual understanding;
- assessing the reduction of academic dishonesty through randomised problem variants.

Hypothesis: Students evaluated using STACK-based parametric items will outperform peers on conceptual understanding, show increased engagement, and receive more targeted feedback, while teachers will experience a significant reduction in grading effort.

Statistical Analysis. Pre- and post-test data were screened for normality (Shapiro–Wilk) and homogeneity of variance (Levene). Independent-samples t-tests were complemented with effect-size estimates (Cohen's d) and **95% confidence intervals.** Where baseline differences emerged, an ANCOVA was conducted with pre-test scores as a covariate, following the guidelines of Field (2018) and Tabachnick and Fidell (2019).

Assessment content and STACK configuration

The topic chosen for implementation was **Linear Functions**, aligned with the Romanian national mathematics curriculum (CNEE, 2025). The assessment framework included:

- **a pre-test**: the overarching goal was to determine the impact of parameterised, symbolic digital testing on students' mathematical understanding and motivation, while assessing its scalability and alignment with neurodidactic principles.
- three **formative quizzes** with STACK items and stepwise feedback;
- a **post-test** (15 items) assessing learning outcomes.

Types of STACK items included:

- *symbolic algebra tasks* (e.g., slope from two points, equation derivation);
- *calculated numerical inputs* with randomised coefficients;
- *graph-based interpretation* (manually graded);
- *multi-step open-ended problems* using decision trees for feedback.

Implementation of STACK in a neurocognitive assessment architecture

STACK allows for the *parameterisation* of complex mathematical tasks. Each student receives a *unique version* of a question, eliminating the risk of *cheating* and encouraging *critical thinking* over *memorisation*.

Features aligned with neurocognitive principles include:

- *stepwise grading*: mirrors the teacher's diagnostic process
- *immediate feedback*: may stimulate reward-related learning processes (Hattie and Timperley, 2007)
- *repetition with variation*: reinforces procedural fluency
- adaptive difficulty: supports the zone of proximal development (Vygotsky, 1978)

Data collection instruments

To evaluate outcomes, the following data sources were systematically collected

- *quantitative*: pre-/post-test scores, time-on-task logs, answer accuracy rates;
- *qualitative*: student surveys, teacher interviews, system feedback analytics.

Ethical considerations

All participants and their guardians provided informed consent. The research adhered to national educational ethics guidelines and ensured the anonymity of student data.

Experimental setup and test design

During the 'Linear Functions' unit, one class used traditional paper-based testing, and the other engaged with parameterised assessments via Moodle. The digital assessments included pre-tests, practice quizzes with STACK, and post-tests.

The creation of a STACK item in Moodle includes the following components:

- Question title
- Random variables (randomisation of coefficients, variables, signs, etc.)
- Question text (using the specific Moodle stack syntax)
- Response validation (including [[validation:ans1]])
- General feedback
- Question description
- Question notes
- Answer model
- Potential response tree (prt)
- Feedback for correct and incorrect answers (including multiple nodes for different cases)

Example: Linear functions assessment with stepwise grading

This section illustrates a STACK item in the "Linear Functions" chapter, where students are required to:

1. Determine the slope from two given points.
2. Use the slope and one point to find the linear equation.
3. Write the equation in the form f(x) = ax + b.
4. Simplify the final expression.

With STACK:

- If the student calculates the correct slope in step 1, they immediately receive positive feedback.
- If they make a calculation mistake, the system offers a hint or a prompt (e.g., "Check how you compute the difference of y-values.").
- The student can retry without penalising previous steps, encouraging diagnostic learning.
- At the end of the process, the teacher can configure custom grading logic, assigning weight to each step (e.g., 30% for the slope, 40% for equation formation, 30% for simplification).

This structure mirrors the grading logic of an experienced teacher but executes it instantly for every student, regardless of class size.

Converting a traditional test to a digital parameterised test in Moodle

Consider the function $f : R \to R, f(x) = ax + b\, f : R \to R, f(x) = ax + b$, defined such that:

- *a* is randomly selected between [-5,5]
- *b* is randomly selected between [-10,10]

1. Compute f(2). (Automatically graded numerical input question)
2. Find the x-intercept. (Automatically graded formula-based question)
3. Identify the slope. (Automatically extracted from function parameters)
4. Only the graphing task (point 4) requires manual grading (Brănoaea, 2025).

Student guidance: Input syntax and live feedback with MathJax and Maxima

One common challenge in digital mathematics assessments is ensuring that students know how to input their answers correctly in algebraic form. To address this, STACK provides a structured input guide based on the MathJax and Maxima syntax. This is essential because even correct mathematical thinking can be marked as incorrect if not properly formatted.

Before attempting the test, students receive a tutorial sheet or interactive guide explaining the conventions. For example:

- To write a square root, they must enter: sqrt(x+1)
- For multiplication, the format requires:2*x (as opposed to 2x)
- Fractions are written using division: (x+1)/(x-2)
- Exponents are typed as: x^2, or x^(1/3) for cube roots.
- Parentheses are required to ensure syntactic disambiguation:sqrt((a+b)^2 + 4*c)

As students type their answers, STACK uses MathJax to render the expression live, showing them exactly how the system interprets their input. This immediate visual feedback helps students avoid syntax errors and gives them the confidence that their answer is syntactically coherent, even before submission. Suppose an answer is mathematically equivalent but syntactically incorrect (e.g., omitting a multiplication sign). In that case, STACK can detect it and provide syntax-sensitive feedback prompts. This kind of responsive feedback system, driven by applied informatics, mimics real-time teacher intervention and dramatically enhances digital learning experiences.

Stepwise grading and adaptive feedback in STACK: A digital analogue of traditional evaluation

One of the most powerful features of the STACK plugin is its ability to emulate teacher-style, paper-based assessment through a digital framework. This is made possible by its built-in stepwise evaluation system, which guides the student through successive stages of problem-solving while offering contextual feedback and partial grading at each stage.

In traditional math assessment, teachers evaluate not just the final answer but also the logical reasoning, intermediate steps, and methods applied by students. STACK replicates this process digitally through:

- Input validation trees, where each branch checks a specific intermediate step;
- Conditional feedback, triggered by the student's actual input;
- Incremental scoring, based on the completion of each logical stage.

Benefits of using decision trees in STACK

- **Automatic grading of problems**: automatically evaluates problems that would otherwise require manual checking.
- **Individualised and fair scoring**: scoring is tailored to each student's progress.
- **Detailed feedback**: provides feedback for every incorrect step, allowing for conceptual error correction.
- **Reduced subjectivity**: the automated nature of the grading system eliminates subjectivity, saving valuable time for educators.

By utilising STACK, Moodle enables interactive assessments, instant feedback, and the dynamic generation of tasks. This eliminates the disadvantages of traditional testing and enhances learning efficiency.

5. Experimental Results

The experimental data collected during the implementation phase were analysed to determine the effects of STACK-based parameterised assessment on both student learning outcomes and teacher efficiency. This section discusses the key findings, highlighting improvements in conceptual understanding, student cognitive engagement, and instructional scalability.

Table 1. Traditional Mathematics education issues vs. solutions offered by STACK

Identified issue	**Source**	**Solution provided by STACK**
Cheating and copying in online tests	Uttl & Smothers, 2019;	The automatic generation of unique items and random variables eliminates the possibility of copying answers.
Memorisation of answers	Pelkola, Rasila & Sangwin, 2017	Parameterised items require critical thinking, as each test is unique for each student.
Deficit of qualified mathematics teachers (10-30%)	Ministry of Education, 2024a	Automated grading reduces teacher workload, enabling a stronger focus on teaching.
Excessive teacher workload	Grosseck, Bran, & Țîru, 2024	Eliminating manual grading reduces work time by over 75%.
Lack of personalised and immediate feedback	Sharma, Van Hoof & Ramsay, 2019	STACK provides instant and detailed feedback for each step in solving a problem.
Low student motivation	Domagk, Schwartz & Plass, 2010	Adaptive tests stimulate active learning and student interaction with diverse problems.
Difficulty in objective assessment of critical thinking	Zull, 2002	STACK analyses intermediate responses and allocates proportional points according to the student's progress.
Inefficient evaluation and long grading times	Ministry of Education, 2024b	STACK allows automatic grading, reducing the time needed for evaluation to zero hours.

Table 1 highlights how advanced technologies such as STACK can improve the educational process by optimising assessments and supporting the development of students' mathematical skills.

Quantitative results: pre-test/post-test analysis

Following the implementation of the two teaching approaches, significantly different results were obtained in terms of student performance. The class that used the Moodle platform and interactive educational games showed considerable improvements in understanding and applying mathematical concepts, compared to the class that followed a traditional learning process, as illustrated in Figure 1 (Brănoaea, 2025).

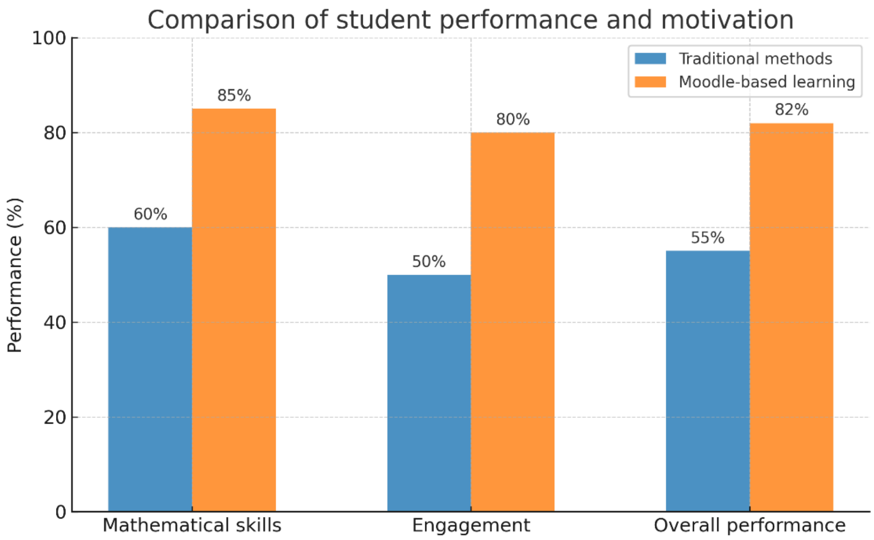

Figure 1. Student performance and motivation levels: comparison between control and experimental groups

- **Student performance:** Students in the class who benefited from educational games achieved higher scores on mathematical competency assessments. Analysing the results of exercises involving the development of algebraic expressions, area and volume calculations, and solving geometric problems, a 25% improvement in answer accuracy was observed compared to the control class.
- **Active student engagement:** Students in the class who used the Moodle platform demonstrated a higher level of engagement and motivation, being more active during lessons and in completing learning tasks. They received immediate feedback, which allowed them to correct mistakes and consolidate their knowledge in an interactive and personalised manner (Brănoaea, 2025).
- **Differences in approach:** As anticipated, there were differences in how students approached activities. Students in the traditional methods class had a more limited understanding of the concepts, requiring more time to assimilate the notions and to connect theory with practice (Brănoaea, 2025).

A comparison of the pre- and post-test results between the control and experimental groups revealed substantial learning gains among students using STACK-enhanced assessments, as illustrated in Table 2.

Table 2. Comparison of learning gains between control and experimental groups

Group	Pre-test Mean (%)	Post-test Mean (%)	Gain (%)	Cohen's d	95 % CI
Control (n = 28)	56.8	65.2	8.4	0.32	0.05 – 0.58
Experimental (n = 30)	55.5	81.1	25.6	1	0.57 – 1.42

The experimental group achieved a large effect size (d = 1.00), indicating a practically meaningful improvement in conceptual understanding compared with the control group (d = 0.32). The 95 confidence interval does not cross zero, confirming the robustness of the result. An ANCOVA controlling for pre-test scores produced a similar pattern, $F(1, 55) = 29.7$, $p < .001$.

Data analysis from pre- and post-tests, system logs, and student feedback indicates:

- accuracy improvement: 25% increase in correct responses
- time-on-task: increased persistence in solving problems
- motivation: higher engagement levels in the experimental group

Students demonstrated greater *conceptual retention* and *procedural understanding*, aligning with *neurocognitive models* of learning that emphasise *timely feedback* and *task variability*.

Qualitative results: student engagement and feedback experience

Survey data and classroom observations indicated that students in the experimental group:

- spent more time on tasks and demonstrated greater persistence in problem-solving;
- reported higher satisfaction due to instant feedback and the opportunity to retry problems;
- perceived the tasks to be more engaging and less stressful compared to traditional paper-based assessments.

Representative student comments included:

- *"I liked that I could see where I went wrong immediately and try again."*
- *"Every test was different. It felt more like a challenge than an exam."*

Teacher experience and workload efficiency

The following table compares teacher workload and assessment efficiency across three formats commonly used in middle school mathematics: **traditional paper-based tests**, **oral examinations at the board**, and **digital assessments using Moodle with the STACK plugin**. Key factors such as preparation time, grading effort, feedback speed, objectivity, and risk of cheating are analysed to highlight the practical implications of each method. These findings are summarised in Table 3, which outlines the comparative time and effort associated with each assessment modality.

Table 3. Comparison of the time and effort required for different assessments (Brănoaea, 2025)

Assessment type	Traditional paper-based test	Oral examination at the board	Digital assessment in Moodle
Test format	5 objective, 5 semi-objective, 2 subjective items	Individual oral responses at the board	Parameterised questions, automatically generated values
Preparation time	30 min (test creation) + 5-10 min (printing)	No test creation, only question selection	30 min (reusable test creation) + 10 min (variable setup)
Execution time	50 min per class	150 min (5 min/student)	50 min (same as paper test)
Grading time	210 min (manual grading) + 20 min (reporting)	Immediate but subjective	0 min (automatic grading) + 20 min (reporting)
Total teacher effort	~4h 30min per test	~3h 30min per full class assessment	~1h per test (75% time reduction)
Accuracy & objectivity	Possible grading inconsistencies	High subjectivity	Objective and consistent grading
Feedback speed	Delayed (manual correction required)	Instant, but lacks written feedback	Immediate, with detailed analytics
Student personalisation	Same test for all students	Individual, but limited engagement for peers	Unique tests for each student, adapted to difficulty
Risk of cheating	Moderate (students can copy answers)	Low	Very low (each student receives a unique test)
Reusability & sustainability	Requires reprinting for each test	Not reusable, requires teacher repetition	Fully reusable, no paper waste

As Table 3 illustrates, digital assessments using Moodle with STACK significantly reduce teacher workload while enhancing assessment objectivity and feedback quality.

Impact on teachers and the efficiency of the teaching process (Brănoaea, 2025)

✔ **Reduction of workload**

- Time saved per assessment: ~3h 30min
- Creating the parameterised test is a single-use activity – the test can be reused annually
- More time available for interactive teaching activities

✔ **Improvement in education quality**

- Minimisation of cheating risks – each student receives a unique test
- Immediate feedback for students – they can correct their mistakes instantly
- Detailed analysis of results – Moodle generates charts and progress reports

From the teacher's perspective, the STACK implementation offered considerable benefits:

- grading time per class was reduced by approximately 75%;
- analytics from the Moodle platform allowed for real-time diagnostics of student misconceptions;
- tests were reusable across years, enabling long-term scalability.

Pedagogical implications in neurodidactic contexts

The STACK-based system aligns strongly with *neurodidactic principles*:

- **feedback immediacy** supports dopamine-mediated learning;
- **stepwise progression** scaffolds cognitive load and procedural fluency;
- **adaptive item generation** supports individual ZPD (zone of proximal development);

In addition, parameter variation reduces item redundancy and supports long-term retention without overloading working memory. These effects collectively foster a learning environment that is both more effective and cognitively sustainable. The results support the hypothesis that digitally parameterised testing is not only feasible but desirable in brain-aligned, technology-enhanced pedagogy.

Practical implementation guidance

To support deployment in schools with limited IT resources, the following measures are recommended:

- Cloud-hosted STACK containers. A pre-configured Docker image (Maxima, STACK, Moodle) can be deployed on Google Cloud Run or DigitalOcean at approximately €10 per month for 200 concurrent users.
- Local plug-and-play server. For settings without stable connectivity, a mini-PC such as a Raspberry Pi 4 (8 GB) can run Ubuntu Server with pre-installed STACK packages; total hardware cost is about €120.
- IT partnerships. Schools can establish agreements with local universities for quarterly maintenance and security updates.
- Accelerated teacher training. A six-hour MOOC (video tutorials and quizzes) provides the fundamentals of item creation and analytics interpretation.
- Community support forum: A Romanian-language Moodle/STACK forum moderated by volunteers can significantly reduce incident-resolution time to under 24 hours.

These measures ensure scalability and sustainability even in contexts with minimal technical support.

6. Challenges and Barriers to the Implementation of STACK

Despite its powerful features, STACK also presents several challenges that institutions must consider before adopting it at scale:

- **Installation and configuration**: STACK requires the **Maxima computer algebra system** to be installed and properly configured on Moodle servers. This process can be technically complex, requiring server-side knowledge, and may be daunting for institutions with limited IT infrastructure or support staff.
- **Technical expertise**: To fully utilise the power of STACK, educators need to understand the **Maxima** language to create advanced symbolic questions. While the plugin provides a graphical interface for question creation, more complex mathematical problems require manual coding of algorithms, which may not be feasible for all instructors (Sangwin, 2015).
- **Server resource demands**: Running symbolic computations, especially with large question datasets or high numbers of students, can place significant demands on server resources. This can lead to performance issues, particularly in large-scale implementations, where the demand on computational resources may exceed the available capacity (Maths/moodle-qtype_stack, 2021).
- **Training and support**: Due to the complexity of the plugin, both educators and system administrators need ongoing training in the use and maintenance of STACK. Many institutions may lack the resources to provide such training or might face resistance from educators unaccustomed to more advanced digital tools.

7. Conclusions

STACK, as implemented in Moodle, functions as a neuroadaptive tool that supports more personalised and neurocognitively attuned mathematics assessment. By enabling individualised and formative assessments, this model aligns with contemporary neuroscience and supports the development of AI-enhanced educational systems. The integration of STACK within a neurodidactic framework reflects a growing emphasis on evidence-based, learner-centred assessment practices.

This study demonstrates that STACK-based parametric assessment represents a powerful and scalable approach to enhancing mathematics education at the middle school level. Through symbolic computation, adaptive feedback, and individualised item generation, the system addresses the limitations of static testing models while aligning with key neurodidactic principles.

Quantitative and qualitative data clearly show that students who engaged with STACK-generated assessments achieved significantly higher gains in conceptual understanding, reported greater motivation, and benefited from immediate feedback loops. For educators, the shift to STACK enabled substantial time savings, streamlined grading workflows, and provided deep insight into student performance trends.

From a neuroeducational perspective, the approach reinforces cognitive engagement through variation, repetition, and just-in-time feedback, mechanisms proven to enhance learning retention and procedural fluency. These findings suggest that parametric testing offers pedagogical value beyond technical convenience.

While the findings are encouraging, this study was conducted in a single educational context with a relatively small sample size, and random assignment was not feasible. Future research should replicate these results across diverse settings and include randomised controlled designs for stronger generalizability.

In summary, STACK stands as a transformative tool for digital, brain-aligned assessment, paving the way toward more equitable, engaging, and effective learning environments in mathematics. The integration of symbolic computation, adaptive feedback, and parametric variation situates STACK at the forefront of educational innovation (Sangwin, 2019). This study recommends its integration as part of a broader shift toward scalable, neuroscience-informed digital pedagogy.

8. Future Directions: Integrating AI into Neuroadaptive Assessment Ecosystems

Building on the demonstrated success of STACK, future research should explore how artificial intelligence can further enhance the personalisation, adaptability, and diagnostic power of digital assessment systems.

Key directions include:

- **Natural language processing (NLP)**: Enabling students to explain their reasoning in natural language, with automated semantic analysis and concept tagging to assess understanding beyond symbolic accuracy.
- **AI-based feedback generators**: Utilising large language models (LLMs) to deliver context-aware, personalised hints and scaffolding based on a student's past responses and learning trajectory.
- **Reinforcement learning algorithms**: Developing systems that dynamically adapt question difficulty, format, or feedback strategy in real-time, optimising the learning path based on mastery prediction.
- **Integration with intelligent tutoring systems (ITS)**: Creating multi-modal learning environments that combine STACK's symbolic computation with AI-driven tutoring dialogues, visual aids, and conceptual diagnostics.
- **Visual learning analytics dashboards**: Designing administrator and teacher interfaces that provide macro-level insights into curriculum effectiveness, cohort performance, and neural engagement markers via real-time data tracking.

Moreover, the automation of parametric item generation via AI holds promise for reducing educator workload while expanding content diversity and cognitive challenge levels. As generative AI evolves, it may play a central role in building complex, differentiated assessments that adapt not only to what a student knows but to **their detailed optimal cognitive strategies**

These innovations align with Action 3 of the European Commission's Digital Education Action Plan 2021–2027 (2023) and Romania's 4E-Education (2024a) initiative, both of which emphasise the need for intelligent, inclusive, and evidence-based use of digital tools in education. Continued interdisciplinary research at the intersection of neuroscience, AI, and pedagogy is essential to realise this vision.

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