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Attention and academic performance: AI-driven prediction and intervention

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Abstract

Generational changes in cognitive performance and recent results from large-scale educational assessments have renewed interest in attention as a key factor in learning outcomes, particularly in the Brazilian context. This study investigates the role of focused, sustained, alternating, and divided attention in learning and presents an exploratory, performance-based digital assessment tool integrated with an artificial intelligence (AI)–assisted interpretative system to support educational research and decision-making. The system was developed using .NET MAUI and applied to a sample of 144 undergraduate students from Universidade Estadual do Norte Fluminense Darcy Ribeiro (UENF). Teachers provided qualitative ratings of student engagement and academic performance. The AI component, named Samantha, was designed to interpret attentional profiles and generate context-sensitive feedback for educators based on predefined psychometric and neuroscientific principles. Results showed weak positive associations between student engagement and both focused and sustained attention. An inverse association was observed between sustained attention and teacher-rated academic performance. This unexpected pattern should be interpreted cautiously and is treated as exploratory, given the study design and analytical constraints. Overall, the iGnosi® application demonstrated operational stability and practical usability during data collection. While not intended as a validated diagnostic instrument, the system represents a feasible framework for exploratory investigation of attentional patterns in educational settings and provides clear directions for future psychometric validation and controlled empirical testing.

Keywords: artificial intelligence, attention, education, academic performance, cognitive skills, ai intervention, predictive analytics

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1. Introduction

Discussions about educational challenges in Brazil are longstanding and become particularly salient when examined through standardized assessments. In the 2018 edition of the Programme for International Student Assessment (PISA)—which motivated the present study—Brazil ranked 54th on average (Brasil, 2020). Although the 2022 edition showed slight improvements in specific domains, the country reached its lowest absolute performance in the history of the assessment (OECD, 2023). These results are especially concerning given that countries with fewer economic resources achieved better outcomes.

Standardized assessments such as PISA present well-known limitations. Their uniform structure often fails to account for cultural and historical differences among populations (D'Ambrósio, 2005). Acknowledging these constraints, the OECD has announced methodological changes for the 2025 edition, which will be discussed later in this section. Even when cultural bias is taken into account, however, PISA results consistently point to persistent difficulties in Brazilian education, suggesting the need to examine underlying cognitive factors that influence learning in real classroom contexts.

Concerns about cognitive performance trends extend beyond educational assessments. Since the publication of The Mean IQ of Americans: Massive Gains 1932 to 1978 (Flynn, 1984), research has documented generational changes in psychometric performance, later termed the "Flynn Effect." While IQ scores increased throughout much of the twentieth century, more recent studies have reported a reversal of this trend across several countries (Flynn & Shayer, 2018). Importantly, these declines have been observed regardless of economic or geographic context, as evidenced in countries such as Denmark (Teasdale & Owen, 2008) and Portugal (Carvalho et al., 2020).

Flynn himself emphasized that IQ tests do not measure intelligence per se, but rather the interaction between cognitive abilities and environmental demands (Flynn, 1987). From this perspective, shifts in psychometric performance may reflect changes in how cognitive resources are engaged in increasingly complex and digitally mediated environments. Among the cognitive skills implicated in academic performance—such as memory, reasoning, and problem-solving—attention plays a central role, as it governs the allocation of limited cognitive resources during learning activities.

Evidence from the Brazilian context reinforces this interpretation. Analyses of PISA 2018 data, including response time measures, suggest that cognitive skills exert a stronger influence on student performance than socioeconomic factors alone (Sassaki et al., 2018). These findings highlight attention as a particularly relevant construct in Brazilian classrooms, where students are exposed to high cognitive demands amid diverse social and educational challenges.

Recent initiatives by the OECD further underscore the importance of attention in contemporary learning environments. The 2025 PISA framework places greater emphasis on problem interpretation, computational tools, and context-based reasoning across personal, local, national, and global domains (OECD, 2025). Although the effectiveness of these changes remains to be evaluated, they reflect growing concern about how cultural and technological transformations shape cognitive engagement in education.

In light of these issues, the present study investigates attention as a key cognitive skill in the learning process. Specifically, we examine major attentional models and their perception by teachers in classroom settings. To support this investigation, we developed a psychometric instrument to assess selected attentional components and integrated it into a Large Language Model (LLM)-based artificial intelligence system designed to interpret and predict academic difficulties and classroom conflicts. The methodological procedures and empirical findings are presented in the following sections.

It is important to clarify the scope of the psychometric instrument proposed in this study. The iGnosi® system is not presented as a standardized or diagnostic attention test, nor does it aim to replace validated neuropsychological assessments. Instead, it was designed as an applied and ecologically oriented tool to operationalize attentional dimensions within real educational contexts, supporting teachers' perceptions and decision-making processes. Given this objective, the present study prioritizes feasibility, usability, and functional associations between attentional indicators and classroom engagement, rather than classical psychometric validation. Reliability and validity analyses such as internal consistency, test–retest stability, and normative comparisons would require a distinct research design and a longer data collection cycle, and therefore fall outside the scope of the current investigation.

2. Literature Review

Attention is a complex construct composed of multiple interacting components that enable individuals to filter and select the most relevant information at any given moment. It is commonly described in terms of sustained, selective, alertness or vigilance, divided, and alternating attention (Shayer et al., 2015). However, existing psychometric tools do not consistently adopt the same classification system; their frameworks vary depending on the author, theoretical model, or purpose of the instrument. For example, the Brazilian tool Rotas de Atenção, published by Nillpress, categorizes attention into Focused, Divided, and Alternating attention (Rabelo et al., 2020), as does the Bateria Psicológica para Avaliação da Atenção (BPA) (Rueda, 2013). Computerized assessments often introduce sustained attention as a separate domain, as seen in the Conners' Continuous Performance Test (CPT-II), in which individuals are instructed to press a key whenever any letter appears on the screen except the letter "X."

For the present study, the following attentional classifications were adopted: focused attention, sustained (or alertness) attention, divided attention, and alternating attention. Each of these categories reveals distinct cognitive capacities. Focused attention refers to the individual's ability to select a specific stimulus amid distractors. Divided attention involves responding to two or more target stimuli simultaneously. Alternating attention refers to the capacity to shift focus between different stimuli or tasks (Rueda, 2013). Sustained attention, in contrast, reflects the ability to maintain consistent focus on a single stimulus over an extended period, producing stable responses (Bauer, 2021).

Beyond its cognitive significance, attention is closely associated with classroom functioning. Difficulties in attention are commonly observed in neurodivergent conditions, such as Attention-Deficit/Hyperactivity Disorder (ADHD) (Moura & Silva, 2019). Moreover, attention problems can predict classroom conflicts and behavioral challenges. When dysregulated, attention may contribute to impulsivity, reduced academic performance, and rule violations, making it a key predictor of learning difficulties as well (Marturano et al., 2016). Early detection of attentional deficits could therefore support teachers in adapting their pedagogical strategies before such difficulties intensify. When integrated into the LLM-based tool proposed in this study, attention-related data may allow the system to operate predictively—combining both statistical and qualitative analysis. This will be discussed further in later sections.

Understanding the role of attention may also reveal critical weaknesses in teaching methods or classroom environments. Attention is a modifiable and context-dependent skill influenced by external stimuli. When a sensory stimulus is associated with reward, attention tends to prioritize it—a phenomenon known as value-driven attentional capture (Anderson, 2016). Conversely, when a stimulus becomes linked to stress or threat, attention shifts toward cues associated with predictive fear (Sharpe & Killcross, 2015). Therefore, attention is not merely a passive cognitive function but a dynamic system shaped by reinforcement, emotion, and context. When instructional methods are designed with these mechanisms in mind, attention can become a powerful ally in the learning process.

3. Materials and Methods

3.1. Participants Selection (Volunteer Recruitment)

To investigate the role of attention in students' learning processes, undergraduate volunteers were recruited from the Universidade Estadual do Norte Fluminense Darcy Ribeiro (UENF). All genders, ages, and academic programs were eligible, provided that participants were regularly enrolled during the first semester of 2024. The study involved human participants and was approved by the Ethics Committee via Plataforma Brasil under protocol number 6.602.811.

All regularly enrolled undergraduate students at UENF (N = 2,163) were invited to participate through institutional email lists, notices posted on campus bulletin boards, and direct invitations mediated by course instructors. Participation was entirely voluntary. A total of 144 students agreed to participate and completed the experimental procedures (Ribeiro & Sousa, 2025), corresponding to a 95% confidence level with a 7.9% margin of error.

Sample size estimation followed the procedure described by Barbetta (2012):

$$n = \frac{\frac{z^2.p(1-p)}{e^2}}{1 + \left(\frac{z^2.p(1-p)}{e^2 N}\right)}$$

Where N represents the population size, e is the margin of error, p is the assumed variability (0.5), and z is the corresponding Z-score.

Regarding demographic characteristics, 103 participants identified as female, 34 as male, and 2 as non-specified or non-binary. This gender distribution reflects a higher proportion of female participants, which may be influenced by broader trends in Brazilian higher education enrollment. Although gender-related factors were not explored in the present study, this imbalance is acknowledged as a limitation and warrants caution in generalizing the findings.

From the total sample, 62 students were included in the qualitative component of the study. These students were drawn from classes whose instructors voluntarily agreed to participate.

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Eligible instructors were required to be the primary teacher of at least one course attended by participating students, to have initiated the course with the class, and to have already conducted at least one formal academic assessment.

Each participating instructor completed a brief evaluation form for their students, addressing three dimensions: engagement, commitment, and academic performance. The questions were: "*How do you evaluate the student's engagement?*", "*How do you evaluate the student's commitment?*", and "*How do you evaluate the student's performance?*". Responses were recorded using a three-point ordinal scale (low, medium, high). This simplified scale was initially adopted to facilitate instructor participation; however, it is recognized as a limitation, and future stages of the project will consider finer-grained rating scales.

All students provided written informed consent prior to participation. Before initiating the tasks, participants were informed—both verbally and within the application interface—about the study objectives, procedures, duration, and their right to withdraw at any moment without penalty. Printed copies of the informed consent form were available for consultation upon request. No personally identifiable information was collected. Each participant was assigned an anonymized alphanumeric identification code automatically generated by the application described later, ensuring participant confidentiality and data protection.

The study followed a blind design, in which researchers had access only to anonymized data and no means to identify individual participants.

Six qualitative evaluations were excluded due to missing or invalid information. Exclusion criteria included one form containing a non-existent identification code and five forms lacking essential data. These cases were excluded solely from the qualitative analysis; their corresponding attentional metrics, obtained through the application, remained valid and were retained for the quantitative component of the study.

3.2. Psychometric Tool for the Attention Models

The psychometric tool developed for this study was named iGnosi® (Registration: BR 512024001850-6). The application was developed in C# using the .NET MAUI framework, allowing a multiplatform architecture. For the present study, the system was compiled exclusively for Android, enabling standardized administration on 7″ and 10″ tablets during data collection.

For remote data storage, Google Firebase Realtime Database and Google Cloud Storage services were used. Third-party components from Syncfusion, DevExpress, and Gembox were implemented to support interface design, data handling, and report generation. All records were encrypted using a BCrypt algorithm with Salt, applied before cloud transmission.

To ensure participant anonymity, no personal identifiers were collected. At the beginning of each session, the application automatically generated a random alphanumeric code, which served as the sole identifier for the participant. This code was also recorded by the participant on a separate form to allow subsequent data matching between quantitative and qualitative stages. Access to the database was restricted to the research team, and stored data cannot be linked back to individuals outside the experimental context. Data were accessed exclusively for research purposes related to the present study and were not used for automated decision-making or individual-level interventions. No data were shared with third parties, and records are retained only for the duration required by institutional research regulations.

The iGnosi® protocol consists of four performance-based tasks designed to assess distinct attentional components: focused attention, sustained attention, alternating attention, and divided attention. Each task produces behavioral indicators such as correct responses, errors (including omission and switching errors, depending on the task), and task-specific performance metrics. After completion of all tasks, raw performance data are processed and stored securely in the cloud.

For descriptive and interpretative purposes within this study, raw scores are converted into standardized scores internal to the sample, where a value of 100 represents the absolute mean of the collected dataset. Scores above or below this value indicate relative performance compared to the study population. Based on this transformation, results are classified into qualitative performance bands (**Erreur ! Source du renvoi introuvable.**). This standardized output is also used in subsequent analytical stages, including the artificial intelligence–based interpretation described later.

It is important to note that the standardization procedure is **sample-referenced**, intended to support internal comparisons within the study rather than normative generalization. As such, iGnosi® is positioned as an **exploratory psychometric instrument**, designed to support the investigation of attentional patterns in educational contexts. Formal psychometric validation procedures, such as test–retest reliability, internal consistency indices, or external validation against gold-standard attention tests, were not conducted at this stage and are planned for subsequent validation studies.

A video demonstration illustrating the application's interface and task flow is available online (https://youtu.be/m5_VNjixkpE).

Table 1. *Standardized Score Interpretation*

Score	Classification
Below 70	Very Low
70–79	Low
80–89	Low Average
90–109	Average
110–119	High Average
120–129	High
130 or above	Superior

3.3. LLM-Based Artificial Intelligence

The artificial intelligence component, named Samantha, was implemented as a large language model (LLM)–based decision-support agent designed to assist in the interpretation of attentional profiles and to provide contextualized feedback to educators. Several contemporary LLM architectures were considered during the system design phase, including GPT-4, Gemini, and LLaMA-2. For the present study, the deployed implementation relied on OpenAI's GPT-4o Mini model, selected due to its balance between performance, cost, and integration stability.

Rather than training a language model from scratch, Samantha was configured through instruction tuning and contextual prompting. A curated dataset containing 577 entries was used to guide the model's behavior and domain adaptation (Ribeiro & Sousa, 2025). This dataset included examples of psychometric score interpretation, attention-related neuroscience concepts, and simulated interactions reflecting typical teacher and researcher queries. The purpose of this procedure was to constrain the model's responses to the educational and psychometric scope of the study, rather than to optimize predictive accuracy.

Interactions with the model followed a structured conversational format consisting of three roles: System, which defines Samantha's behavioral constraints, ethical boundaries, and domain limits; User, representing queries posed by educators or researchers; and Assistant, providing reference examples of appropriate responses. This role-based structure allows the AI to remain aligned with the intended task and to avoid generating content beyond the scope of attentional assessment and educational support (OpenAI, 2024).

Importantly, Samantha is not intended to function as an autonomous diagnostic system. Its role is to support human interpretation by summarizing patterns, highlighting potential attentional difficulties, and offering hypothesis-generating feedback. Final decisions and interpretations remain under the responsibility of educators and researchers. This design choice reflects a conservative and ethically grounded approach to the use of LLMs in educational and psychological contexts.

4. Results

4.1. Training of the Samantha AI

The training of the Samantha AI lasted 3 epochs, consumed 253,515 tokens, and achieved a training loss of 0.5932 (*Figure 4* and *Figure 2***.** Samantha's training graph. Source: Research data) (Ribeiro & Sousa, 2025). Although a new training cycle is not ruled out, following this training configuration, Samantha was able to generate context-consistent responses aligned with the predefined system instructions. No formal performance evaluation, accuracy benchmarking, or human rating protocol was conducted at this stage.

When activated, the iGnosi® app sends a structured system-level prompt containing psychometric data and interaction context. This mechanism acts as a guardrail, constraining the AI's responses to the intended educational and interpretative scope and reducing the risk of off-topic or inappropriate suggestions.

The present study does not report quantitative performance metrics, error rates, or comparative evaluations of the AI outputs. The AI component is therefore presented as a supportive interpretative layer rather than as a validated decision-making system.

4.2. Data Availability Statement

The datasets generated and analyzed during the current study are available for academic and replication purposes. An anonymized dataset containing raw task outputs and internally standardized scores from the iGnosi® psychometric protocol is available upon reasonable request. No personally identifiable information is included, and all records are sample-referenced and intended solely for exploratory analysis.

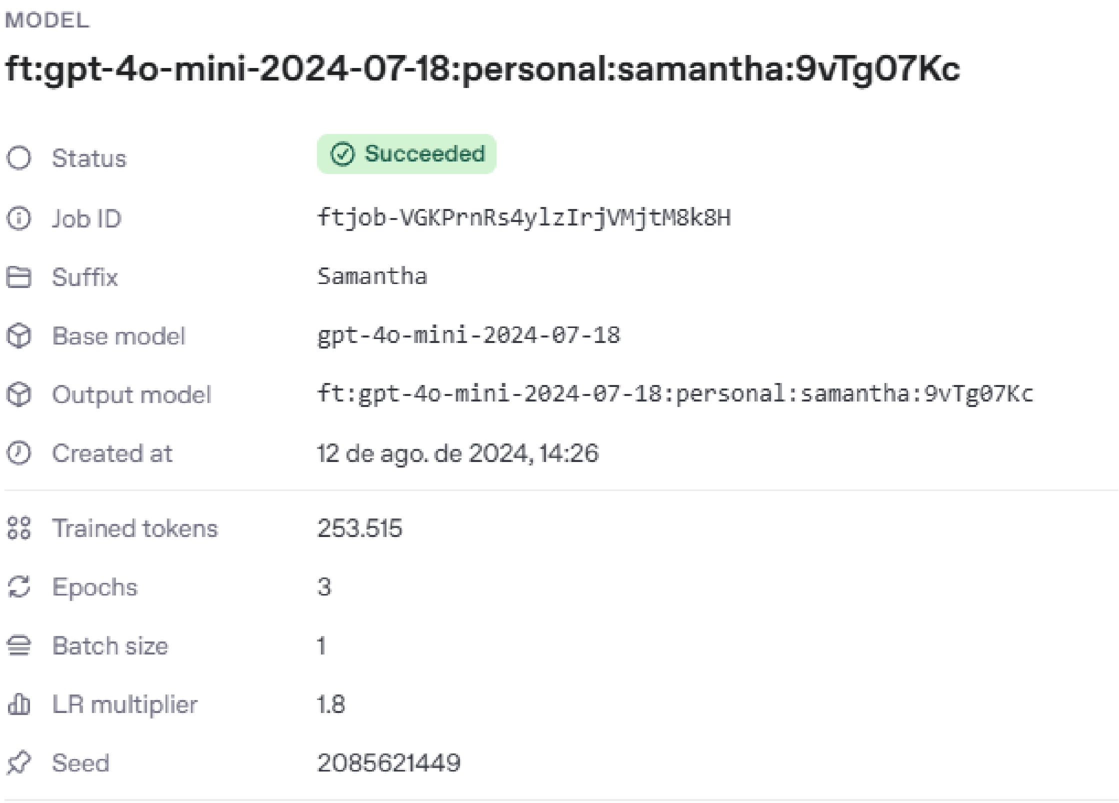

Figure 4. *Samantha's training dashboard*

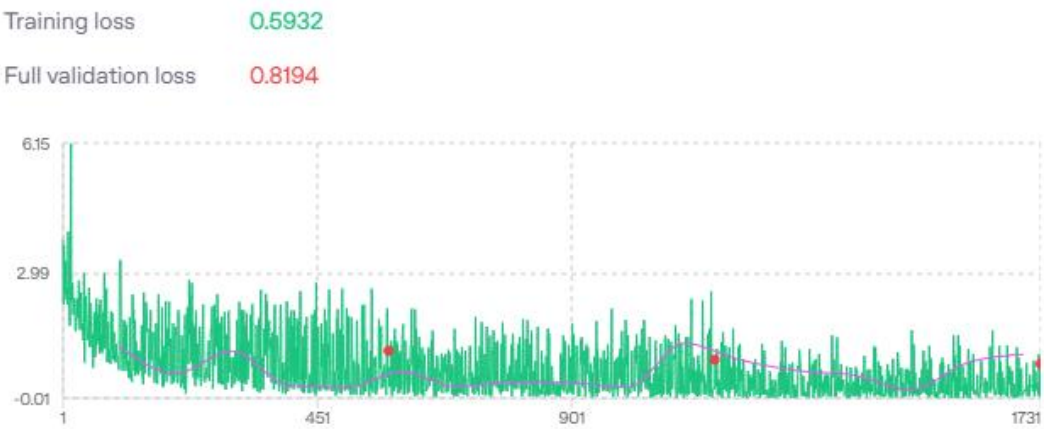

Figure 2. *Samantha's training graph. Source: Research data*

In addition, illustrative examples of prompts and responses used in the training and operation of the Samantha AI system are provided to support transparency regarding the AI-assisted interpretative process. The full training dataset is not publicly released due to ethical considerations and the presence of sensitive educational and interpretative content, but representative samples are available for inspection. Data access will be granted for non-commercial academic purposes upon request to the corresponding author.

4.3. Outliers

The psychometric data presented outliers across several attention measures. Given the size of the standardized sample and the exploratory nature of the analyses, excluding extreme values was not feasible without compromising statistical power. Therefore, all observations were retained, and the analyses combined descriptive statistics with non-parametric inferential tests.

Spearman's rank-order correlations were used due to non-normal distributions and the ordinal nature of teacher ratings. This approach allowed the examination of associations between attention models and teacher-rated engagement, commitment, and performance, while remaining robust to outliers.

Overall, weak to moderate correlations were observed between some attentional models and teacher ratings, particularly engagement. An unexpected inverse association between sustained attention and academic performance was observed at the descriptive and correlational level; this finding is examined cautiously in the subsequent analyses. No statistically meaningful associations were found between attentional measures and student commitment.

Outliers were identified through inspection of score distributions and boxplots for each attentional measure.

4.3.1. *Relationship Between Focused Attention, Sustained Attention, and Engagement*

Focused attention showed a weak positive association with teacher-rated engagement (Spearman's $\rho = 0.168$, $p = .216$), which did not reach statistical significance. Descriptively, students classified with average focused attention were predominantly rated by teachers as having average engagement, whereas those with above-average focused attention were more frequently perceived as highly engaged.

The mode of focused attention scores among students rated as having average and high engagement was 109 and 112 points, respectively, corresponding to the average and above-average standardized categories. Although these descriptive patterns suggest some alignment between focused attention and engagement, the magnitude of the association was small and should be interpreted cautiously (see *Table 2*. Relationship between focused attention scores and engagement).

Table 2. *Relationship between focused attention scores and engagement*

	Focused Attention						
Teachers' Perception	**Very low**	**Low**	**Medium Low**	**Medium**	**Medium High**	**High**	**Superior**
Low	1	1	0	1	0	0	0
Medium	0	2	4	13	6	2	0
High	0	0	3	14	8	1	0

Mean	**Median**	**Standard deviation**	**Mode**	**Spearman correlation**	**Highest standardized score**	**Lowest standardized score**
81	***71***	***18***	***Insufficient data***	***0,168***	***107***	***66***
101	***101***	***13***	***109***		***122***	***75***
103	***104***	***11***	***112***		***120***	***83***

Regarding sustained attention, a weak positive correlation with engagement was observed (Spearman's $\rho = 0.239$, $p = .077$). While this result did not meet the conventional threshold for statistical significance, it may be interpreted as a trend-level association. Students classified as having low engagement showed lower sustained attention scores (median and mode = 86, below average), whereas those rated as having medium or high engagement tended to present higher sustained attention scores (median = 98 and 110, respectively).

Despite the presence of outliers—particularly within the medium engagement group—the descriptive indices suggest a gradual increase in sustained attention scores as teacher-rated engagement increases (see *Table 3*. Relationship between sustained attention scores and engagement). Overall, these findings indicate that lower sustained attention tends to co-occur with lower engagement, although the observed relationships are modest in strength.

4.3.2. *Relationship Between Sustained Attention and Performance*

In contrast to engagement, the association between sustained attention and teacher-rated academic performance revealed a weak negative correlation (Spearman's $\rho = -0.172$, $p = .205$).

Although this relationship was not statistically significant, the inverse pattern was consistently observed across descriptive indices, including mean, median, and mode.

Table 3. *Relationship between sustained attention scores and engagement*

	Sustained Attention						
Teachers' Perception	**Very low**	**Low**	**Medium Low**	**Medium**	**Medium High**	**High**	**Superior**
Low	**0**	**0**	**2**	**1**	**0**	**0**	**0**
Medium	**3**	**1**	**4**	**6**	**11**	**2**	**0**
High	**0**	**0**	**4**	**8**	**10**	**4**	**0**

Mean	**Median**	**Standard deviation**	**Mode**	**Spearman correlation**	**Highest standardized score**	**Lowest standardized score**
90	**86**	**6**	**86**	**0,239**	**98**	**86**
97	**98**	**19**	**110**		**123**	**48**
105	**110**	**11**	**110**		**123**	**86**

Students perceived by teachers as having higher academic performance tended to present lower sustained attention scores (median = 98; mode = 86), whereas those perceived as having lower performance showed comparatively higher sustained attention scores (median = 110). This pattern was not anticipated during the study design and contrasts with conventional assumptions regarding the role of sustained attention in academic success (see *Table 4*. Relationship between sustained attention scores and performance).

Table 4. *Relationship between sustained attention scores and performance*

	Sustained Attention						
	Qualitative Classification in the test applied by iGnosi						
Teachers' Perception	**Very low**	**Low**	**Medium Low**	**Medium**	**Medium High**	**High**	**Superior**
Low	**0**	**1**	**0**	**0**	**1**	**1**	**0**
Medium	**3**	**0**	**6**	**13**	**17**	**5**	**0**
High	**0**	**0**	**4**	**2**	**3**	**0**	**0**

Mean	Median	Standard deviation	Mode	Spearman correlation	Highest standardized score	Lowest standardized score
102	**110**	**21**	***Insufficient data***	**-0,172**	**123**	**73**
101	**104**	**16**	**110**		**123**	**48**
97	**98**	**10**	**86**		**110**	**86**

Given the small effect size and lack of statistical significance, this inverse association should be interpreted as exploratory. Nevertheless, its consistency across descriptive measures warrants further investigation in future studies employing larger samples, refined performance indicators, and additional controls.hile this inverse relationship should be interpreted with caution due to its small effect size and lack of statistical significance, it raises important questions regarding compensatory strategies, task-specific attentional demands, or differences between classroom-based performance and computerized sustained attention tasks.

5. Discussion

This study yielded two complementary contributions. First, it demonstrated the feasibility of integrating a mobile psychometric tool (iGnosi®) with an AI-based conversational interface (Samantha) to support attention assessment and facilitate communication with teachers and parents. Second, it offered exploratory empirical indications of associations between attentional profiles and teacher-rated engagement and academic performance.

From a technological standpoint, the chatbot-based interface showed clear advantages in applied educational contexts. Samantha’s tolerance for grammatical variability and regional linguistic forms facilitated communication among heterogeneous user groups, including teachers, parents, and researchers. This feature is particularly relevant in linguistically diverse settings, as it lowers barriers to adoption and reduces the need for extensive user training. Importantly, the AI component was designed as an interpretative and communicative layer rather than a psychometric instrument, supporting understanding and contextualization of results without generating independent diagnostic inferences. Planned migration to open-source language models and locally hosted servers may further enhance scalability, reduce operational costs, and increase institutional control over data governance and system behavior.

Regarding the psychometric findings, the results suggest coherent relationships between attentional measures and teacher-rated engagement. Higher levels of focused and sustained attention were generally associated with higher engagement, whereas lower sustained attention tended to co-occur with reduced engagement. These patterns were most evident in the average and above-average score ranges and are broadly consistent with theoretical models linking attentional control to classroom participation and task persistence. In contrast, no meaningful associations were observed between attentional measures and teacher-rated commitment, indicating that perceived commitment may be more strongly influenced by motivational, contextual, or socio-emotional factors than by attentional performance alone.

An unexpected finding was the inverse association between sustained attention and perceived academic performance. In the present sample, students with higher sustained-attention scores were sometimes rated by teachers as lower-performing academically. This pattern was consistent across descriptive indicators (mean, median, and mode) but must be interpreted with caution. Sample size constraints, the presence of psychometric outliers, and the exploratory nature of the analyses limited the use of inferential modeling, precluding firm conclusions.

Rather than offering a definitive explanation, this result should be regarded as hypothesis-generating. One plausible interpretation is that sustained attention, as operationalized in the task, may reflect persistence toward a stimulus irrespective of its relevance. In contemporary digital environments, students may demonstrate prolonged attentional engagement with non-task-relevant stimuli while exhibiting reduced flexibility in attentional shifting. Under this framework, high sustained-attention scores would not necessarily translate into improved academic outcomes. This hypothesis cannot be tested within the present dataset and requires targeted follow-up studies.

These findings reinforce the importance of conceptualizing attention as a dynamic and context-dependent process rather than a unitary predictor of academic success. From a pedagogical perspective, the results support interventions that emphasize task relevance, motivational salience, and adaptive instructional design. Aligning learning activities with students' experiential frameworks—such as technology-mediated or gamified environments—may facilitate selective attention and improve engagement, consistent with prior educational research (Anderson, 2016; Júnior, 2018).

5.1. Limitations

The study has several limitations. The sample size was modest, limiting statistical power and the application of robust inferential analyses. Psychometric outliers could not be excluded without compromising representativeness. Additionally, no screening for neurodivergent conditions (e.g., ADHD) was conducted, despite their known influence on attention regulation and academic functioning. Finally, teacher ratings were used as the primary qualitative indicator and may reflect contextual or subjective biases.

5.2. Future directions

Future research should address these limitations by:

a) expanding the sample to enable sensitivity analyses and more robust handling of outliers;
b) incorporating neurodivergence screening or self-report measures to control for attentional heterogeneity;
c) triangulating teacher perceptions with objective academic indicators (e.g., grades or standardized assessments);
d) manipulating task relevance or incorporating screen-time measures to directly test the sustained-attention hypothesis; and
e) further refining the AI component through domain-specific training and open-source deployment on local infrastructure.

Collectively, these steps will help determine whether the observed inverse relationship between sustained attention and academic performance reflects a genuine cognitive pattern or a context-dependent artifact.

6. Conclusion

The iGnosi® application demonstrated feasibility and operational stability as a mobile tool for collecting attention-related data, offering internally standardized scoring that facilitates interpretation within educational contexts. Its deployment on Android tablets and its lower cost relative to traditional psychometric instruments highlight its potential applicability in school and higher-education settings, particularly as a screening and exploratory resource.

The Samantha AI system supported data interpretation and communication among stakeholders, suggesting its utility as an assistive interface for educators and researchers rather than as an evaluative or diagnostic agent. With continued training and empirical validation, such systems may help bridge the gap between psychometric data and pedagogical reflection.

Overall, the findings indicate consistent but modest associations between attention and teacher-rated engagement, while also revealing unexpected patterns—such as the inverse relationship between sustained attention and academic performance—that should be interpreted cautiously and treated as hypothesis-generating results.

Future studies integrating objective academic measures, neurodiversity screening, and experimental manipulation of task relevance will be essential to clarify these relationships. In sum, iGnosi® combined with Samantha represents a promising and accessible framework for exploratory attention assessment and educational support, with clear directions for methodological refinement and empirical validation prior to large-scale implementation.

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Disclosure Statement

The authors declare that there is no conflict of interest regarding the publication of this article. No financial, personal, or professional relationships have influenced the research, analysis, or conclusions presented in this work.

Notes on Contributors

Elias Souza Ribeiro is a researcher in neuroeducation and cognitive assessment. He holds an M.Sc. in Natural Sciences from Universidade Estadual do Norte Fluminense (UENF), where he investigated attentional processes and learning outcomes using iGnosi®, a cross-platform psychometric instrument he developed and integrated with a custom-trained artificial intelligence model. His research focuses on attention, executive functions, computational psychometrics, and the use of AI-driven tools to support educational evaluation and evidence-based decision-making in learning environments.

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References

Anderson, B. A. (2016). The attention habit: how reward learning shapes attentional selection. *Annals of the New York Academy of Sciences*, *1369*(1), 24–39. https://doi.org/10.1111/nyas.12957

Barbetta, P. A. (2012). *Estatística aplicada às Ciências Sociais* (P. R. da Silva, Ed.; 8th ed.). Editora UFSC.

Bauer, V. B. (2021). Neuropsicologia da aprendizagem em funções executivas e atenção. In *Políticas e estratégias educacionais*. Mérida Publishers. https://doi.org/10.4322/mp.978-65-994457-6-7.c3

Brasil. (2020). Brasil no Pisa 2018. *INEP/MEC*. https://www.gov.br/inep/pt-br/areas-de-atuacao/avaliacao-e-exames-educacionais/pisa/resultados

Carvalho, I. P., Costa, A., Silva, S., Moreira, B., Almeida, A., Moreira-Rosário, A., Guerra, A., Peixoto, B., Delerue-Matos, C., Sintra, D., Pestana, D., Pinto, E., Mendes, F. de C., Martins, I., Leite, J. C., Caldas, J. C., Fontoura, M., Maia, M. L., Queirós, P., … Calhau, C. (2020). Children's performance on Raven's Coloured progressive matrices in Portugal: The Flynn effect. *Intelligence*, *82*. https://doi.org/10.1016/j.intell.2020.101485

D'Ambrósio, U. (2005). Sociedade, cultura, matemática e seu ensino. *Educação e Pesquisa*, *31*(1), 99–120. https://doi.org/10.1590/S1517-97022005000100008

Flynn, J. R. (1984). The mean IQ of Americans: Massive gains 1932 to 1978. *Psychological Bulletin*, *95*(1), 29–51. https://doi.org/10.1037/0033-2909.95.1.29

Flynn, J. R. (1987). Massive IQ gains in 14 nations: What IQ tests really measure. *Psychological Bulletin*, *101*(2), 171–191. https://doi.org/10.1037/0033-2909.101.2.171

Flynn, J. R., & Shayer, M. (2018). IQ decline and Piaget: Does the rot start at the top? *Intelligence*, *66*, 112–121. https://doi.org/10.1016/j.intell.2017.11.010

Júnior, A. G. (2018). ATENÇÃO E ENGAJAMENTO DISCENTE EM SITUAÇÕES DE SALA DE AULA ATTENTION AND STUDENT ENGAGEMENT IN THE CLASSROOM. *Revista Habitus: Revista Da Graduação Em Ciências Sociais Do IFCS/UFRJ*, *15*(2), 46–62. https://revistas.ufrj.br/index.php/habitus

Marturano, E. M., Carla, L., & Elias, S. (2016). Família, dificuldades no aprendizado e problemas de comportamento em escolares. *Educar Em Revista*, *59*, 123–139. https://doi.org/10.1590/0104-4060.44617

Moura, L. T., & Silva, K. P. M. (2019). O Transtorno de Déficit de Atenção e Hiperatividade (TDAH) e as práticas pedagógicas em sala de aula. *Revista Eletrônica Acervo Saúde*, *22*, e216–e216. https://doi.org/10.25248/REAS.E216.2019

OCDE. (2023). NOTA SOBRE O BRASIL NO PISA 2022 DIRETORIA DE AVALIAÇÃO DA EDUCAÇÃO BÁSICA DAEB. *INEP*.

OCDE. (2025, May). *Matriz de Ciências do PISA 2025*. https://pisa-framework.oecd.org/science-2025/bra_por/

Oliveira, P. V. de, Muszkat, M., & Fonseca, M. F. B. C. da. (2019). Relação entre índice de motivação escolar e desempenho acadêmico de crianças com transtorno de déficit de atenção/hiperatividade e grupo controle. *Revista Psicopedagogia*, *36*(109), 24–33.

http://pepsic.bvsalud.org/scielo.php?script=sci_arttext&pid=S0103-84862019000100004&lng=pt&nrm=iso&tlng=pt

OpenAI. (2024). *Fine-tuning - OpenAI API*. https://platform.openai.com/docs/guides/fine-tuning

Rabelo, I. S., Cruz, R., & Castro, N. R. De. (2020). *BATERIA ROTAS DE ATENÇÃO Rota da Atenção Concentrada (Rota C) Rota da Atenção Dividida (Rota D) Rota da Atenção Alternada (Rota A) MANUAL TÉCNICO* (I. B. Guntert, Ed.; 1st ed.). NilaPress.

Ribeiro, E. S., & Sousa, C. E. B. de. (2025). SAMANTHA: IA APLICADA AO ESTUDO DA RELAÇÃO ENTRE ATENÇÃO E APRENDIZAGEM. *Revista Interinstitucional Artes de Educar*, *11*(1), 245–261. https://doi.org/10.12957/RIAE.2024.86267

Rueda, F. J. M. (2013). *Bateria Psicológica para Avaliação da Atenção - BPA* (Vol. 1). Vetor.

Sassaki, A. H., Di Pietra, G. A. C., Filho, N. A. M., & Komatsu, B. K. (2018). Por que o Brasil vai Mal no PISA? Uma Análise dos Determinantes do Desempenho no Exame. *INSPER*. https://www.researchgate.net/publication/326718184

Sharpe, M. J., & Killcross, S. (2015). The prelimbic cortex directs attention toward predictive cues during fear learning. *Learning & Memory*, *22*(6), 289–293. https://doi.org/10.1101/lm.038273.115

Shayer, B., Carvalho, C., Mota, M., Argollo, N., Abreu, N., & Bueno, O. F. A. (2015). Desempenho de escolares em atenção e funções executivas no Nepsy e inteligência. *Revista Psicologia: Teoria e Prática*, *17*(1), 120–135. https://doi.org/10.15348/1980-6906/psicologia.v17n1p120-135

Teasdale, T. W., & Owen, D. R. (2008). Secular declines in cognitive test scores: A reversal of the Flynn Effect. *Intelligence*, *36*(2), 121–126. https://doi.org/10.1016/J.INTELL.2007.01.007