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Assessing the Psychological Impact of AI on Computer and Data Science Education: An Exploratory Study

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Abstract. This study assesses the impact of Generative AI on the educational experiences of computer and data science students at the Center for Informatics, Federal University of Paraíba (CI/UFPB), Brazil. Through Exploratory Factor Analysis (EFA) of five psychometric scales, the research examines students' acceptance of LLMs, their levels of academic burnout, technology-related anxiety, and the prevalence of both metacognitive and dysfunctional learning strategies associated with LLM use. Results revealed high adoption of LLMs, low levels of AI-related technology anxiety, and frequent use of metacognitive strategies. However, dysfunctional learning patterns were still present, particularly among students experiencing higher levels of academic burnout. This study contributes to the ongoing discourse on AI in education, emphasizing the need for pedagogical frameworks that support the effective and ethical adoption of AI while addressing the psychological demands placed on students. The validated instruments are made available for future research in educational and psychological contexts, along with their versions back-translated into English.

Keywords: Psychopedagogy, LLMs, GenAI, Computer Education, Validity Assessment, Psychometric Properties

1 Introduction

In the era of Artificial Intelligence (AI), the academic landscape is undergoing a rapid transformation [Okonkwo and Ade-Ibijola, 2021; Dwivedi et al., 2023]. AI-powered technologies, such as ChatGPT, now provide nuanced responses to a broad range of topics in mere seconds, aiding undergraduate students in their coursework and learning processes [Tu et al., 2023; Zhai, 2023; Cooper, 2023]. Despite these significant benefits, professors express concerns about the responsible use of such technologies. They emphasize the risk of students developing an excessive reliance on these tools, potentially undermining their long-term creative and problem-solving skills [Choi et al., 2023; Hung and Chen, 2023; Tu et al., 2023]. Additionally, ethical issues such as AI system bias, plagiarism, and lack of transparency need to be considered [Zhai, 2023; Dwivedi et al., 2023].

As AI continues to influence education, universities worldwide are grappling with emerging challenges and opportunities. For instance, the Chinese University of Hong Kong was among the first Chinese institutions to ban the use of ChatGPT, aiming to uphold academic integrity [Hung and Chen, 2023]. Students caught using ChatGPT could face penalties ranging from grade reduction to course failure, or even dismissal, on grounds of academic plagiarism and misconduct [Hung and Chen, 2023]. In contrast, the Hong Kong University of Science and Technology has embraced the use of ChatGPT and other Large Language Models (LLMs), asserting their responsibility as educators to prepare students for an AI-driven world where tasks can be completed in a timely and cost-effective manner [Hung and Chen, 2023].

Popularized by ChatGPT and commonly referred to as Generative AI (GenAI), LLMs are powerful tools with remarkable capabilities for generating human-like text. Beyond major tech giants such as Google and OpenAI, smaller research groups are increasingly training their own LLMs [Gao and Gao, 2023]. Stemming from the Machine Learning (ML) branch of AI, these models require vast amounts of training data, easily sourced from the internet, and are increasingly feasible due to the surge in computational power in recent years. As of 12 PM (GMT -5) on July 18, 2023, there were 15,821 LLMs registered with Hugging Face, a popular machine learning repository [Gao and Gao, 2023].

The expanding number of LLMs encompasses various architectures, settings, training methods, and families, reflecting not only the growing presence of these models but also the emergence of diverse types. This rapidly evolving field of GenAI presents profound implications for computer and data science education, necessitating a shift in both curriculum content and pedagogical approaches [Tu et al., 2023]. In line with recent findings [Lee; Hwang and Chen, 2023; Yin et al., 2020; Essel et al., 2022; Okonkwo and Ade-Ibijola, 2021;

Pahune and Chandrasenkharan, 2023; Zhai, 2023; Hadi et al., 2023; Urban et al., 2024], the integration of GenAI in education is seen as both promising and complex. Despite concerns about misinformation, overdependence, and uneven access, GenAI holds great promise for education by enabling personalized learning paths that respond to students' unique cognitive profiles and learning styles.

Amid these transformations, there is a growing need to accurately assess how students perceive, respond to, and cognitively engage with GenAI technologies. Responding to this gap, Lintner [2024] conducted a systematic review of 16 AI literacy instruments used across 22 studies. Notably, the earliest instrument was published in 2021, and the majority emerged only in 2023, underscoring how recent and underdeveloped this measurement field still is. While Lintner's review found that many instruments demonstrated good structural validity and internal consistency, it also revealed critical limitations—particularly in areas such as content validity, cross-cultural adaptation, and responsiveness to change. Among the most promising tools were the Scale for the Assessment of Non-experts AI Literacy (SNAIL), built through Delphi consensus; the Meta AI Literacy Scale (MAILS), incorporating self-efficacy dimensions; and the AI Literacy Test, one of the few performance-based measures validated with university students.

These findings reinforce the importance of developing psychometric tools that are theoretically sound, methodologically rigorous, and sensitive to cultural and educational contexts. Building on this emerging body of research, the present study introduces five original instruments designed to assess the psychological and educational impact of GenAI on students in computer and data science education. To our knowledge, this is the first set of GenAI-related psychometric scales validated for Brazil. In a sample of undergraduate students, the vast majority reported everyday LLM use; efficient metacognitive engagement with LLMs was strongly associated with higher acceptance and intention to use, whereas dysfunctional patterns of use were associated with greater academic burnout. An association between AI-technology anxiety and acceptance was also observed—an apparently paradoxical pattern that we interpret as reflecting students' ethical concern and risk awareness as they adopt these technologies.

2 Related Works

The growing presence of GenAI and LLMs in education has motivated researchers to develop instruments capable of capturing students' cognitive, emotional, and behavioral engagement with these technologies. While some early efforts prioritized exploratory experimentation, more recent studies have sought to ground their instruments in established theoretical frameworks, such as Bloom's Taxonomy, the Technology Acceptance Model (TAM), and models of digital literacy.

Among the most comprehensive contributions is the MAILS, proposed by Carolus et al. [2023]. The instrument was designed to go beyond classical notions of AI literacy by integrating constructs such as emotion regulation, problem-solving, and self-management in AI learning contexts. The framework draws on Bloom's Taxonomy and builds a second-order model composed of AI Literacy, Self-Efficacy, and Competency. Results from a German-speaking adult sample showed that MAILS successfully differentiates between conceptual knowledge and psychological readiness for AI integration, positioning the instrument as a bridge between technical skill and human-centered AI interaction.

Complementing this psychological focus, the study by Ng et al. [2024] introduced the AI Literacy Questionnaire (AILQ) to evaluate literacy among secondary school students in Hong Kong. Grounded in a four-dimensional ABCE framework—Affective, Behavioral, Cognitive, and Ethical—the AILQ captures how students feel about, engage with, understand, and reflect on AI. The scale was rigorously developed through qualitative interviews, expert consultations, and multistage testing, ultimately targeting adolescents aged 12–17.

Exploring its effects on motivation, engagement, and learning strategies, recent studies have examined student perceptions of ChatGPT exclusively. Alnaim [2024], for example, surveyed over 400 Saudi university students to explore constructs such as academic motivation, skills development, and perceived negative impacts of ChatGPT. While the instrument was not psychometrically validated, it provided valuable descriptive insights, highlighting students' recognition of ChatGPT as a useful academic support tool, particularly in writing and language tasks. Similarly, Hanum; Hasmayni and Lubis [2023] investigated how ChatGPT influenced the learning motivation of high school students in Indonesia. Grounded in learning motivation frameworks, the study used adapted instruments to show that ChatGPT use was positively associated with increased motivation.

Additionally, Hwang et al. [2023] proposed a Digital Literacy Scale for the AI Era, focusing on university students in South Korea. Their theoretical model was informed by both digital literacy literature and TAM constructs. Notably, the scale included items measuring critical evaluation, ethical awareness, and technical engagement, providing a multidimensional view of AI literacy that aligns with the needs of modern academic and professional contexts. Sallam et al. [2023] also developed the TAME-ChatGPT scale, an adaptation of the TAM framework tailored to assess students' perceived usefulness, ease of use, social influence, anxiety, and risk perception regarding ChatGPT. The study was conducted with health sciences students in Jordan and revealed that perceived usefulness and social influence were among the strongest predictors of behavioral intention to adopt ChatGPT.

Together, these studies underscore the diversity of theoretical lenses through which AI literacy and GenAI integration can be understood—from behavioral intention models and ethical reflection to psychological readiness and self-regulated learning.

3 Methodology

The primary objective of this research is to explore five psychological constructs related to the impact of GenAI on computer and data science education in a sample of brazilian university students. To address this, psychometric scales specifically designed to measure those constructs were developed. **Table 1** presents a methodological comparison of scale validation procedures used in the current study and related works.

3.1 Procedures and participants

Data collection was conducted exclusively at the Center for Informatics, University of Paraíba (CI/UFPB), in Brazil, using Google Forms. This platform automatically notified participants of any missing values, ensuring the completeness and accuracy of each submission. To maximize participation and reach, a diverse dissemination strategy was employed. This strategy included using WhatsApp for communication within CI/UFPB academic groups; distributing informative leaflets with QR codes for straightforward access to the online form; and facilitating educational discussions in classroom environments led by faculty members and students. This effort yielded a substantial dataset, with 178 respondents: 143 males, accounting for 80.3% of the total, and 35 females, comprising 19.7%.

Participants were students enrolled in CI/UFPB's computing and data-science degree programs, and data were collected in the second semester of 2023; a detailed discussion of these programs' curricula is beyond the scope of this article. To maintain data integrity and reduce potential response bias, the order of psychometric scales was randomized during data collection. This methodological choice is known to mitigate the effects of question order, promoting more reliable and unbiased responses [Podsakoff et al., 2001].

All data were collected in strict adherence to ethical research standards. Participants' sociocultural values, autonomy, and anonymity were fully respected throughout the process, and all foreseeable risks were carefully assessed and minimized. Informed consent was obtained from all participants prior to their involvement. In accordance with Resolution 510/2016 of the Brazilian National Health Council (*Conselho Nacional* de Saúde – CNS), research involving non-identifiable human subjects does not require formal approval from an ethics committee. Given the low-risk nature of the study and full compliance with applicable regulatory frameworks, formal ethical clearance was not required.

3.2 Instruments

Five psychometric scales were developed, each using a 7-point Likert format to capture nuanced responses. Our target population and analysis were intentionally restricted to students in computing disciplines. Accordingly, all instruments were purpose-built for the study's context: learning in computing with LLMs in GenAI-rich coursework. This tailoring ensured construct relevance and sensitivity to the practices and challenges unique to computing students who are both learning about and working with AI tools.

- **Academic Burnout Model, 4 items (ABM-4):** Adapted from the burnout instrument developed by [Kristensen et al., 2005], originally intended to assess work-related burnout, this adaptation captures a unidimensional construct of academic burnout. The ABM-4 gauges the extent to which students experience exhaustion due to study demands, emotional strain from academic pressures, and overall depletion associated with sustained, intensive study. Responses are provided on a 7-point Likert scale (Strongly disagree–Strongly agree).
- **AI Technology Anxiety Scale, 3 items (AITA-3):** This scale measures the anxiety students may feel when interacting with generative AI technologies, including fears of job displacement or subject matter obsolescence. The scale was adapted from Wilson et al. [2023, p. 186], which defined technology anxiety as "the tension from the anticipation of a negative outcome related to the use of technology deriving from experiential, behavioral, and physiological elements". Responses are provided on a 7-point Likert scale (Strongly disagree–Strongly agree).
- **Intrinsic Motivation Scale, 3 items (IMOV-3):** Developed based on the work of Hanum; Hasmayni and Lubis [2023], this scale measures students' intrinsic motivation toward learning—that is, the inherent satisfaction and interest in the learning process itself. It was created to capture the internal drivers of engagement. Responses are provided on a 7-point Likert scale (Strongly disagree–Strongly agree).
- **Learning Strategies with Large Language Models Scale, 6 items (LS/LLMs-6):** This scale evaluates how students employ learning strategies while interacting with LLMs. The scale is divided into two theoretically grounded subscales or factors: Dysfunctional Learning Strategies (DLS/LLMs-3) and Metacognitive Learning Strategies (MLS/LLMs-3). The DLS subscale captures unproductive behaviors—such as passively copying answers or skipping cognitive engagement. In contrast, the MLS subscale reflects intentional self-regulatory actions, such as planning, monitoring, and evaluating one's understanding while using LLMs. The items were adapted from previous scales on academic learning strategies [Oliveira and Caliatto, 2018; Pereira; Santos and Ferraz, 2020], ensuring contextual relevance to GenAI-supported learning. To compute a composite score that reflects the overall quality of learning strategies, the final score is derived by subtracting the DLS score from the MLS score: *Total Score* = Sum[MLS] – Sum[DLS]. Responses are provided on a 7-point Likert scale (Almost rarely–Very frequently).
- **LLMs Acceptance Model Scale, 5 items (TAME/LLMs-5):** This scale assesses students' readiness to integrate LLMs into their learning process. It is adapted from the TAME model described by Sallam et al. [2023], specifically corresponding to Factor 1—*perceived usefulness*—identified through EFA. The items measure students' perceptions of the usefulness and efficiency of LLMs in academic tasks such as programming. Item 5 is reverse-coded. Responses are provided on a 7-point Likert scale (Strongly disagree–Strongly agree).

Table 1. Methodological comparison between the present study and related works

Study	Factorial Extraction	Sample Adequacy	Internal Reliability	Factorial Retention
Current Study	EFA, Principal Axis Factoring	KMO, Bartlett's Test, Box and Violin Plots	Cronbach's Alpha (α), McDonald's Omega (ω)	Parallel Analysis, Factor Forest, Kaiser Criterion
Alnaim, 2024	None	None	Cronbach's Alpha (α)	None
Carolus et al., 2023	Confirmatory Factor Analysis (CFA), Satorra-Bentler estimation	Theory-driven model	Cronbach's Alpha (α)	Theory-based retention, Model Fit Indices (CFI, RMSEA, SRMR)
Hanum et al., 2023	Corrected Item-Total Correlation	Kolmogorov-Smirnov test, VIF	Cronbach's Alpha (α)	None
Hwang et al., 2023	Principal Component Analysis (PCA), CFA	KMO = 0.84, Bartlett's Test	Cronbach's Alpha (α)	Kaiser Criterion, Model Fit Indices (GFI, AGFI, CFI, TLI, RMSEA, RMR, χ^2/df)
Laupichler et al., 2023	EFA, Maximum Likelihood Estimation	KMO = 0.97, Bartlett's Test	Cronbach's Alpha (α)	Parallel Analysis, MAP Test, Scree Plot
Ng et al., 2024	CFA, Second-order modeling	Theory-driven model	Cronbach's Alpha (α), McDonald's Omega (ω), AVE, HTMT	Model Fit Indices (CFI, TLI, RMSEA, SRMR), AVE/HTMT thresholds, AIC comparison
Sallam et al., 2023	PCA	KMO, Bartlett's Test	Cronbach's Alpha (α)	Kaiser Criterion

Table 2 presents all item wordings organized by scale, shown in their original Brazilian Portuguese (PT-BR) alongside an English back-translation prepared by our research team.

3.3 Data analysis

Exploratory Factor Analysis (EFA) was conducted to simplify the complex data structure and uncover the fundamental dimensions within the observed variables, thereby validating the psychological properties of the scales. This analysis was performed using the factor-analyzer package in Python and the psych package in R [Revelle, 2023; Brown, 2023]. In addition, descriptive analyses of the scales are visualized with box plots and violin plots to summarize central tendency, dispersion, and distributional patterns, and all pairwise Spearman rank correlations are presented.

3.3.1 EFA decision processes

Factorial analysis is not a singular technique but rather a group of associated methods that should be considered and applied in concert [Damasio, 2012]. The objectives of EFA are multifaceted and include the reduction of variables to a smaller number of factors, assessment of multicollinearity, development of theoretical constructs, and testing of proposed theories [Taherdoost et al., 2022]. The sequential and linear approach to EFA demands careful consideration of various methodological steps to ensure the validity and reliability of the results. The decisions made throughout this process are detailed below:

1. **Sample adequacy:** Prior to factor extraction, it's imperative to evaluate whether the data set is suitable for factor analysis. To this end, Bartlett's test of Sphericity and the Kaiser-Meyer-Olkin (KMO) measure were employed [Damasio, 2012; Taherdoost et al., 2022]. Bartlett's test is used to test the hypothesis that the correlation matrix is not an identity matrix, essentially assessing whether the variables are interrelated and suitable for structure detection. A significant result from Bartlett's test allows for the rejection of the null hypothesis, indicating the factorability of our data [Taherdoost et al., 2022]. On the other hand, the KMO measure evaluates the proportion of variance among variables that could be attributed to common variance. With the KMO index ranging from 0 to 1, values above 0.5 are considered suitable for factor analysis [Damasio, 2012; Taherdoost et al., 2022].
2. **Factor retention:** Determining the optimal number of factors to retain is a crucial aspect of EFA, as it defines the dimensionality of the constructs. In this study, three distinct methods were adopted to identify the optimal number of factors: the Kaiser-Guttman criterion [Taherdoost et al., 2022], Parallel Analysis [Crawford et al., 2010], and Factor Forest [Goretzko and Bühner, 2020]. Factor extraction plays a significant role in simplifying data complexity and revealing the dataset's underlying structure.
3. **Internal reliability:** A critical component of EFA is the evaluation of the internal reliability of the scales. Reliability assessment refers to the process of examining how consistently a scale measures a construct. Ensuring consistent measurement is pivotal, as it confirms that any observed variations in data accurately reflect differences in the underlying construct, rather than resulting from measurement error or inconsistencies [Dunn; Bag-

Table 2. Original and back-translated items of the psychometric scales.

Scale	Item	English Version	Portuguese Version
ABM-4	1	I never feel able to achieve my academic goals.	Nunca me sinto capaz de alcançar meus objetivos acadêmicos.
	2	I find it hard to unwind after classes.	Tenho dificuldade para relaxar depois das aulas.
	3	I get exhausted when I have to go to college.	Fico esgotado quando tenho que ir à universidade.
	4	The demands of my course make me emotionally tired.	As demandas do meu curso me deixam emocionalmente cansado(a).
AITA-3	1	I feel like I can't keep up with the changes caused by AI models.	Sinto como se não pudesse acompanhar as mudanças causadas pelos modelos de IA.
	2	I worry that programmers will be replaced by AI models.	Me preocupo que programadores sejam substituídos pelos modelos de IA.
	3	I'm afraid AI models will render content I learned in college obsolete.	Tenho medo que modelos de IA tornem conteúdos que aprendi na faculdade obsoletos.
IMOV-3	1	I like to go to every class in my course.	Gosto de ir em todas as aulas do meu curso.
	2	I'm often so excited that I lose track of time when involved in a project.	Muitas vezes, fico tão empolgado que perco a noção do tempo quando estou envolvido em um projeto.
	3	For me, learning about programming is a personal interest.	Para mim, aprender sobre programação é um interesse pessoal.
LS/LLMs-6	1	I use LLMs to clarify doubts and fill gaps in programming knowledge.	Utilizo LLMs para tirar dúvidas e preencher lacunas no meu conhecimento sobre programação.
	2	I use LLMs to formulate and solve programming activities.	Utilizo LLMs para formular e resolver atividades de programação.
	3	I correct my codes using LLMs.	Corrijo meus códigos utilizando LLMs.
	4	I tend to cram for exams at the last minute.	Deixo para estudar para as provas de última hora.
	5	I have difficulty finding errors in responses and codes from LLMs.	Tenho dificuldade para encontrar erros em respostas e códigos gerados por LLMs.
	6	I feel like I'm just memorizing information instead of understanding it.	Sinto que estou apenas memorizando informações em vez de realmente entender os conteúdos.
TAME/LLMs-5	1	LLMs make programming more democratic and accessible.	LLMs tornam a programação mais democrática e acessível para as pessoas.
	2	I believe LLMs can be better explored by teachers in class and tests.	Acredito que LLMs podem ser melhor exploradas pelos professores nas aulas e provas.
	3	I feel confident with texts or codes generated by LLMs.	Me sinto confiante com os textos e códigos gerados por LLMs.
	4	I think LLMs are very efficient in programming.	Penso que LLMs são muito eficientes em programação.
	5	I prefer programming without the help of LLMs.	Prefiro programar sem ajuda de LLMs.

uley and Brunsden, 2013]. For this purpose, we employed two key metrics: McDonald's omega (ω) and Cronbach's alpha (α) [Dunn; Baguley and Brunsden, 2013].

4. **Factor extraction:** A fundamental next step involves selecting an appropriate method for factor extraction, which dictates how factors are derived from the data. In this research, Principal Axis Factoring (PAF) was employed. Unlike methods that require multivariate normality, PAF is adept at handling data that may not fully meet these criteria, making it a suitable choice in exploratory contexts, especially with smaller sample sizes [Taherdoost et al., 2022; Goretzko; Pham and Bühner, 2021].
5. **Rotation method:** The final step in factorial analysis often involves choosing a rotation method to achieve a theoretically coherent and interpretable factor solution. In this study, promax rotation, a widely used method for oblique rotation, was selected [Sass and Schmitt, 2010]. The rationale for using an oblique rotation like promax lies in its suitability for scenarios where factors are presumed to be correlated. Unlike orthogonal rotations, which assume factors are independent, oblique rotations acknowledge and accommodate the possibility of interfactor correlations [Sass and Schmitt, 2010; Damasio, 2012].

3.4 Gen AI usage statement

The ChatGPT-4 model contributed significantly to this project by assisting in various stages, including grammar correction, paragraph refinement, and data analysis coding. All outputs generated by the model were meticulously reviewed to ensure precision and reliability, aligning with the rigorous standards of academic research.

4 Results

4.1 LLMs usage preferences among students

In the assessment of LLMs' preferences at the CI/UFPB, the data revealed a predominant usage of ChatGPT 3.5, with a staggering 92.7% of the respondents utilizing this free version. ChatGPT 4, despite being a paid version in 2023, is used by 5.6% of the participants, demonstrating a willingness to invest in more advanced AI tools. Bing Chat and Bard are used by 23% and 18% of the students, respectively, reflecting the diversity of AI platforms supporting their educational pursuits. Only 4.5% reported not using any LLM, underscoring the widespread penetration of these technologies in the academic environment.

4.2 Development, validity and reliability

The results of the EFA demonstrated psychometric adequacy for all scales evaluated. As shown in **Table 3**, the KMO test values exceeded the minimum threshold of 0.5, indicating the adequacy of the sample. Furthermore, Bartlett's sphericity test was statistically significant ($p < 0.05$), confirming that the data were suitable for structure detection [Taherdoost et al., 2022; Damasio, 2012].

The factorial retention procedure further elucidates the dimensionality of the scales, as detailed in **Table 4**. All factorial retention methods were consistent in their results, except for the TAME/LLMs-5 scale, where Parallel Analysis identified two factors, while both Factor Forest and Kaiser criterion indicated a single factor. We opted for a single-factor solution because the scale was originally designed to be unidimensional. Moreover, all scales are intentionally small and exploratory in nature.

After evaluating sample adequacy and determining the number of factors to retain, the study progressed to assess the internal reliability of the scales. This evaluation, detailed in **Table 3**, involved an analysis of Cronbach's alpha (α) and McDonald's omega (ω). Notably, the ABM-4 and LS/LLMs-6 scales displayed strong reliability, with both ω values surpassing the 0.7 benchmark, suggesting high consistency. The TAME/LLMs-5 scale showed a well-balanced reliability profile, evidenced by closely matched α and ω values. In contrast, the AITA-3 and IMOV-3 scales, while still reliable, recorded slightly lower scores, indicating moderate consistency.

At last, the cornerstone of EFA is the factorial extraction procedure. The factorial loadings in EFA are critical as they represent the strength and direction of the relationship between observed variables (scales's items) and underlying latent factors [Damasio, 2012; Taherdoost et al., 2022]. Essentially, these loadings measure how much variance in an item is explained by the factor, providing insights into how well each variable aligns with a particular factor. Analyzing the EFA loadings presented in **Table 5**, it's evident that most items demonstrate strong correlations with their theoretical factors, indicating a coherent pattern associations across the scales, and the effectiveness of the factorial analysis in simplifying the data's complexity into a small number of factors.

4.3 Descriptive statistics

The exploration into the scales' characteristics will be visualized through the strategic use of box and violin plots, which will illustrate the core tendencies and variations within the students' data. Box plots are designed to highlight central measures—the mean (indicated by a white dot) and median (depicted as a red line)—along with the spread of responses. This spread is represented by quartiles, which divide the data into four equal parts. The interquartile range, marking the distance between the first and third quartiles, encompasses the central 50% of the data, shown as a blue box. In parallel, violin plots will provide insights into the data's density and distribution, offering a more nuanced interpretation of variability and frequency across different values.

Beginning with an assessment of students' mental health, the ABM-4 scale uncovers significant patterns in students' exhaustion, stress and depletion (Figure 1). The mean and median, positioned above the midpoint scale of 16, suggest a high level of academic burnout among the students. The box plot displays a wide interquartile range, indicating a diverse dispersion in the severity of students' experiences.

Table 3. Psychometric properties of scales.

Scales	KMO Test	Bartlett's Test of Sphericity	McDonald's ω	Cronbach's α
ABM-4	0.742	0.000	0.702	0.702
AITA-3	0.562	0.000	0.664	0.619
IMOV-3	0.581	0.000	0.625	0.578
LS/LLMs-6	0.682	0.000	0.739	0.640
TAME/LLMs-5	0.689	0.000	0.663	0.656

Table 4. Factorial retention methods and cumulative variance explained.

Scales	Parallel Analysis	Factor Forest	Kaiser Criterion	Cumulative Variance Explained
ABM-4	1	1	1	0.528
AITA-3	1	1	1	0.579
IMOV-3	1	1	1	0.545
LS/LLMs-6	2	2	2	0.618
TAME/LLMs-5	2	1	1	0.426

Table 5. Factor loadings

Scales	Items	Factor 1	Factor 2
ABM-4	Item 1	0.70	-
	Item 2	0.74	-
	Item 3	0.72	-
	Item 4	0.74	-
AITA-3	Item 1	0.53	-
	Item 2	0.85	-
	Item 3	0.86	-
LS/LLMs-6	Item 1	**0.83**	0.00
	Item 2	**0.85**	0.05
	Item 3	**0.86**	0.04
	Item 4	0.11	**0.68**
	Item 5	0.02	**0.71**
	Item 6	0.09	**0.76**
IMOV-3	Item 1	0.72	-
	Item 2	0.82	-
	Item 3	0.67	-
TAME/LLMs-5	Item 1	0.69	-
	Item 2	0.69	-
	Item 3	0.63	-
	Item 4	0.74	-
	Item 5	0.47	-

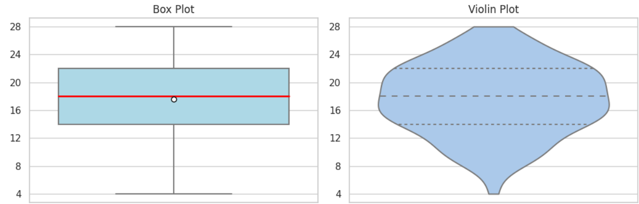

Figure 1. ABM-4.

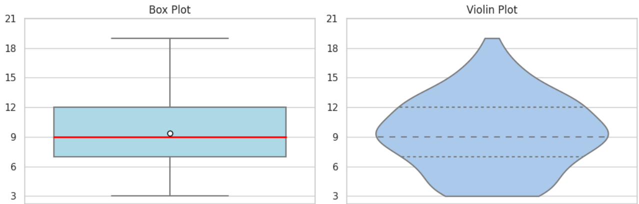

Figure 2. AITA-3.

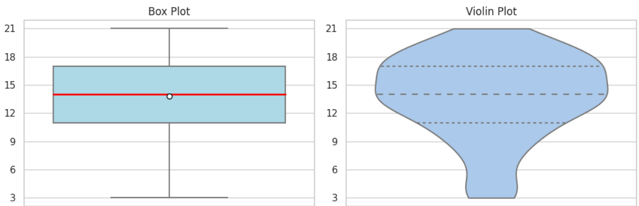

Figure 3. MLS/LLMs-3.

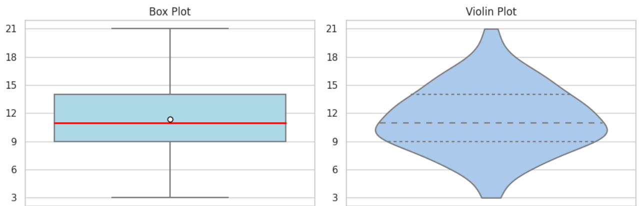

Figure 4. DLS/LLMs-3.

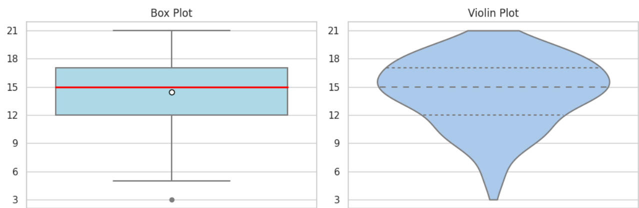

Figure 5. IMOV-3.

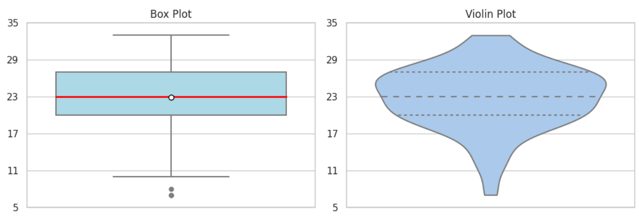

Figure 6. TAME-5.

In contrast, the AITA-3 scale, which focuses on technology anxiety related to AI, presents a different data distribution (Figure 2). The box plot demonstrates that the interquartile range is below the mid-scale value of 12, indicating a trend toward lower anxiety levels within the group. Results indicates that 75% of students' anxiety levels are comfortably below the midpoint, and none have reached the maximum level of technology anxiety.

Regarding learning strategies, the analysis of the MLS/LLMs-3 sub-scale through its descriptive statistics unveils a median that is marginally above the midpoint, indicating a propensity for higher engagement with metacognitive strategies (Figure 3). Nevertheless, the wide interquartile range indicates a variety in students' responses. The DLS/LLMs-3 visualizations shed light on another dimension of student learning strategies (Figure 4). When comparing these sub-scales, it appears that students are generally more consistent in their use of metacognitive strategies than in avoiding dysfunctional ones, which seem to be more scattered.

The IMOV-3 provides an intriguing overview of the distribution of students' inherent enthusiasm for learning (Figure 5). The median value of 15, with the entire interquartile range situated above the midpoint, reflects a collective tendency toward a more motivated approach to learning. An outlier, represented as a solitary dot, hints at an exceptional case where a student's motivation significantly diverges from the norm. This data leads us to a plausible conclusion that students demonstrate strong motivation for learning, evidenced by 75% of them scoring beyond the midpoint threshold.

Lastly, TAME/LLMs-6 provides insights into students' perceptions and acceptance of LLMs (Figure 6). The box plot reveals a small interquartile range positioned above the scale's midpoint, indicating a cohesive attitude toward LLMs among the respondents. This compact range suggests a consensus in acceptance levels, with only a few outliers indicating some reservations.

4.4 Correlation Matrix

The Spearman's correlation matrix unveils a complex network of relationships among the scales described before. A pattern emerges where academic burnout subtly correlates with technology anxiety and more notably, with dysfunctional learning strategies. This triad forms a nexus, indicating a dynamic interplay where each construct potentially exacerbates the influence of the others. Yet, the most pronounced relationship in the matrix is observed between the acceptance of LLMs and the metacognitive strategies employed by students, strongly suggesting that embracing these advanced tools could be aligned with more sophisticated and reflective learning approaches.

5 Discussion

5.1 An overwhelming acceptance of LLMs

The findings unveil significant psychological and behavioral patterns among data science students, especially their

Table 6. Spearman's correlation matrix (ρ) among the study scales. Statistically significant correlations are shown in bold.

Scales	ABM-4	AITA-3	IMOV-3	MLS/LLMs-6	DLS/LLMs-6	TAME/LLMs-5
ABM-4	1	**0.27**	-0.14	0.05	**0.41**	**0.16**
AITA-3	**0.27**	1	0.00	0.09	**0.34**	**0.16**
IMOV-3	-0.14	0.00	1	-0.03	**-0.31**	-0.04
MLS/LLMs-6	0.05	0.09	-0.03	1	0.11	**0.60**
DLS/LLMs-6	**0.41**	**0.34**	**-0.31**	0.11	1	0.13
TAME/LLMs-5	**0.16**	**0.16**	-0.04	**0.60**	0.13	1

overwhelming acceptance of LLMs like ChatGPT and Bard. This trend reflects a forward-thinking approach to incorporating AI technologies into their academic toolkit. With only eight students reporting no use of LLMs, and considering the descriptive results from the TAME/LLMs-6 scale, the data underscores a pervasive, technology-oriented ethos at CI/UFPB. As documented in recent studies [Tu et al., 2023; Dwivedi et al., 2023; Zhai, 2023; Choi et al., 2023; Cooper, 2023], the influence of LLMs is reshaping educational practices across institutions worldwide. These AI technologies are not merely transient tools but are becoming integral to the future of teaching and learning, with their impact evolving more rapidly in fields like data science, which are inherently connected to technological advancements.

5.2 The role of GenAI in education

This technology-friendly environment likely contributes to the notably low levels of AI-related anxiety, as seen in the descriptive results of the AITA-3 scale. The students' regular interactions with advanced technological tools seem to buffer them from the typical apprehensions concerning new technological integrations. Rather than viewing AI as a threat to their skills or future job prospects, they appear to recognize its potential to enhance their capabilities and autonomy.

However, a minor positive correlation was observed between the acceptance of LLMs and technology anxiety (ρ = 0.16, p-value = 0.03). This finding somewhat diverges from Wilson et al. [2023], which suggested that anxiety regarding technology typically has a negative correlation with the acceptance, usage, and integration of such tools. Nevertheless, it is essential to distinguish that the ATAS scale from Wilson et al. [2023] is concerned with general technology anxiety and not crafted for the evolving AI context, whereas the AITA-3 is dedicated to exploring the societal issues triggered by those technologies. This distinction implies that for students regularly using LLMs, the perceived effectiveness of AI might paradoxically induce more anxiety about its societal integration, highlighting a nuanced relationship between familiarity with AI and perceptions of its broader implications.

The concern about the displacement of programming jobs by AI mirrors a general expectation of profound changes across various sectors. This anticipated shift accent the critical need for strategic upskilling in education, encouraging programmers to expand their expertise beyond the conventional pipeline. Now, "students need to learn to view themselves as product managers rather than software engineers" [Tu et al., 2023, p. 3], which not only prepares them for the evolving demands of the job market but also positions them to navigate the future of work with agility and foresight.

It is known that the emergence of digital technologies, such as calculators, smartphones, and GPS systems, has profoundly impacted human cognition [Dwivedi et al., 2023]. Similarly, AI is poised to bring about significant psychological changes, but the specifics of these changes remain largely unknown. These evolving cognitive landscapes, influenced by AI's unique interactions and capabilities, underscore the need for new forms of literacy and adaptability in the 21st century, which goes beyond traditional digital navigation skills. A crucial aspect of effective AI interaction is the skill to craft precise prompts, a capability that varies among individuals; some find it easier to formulate than others [Dwivedi et al., 2023; Shanahan, 2022]. As AI becomes increasingly integral in various aspects of life, the skill of prompt formulation should be recognized and developed with the same emphasis as the overall digital literacy.

5.3 How metacognition shapes higher education adoption of LLMs?

The integration of LLMs with metacognitive strategies, which refer to the conscious control over cognitive processes involved in learning such as organizing, prioritizing, and actively monitoring one's comprehension and progress, indicates a sophisticated approach to learning [Oliveira and Caliatto, 2018; Pereira; Santos and Ferraz, 2020].

According to the MLS/LLMs-6 descriptive results, students are not merely relying on LLMs; they are integrating them into their study routines to deepen understanding and refine problem-solving. This strategic use aligns with the strong positive association between TAME/LLMs-6 and MLS/LLMs-3 (ρ = 0.60, p < 0.01), indicating that greater AI acceptance accompanies higher metacognitive engagement. Taken together, the data portray deliberate, goal-directed adoption rather than indiscriminate reliance. This profile is consistent with the elevated motivation observed in IMOV-3, reinforcing a picture of strategic rather than shortcut-based use.

The meta-analysis by Theobald [2021] highlights the intricate relationship between various factors in academic settings, emphasizing the positive impacts of cooperative learning on cognitive and metacognitive strategies. The analysis suggests that programs centered around feedback more effectively enhance metacognitive skills, resource management, and motivation. Notably, programs grounded in a metacognitive theoretical framework achieve greater success in academic achievement compared to those that focus solely on cognitive aspects—copying, memorizing, reading, summarizing etc.

This is particularly relevant in the context of AI educational technologies, such as chatbot-based learning environments, which excel in offering personalized, immediate feedback. Studies by Chiu et. al. [2023]; Urban et al. [2024] and Yin et al. [2020] have demonstrated the effectiveness of AI technologies in these areas. They argue that such technologies, by providing personalized feedback, can substantially aid students' development.

In contrast, the analysis of the DLS/LLMs-3 sub-scale reveals that despite general confidence in using LLMs, students recognize certain challenges. Difficulties in identifying inaccuracies in outputs from LLMs emphasize the complexities of relying on AI for learning. This complexity is further elucidated by the moderate negative correlation between the IMOV-3 and the DLS/LLMs-6 (ρ = -0.31, $p < 0.01$), indicating that students employing more dysfunctional learning strategies tend to be less intrinsically motivated.

5.4 LLMs and mental health among students

The high scores on academic burnout highlight a critical aspect of student life, emphasizing how the pressures for academic achievement and the competitive nature of academia significantly contribute to elevated stress levels and impact students' overall educational experiences. An important aspect to consider is the interaction between this widespread stress and students' use of LLMs. Research findings reveal a positive and moderate correlation between ABM-4 and DLS/LLMs-3 (ρ = 0.41, p-value = 0.00). This correlation suggests that higher levels of academic burnout are associated with an increased reliance on ineffective learning strategies involving LLMs. Additionally, a small but significant correlation exists between ABM-4 and AITA-3 (ρ = 0.27, p-value = 0.00), indicating a relationship between academic stressors and students' apprehensions regarding AI's role in society.

In the context of the scholarly consensus highlighted by Mofatteh [2020], which elucidates the impact of psychological and academic variables on stress and anxiety levels in university students, the correlations identified in the present study acquire considerable importance. These correlations, when placed within a broader context, contribute to a nuanced understanding of student experiences. Recognized factors such as low self-esteem, personality traits like high neuroticism and low extraversion, and feelings of loneliness are known to increase susceptibility to stress, anxiety, and depression during university years. The findings from the study in question add an additional layer to this complex dynamic, which is particularly relevant in the current educational landscape where technology and digital tools have become increasingly integral to the learning process.

6 Conclusion

In summary, the study sheds light on the complex dynamics between students' engagement with LLMs and their psychological and academic well-being. The findings reveal a dichotomy: on one side, there is a discernible trend of acceptance and strategic utilization of LLMs among data science students, indicating a positive shift towards the integration of AI in educational paradigms. On the other side, the study also unveils a nuanced interplay between the use of these advanced tools and academic stressors. The identified correlations between academic burnout, dysfunctional learning strategies, and AI-related anxiety highlight the necessity for educational institutions to cultivate not just students outcomes but also a supportive environment for student development.

This study's insights must be contextualized within the scope of its methodological constraints. The relatively small sample size may limit the generalizability of our findings to broader populations. Additionally, the brevity of the psychometric scales, while necessary to cover a range of constructs without overburdening respondents, may yield less granularity compared to more extensive conventional scales. Such constraints could potentially affect the accuracy and depth of our insights into the multifaceted impacts of generative AI on education. Moreover the scales were not reviewed by professionals specializing in the constructs being measured, which may have provided further validation of the instruments used.

Future research endeavors could aim to mitigate these limitations by employing larger and more diverse samples to enhance the representativeness of the results. Further refinement and validation of the scales by subject matter experts would bolster the reliability of the measurements. An exploration of correlations between scale results and sociodemographic variables could yield rich insights; for instance, comparing the metacognitive and disfunctional learning strategies of newer students with those more advanced in their studies could reveal how adaptability and coping mechanisms evolve through the university experience. Such investigations could offer valuable information on the developmental trajectory of learning strategies in relation to the integration of AI in academic settings.

Declarations

Authors' Contributions

Conceptualization, Lira, P. D., Araújo, V. M. U., Beltrão, J. V. C., Aguiar, G. S., Ferreira Junior, C. S., Avelino, E. L. and Mendes, S. J. F.; methodology, Lira, P. D., Araújo, V. M. U., Ramos, P. H. R., Ferreira Junior, C. S. and Mendes, S. J. F.; validation, Ramos, P. H. R.; formal analysis, Ramos, P. H. R.; investigation, Lira, P. D.; Mendes, S. J. F., Monteiro, F. L. V.; Aguiar, G. S., Ramos, P. H. R. and Beltrão, J. V. C.; resources, Ramos, P. H. R., Monteiro, F. L. V. and Goulart, L. L.; data curation, Ramos, P. H. R., Goulart, L. L.; writing—original draft preparation, Ramos, P. H. R.; writing—review and editing, Araújo, V. M. U. and Ferreira Junior, C. S.; visualization, Ramos, P. H. R.; supervision, Araújo, V. M. U.; project administration, Araújo, V. M. U.; All authors have read and agreed to the published version of the manuscript.

Competing interests

The authors declare that they have no competing interests.

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Availability of data and materials

The datasets generated and analyzed during the current study are available on Kaggle [Pinto, 2025].

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