Surveying the Future of Computer and Data Science Education: Prospects and Pitfalls of Generative AI on Pedagogical Approaches

Vitor Meneghetti Ugulino de Araújo[1], Pedro Henrique Ramos Pinto[2], Cleydson de Souza Ferreira Junior[3], Maria Jullyanna Ferreira Marques[4], Lutero Lima Goulart[3] , Gabriel Silva Aguiar[3], Paloma Duarte de Lira[3], Samuel José Fernandes Mendes[3]

[1] Departamento de Informática – Universidade Federal da Paraíba (UFPB) – João Pessoa, PB – Brazil

[2] Centro de Educação (CE) – Universidade Federal da Paraíba (UFPB) – João Pessoa, PB – Brazil

[3] Centro de Informática (CI) – Universidade Federal da Paraíba (UFPB) – João Pessoa, PB – Brazil

[4] Centro de Ciências da Saúde (CCS) – Universidade Federal da Paraíba (UFPB) – João Pessoa, PB – Brazil

vitor@ci.ufpb.br, {phrp, csfj, maria.jullyanna, lutero.goulart, gsa3, paloma.duarte, sjfm}@academico.ufpb.br

Abstract. *This study investigates the role of generative Artificial Intelligence (AI), like ChatGPT and other Large Language Models (LLMs), on learning strategies among computer and data science students at the Center for Informatics, University of Paraíba (CI/UFPB), Brazil. Analyzing 178 responses, the research highlights a significant engagement with LLMs and discovers a moderate correlation between students' LLM knowledge and their use of metacognitive learning strategies. Additionally, findings suggest a decrease in dysfunctional learning strategies with academic progression. The study reveals AI's potential to improve personalized learning while emphasizing the need for educational adjustments to avoid overreliance on AI.*

1. Introduction

As Artificial Intelligence (AI) advances, the academic landscape is experiencing a rapid transformation [Dwivedi et al. 2023; Okonkwo and Ade-Ibijola 2021]. AI-powered technologies, such as ChatGPT, now provide nuanced responses to a broad range of topics, aiding undergraduate students in their coursework and learning processes [Cooper 2023; Tu et al. 2023; Zhai 2023]. Despite these 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]. Moreover, ethical concerns like AI bias, plagiarism, and transparency need addressing [Dwivedi et al. 2023; Zhai 2023].

As generative AI continues to influence education, universities worldwide are grappling with emerging challenges and opportunities [Kasneci, 2023]. 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 this kind of technology could face penalties ranging from grade reduction to course failure [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].

In fact, AI are now employed in a range of applications, including virtual assistants, customer service, content creation, and researchers are also benefiting from their support in academic pursuits [Dwivedi et al. 2023; Ramos 2023; Rahman et al. 2023]. Several prestigious publishers, including Taylor and Francis, Nature, and Elsevier, have revised their authorship policies to accommodate this new research paradigm. As standard practice, these publishers disallow listing LLMs as authors, emphasizing a "human-centric" approach by detailing the use of AI technologies in the methods section without granting them co-authorship [Dwivedi et al. 2023]. Furthermore, researchers remain responsible for the integrity of their academic publications.

1.1 Objectives

Building on the preceding discussion, this study aims to survey the profound impact of generative AI, specifically LLMs, on education within computer and data science. The objectives are threefold: (1) To assess the extent of generative AI integration within Information Technology (IT) courses; (2) To evaluate the metacognitive and dysfunctional learning strategies employed by students when interacting with LLMs. This involves the development and validation of a psychometric scale to measure these strategies effectively; (3) To investigate how the use of LLMs correlates with students' overall academic experiences, exploring both the benefits and potential drawbacks of AI in educational settings.

1.2 State-of-the-art

Popularized by ChatGPT and commonly referred to as generative AI, 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 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 July 18, 2023, there were 15,821 LLMs registered with Hugging Face, a popular machine learning repository [Gao and Gao 2023].

This burgeoning field of AI has significant implications for computer and data science education, as highlighted by Tu et al. (2023), necessitating a shift in both curriculum content and pedagogical approaches. Their study showed that LLMs can execute all stages of data analysis, allowing students to manipulate conventional exam questions. Despite the challenges, the authors remain optimistic about integrating AI into the educational landscape. Among the foremost advantages of LLMs is their ability to provide personalized learning experiences [Zhai 2023]. By analyzing students' responses and learning patterns, LLMs can tailor educational content to individual needs, catering to diverse learning styles and abilities [Cooper 2023; Chiu et al. 2023; Rahman et al. 2023 and Kasneci et al. 2023].

Regrettably, while there is an abundance of reviews and opinion pieces on ChatGPT, there is a dearth of experimental studies evaluating student performance using LLMs as a one-to-one tutoring method. This gap in empirical research may be attributed to the novelty of the subject, suggesting that it might be premature for comprehensive, controlled experiments to have been conducted. However, in an encouraging development, Urban et al. (2024) recently published their research, which involved experimental and control groups focusing on creative problem-solving performance among undergraduates. Their findings suggest that students utilizing ChatGPT demonstrated a capacity to formulate solutions that were more innovative, detailed, and closely aligned with task objectives compared to those not using such advanced tools.

1.3 Related Works

Delving deeper, two surveys have provided valuable insights into the current state of research on the impact of ChatGPT in educational settings. In their study, Hanum, Hasmayni and Lubis (2023) highlighted the significant positive effect of ChatGPT on students' learning motivation. Leveraging validated psychometric scales for their analysis, they found that approximately 57.3% of the variance in student motivation could be attributed to the use of ChatGPT. Separately, Sallam et al. (2023) introduced a TAM-based survey instrument, the TAME-ChatGPT (Technology Acceptance Model Edited for ChatGPT Adoption), designed to assess the successful integration and application of this technology in healthcare education. Both studies used and validated psychometric scales through Exploratory Factor Analysis (EFA), effectively quantifying their respective constructs. This approach enabled them to establish reliable correlations between the use of ChatGPT and various educational outcomes.

2. Methodology

2.1 Procedures and Participants

The study was conceptualized as a probabilistic sampling-based survey, leveraging opinion-driven questionnaires (available on GitHub). Data collection was conducted exclusively at the Centro de Informática, Universidade Federal da 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 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%.

Sociocultural values, participant autonomy, and anonymity were respected throughout the data collection process. All potential risks were carefully measured and mitigated. The deployment of the Informed Consent Statement was integral to this process, and according to Resolution 510/2016 of the Conselho Nacional de Saúde (CNS), survey research involving unidentifiable participants does not require approval from an ethics committee. Therefore, given the low-risk nature of the experiment and the normative character of the resolution, the current study was not submitted for approval.

3.2 Instruments

The first part of the questionnaire gathers sociodemographic information from the participants, including questions on age, gender and academic level. The next section delves into students' perceptions of their knowledge and understanding of AI technologies, and the last part features a psychometric scale tailored to assess the learning strategies utilized by students in the context of programming and interactions with LLMs, referred to as the Learning Strategies Scale with LLMs (LSS/LLMs-6). This scale is grounded in metacognitive theory, which aligns with the necessities of computational thinking, such as problem decomposition, abstraction, pattern identification, generalization, and focused evaluation of solutions [Leite, Guarda and Silveira 2023].

Comprising six statements, the LSS/LLMs-6 employs a 7-point Likert format, with responses ranging from "Strongly Disagree" to "Strongly Agree". This scale encompasses two distinct dimensions, one focusing on Dysfunctional Learning Strategies (DLS/LLMs-3) and the other on Metacognitive Learning Strategies (MLS/LLMs-3), each consisting of three items. The DLS/LLMs-3 sub-scale investigates potential counterproductive learning strategies that students might adopt, which could impede effective learning. Conversely, the MLS/LLMs-3 sub-scale assesses the self-regulatory practices that students employ while learning with LLMs, aimed at enhancing learning outcomes. Based on the foundational work of Oliveira and Caliatto (2018), and Pereira et al. (2020), the LSS/LLMs-6 provide a comprehensive assessment of learning strategies in the context of LLMs, covering both the metacognitive techniques that enhance learning and the dysfunctional methods that may potentially hinder it.

3.3 Data Analysis

The collected data underwent a meticulous statistical examination, with EFA serving as a pivotal technique for dimensionality reduction. This approach was crucial in simplifying the complex data structure and unveiling the fundamental dimensions within the observed variables, thereby validating the psychological properties of the LSS/LLMs-3. For descriptive statistics, both box plots and violin plots were utilized to provide visual representations of data distribution and variance.The Spearman correlation analysis, suited for the data’s non-parametric nature, was employed to apprehend the relationships between variables. These combined methods offered a comprehensive understanding of the data's characteristics and interrelations. Python and R were utilized for the analysis in this study, with the study's code and questionnaire available on GitHub.

3.4 Use of AI Tools

The ChatGPT-4 played a substantial role in this project, being utilized not only for correcting grammar but also for refining paragraphs, and assisting with coding in data analysis. Additionally, a specialized GPT model was developed, designed to assist in enhancing the writing process for this research. This model was custom-designed to respond to queries related to scientific writing, providing more focused and effective support, with every output rigorously checked for precision and reliability.

4 Results

4.1 LLMs Usage Preferences Among Students

In the assessment of LLMs' preference 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, is used by 5.6% of the participants, showcasing a willingness to invest in more advanced AI tools. Bing Chat, another LLM, is used by 23% of the students, indicating a diversity in the AI platforms engaged for their educational pursuits. A smaller fraction have adopted Bard, comprising 18% of the users, and only a minority, 4.5%, reported not using any LLMs at all, which underscores the widespread penetration of these technologies in the academic environment.

4.2 Validity Assessment of the LSS/LLMs-6 Through EFA

Factor analysis is not a singular technique but rather a group of associated methods that should be considered and applied in concert [Goretzko, 2021; 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 [Goretzko, 2021; 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.

Prior to factor extraction, it's imperative to evaluate whether the dataset 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; Goretzko, 2021]. Bartlett's test is used to test the hypothesis that the correlation matrix is not an identity matrix. A significant result from Bartlett's test allows for the rejection of the null hypothesis (p-value < 0.05), indicating the factorability of the data [Taherdoost et al. 2022; Goretzko, 2021]. 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; Goretzko, 2021]. These assessments, highlighted in Table 1, collectively underscore the data's aptness for structure detection.

Table 1. Samples Adequacy for Structural Detection

	KMO	Bartlett's Test of Sphericity
LSS/LLMs-6	0.682	0.000

After evaluating sample adequacy the study progressed to assess the internal reliability of the scales. This evaluation, detailed in Table 2, involved an analysis of Cronbach's Alpha (α), McDonald's Omega (ω), and the Cumulative Variance Explained, all ranging from 0 to 1. The LSS/LLMs-6 scale displayed strong reliability, with ω value surpassing the 0.7 benchmark, suggesting high consistency. It confirms that any observed variations in data accurately reflect differences in the underlying construct, rather than resulting from measurement error or inconsistencies [Damasio 2012; Dunn; Baguley and Brunsden 2013].

Table 2. Internal Reliability Assessment.

	α	ω	Cumulative Variance Explained
LSS/LLMs-6	0.640	0.739	0.618

At last, the cornerstone of EFA is the factorial extraction procedure. In this research, Principal Axis Factoring (PAF) was employed. The factorial loadings in EFA are critical as they represent the strength and direction of the relationship between observed variables (questionnaire's items) and underlying latent factors (metacognitive and dysfunctional strategies). 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 theoretical construct [Taherdoost et al. 2022; Goretzko, 2021; Damasio 2012]. Analyzing the EFA loadings presented in Table 3, it's evident that most items demonstrate strong correlations with their respective factors, indicating a clear bidimensional structure, with Factor 1 representing MLS/LLMs-3 and Factor 2 representing DLS/LLMs-3 sub-scales.

Table 3. Loadings (PAF).

Scales	Scale's Items	Factor 1	Factor 2
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**

4.3 LSS/LLMs-6 Descriptive Statistics

The exploration into the MLS/LLMs-3 and DLS/LLMs-3 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. The analysis of the MLS/LLMs-3 sub-scale unveils a median that is marginally above the midpoint, indicating a propensity for higher engagement with metacognitive strategies (Figure 1).

Nevertheless, the wide interquartile range indicates a variety in students' responses. The corresponding violin plot supports this conclusion, displaying a response density that decreases slowly as one moves away from the median.

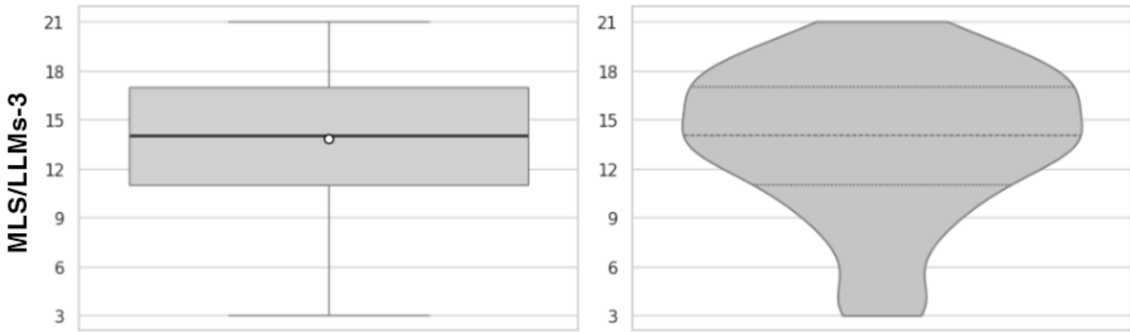

Figure 1. Metacognitive Learning Strategies Descriptive Statistics

Furthermore, the DLS/LLMs-3 visualizations shed light on another dimension of student learning strategies (Figure 2). When comparing these results, 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. This is reinforced by the DLS/LLMs-3 violin plot's bimodal peaks, which imply two main clusters of responses among the participants. The two scales range from 3 to 21 points. Additionally, the closeness of the median and the mean suggests that the data is normally distributed.

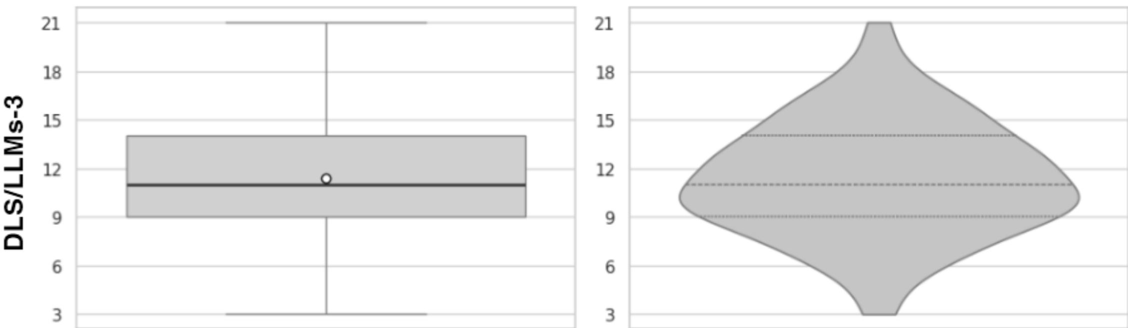

Figure 2. Dysfunctional Learning Strategies Descriptive Statistics

4.4 Spearman's Correlation Test

A correlation, in research, refers to a statistical relationship between two variables, indicating how one may predict or relate to the other. At a moderate level ($\rho = 0.335$; p-value < 0.000), a correlation was found between the MLS/LLMs-3 and students' self-reported level of knowledge about LLMs (single item). Specifically, it demonstrates that students who perceive themselves as more knowledgeable about LLMs are also those who are more adept at leveraging these tools for effective study strategies. This relationship suggests that enhancing students' understanding of LLMs could be a key strategy in optimizing their educational outcomes, as a deeper comprehension of these technologies appears to be linked with the deployment of more sophisticated and efficient study techniques. As well, a moderate correlation ($\rho = 0.447$; p-value < 0.000) was observed between MLS/LLMs-3 and feeling confident about LLMs' outputs (single item), indicating that individuals who possess greater awareness of their own learning strategies while using LLMs not only utilize these tools more effectively but also have greater confidence in the information and assistance provided by them (Figure 3).

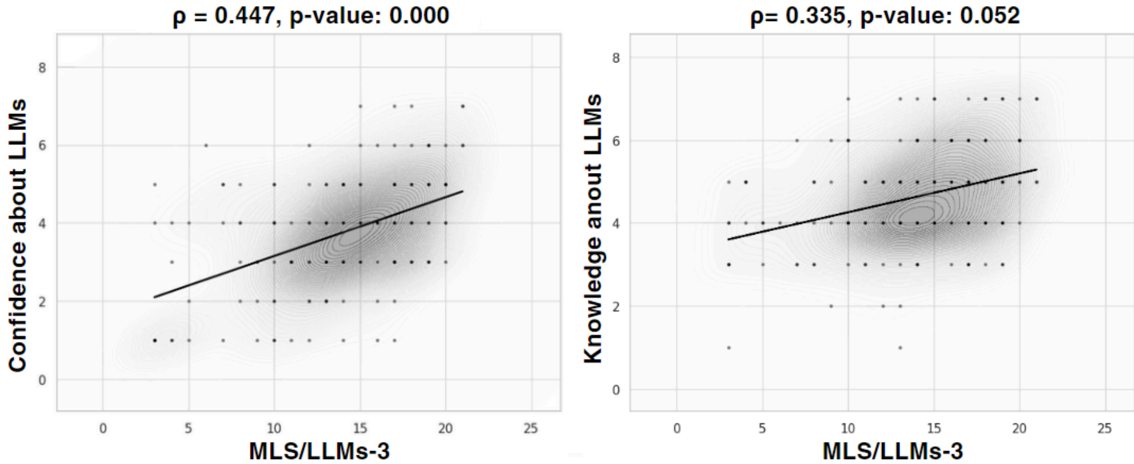

Figure 3. Metacognitive Learning Strategies Correlations.

A third correlation identified involves the DLS/LLMs-3 and students' academic progression, yielding a weak negative correlation (ρ = -0.145; p-value < 0.052). This suggests that students tend to exhibit fewer dysfunctional strategies as they advance in their course. Although the correlation is weak and the p-value marginally exceeds the conventional threshold for significance, it hints at a trend where more advanced students, possibly through greater academic experience, show a diminished reliance on ineffective learning strategies. Conversely, the findings reveal that students employing greater dysfunctional strategies (DLS/LLMs-3) are more likely to perceive themselves as less capable of achieving their academic objectives (single item), as evidenced by a moderate correlation (ρ = 0.443; p-value < 0.000). The same holds true for feelings of exhaustion related to university life (single item), which also exhibit a moderate correlation (ρ = 0.409; p-value < 0.000) with DLS/LLMs-3 (Figure 4).

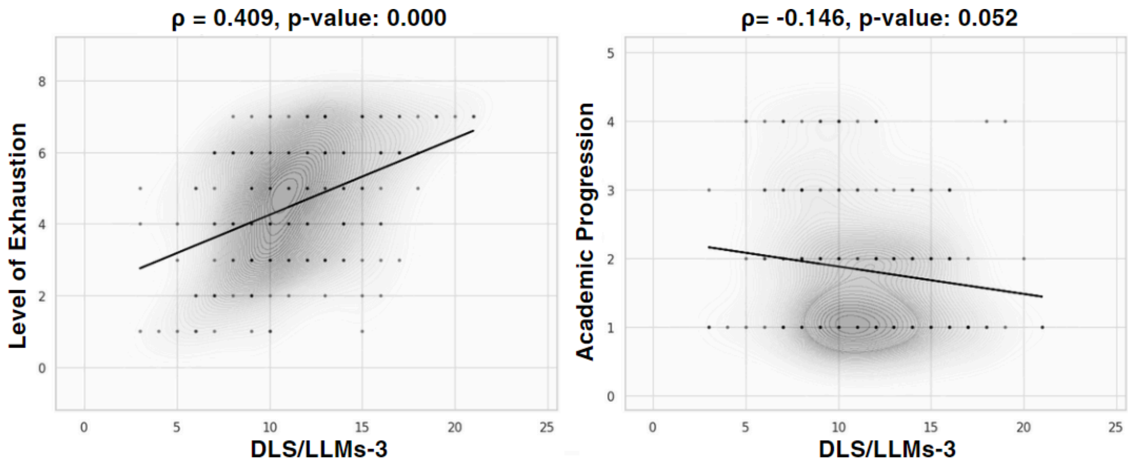

Figure 4. Dysfunctional Learning Strategies Correlations.

No significant p-value was obtained regarding the gender of the participants or the type of LLM used. This is likely due to the small sample sizes of these groups, although no specific tests were applied to explore these differences in depth. Also, no significant correlation (p-value < 0.05) between metacognitive strategies (MLS/LLMs-3) and dysfunctional ones (DLS/LLMs-3) was observed, which does not mean that this relationship does not exist, but rather that the sample size was insufficient to determine that the observed relationship did not occur by chance.

5 Discussion

The findings unveil significant psychological and behavioral patterns among data science students, especially their overwhelming acceptance of LLMs. This trend reflects a forward-thinking approach to incorporating AI technologies into their academic toolkit. As documented in recent studies [Cooper 2023; Choi et al. 2023; Dwivedi et al. 2023; Tu et al. 2023; Zhai 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.

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 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 [Shanahan 2022; Dwivedi et al. 2023]. 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 and computational thinking.

Furthermore, the findings underscore a particularly striking relationship between metacognition and knowledge about LLMs. This relationship suggests that enhancing students' understanding of LLMs could be a key strategy in optimizing their educational outcomes, as a deeper comprehension of these technologies appears to be linked with the deployment of more refined and efficient study techniques. 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]. MLS/LLMs-6 descriptive results suggest that students are not merely relying on LLMs; rather, they are thoughtfully incorporating them into their study habits, utilizing their capabilities to enhance understanding and refine problem-solving skills.

The integration of AI educational technologies plays a unique role in enhancing metacognitive strategies through their provision of personalized, immediate feedback. Studies underscore the significant impact of these technologies in fostering students' development [Chiu et al. 2023; Urban et al. 2024, Okonkwo and Ade-Ibijola 2021; Yin et al. 2020]. By offering tailored responses and interactions, AI-driven chatbots excel in addressing individual learning needs, thereby promoting a deeper engagement with metacognitive practices. This personalized approach not only facilitates the improvement of fundamental programming skills but also bolsters students' ability to manage resources and maintain motivation, aligning with the metacognitive framework's emphasis on self-regulated learning proposed by Leite, Guarda and Silveira (2023).

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. Theobald's 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 insight is particularly relevant in the context of computational thinking. It has been evaluated that the mastery of fundamental programming skills can be enhanced with the use of metacognitive strategies. This process has been cited as one of the top theories in computing education venues [Leite, Guarda and Silveira 2023].

Moreover, 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 reinforces the necessity of teachers' support in optimizing students' use of AI for educational purposes, corroborating Chiu et. al. (2023) findings which indicate that both student expertise and teacher assistance are crucial for effectively fostering learning competence with AI-based chatbots. However, the data also reveal a clear trend: seasoned students, commonly referred to as veterans, demonstrate less use of dysfunctional strategies compared to newer students, though the correlation is weak ($\rho = -0.145$; p-value < 0.052). This hints at a modest influence of the educational journey on students' ability to sidestep ineffective learning strategies. The development of these skills depends significantly on both the students' expertise and the support they receive from teachers [Chiu et. al., 2023]. Therefore, the curriculum should be designed with this dynamic relationship in mind; nonetheless, this has not yet been implemented at CI/UFPB in the context of AI technologies, which explains the weak association presented.

6 Conclusions

Results indicate that while CI/UFPB students display a high level of metacognition in using AI technologies for studying, they also engage in considerable dysfunctional strategies that may undermine their study effectiveness. Overall, these findings emphasize the importance for educational interventions that equip students with the skills to critically evaluate and effectively utilize LLMs, optimizing their learning outcomes by discerning and correcting errors. This aligns with recent research suggesting that strategic use of LLMs, combined with a deep understanding of their limitations, can empower students to deviate potential pitfalls and maximize the benefits of these advanced tools, thus enhancing educational outcomes (Cooper 2023; Tu et al. 2023; Urban et al. 2024; Zhai 2023).All study objectives were achieved. For future studies, it is recommended to increase the sample size and include other undergraduate programs beyond IT courses, due to the importance of the subject.

References

Cooper, G. (2023). "Examining Science Education in ChatGPT: An Exploratory Study of Generative Artificial Intelligence", Journal of Science Education and Technology, v. 32, p. 444–452. DOI: 10.1007/s10956-023-10039-y

Chiu, T. K. F., Moorhouse, B. L., Chai, C. S. and Ismailov, M. (2023). "Teacher support and student motivation to learn with Artificial Intelligence (AI) based chatbot", Interactive Learning Environments. DOI: 10.1080/10494820.2023.2172044

Choi, J. H., Hickman, K. E., Monahan, A. and Schwarcs, D. B. (2023). "ChatGPT Goes to Law School.", 71 Journal of Legal Education, v. 387, p. 1–16. DOI: 10.2139/ssrn.4335905

Damasio, B. (2012). "Uses of Exploratory Factorial Analysis in Psychology.", Avaliação Psicológica, v. 11(2), p. 213–228. DOI: S1677-04712012000200007

Dunn, T. J., Baguley, T. and Brunsden, V. (2013). "From alpha to omega: A practical solution to the pervasive problem of internal consistency estimation.", British Journal of Psychology, v. 105(3), p. 399–412. DOI: 10.1111/bjop.12046

Dwivedi, Y. K., Kshetri, N., Huges, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M.; Albanna, H., Albashrawi, M. A., Al-Busaidi, A., Balakrishnan, J., Barlette, Y.; Basu, S., Bose, I., (...) and Wright, R. (2023). "Opinion Paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy", International Journal of Information Management, v. 71. DOI: 10.1016/j.ijinfomgt.2023.102642

Gao, S., and Gao, A. K. (2023). "On the Origin of LLMs: An Evolutionary Tree and Graph for 15,821 Large Language Models", ArXiv preprints, p. 1–14. DOI: 10.48550/arXiv.2307.09793

Goretzko, D., Pham, T.T.H. and Bühner, M. (2021). "Exploratory factor analysis: Current use, methodological developments and recommendations for good practice", Current Psychology, v. 40, p. 3510–3521. DOI: 10.1007/s12144-019-00300-2

Hadi, M. U., Al-Tashi, G.; Qureshi, R., Shah, A., Muneer, A., Shaikh, M. B., Al-Garadi, M. A., Wu, J. and Mirjalili, S. (2023). "Large Language Models: A Comprehensive Survey of Applications, Challenges, Limitations, and Future Prospects", TechRxiv preprints, p. 1–44. DOI: 10.36227/techrxiv.23589741.v4

Hanum S. F., Hasmayni, B. and Lubis, A. H. (2023). "The Analysis of Chat GPT Usage Impact on Learning Motivation among Scout Students", International Journal of Research and Review, v. 10(7), p. 632-–638. DOI: 10.52403/ijrr.20230774

Hung, J. and Chen, J. (2023). "The Benefits, Risks and Regulation of Using ChatGPT in Chinese Academia: A Content Analysis", Social Sciences; 12(9), pp. 380. DOI: 10.3390/socsci12070380

Kasneci E., Sessler K., Küchemann S., Bannert M., Dementieva, D., Fischer F., Gasser, U, Groh G., Günnemann S., Hüllermeier E., Krusche S., Kutyniok G., Michaeli T., Nerdel C., Pfeffer J., Poquet O., Sailer M., Schmidt A., Seidel T., Stadler M., Weller

J., Kuhn J. and Kasneci G. (2023). "ChatGPT for good? On opportunities and challenges of large language models for education", Learning and Individual Differences, v. 103. DOI: 10.1016/j.lindif.2023.102274

Oliveira, A. F.; Caliatto, S. G. (2018). "Exploratory Factor Analysis of a Scale of Learning Strategies. Educação: Teoria e Prática", v. 18(59), p. 548-565. DOI: 10.18675/1981-8106.vol28.n59.p548-565

Okonkwo, C. W. and Ade-Ibijola, A. (2021). "Chatbots applications in education: A systematic review. SComputers and Education: Artificial Intelligence", v. 2, p. 380. DOI: 10.1016/j.caeai.2021.100033

Pereira, C. P. da S., Santos, A. A. A. and Ferraz, A. S. (2020). "Learning Strategies Assessment Scale for Vocational Education: Adaptation and psychometric studies", Revista Portuguesa de Educação, v. 33(1), p. 75–93. DOI: 10.21814/rpe.19127

Ramos, A. S. M. (2023). "Generative Artificial Intelligence based on large language models - tools for use in academic research", Scielo preprints. DOI: 10.1590/SciELOPreprints.6105

Rahman, M., Terano, H. J. R., Rahman, N. Salamzadeh, A. and Rahaman, S. (2023). "ChatGPT and Academic Research: A Review and Recommendations Based on Practical Examples", Journal of Education, Management and Development Studies, v. 3(1), p. 1–12. DOI: 10.52631/jemds.v3i1.175

Shanahan, M. (2022). "Talking About Large Language Models", ArXiv preprint, v. 5, p. 1–13. DOI: 10.48550/arXiv.2212.03551

Taherdoost, H., Sahibuddin, S. and Jalaliyoon, N. (2022). "Exploratory Factor Analysis: concepts and theory", In: Advances in Applied and Pure Mathematics, organized by Jerzy Balicki, p.375–382. Available from: https://hal.science/hal-02557344/document

Theobald, M. (2021). "Self-regulated learning training programs enhance university students' academic performance, self-regulated learning strategies, and motivation: A meta-analysis", Contemporary Educational Psychology, v. 66. DOI: 10.1016/j.cedpsych.2021.101976

Tu, X., Zou, J. Su, W. J. and Zhang, L. (2023). "What Should Data Science Education Do with Large Language Models?", arXiv preprints, p. 1–18. DOI: 10.48550/arXiv.2307.02792

Urban, M., Dˇechtˇerenko, F., Lukavsky, J., Hrabalová, V., Švácha, F.; Brom, C. and Urban, K. (2024). "ChatGPT Improves Creative Problem-Solving Performance in University Students: An Experimental Study", Computers & Education, v. 215. DOI: 10.1016/j.compedu.2024.105031

Yin, J., Goh, T., Yang, B. and Xiaobin, Y. (2023). "Conversation Technology With Micro-Learning: The Impact of Chatbot-Based Learning on Students' Learning Motivation and Performance", Journal of Educational Computing Research, v. 59(1). DOI: 10.1177/0735633120952067

Zhai, X. (2023). "ChatGPT User Experience: Implications for Education", SSRN Eletronic Journal. DOI: 10.2139/ssrn.4312418