NeoAVA: A virtual learning environment for Self-Regulated Learning to be used by students and teachers

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Abstract. *Many students face difficulties in self-managing their studies and making efficient choices about which resources to use, resulting in lower academic performance when using Virtual Learning Environments (VLE). The study proposed a web application integrated with Google Classroom, aimed at enhancing student performance through personalized educational recommendations based on self-regulated learning (SRL) strategies and Big Five (BF) personality traits. The research employs a Design Science Research methodology, involving problem identification, solution design, and evaluation using the Technology Acceptance Model (TAM) to assess the system's usability and effectiveness. The methodology involved experiments with a small group of participants who provided feedback via a TAM survey. The results indicate positive acceptance of the system, with participants reporting that NeoAVA is useful, easy to use, and enhances their learning experience. The system leverages SRL and BF profiles to generate personalized recommendations that guide students toward better academic outcomes, showing promise in improving student performance through tailored interventions. The findings suggest the potential for broader application of NeoAVA across different educational platforms.*

1. Introduction

Student success does not depend entirely on teachers' teaching skills; rather, it is intrinsically linked to specific factors such as student behavior, personality characteristics, social and psychological considerations, among others [Robbins et al. 2004]. Therefore, greater investment in the course development phase with the integration of various teaching methods for different personality traits and learning styles can positively affect student satisfaction and reduce dropout rates [Cohen and Baruth 2017]. It is important that teachers manage and plan personalized pedagogical actions to help students, aiming to improve their academic results by taking these factors into consideration.

In addition to these considerations, there is a positive relationship between Self-Regulated Learning (SRL) strategies and the academic performance of students who use

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Virtual Learning Environments (VLEs) [Broadbent and Poon 2015]. SRL is a process in which learners actively control their learning by setting goals, self-monitoring, self-assessing, and reflecting. This process involves establishing clear objectives, developing strategies to achieve them, continuously tracking progress, evaluating performance, and reflecting on the learning experience to enhance future outcomes. Self-regulated learners are proactive, motivated, and adaptable, making necessary adjustments to achieve better results and fostering independence, critical thinking, and lifelong learning skills.

Furthermore, the Big Five (BF) personality traits, also known as the five-factor model, is a widely recognized framework for understanding human personality. It identifies five dimensions: Openness to Experience (creativity, intellectual curiosity), Conscientiousness (organization, dependability), Extraversion (sociability, assertiveness), Agreeableness (empathy, cooperation), and Neuroticism (emotional instability). These traits are used to describe and measure the core aspects of personality and have been validated across various cultures and populations [Raad and Perugini 2002].

Moreover, the inclusion of pedagogical tools in this process, along with the use of pedagogical recommendations, using Recommendation Systems (RS), has shown promising results and can also positively impact students [Baptista 2023, Silva et al. 2021]. Recommendations are important for the learning process by allowing teachers and students to find content in a more appropriate way, according to their profile and needs. Given this, it is essential to investigate how these SRL strategies can be recommended to help students, with different BF profiles, to improve their academic performance.

With these foundations in place, this article aims to describe how to improve students' performance with an educational recommendation system that uses data from interaction performance in a VLE and recommends actions most suited to the students SRL and BF profiles using rules (or scenarios) that can be extended. The hypothesis is that following these personalized recommendations, the student will obtain better performance.

This article is organized as follows. Section 2 provides basic concepts, terminologies and a theoretical basis through the presentation of studies related to the topic. Section 3 describes the research methodology used (Design Science Research). The evaluation used the Technology Acceptance Model (TAM) to analyze the acceptance of the tool. Section 4 presents details about our proposal a VLE that (i) calculates self-regulation constructs and integrates with Google Classroom, and (ii) generates personalized recommendations based on students' self-regulation profiles and offers teachers dashboards for monitoring. Section 5 presents the results of the validation with participants. The results of the TAM questionnaire indicate a positive acceptance of the system in terms of usefulness, ease of use and overall experience. Section 6 concludes that the proposal has significant potential to improve student performance through data-driven personalized recommendations. The system shows promise for personalizing learning and improving academic performance through tailored educational interventions.

2. Background

This section is organized as follows. Section 2.1 defines VLEs and introduces Google Classroom, describing its features and structure. Section 2.2 defines SRL and its characteristics, highlights the positive correlation between SRL strategies and academic performance in VLE, and explores the relationship between the BF personality model and SRL. Moreover, it suggests that combinations of BF influence SRL and can be used to personalize teaching. Section 2.4. discusses the importance of recommender systems in various sectors, including education. It explains how they work and their relevance to improving learning.

2.1. Virtual Learning Environment (VLE)

VLEs are computer systems that integrate different media, languages, resources and provide it to the student at any time. However, it is not enough to simply conclude that the benefit arises solely and exclusively from the simple adoption of VLE. The incorporation of VLE itself does not generate processes of innovation and improvement in teaching and learning, but there are certain specific uses of technology that can influence these processes [Coll and Monereo 2010]. For example, the excess data that students receive in a disorderly manner is absorbed without necessarily making specific customization for the message receiver, creating an opportunity for error and wasted time when choosing the next action to be done. The information to do better educational choices is there, but a prior analysis of the data available to the students' personal need is necessary.

Furthermore, the frequent use of a VLE by students generates data that can be structured to extract relevant information. For example, a student who is preparing for a new area of study may superficially understand a certain topic, but not at the appropriate level of depth. The student may have doubts about what would be the next action to be taken among the options: a) answer a test, b) watch another video, or c) study another subject. Leaving this choice in the hands of the user may not necessarily be the best solution, as the decision made by the student may lead them to non-inefficient choices, especially if they do not have mastery of knowledge or study techniques. Therefore, a good and personalized academic recommendation, content, questions or videos, can improve the learning process, distinguishing the content relevant from another already assimilated by the student.

Among the various VLE options available, there is one called Google Classroom[1] from the company Alphabet. This educational environment allows it to be used according to the needs of teachers without using programming, based on available options and screens. This way, the institution, or school, that is using it can plan its subjects. It provides several resources, for example, a place to display videos and subject materials and questionnaires. This platform has been widely used by universities and schools. A class in Google Classroom is made up of activities and material. Activities can be of the type: questions, meetings on Google Meet, forum, etc. material can be a slide or a video. For example, a class can be divided into 3 modules. Each module can have activities and materials. An item of Module 1 could be: slide 1 (material); video 1 (material); quiz 1 (activity); meet 1 (activity); forum 1 (activity).

2.2. Self-Regulated Learning (SRL) and Big Five (BF)

A student who uses SRL strategies approaches educational tasks with confidence, diligence, and resourcefulness. Self-regulated students can evaluate their learning strategies and understand their skills and areas of weakness. A self-regulated learner is aware of this feedback and will modify learning strategies accordingly to achieve the desired

[1] `https://classroom.google.com/`

academic outcome [McLellan and Jackson 2017]. SRL is acquired through an interaction between self-observation (monitoring one's actions), self-judgment (evaluating performance) and self-reactions (a response to performance results). Learning can be influenced and improved with the aim of achieving successful academic results [Wong et al. 2019].

Besides, there is a positive relationship between SRL strategies and the academic performance of students in online courses, according to a systematic review, which covered 12 studies on self-regulation of learning carried out by [Broadbent and Poon 2015]. The strategies of time management, metacognition, effort regulation, and critical thinking were positively correlated with academic outcomes, while the cognitive strategies of elaboration, recitation, and organization were not related to online academic performance [Broadbent and Poon 2015].

Equally important is the Big Five (BF) personality framework. It is a technique that maps the following five personality domains [Raad and Perugini 2002]: extroversion, agreeableness, conscientiousness, emotional stability, and openness to experience. A relationship between SRL and the BF personality theory was presented by [McLellan and Jackson 2017]. They suggest that combinations of personality variables may be more significant than individual personality traits when it comes to differences in SRL. Additionally, it is important to develop course formats that facilitate the use of SRL for individuals characterized by high conscientiousness and openness to experience. However, these course formats should also be suitable for students who do not exhibit high levels of conscientiousness or openness to experience and therefore may employ fewer SRL strategies [Cohen and Baruth 2017]. Individuals with high levels of conscientiousness and openness are more likely to use SRL strategies than those who score lower in these traits. Finally, individuals with low openness and neuroticism, combined with high agreeableness and conscientiousness, tend to be more self-regulated compared to individuals with different combinations of personality variables [McLellan and Jackson 2017].

2.3. Recommendation, Recommendation Systems (RS) and Educational RS

Recommendations, or suggestions, are associated with various decision-making processes based on algorithms such as which item to buy, which music to listen to, which book to read and where to go. The most common uses are in films, music, television, books, documents, e-learning, e-commerce, web searches and others [Brito et al. 2014], [Dwivedi and Roshni 2017], [Obeid et al. 2018]. RS are software tools and techniques that provide suggestions of items that are most likely to arouse the interest of a particular user [Ricci et al. 2010]. They are used commercially in online systems such as the Amazon product store, Facebook and Twitter. A large part of these companies' revenue comes from advertising. Companies use their users' data to execute a segmented marketing strategy. Advertisements that reach a more specific audience tend to obtain better sales results, increasing the revenue of the companies that advertise the products, as they would be better reaching the advertisers' desires.

In addition, an educational RS it is a software that can be used to identify interesting learning materials from a large set of resources. They can reduce student information overload by recommending the "right" information at the right time and in the right format of interest to the student [Odilinye and Popowich 2020]. A hybrid model for educational recommending learning objects, based on their popularity and students' learning styles, was presented by [Aguiar et al. 2015] and proved to be better than other traditional recommendation approaches. In educational RS, among the techniques used in RS, one of the best known is collaborative filtering, and it is also one of the most used in educational RS to recommend the items best evaluated by users with similar preferences, without being necessarily know the characteristics of the items [Aguiar et al. 2017].

Finally, a recommendation, in this context, is the offer of educational resources, which the system suggests to the student. The explanation is what justifies the reason the recommendation was sent to the student. Pedagogical performance is a calculation of the percentage of your grade on the Task. Interaction performance is a percentage obtained by dividing the number of resources the user used divided by the total number of interactions offered by the system. Below is an example of a recommendation text with an explanation, that a student could receive in his AVA:

*Dear **STUDENT NAME**, we noticed that your performance was satisfactory for the topic **TOPIC NAME**, contained in the subject **SUBJECT NAME**, whose performance value was equal to **PERFORMANCE COEFFICIENT**, but we saw that you did not interact with all the resources, we suggest that you interact with the resources **NAME OF UNUSED RESOURCES** so that you can finish the module with appropriate performance. Because your interaction performance is **ITERATION COEFFICIENT**, lower than expected, which is 60%.*

3. Methodology

The methodology employed in this study involves a combination of experiments, surveys and statistical analysis. For the proposal, we used the "Design Science Research" with 3 phases: problem identification, solution design, and evaluation to develop the proposed tool [Wieringa 2014]. For evaluation, a study was conducted using the Technology Acceptance Model (TAM) framework [Davis et al. 1989]. A literature review was carried out through a bibliographical survey of articles in the areas of education, psychology and educational information technology [Neo et al. 2024].

The proposal is called NeoAVA, it was a web application, integrated with Google Classroom (using API REST), designed to enhance student performance in virtual learning environments by providing personalized educational text recommendations based on performance metrics, SRL and BF constructs, it used Python and StreamLit and was deployed in StreamLit Cloud, more details in Section 4.

The study sample to validate the proposal consisted of 8 participants who voluntarily responded to a detailed questionnaire about their experiences using NeoAVA. These participants were selected based on their regular use of VLE and their willingness to provide comprehensive feedback on the system's usability and effectiveness. We invited 30 possible users, but only 8 could participate as we needed.

Participants were introduced to the NeoAVA and given a brief tutorial on its features and functionality. They were then asked to use the system for a set period, during which their interactions were monitored. After this period, we collected data from participants.

Data collection was conducted using a TAM survey. TAM is a framework designed to assess users' perceived ease of use and usefulness and overall user experience of the NeoAVA. Participants were asked to rate their experiences across several dimensions, including the ease of navigation, clarity of the interface, and the perceived impact of NeoAVA on their academic performance. The questionnaire also included open-ended questions to capture qualitative feedback and suggestions for improvement.

The TAM survey included items such as "Using NeoAVA is useful for improving my performance", "I find the idea of using NeoAVA appealing" and "Using NeoAVA enhances the quality of my work.". Other questions are about usability and emotional impact of NeoAVA. Questions included "NeoAVA has a good usability", "NeoAVA is easy to use", and "NeoAVA is enjoyable to use", these items were rated on a Likert scale from 1 (strongly disagree) to 5 (strongly agree). The collected data was anonymized and analyzed to assess the effectiveness of the personalized recommendations provided by NeoAVA. Key performance constructs from TAM were interpreted such as user satisfaction, ease of use, and perceived impact on academic performance were examined to validate the system's efficacy. Finally, data from the TAM Survey were analyzed using descriptive statistics to determine the mean, standard deviation, and range for each item. This analysis provided insights into the overall acceptance and usability of NeoAVA among the participants.

4. Proposal

Our proposal emphasizes the importance of personalized academic recommendations in enhancing the learning process. It provides tailored content to help students distinguish between relevant material and content they have already mastered by sending textual recommendations. This personalized approach is considered more effective than leaving decisions solely in the hands of students, particularly if they lack the necessary knowledge or study techniques.

The proposed solution is a web application (aka. NeoAVA[2]) integrated with Google Classroom using API REST. This integration is supported by the Script Google Technology[3]. It was coded in Python and StreamLit[4] and deployed in StreamLit Cloud[5]. It has the following functional requirements: (i) load student's SRL/BF profiles from Google Forms questionnaire; (ii) load student's data from Google Classroom; (iii) presents students SRL and BF profiles to both students and teachers with graphs and dashboards (Figure 5(b), Figure 6(c), Figure 5(a), Figure 7(c) and Figure 6(a)); (iv) generates personalized recommendations (Figure 7(a) and Figure 7(b)); (v) teachers can write personalized textual recommendations if needed; (vi) send textual recommendation automatically to Google Classroom.

A default Use Case from NeoAVA is performing the following steps: (a) The process starts with collecting student data (from Google Classroom and SRL/BF questionnaire in Google Forms). (b) SRL/BF profiles/constructs are calculated based on this data. (c) Tailored recommendations are generated based on the profiles and google data. (d) There's a decision point where teachers can choose to modify the recommendations. (f) If needed, teachers personalize the recommendations. (g) Send text recommendation

[2]https://autorregulacao.streamlit.app/
[3]https://script.google.com/
[4]https://streamlit.io/
[5]https://streamlit.io/cloud

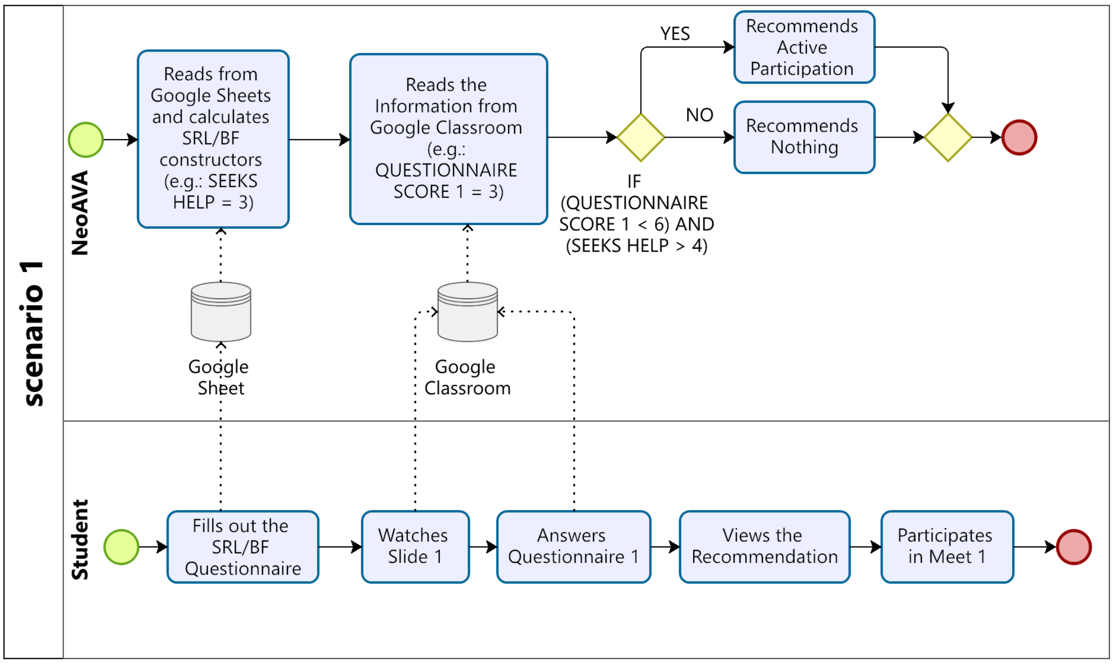


Figure 1. Scenario 1 flow diagram in BPMN.

to Google Classroom. (h) Students receive the textual recommendation.

To generate personalized recommendations, we created custom scenarios (e.g. Figure 1) that utilize the student's SRL/BF profile and data from Google Classroom. Some examples of the SRL constructs that are mapped after the student responds to the questionnaire and are used in these scenarios include "Search for Help" and "Time Management", among many others. We incorporated some constructs from the seminal MSLQ questionnaire [Pintrich et al. 1991]. A set of rules derived from these scenarios was applied in an RS engine that recommends text pedagogical actions. The scenarios for the recommendations were modeled using BPMN notation in Bizagi Modeler [6], which describes in detail the input parameters required for the recommendation. The RS engine has a module that loads these developed scenarios.

The Figure 2 illustrates the architecture of a recommendation engine that integrates Google Classroom with the NeoAVA VLE. Initially, Google Classroom collects data from students' interactions on the platform, such as activities, participation, performance, and more. This data is loaded by NeoAVA, where it is combined with detailed student SRL/BF profiles. The NeoAVA recommendation module uses this combined data to generate personalized recommendations. It does this by considering predefined recommendation scenarios and a list of recommendation texts that can be adapted to the individual needs of students. These recommendations are based on the collected information, merging the students' profiles with their interactions in the learning environment. Finally, these personalized recommendations are sent back to Google Classroom, where they are presented to the students.

Each scenario is translated to a formula by the RS. For example, Figure 3 presents

[6] `https://www.bizagi.com/pt/plataforma/modeler`

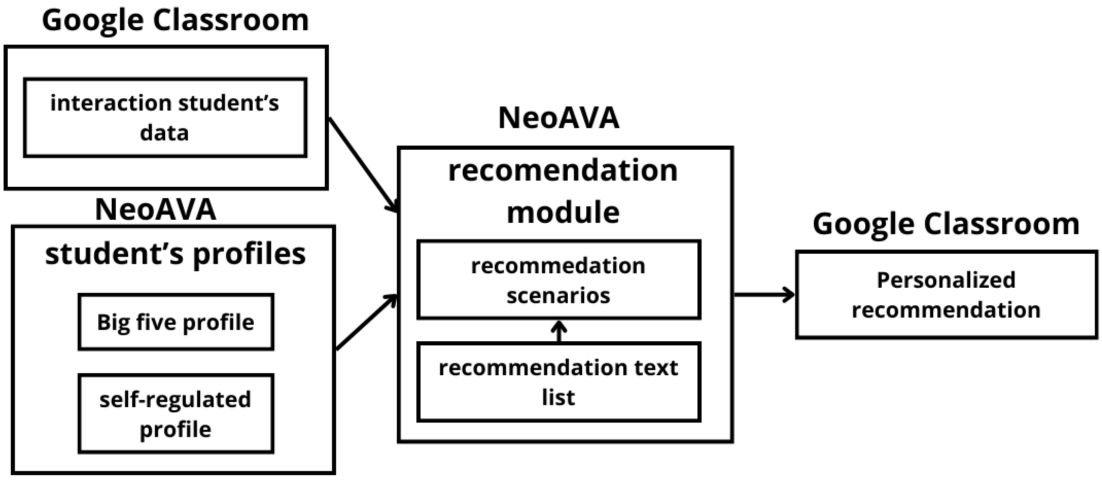


Figure 2. Recommendation engine architecture.

Low **Search for Help** + Low Grade in **Questionnaire X**
= Recommend Active Participation in **Meet X**

Figure 3. Rules for the RS Engine.

a mathematical representation of the recommendation based on certain criteria from one scenario. It suggests that if a person shows both a low tendency to *search for help* (one of the SRL construct) and receives a *low grade on a specific questionnaire* (pedagogical performance), the appropriate course of action is to *recommend that the person actively participate in a specific meeting* (a pedagogical action). In other words, the combination of not seeking help and performing poorly on the questionnaire indicates that the individual might benefit from being more engaged in a related meeting.

An example of the text recommendations in natural language generated by NeoAVA is presented in Figure 4. The pedagogical objects from the module used that exist in that Course are marked in bold. This example is from the scenario "'Recommend Active Participation in the Meet Activity" The classification of the item (explanation or action suggestion) is shown in italics.

An instantiation of a scenario is presented in Algorithm 1. This algorithm represents at a high-level part of the code already considering the student's variables. It is derived from the scenario built in BPMN notation.

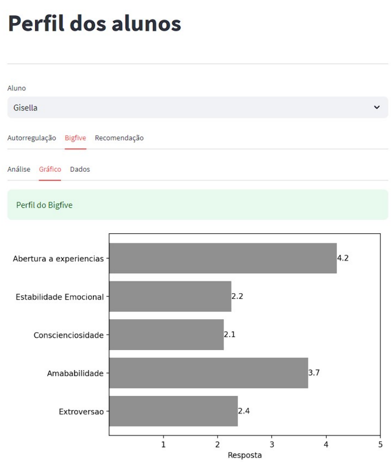
Algorithm 1 Scenario 1

if $studentProfileSearchforHelp \leq 3$ **then**
  if $studentQuestionnaire1Grade \leq 6$ **then**
    sendPersonalizedRecommendation()
  end if
else
  sendDefaultRecommendation()
end if

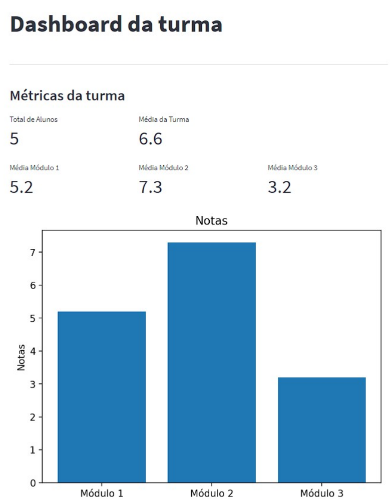
Recommendation created by NeoAVA

- Dear Student, you achieved low performance in **Questionnaire 1** of **Module 1** compared to the objectives established by the subject teacher; *(explanation)*
- Actively Participate in **Meet 1** of **Module 1**; *(action suggestion)*
- Review by reading **Slide 1** of your material before the Meet; *(action suggestion)*
- Try to determine which concepts you don't understand well, create a list of your doubts before the Meet; *(action suggestion)*
- During **Meet 1** inform whether you understood the topic that was discussed; *(action suggestion)*

Figure 4. Recommendation created by NeoAVA

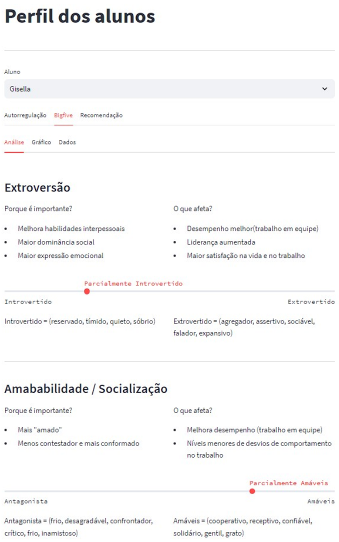


(a) NeoAVA screens with BF constructs.

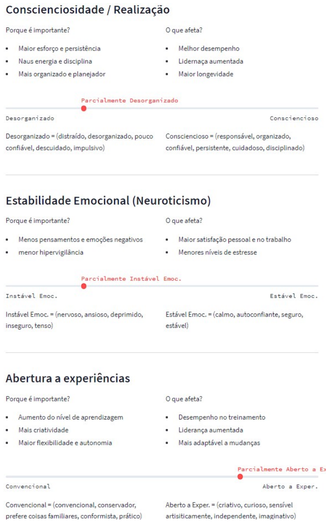


(b) NeoAVA screens with Dashboard.

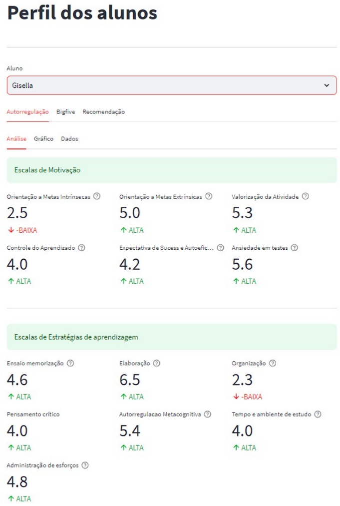
Figure 5. Big five and Dashboard screenshot.



(a) NeoAVA constructos for BF, part 1

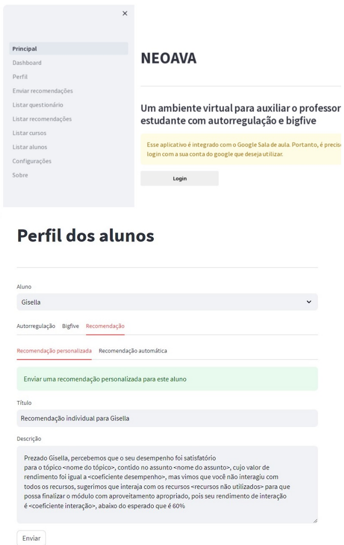


(b) NeoAVA constructos for BF, part 2

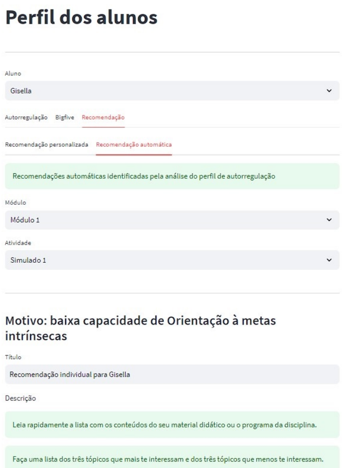


(c) NeoAVA screen with SRL constructs.

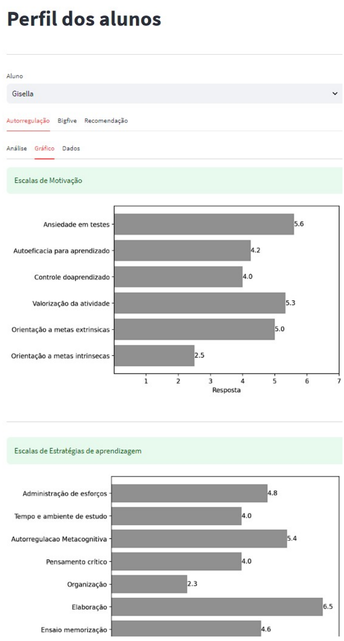
Figure 6. NeoAVA constructs for BF/SRL screenshot.



(a) NeoAVA screens with recommendation texts.



(b) NeoAVA screens with automatic recommendation.



(c) NeoAVA screen with a graphical resume for the self-regulated constructs.

Figure 7. NeoAVA recommendation and SRL construct screenshot.

5. Validation

The sample for this study consisted of eight Brazilian participants who responded to the questionnaire. The results of the questionnaire utilized the TAM (Technology Acceptance Model) indicate a positive acceptance of the NeoAVA system by users. The average response for the usefulness of NeoAVA was 4.6, with minimal variation (standard deviation of 0.55), suggesting that most users find the system beneficial for improving performance. Regarding ease of use, the average was 4.4, with most responses concentrated between 4 and 5, reflecting a positive perception of NeoAVA's usability. The simplicity of searching for information on NeoAVA had an average of 4.0, with a standard deviation of 1.0, indicating a good experience in navigating and accessing content.

Regarding the attractiveness and user experience, the results were also favorable. The NeoAVA interface was well-rated, with an average of 4.0 and a standard deviation of 1.22, suggesting a positive perception, though there is room for improvement. The belief in the efficacy of using NeoAVA compared to not using it had an average of 4.0, with a standard deviation of 0.71, indicating that users see clear benefits in using the system. The intention to continue using NeoAVA obtained a uniform average of 4.0, reflecting a strong intention of continued use among participants.

These results demonstrate that NeoAVA is well-accepted by users in terms of usefulness, ease of use, and overall experience, supporting the feasibility of its implementation and continued use in an educational context.

5.1. Threats to validity

The small sample size of participants in the study, which has only eight people, represents a threat to the validity of the study. A small sample size may not be representative of the general user population, meaning results may not be generalizable to a wider audience. The research team sent invitations to 30 potential users, but only eight responded and completed the questionnaire. This low response rate may indicate a self-selection bias, where participants who chose to participate may have specific opinions or experiences with the NeoAVA system that are not representative of the general user base. A larger, more diverse group of participants would have strengthened the validity of the study and provided more meaningful conclusions. The research team recognizes the need for future research and classroom experiments with a larger number of users and different settings to further validate these preliminary findings. Besides, the NeoAVA interface is only in Brazilian Portuguese, but an internationalization of the web app is ongoing to a more broadly audience.

5.2. Related Works

Some other papers offer valuable insights as related works into the relationship between educational systems and academic performance. [Rogers et al. 2025] link between Moodle interactions and academic performance using educational data mining in a Philippine university, revealing the significant potential for personalized learning through these interactions. [Syukur et al. 2025] delves into how students' motivation, desire to work, and curiosity, especially in the post-COVID-19 era, influence their learning outcomes. This study underscores the importance of considering these factors when designing educational recommendation systems that cater to individual student needs. NeoAVA stands out in comparison to other educational systems analyzed for its innovative approach that integrates personalization based on SRL/BF personality traits. While other systems, such as those utilizing Moodle interactions or focusing on student motivation, provide valuable insights for improving academic performance, NeoAVA goes further by proposing a model that not only tailors educational recommendations to individual student needs but also considers fundamental aspects of student psychology. This contrasts with systems that traditionally focus on behavioral metrics, such as interactions on learning platforms or isolated motivational factors, without deeply integrating personality traits.

6. Conclusion

In conclusion, the NeoAVA — a platform integrated with Google Classroom to provide automatic, personalized recommendations and comprehensive dashboards for teachers to monitor class progress — demonstrates significant potential in enhancing student performance by utilizing data-driven personalized recommendations. This innovative system integrates pedagogical performance, interaction performance, and SRL/BF profiles within VLE to tailor pedagogical actions that align with individual student profiles.

The incorporation of SRL constructs and BF personality traits into the recommendation algorithm enhances the accuracy and relevance of the suggested actions, fostering a more supportive and effective learning environment. Future research and experiments in classrooms with more users and different settings are essential to validate these preliminary findings and to further refine the recommendation engine for broader application. The NeoAVA initiative underscores the importance of personalized learning in modern education and offers a promising pathway to improving academic performance through tailored educational interventions.

The proposed recommendation system is currently tailored specifically for the Google Classroom environment. However, it is highly probable that it could be adapted for use in other learning management systems, e.g., Moodle. This adaptability opens up avenues for future research to explore the potential application and effectiveness of the recommendation system across various educational platforms. Further studies could focus on extending its capabilities and assessing its impact in diverse learning environments, thereby enhancing its utility and broadening its scope of application.

In future work, the integration of advanced artificial intelligence (AI) techniques within NeoAVA could be further explored to enhance its recommendation capabilities. Specifically, the implementation of collaborative filtering algorithms like k-Nearest Neighbors (k-NN) could be investigated to refine the personalization of educational content based on student interaction patterns. Additionally, incorporating reinforcement learning methods such as Q-Learning could allow NeoAVA to dynamically adapt recommendations in real-time, responding to students' evolving needs and improving their learning outcomes. Furthermore, the application of natural language processing models, including BERT, could be explored to analyze student feedback and emotional states, enabling more contextually appropriate and supportive recommendations. These enhancements would not only increase the system's effectiveness but also contribute to a more personalized and emotionally intelligent learning environment, paving the way for more sophisticated AI-driven educational tools.

Artifact Availability

NeoAVA web app is accessible at `http://autorregulacao.streamlit.app/`. The source code is also available at `https://github.com/giseldo/app_autorregulacao/`.

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