AVIN: A Case Study on a Supporting Tool for the Self-Assessment Process in Higher Education Institutions

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Abstract. *Brazilian Higher Education Institutions (HEIs) periodically undergo self-assessment processes to identify weaknesses and opportunities for improvement. These evaluations help analyze issues such as dropout rates, inadequate infrastructure, and student disengagement, supporting the development of strategic actions. This paper presents AVIN, a tool designed to facilitate this process by leveraging Business Intelligence (BI) concepts. AVIN enables HEIs to collect, process, and visualize data efficiently, providing reliable insights for decision-making. The tool aligns with the Ministry of Education self-assessment framework, integrating institutional participant groups to ensure accurate data retrieval and visualization.*

1. Introduction

Higher Education Institutions (HEIs) in Brazil are constantly evaluated by the Ministry of Education. In addition to external on-site evaluations, delegated to technical boards from the governmental Institute Anisio Teixeira (INEP), the current legislation demands that any public or private HEI must also evaluate themselves, attending the federal law that establishes the National Higher Education Evaluation System (known as SINAES)[1]. It covers 10 areas of quality (called dimensions) and determines that an elected internal board (Own-Evaluation Commission, in Portuguese CPA) is responsible for defining and conducting the self-assessment methodology, including the instrumentation to collect, analyze data, and share the results. INEP's technical Note nº 65[2] assigns institutions the responsibility of evaluating their own status, allowing flexibility in prioritizing aspects while ensuring that all dimensions are covered within a three-year assessment cycle. It also emphasizes legitimacy by requiring diverse participation across all hierarchical segments, including professors, students, administrative staff, institutional managers, and local community representatives.

[1]https://www.planalto.gov.br/ccivil_03/_ato2004-2006/2004/lei/l10.861.htm (accessed on February 21, 2025)

[2]http://portal.mec.gov.br/index.php?option=com_docman&task=doc_download&gid=17007&Itemid= (accessed on February 21, 2025)

For higher education, its set of technologies and techniques can be very useful to improve HEIs management and quality capabilities [Khan and Khojah 2022, Santi and Putra 2018, Ong 2016], such as in: *i)* Student data analysis, to identify patterns and trends to create effective teaching strategies and enhance student performance, for instance, dropout rates and lack of interest in certain subjects; *ii)* Professor analysis, to understand professor performance and identify areas for improvement, enabling to provide them adequate training and development; *iii)* Problematic areas comprehension (weakness), such as infrastructural and departmental services gaps, helping to prevent their aggravation; *iv)* Market trending analysis, to determine which skills and knowledge are most valued by employers (and, why not, by students and society), helping in the adjustment of curriculum, internal policies, and regulation, to align organizational mission with market demands.

Complementary, INEP's technical note supposes that a HEI should demonstrate its self-assessment management capability on result appropriation, indicating and classifying topics at each evaluative SINAES dimension, as potentialities or weaknesses, with its respective improvement actions. The current external evaluations conducted by INEP are demanding evidence that appropriation and attendance of these actions are being done properly [Lima et al. 2019, da Silva et al. 2022]. Therefore, regarding administrative management, the data collected by the CPA can also support the HEIs decision-making [Macedo et al. 2017]. By governmental regulation, they are under charge to build their development institutional plans cyclically which must be supported by the internal evaluation processes.

In this sense, the main objective of this work is to develop and implement a decision-support tool, named AVIN (AValiações INstitucionais), designed to enhance the self-assessment process in HEIs by addressing the challenges related to survey application and data assessment, thereby effectively supporting the requirements of CPAs. The AVIN tool has been utilized in a real-world self-assessment context since 2023. This application paper details how surveys were structured using specific models to create a solution that facilitates the survey application process and visualization of the extracted information.

2. Background

The work of [Lima et al. 2019] proposed a four-layered metamodel for institutional self-assessment conduction that is based on INEP's technical note nº 65. The metamodel supports the CPAs in the sense of data modeling, designing their instrumentation to collect, relate, and analyze them, involving the three fundamental references of data, looking at: i) Current Institutional Development Plan (PDI in Portuguese); ii) Segments of participants' perceptions and opinions; iii) Improvement actions characterization (as topics and its state of accomplishment monitoring). The items *i)* and *iii)* are more related to the evaluation of HEI's strategic planning activities and *ii)* is more focused on checking its quality, by segment satisfaction.

Also, this four-layer metamodel discusses how collected data could be arranged to be comprehended faster, putting them in place over analysis perspectives, as follows: i) Dimensionalization: considering each SINAES dimension; ii) Segmentation: relates who evaluates is interested, or is affected by an evaluative issue. An issue can be indicated to belong to one or more segments of participants (by the union), at the same time; iii)

Institutional organization level: determines who or what is being evaluated. An issue can be contextualized recursively in a top-down order: starting from the entire institution, then its respective units or campuses and departments, followed by individual courses, and finally down to the specific disciplines; iv) Temporization: concerns about the institution's progress from one cycle to the next are addressed by temporal labeling, allowing for the tracking of issues that have been evaluated across multiple cycles.

To bridge the gap between structured institutional self-assessment methodologies and modern technological solutions, it is essential to consider how digital solutions can enhance data processing and decision-making in HEIs. While the four-layer metamodel proposed by [Lima et al. 2019] provides a structured approach for organizing and analyzing self-assessment data, its implementation still relies on manual or fragmented processes that may hinder efficiency and scalability. The increasing complexity and volume of institutional assessment data demand automated and adaptable solutions that streamline data collection, analysis, and reporting, making the process more effective and accessible.

In this context, Software as a Service (SaaS) emerges as a viable approach to enhance institutional self-assessment. By integrating automated data processing, interactive visualization, and centralized access, SaaS platforms provide a scalable and efficient framework for HEIs to manage their self-assessment cycles more effectively. These solutions eliminate the overhead of managing on-premise infrastructure, allowing institutions to focus on improving decision-making processes based on reliable, real-time insights [Ghouri and Mani 2019, Ibrahim et al. 2023].

SaaS solutions offer significant advantages for self-assessment systems in HEIs, enhancing real-time data access, scalability, and integration with institutional databases [Ghouri and Mani 2019, Seifert et al. 2023, Stavrinides and Karatza 2020]. AVIN, as a SaaS solution, enables dynamic performance tracking, adapts to varying workloads, and ensures accurate data retrieval from student information systems. Additionally, it promotes collaborative decision-making by engaging professors, administrators, and students in evidence-based discussions. The cloud-based architecture ensures high availability and security, reducing risks related to data loss or unauthorized access. Furthermore, by leveraging BI techniques, AVIN provides intuitive dashboards, analytical reports, and predictive insights to support institutional planning and continuous improvement.

3. Related Work

In [Macedo et al. 2017], the authors highlighted the importance of the contextual-participative evaluations, referred to be formative, that orientate towards institutional identity and democratic participation in the evaluative processes and activities. Considering the contextual-participative role of HEIs self-assessment, the performance of CPAs also assumes the goal of transparency for academic and civil society.

For this reason, to produce useful decision-making information, it is essential to consider aspects such as the cleaning, transformation, and data modeling processes, in order to extract reliable trends and issues [Maia et al. 2018]. Thus, to enhance organizational systemic decisions, it requires that data can be displayed and handled in the clearest or most intuitive way possible [Ain et al. 2019, Lavalle et al. 2019]. BI tools can consume data from different sources and present analytical results in reports, summaries, dashboards, charts, tables, and maps. In this sense, BI tools provide the users an overview of the

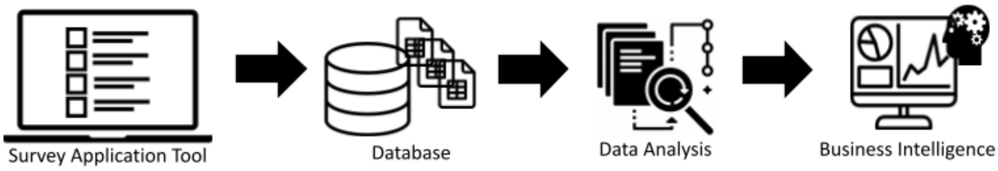

Figura 1. The BI application workflow in the self-assessment process

current scenario of the private or public HEI [Maia et al. 2018]. For instance, business decision-making just can occur with the right data collection and storage, considering a data linkage that provides the best contextualization for a HEI. Data analysis gives meaning to what is going on and why from business results. However, determining what is relevant to be analyzed is related to which data will be selected and converted to achieve this [Ain et al. 2019].

Although these studies highlight the importance of institutional data assessment, none of them directly address the development of a tool that integrates automation and decision-making support for HEIs throughout the self-assessment process, as AVIN is specifically designed to do. Existing approaches primarily discuss data processing techniques, visualization strategies, and the relevance of BI in academic environments [Maia et al. 2018, Ain et al. 2019, Lavalle et al. 2019, Lima et al. 2019, da Silva et al. 2022], but they lack a comprehensive solution that streamlines self-assessment processes while enhancing data-driven decision-making. AVIN addresses this gap by not only automating data extraction, transformation, and visualization but also providing an interactive and structured environment where HEIs can systematically analyze self-assessment results, improving institutional planning and governance.

4. A Decision-support Tool for the Self-assessment Process

Under INEP's policies, HEIs should conduct self-evaluations to inform their continuous improvement efforts. This involves analyzing the current state of the institution through its various segments. In this sense, BI solutions can be applied as a decision-support tool for different organizational levels to identify their respective weaknesses and strengths in a quick and clear way. The AVIN[3] workflow, which covers the whole self-assessment process, is divided into four main components, as illustrated in Figure 1: the survey application tool, the database, data analysis, and business intelligence.

The survey application tool corresponds to the interface for collecting responses from participant segments, constituted by professors, students, and administrative staff. This component could be directly related to a HEI's main information system. In the institution where this project was developed, the system is known as SUAP. Therefore, SUAP serves as a primary data source to be consumed about academic community participants, such as e-mail, home campus, linked courses, and disciplines. This data can be provided assuming an academic term, as a temporal label, about enabled participants over institutional segments and their profiles. The data provided by SUAP are imported into our survey application, which respectively recognizes the tables for HEI's staff (professors and administrative), for students (and its related disciplines), and for the current disciplines from courses (relating to professors).

[3] https://avaliacao.ifpb.edu.br/avin/

It is important to recognize that these participant academic profiles are crucial for determining which surveys and questions are suitable for them. This alignment ensures that when someone decides to participate, they are given the correct set of questions. The surveys must be designed with appropriate matching filters to ensure that only authorized participants, based on their academic profiles, are allowed to take part. For instance, for students or professors, the course type (from technical degree to post-graduation) or its offering conditions (in-person, online) are often needed to provide restriction rules in a survey with matching filters.

Survey models are expressed in flexible JSON format, considering fields such as title, welcome message, submitted message, start/due time of application, and participant matching filters. In a survey, the questions are divided into two main types: closed-dimensionalized (containing a set of indicators as issues to be evaluated under a quality-quantitative scale) and open-dimensionalized (a report of suggestion, a complaint, or just a concern from the participant, depending on question title). The quality-quantitative scale could be expressed with levels of satisfaction under an evaluative issue indicator. For instance, from -2 being “very unsatisfied” to 2 being “very satisfied”, with 0 being neutral. Neutral means that the participant is indifferent or simply does not know about the indicator in the HEI at that time.

The development of the survey application tool was conceived under a full stack architecture, with a front-end (user interface) developed with the React JS[4] library, which enables the creation of web apps with low management and maintenance costs, that can be accessed by any standard web browser. The back-end (with business rules and data storage) was built using Google Apps Script (GAS)[5], which is responsible for managing the surveys and storing them. Thus, the survey tool organizes each participant segment into a separate document within the collection (as shown in the database storage component of the workflow in Figure 1). This setup allows for the association of organizational levels and evaluative data using key-value pairs (participant hash and JSON object).

In this sense, the user interface is dedicated to evaluation management and includes features for automatically tracking participation, monitoring how many are expected to answer each survey and how many have already responded. It also provides tools to generate organizational level context for the closed-dimensional questions and to list context for the open-dimensional ones. Another user interface (developed in React.js) can be deployed on a web server, allowing participants to view their completed surveys and access those they have yet to answer. This interface is designed to be simple and portable, accessible on both computers and smartphones. Finally, when a participant completes the survey, the component stores the answers in the correlated storage structure.

After the data (i.e., survey answers) are available in the database component, the Data Analysis component will consume them to standardize, integrate, and process the data in question. Furthermore, this component is responsible for generating the accounting information, which groups and organizes the answers by the institutional organization levels, enabling contextual analysis. Data analysis is mandatory to provide useful and reliable information to the BI since inaccurate data generates misunderstood information and, consequently, wrong business decisions for a HEI.

[4]`https://pt-br.reactjs.org/` (accessed on February 21, 2025)
[5]`https://www.google.com/script/start/` (accessed on February 21, 2025)

Regarding BI, the last component in the workflow (Figure 1), will be responsible for consuming the information generated in the data analysis and displaying it through graphs, pivot tables, and summarized data. More specifically, this module will provide dashboards where users (members of the academic community and managers) will be able to evaluate information related to disciplines, courses, campuses, and the whole institution. For a more detailed and targeted view, users must be able to select filters and inform parameters that customize the information according to their needs or permissions. To this end, the Google Looker Studio[6] tool was chosen as a BI tool. Note that AVIN is hosted within the Google Ecosystem, which is utilized by various services and tools at the HEI. The Federal Institute of Paraíba (IFPB) has access to the suite of Google Ecosystem products, facilitating the development and implementation of this project. Then, Looker Studio (as a BI component) consumes the data processed in the previous step and provides the user visualization with detailed information reports. It can serve the self-assessment results intuitively as web pages with correspondent data visualization components and filters. The BI component is composed of 12 web pages with different types of charts and graphs. These 12 web pages are divided into 5 pages for professors, 4 for students, and 3 pages for administrative staff.

5. Application and Practical Deployment

During the institutional self-assessment process, members of all segments are invited to answer the survey. This step is one of the challenges since the academic community may not have been correctly encouraged to respond since filling out the form is not mandatory due to the respective policies. Then, a low number of respondents may delegitimize the self-assessment not reflecting the real world. For instance, at the last self-assessment process conducted at IFPB, a specific course had only one respondent considering a universe of 21 students who should have filled out the survey. Clearly, this data should be disregarded since only one student hardly reflects the scenario for the course as a whole. In meetings involving the academic community, one of the facts that discourage the completion of the surveys is the lack of disclosure and access to the surveys themselves. To this end, AVIN appears as a quick way to fill out the surveys since it is a web page that can be easily shared, through a link, among the academic community. Thus, to increase the number of participants during the self-assessment process, the link to the survey was spread by email, posts on the institutional website, and social media. As a result, AVIN contributed to a significant increase in the number of respondents, which will be further explored in Section 6.

In order to provide an overview of the number of respondents during the self-assessment process, the BI component also provides a real-time dashboard with the information regarding the number of respondents compared with the universe that should fill the survey in question, as depicted in Figure 2. It is important to highlight that this dashboard is fundamental to define actions of disclosure in the institution, especially in courses or campuses with a low number of respondents. For instance, directors and coordinators can define actions to encourage survey participation based on real-time data.

To ensure security and confidence in the collected answers, user authentication is required to access the survey application tool. However, to avoid additional steps that can

[6] `https://lookerstudio.google.com/` (accessed on February 24, 2025)

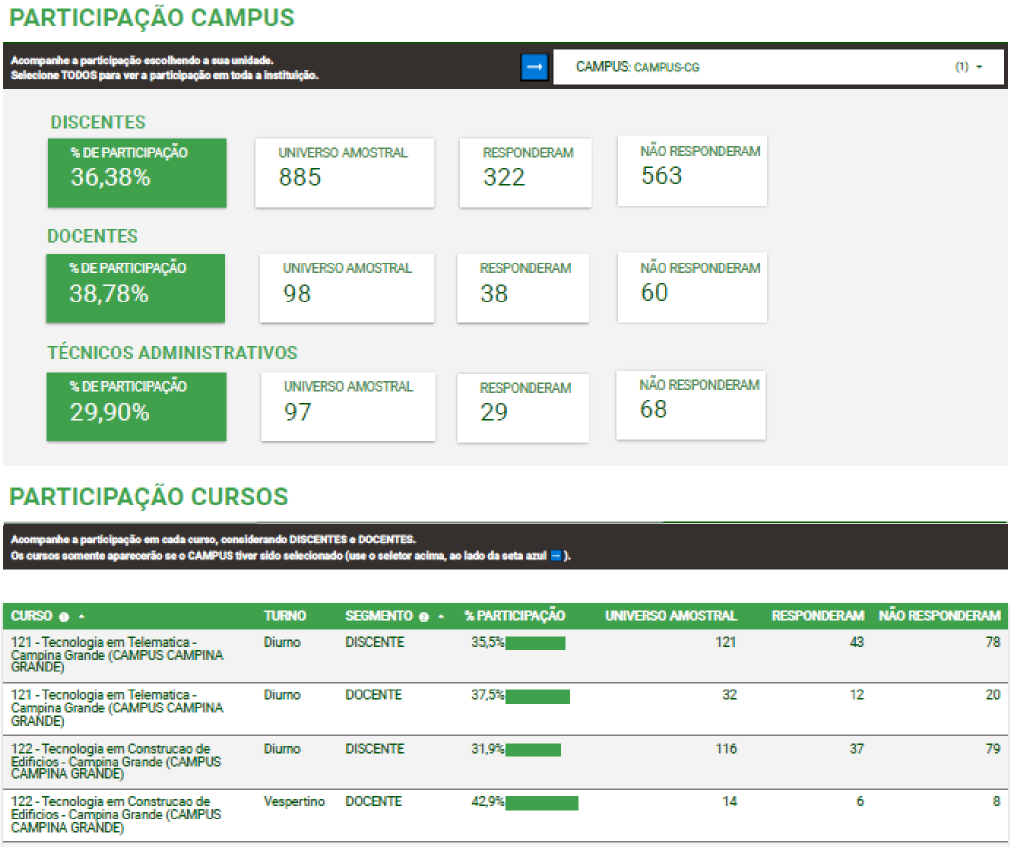

Figura 2. Example of the monitoring dashboard with the number of respondents for a specific campus.

discourage respondents, user authentication is performed through Google sign-in[7]. It is important to clarify that all members of the academic segments have an institutional email address (provided by Google). Therefore, users signed into their institutional Google account are automatically able to answer the survey. Since different surveys are applied according to the academic segment, based on the Google account identification, the survey application tool detects the academic segment of the enabled user participants (imported from the main information system) and applies the appropriate survey to each one of them. Figure 3 depicts an example of questions asked in the survey applied to the student segment using the survey application tool.

Based on data processed by Data analysis, the BI component provides to the user a set of graphs and tabular reports, as illustrated in Figures 4 and 5[8]. Notice that the graph illustrated in Figure 4 provides an overview of the contextualized evaluation at the organizational level of courses, based on the percentage of responses collected for each closed-dimensional question indicator. Each color represents the frequency of responses on the qualitative-quantitative evaluative scale chosen for the self-assessment cycle.

In addition, the user will be able to apply filters on the graphs, such as campus,

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[7] `https://developers.google.com/identity/protocols/oauth2` (accessed on February 24, 2025)

[8] Note, since the data is public, the Figures used throughout this paper illustrate real scenarios of survey application as well as the dashboard visualization.

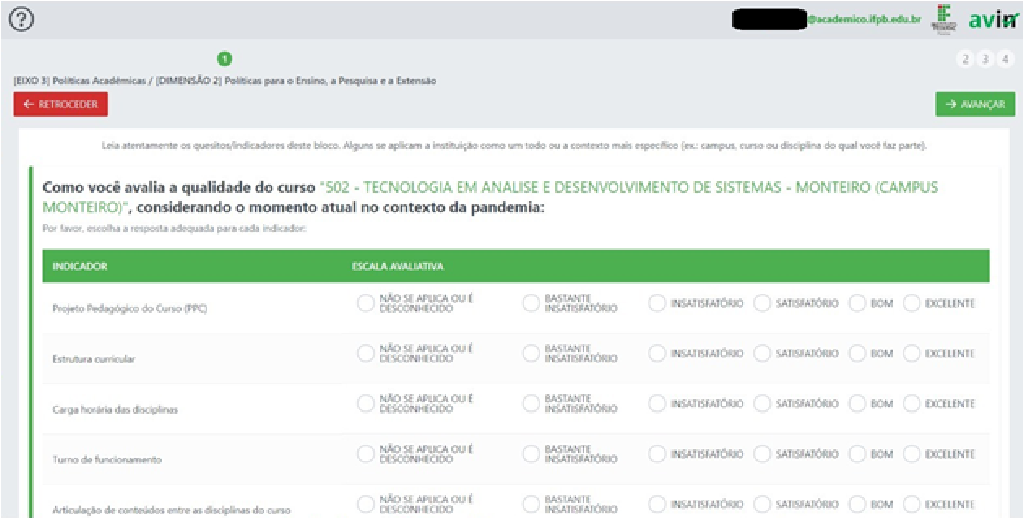

Figura 3. Example of a question in the survey application tool.

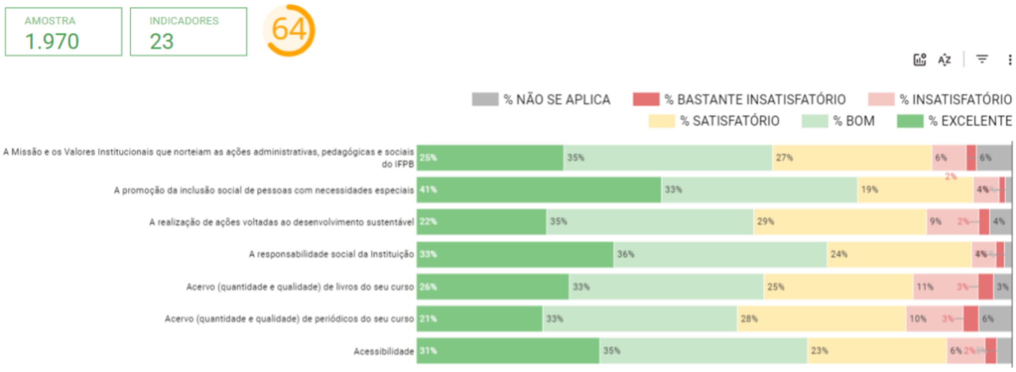

Figura 4. Example of detailed report generated by BI.

course, and teaching modality. Thus, a coordinator can explore data related to their course, a director can focus on a specific campus under their responsibility, and a dean can access a comprehensive overview of the entire HEI. At the top of Figure 4, it is possible to the number of respondents, the number of SINAES indicators considered for the survey in question, and the KPI (Key Performance Indicator) thermometer, which summarizes the mean of the results taking into account all indicators. Based on the KPI thermometer, whose value varies between 0 and 100, the manager can have an overview regarding the evaluation status of the institution or a specific campus. In this scenario, the KPI value is calculated by averaging the answer scores (which vary from -2 to 2) and then normalizing this average score to fit a 0 to 100 scale.

For each closed-dimensional question related to a SINAES dimension, the participant evaluates using an evaluative scale with the following options with the respective score value: 'not applied' (0), 'very unsatisfied' (-2), 'unsatisfactory' (-1), 'satisfactory' (0), 'good' (1), and 'excellent' (2). Note that a 0 score value means a neutral opinion or when the participant feels unable to evaluate the question. In this perspective, Figure 4 provides a detailed view related to the responses reported for each indicator. From this visualization, the managers can evaluate the strengths and vulnerabilities of the institution based on the responses of each indicator. In our experimentation, it is more practical to

INDICADORES SOBRE A INSTITUIÇÃO/CAMPI/CURSOS

MODALIDA...	CAMPUS	CURSO	TURNO	AMOSTRA	% NÃO S...	% BASTA...	% INSATI...	% SATIS...	% BOM	% EXCEL...
Licenciatura	CAMPUS-JP	44 - Licenciatura em Quimica - Joao Pessoa (CA...	Vespertino	26	6%	2%	7%	27%	25%	33%
			Total	**26**	**6%**	**2%**	**7%**	**27%**	**25%**	**33%**
		223 - Licenciatura em Matematica - Joao Pesso...	Vespertino	28	8%	3%	7%	23%	27%	32%
			Total	**28**	**8%**	**3%**	**7%**	**23%**	**27%**	**32%**
		Total		**54**	**7%**	**3%**	**7%**	**25%**	**26%**	**32%**
	CAMPUS-CB	702 - Licenciatura em Ciencias Biologicas - Cabe...	Diurno	65	2%	4%	8%	27%	31%	29%
			Total	**65**	**2%**	**4%**	**8%**	**27%**	**31%**	**29%**
		Total		**65**	**2%**	**4%**	**8%**	**27%**	**31%**	**29%**
	CAMPUS-PI	402 - Licenciatura em Ciencias Biologicas - Cam...	Vespertino	39	+0%	1%	4%	12%	39%	44%
			Noturno	30	+0%	2%	7%	15%	27%	49%
			Total	**69**	**+0%**	**1%**	**5%**	**13%**	**34%**	**46%**
		Total		**69**	**+0%**	**1%**	**5%**	**13%**	**34%**	**46%**

Figura 5. Example of table report generated by BI.

serve indicators that belong to a specific organizational level (i.e. course) being possible to aggregate results over above levels (.i.e an entire campus), and so on. As a next step, with visualizations, hold meetings with the academic community to discuss the results achieved and promote improvement actions. Regarding open-dimensionalized questions, the BI component includes a dedicated page where CPA members can evaluate responses, which gathers suggestions, complaints, and concerns of the participants. Thus, managers can explore individual feedback submitted by members of the academic community.

In Figure 5, it is possible to evaluate an overview of the self-assessment results in a tabular perspective, dividing them by the academic organizational hierarchy: teaching modality (e.g., degree, bachelor, master, and doctoral), campus, course, and shift. This hierarchy order of visualization in the table was defined by the members of CPA according to their needs. Notice that this table summarizes the results of all SINAES dimensions addressed during the self-assessment in question. To this end, a grouping and merging function was applied to take into account individual values (i.e., fine-grained visualization) as well as the combination of values according to the academic hierarchy (i.e., overall visualization). Thus, assuming a manager position, this kind of report is fundamental to evaluate a generic perspective of the HEI. Furthermore, the CPA extracts the tables to be inserted in the reports to be sent to the appropriate governmental agencies. Hence, information with a low graphic level (such as tables) is also useful for CPAs.

6. Results and Discussions

To evaluate the performance, effectiveness, and usability of the proposed system, we conducted a series of tests in both controlled environments and real-world applications in the self-assessment process at IFPB. The evaluation was divided into two main aspects: quantitative and qualitative metrics.

6.1. Quantitative Evaluation

Response Time. The AVIN system's performance was evaluated based on response time to ensure efficient data processing and timely information retrieval. The ETL process—including data extraction, transformation, and loading—was completed within an average of 2.4 minutes during the 2023 self-assessment cycle. This efficiency is maintained through structured data extraction and asynchronous processing, enabling the system to handle large volumes of responses effectively. Optimized data transformation routines ensure minimal delays, while the centralized online database provides an interactive

BI dashboard with real-time updates. Performance tests showed that dashboard queries had an average response time between 800 ms and 1.9 seconds, depending on filter complexity. The system maintains low latency even under high demand, leveraging caching mechanisms and optimized database indexing for seamless data access.

Data Accuracy. To ensure the reliability of the data presented in the BI dashboard, two validation approaches were employed. The first approach involved a manual cross-checking process, where data displayed in the BI system was systematically compared with the raw data stored in the database. This validation was conducted using automated data collection algorithms combined with an expert evaluation performed by institutional specialists. The second approach leveraged the prior knowledge of the Own-Evaluation Commission members, who reviewed the BI-generated results based on their expertise and familiarity with institutional assessment trends. These complementary methods helped confirm the consistency and accuracy of the extracted and processed data, reinforcing the system's credibility for institutional decision-making.

System Availability. To monitor system availability, users were provided with an email contact and a dedicated link to report any downtime or access issues. Throughout the evaluation period, no reports of unplanned system unavailability were received since 2023, indicating a high level of reliability. The only recorded instances of system downtime corresponded to scheduled maintenance periods for the institutional server. This suggests that AVIN has maintained stable and continuous operation, ensuring that self-assessment data remains accessible to users without unexpected disruptions.

6.2. Qualitative Evaluation

The qualitative evaluation of AVIN was conducted through a feedback meeting with the president of the Own-Evaluation Commission and nine of its members. Additionally, information from the 2023 official self-assessment report[9] was reviewed, including sectoral meetings across different campuses where feedback about the system was collected. During these meetings conducted by the Own-Evaluation Commission, the adoption of AVIN was highlighted as one of the positive aspects of the 2023 self-assessment process, and these acknowledgments were officially documented in the report. These sources provided a comprehensive understanding of the system's usability, user satisfaction, and the perceived utility of its features.

Ease of Use. The AVIN platform was designed to facilitate institutional self-assessment through an accessible web-based interface. According to the collected feedback, users appreciated the system's ability to provide seamless authentication using institutional credentials, reducing access barriers. The interface's intuitive design enabled users to navigate between different assessment instruments efficiently. Moreover, faculty members and administrative staff highlighted the clarity of question categorization and the straightforward nature of data input, which streamlined the evaluation process.

User Satisfaction. Overall, user satisfaction with AVIN was high. Members of the Own-Evaluation Commission emphasized that the platform significantly improved data collection and analysis efficiency. The ability to generate interactive visual reports through BI tools was particularly well-received, as it enabled stakeholders to explore self-assessment results in a more dynamic and informative manner. Additionally, feedback

[9] https://www.ifpb.edu.br/cpa/RELATRIODEAUTOAVALIAOINSTITUCIONAL2023.docx1.pdf

from the official report indicated that respondents found the system reliable and effective in consolidating institutional evaluation data.

Utility of Features. The most frequently praised feature of AVIN was its interactive BI dashboard, which allowed for real-time data visualization and filtering. According to reports from the Commission, this capability enhanced institutional decision-making by making historical and comparative analysis more accessible. Additionally, the system's ability to categorize feedback by institutional segments (i.e., students, professors, and administrative staff) enabled a more granular understanding of institutional strengths and areas for improvement. Furthermore, the integration with previous self-assessment results facilitated longitudinal analysis, helping decision-makers track institutional progress over multiple evaluation cycles.

6.3. Discussion and Impact

The adoption of AVIN significantly enhanced the self-assessment process by improving data collection efficiency and increasing user engagement. One of the most notable impacts was the substantial growth in the number of respondents, ensuring a more representative dataset for institutional decision-making. This positive impact is reinforced by quantitative results, which show a 68% increase in student participation, a 17.6% in professor responses, and a 6.6% in administrative staff engagement compared to the previous self-assessment cycle, which did not use AVIN. By offering an intuitive interface, real-time data visualization, and seamless accessibility, AVIN facilitated broader participation among students, professors, and administrative staff. Additionally, the structured BI dashboard enabled stakeholders to explore self-assessment results in greater depth, promoting a more data-driven approach to institutional evaluation.

7. Conclusion

The success of AVIN was confirmed by its insertion in the real world, considering the efficiency gains of the self-assessment process throughout the last years in IFPB. Processes that previously required several months now operate on shorter cycles, typically lasting 1 to 2 months. Moreover, there has been an increase in the number of survey respondents, coupled with greater confidence in the stored results. In previous cycles, certain data had to be discarded due to inconsistencies. Managers have emphasized the fundamental role of AVIN in facilitating informed decision-making processes and monitoring the steps of the self-assessment process such as the number of respondents in real-time. As the main result, AVIN is the official mechanism in IFPB to conduct the self-assessment process.

In future work, we aim to extend the application of AVIN to support the self-assessment processes of other HEIs. The good results achieved by the tool in a real-world scenario indicate its viability and potential benefits for a broader academic community. Moreover, another component is being developed to be coupled in the self-assessment workflow, the module of improvement actions panel. This module will be responsible for managing the improvement actions, which should be linked to the problems detected through the evaluation of scenarios using the BI component. Finally, we also consider applying machine learning algorithms. This enhancement will enable the tool to learn from data and offer valuable insights such as predictions, pattern recognition, and correlations between variables within the educational setting.

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