A Framework for Self-Service Business Intelligence

Rosa Matias and Maria Beatriz Piedade
Computer Science and Communications Research Centre (CIIC), School of Technology and Management (ESTG), Polytechnic University of Leiria, Portugal

Keywords: Self-Service Business Intelligence, Data Visualization, Data Storytelling.

Abstract: Building an effective Business Intelligence solution involves several key steps. Recently, low-code software tools have allowed casual users - those with domain-specific knowledge of a case study - to develop custom solutions independently of IT teams. This is the era of Self-Service Business Intelligence. However, some drawbacks have been identified due to casual users' lack of Business Intelligence expertise. In response, a framework is proposed, introducing the role of casual power users and specifying the Business Intelligence knowledge they should possess. Additionally, the framework aims to integrate Business Intelligence methodologies more cohesively with data visualization and data storytelling development cycles. As a proof of concept, the framework was applied to develop a solution for monitoring class attendance at a higher education institution. In this case study, a casual power user is able to identify, early in the semester, which classes require adjustments to improve resource management and pedagogical outcomes. The contextualization provided by the framework enabled that user to successfully uncover critical insights.

1 INTRODUCTION

For quite some time, the digital technological expansion has contributed to the accumulation of data. Depending on the amount of data, the size of datasets may vary from small to medium or even enormous. Regardless of dataset size, data analysis is essential for gaining insights, as datasets consist solely of facts. Data analysis facilitates the transformation of these facts into information, that together with the users' background knowledge about the domain of analysis, enables wisdom and consequentially impactful decisions. Data analysis can be utilized to explore historical data, forecast future events, and recommend actions to achieve optimal outcomes. The first is called descriptive analysis, the second predictive and the third prescriptive (Sharda, Delen, & Turban, 2018). Business Intelligence (BI) solutions are data-driven systems created to help organizations gather, organize, and present data, from multiple systems, providing insights that facilitate informed decision-making. It may also support data analysis as part of a larger process. In organizations such a solution comprises a set of methods, processes, architectures, applications, and technologies that collectively transform raw data into insights (Evelson, & Norman, 2008), facilitating operational, tactical, or strategic decision-making.

Lennerholt, Van Laere, and Söderström (2021) identify 2 types of BI users: power users and causal users (Lennerholt, Van Laere, & Söderström, 2021). The first type has technical and theoretical knowledge to develop BI solutions but lacks problem-domain specific knowledge. The second type has no technical or theoretical knowledge to develop BI solutions but possesses problem-domain specific knowledge about the scenario under study.

Until recently, BI solutions were typically developed by users with technical and theoretical expertise and teams integrates users with domain knowledge for requirements gathering (for instance).

The emergence of tools such as Power BI (Microsoft, 2024), Tableau (Tableau,2024), and Qlik (Qlik, 2024) enable the development of Self-Service Business Intelligence (SSBI) solutions by casual users that usually do not possess technical expertise (Arnaboldi, Robbiani, & Carlucci, 2021). Those tools intend to be interactive, visual oriented, user-friendly, with low code features. As a result, casual users, with their background knowledge, are now apparently capable of interacting with BI tools and building their own dedicated solutions.

Matias, R. and Piedade, M.
A Framework for Self-Service Business Intelligence.
DOI: 10.5220/0013015700003838

In *Proceedings of the 16th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K 2024) - Volume 1: KDIR*, pages 408-415
ISBN: 978-989-758-716-0; ISSN: 2184-3228

By definition, a SSBI solution consists of a set of processes and tools that enables non-technical users to obtain, integrate, analyse, and visualize data without the need for traditional BI solution (Lennerholt, Van Laere, & Söderström, 2018).

Nevertheless, despite the possibility of developing a SSBI solution with low code, there are studies that identify difficulties in doing so. Suprata (2019) stated that several companies struggle to develop impactful data-driven dashboards due to complex datasets, inadequate dashboard design, and ineffective data storytelling (Suprata, F. ,2019).

This work proposes a new SSBI role: the casual power user. It is a user with domain knowledge about the scenario under analysis who also possesses fundamental theoretical and technical knowledge about BI. A framework is proposed for them to serve as a guide for developing SSBI solutions. It aims to bridge the gap between causal users and the concepts associated with BI. The framework considers well-known stages in BI methodologies but presents simplified, dependent, and interrelated stages for SSBI. Usually, BI methodologies have sequential steps, with some stages done in parallel. To the best of our knowledge, there is no framework capable of helping causal power users in the development of SSBI solutions with simplified, dependent and interrelated stages. The framework intends to incorporate in a stricter way traditional BI methodologies with dashboard and data storytelling development cycles.

As a proof of concept, a prototype has been built by a casual power user using the proposed framework. The case study aims to discover patterns regarding class attendance in a higher education institution. The project objectives are to assist managers in identifying classes with the highest and lowest number of student and to determine attendance behaviour over the weeks. With the identified insights, they can make informed decisions about class rearrangements and improve resources management.

The structure of the document is organized as follows: first, theoretical background; then, the proposed framework; and next, the case study. Finally, considerations are discussed, and conclusions are drawn.

2 THEORICAL BACKGROUD

This section provides an overview of concepts associated with BI and SSBI and about dashboards and data storytelling.

2.1 From Business Intelligence to Self-Service Business Intelligence

Bost by activities such as day-to-day events, social media or IoT sensors the data is being generated at impressive velocity, with variety and high volume. The raw data hide patterns with valuable insights. Generally, users want to explore it in an agile, interactive, and efficient manner. Regardless of the type of organization users belong to, or the role they play, at any given time, they want to access summarized data, drill down into the details, and study it from diverse perspectives. Also enrich it with data from external sources. In organizations one of the solutions to analyse the data and to monitor performance indicators is through BI systems. Therefore, organizations from various sectors have begun to adopt them, and they are now widely used for multiple purposes. For instance, in sectors such as education, health, commerce, industry, government, among others.

A BI system may include a data warehouse structured in agreement with the dimensional model, which supports data querying and data exploration. It is also be supported by extract, transform and load (ETL) processes and dedicated applications (Kimball, 2016).

In a BI project it is essential the stakeholders' background knowledge regarding subjects to ensure that the objectives are properly understood and addressed. With the rise of SSBI they turn into casual users and usually do not possess technical and theoretical expertise to build common a BI solution. Nevertheless, they have an enormous knowledge about the scenario or case under study. The advent of SSBI solutions has gaining popularity because the stakeholders have now interactive and low-code applications capable of certain independence from power users. The necessity for SSBI is unavoidable, as it enables businesses to extract information as needed and make informed decisions. (Zaghloul, Ali-Eldin, & Salem, 2013). It is a democratization process where users have the possibility and independence of building their own BI solutions (Arnaboldi, Robbiani, & Carlucci, 2021). A SSBI allows non-technical users to independently utilize BI tools, reducing their dependence on technical support (Lennerholt, Van Laere, & Söderström, 2021). Consequently, the role of casual users has changed (Dedić, & Stanier, 2017) and at present they have dedicated tools to perform specific analysis as required and on-the-fly.

Recently, Olaoye, & Potter (2024) stated the key components that work together in a BI environment are: data integration, data warehousing, reporting and dashboards, data visualization, advanced analytics, self-service analytics, data governance and collaboration (Olaoye, F., & Potter, K., 2024).

2.2 From Data Visualization to Data Storytelling

A dashboard is a visual tool that displays the key information required to accomplish the organization's goals. The data is organized on a screen, enabling easy and immediate monitoring (Few, 2006; Schwendimann et al., 2016). In agreement with the well-known enterprise organizational pyramid, the dashboards are classified as operational, tactical or strategic (Few, 2006). The first to monitor day-to-day activities, the second to take medium term decisions and the third to perform long-term strategic decisions by senior management executives.

A useful starting point for organizing the elements in a dashboard is the following Information Visual Mantra (Shneiderman, 2003): overview first, zoom and filter, then details on demand. Additionally, when building a dashboard, it's important to consider the appropriate visual elements to effectively display the relevant data. Suprata (2019) gives an overview about the relationship between charts and specific display proposes (Suprata, 2019).

Chokki et al. (2022) specifies the stages to build a dashboard, for instances, pick the metrics, collect the data, ensure quality, consider the audience, choose the best visualization practices, choose the best charts, provide easy to use tools, provide clear presentation, context and data interpretation, think of the audience, ensure data is up to date, allow access to data source and privacy, provide interactive support and allow customization (Chokki et al., 2022).

Sorour & Atkins (2024) propose a data cycle to develop dashboards with following steps: metrics choice, data collection, data processing, data analysis, building the dashboard layout, integrating visualizations in the layout and deployment (Sorour & Atkins, 2024).

The development of dashboards is a main factor for good stories as they are based on frames and pictures obtained from them.

For all the times humans use stories to gain attention, communicate and pass knowledge (Dykes, 2019). As so data storytelling has become an essential step in BI. The data only speaks if the right message is passed to users. Suprata (2019) proposed the following approach to develop a data story (Suprata, 2019): define the audience, frame insights, establish setting or context, focus on the story elements and consolidate and practices.

3 THE PROBLEM

Although casual users can interact with SSBI tools, they may lack the fundamental theoretical and technical concepts necessary to develop an effective SSBI solution. A SSBI software tool is a simplified version of traditional BI software, specifically designed for casual users. However, it is essential that these users also possess theoretical and technical knowledge to build a high-quality solution. In an SSBI tool, the user interaction is apparently easy, but this does not necessarily mean that data will be handled correctly. Indeed, it may happen that casual users interact with visual elements without being aware of all the available features and their relationships to underlying concepts. As above-mentioned SSBI is a simplified version of BI, but it does not decline important ideas necessary for efficient and effective solutions and results. Such question highlights the fact that in practice, implementing SSBI is not as easy as expected (Lennerholt, Van Laere, & Söderström, 2021).

Also, traditional BI methodologies (Kimball, 2016; Inmon, 2006) already contemplate briefly the development of dashboards and data communication. However, since they were developed with a focus on data integration and building a centralized repository, they are not as oriented toward the latest developments in data visualization and storytelling. Dashboard development and data storytelling are gaining attention but generally as separated approaches with their own development cycles (Suprata, 2019; Zhang, et al. 2022).

The Kimball methodology is a widely used bottom-up approach that remains relevant for developing BI systems. The methodology was developed in the 80s and it is considered a guide for experts. On the other hand, data storytelling in the context of data visualization is gaining momentum, and it is not fully considered in that methodology. Kimball and Inmon are well known authors of approaches to development BI. They gave importance to aspects such as data integration and to the develop of centralized sources. But cloud computing changed the paradigm and cloud providers currently enable to store enormous data volumes in structured, unstructured or semi-structured formats. Data may be stored in the cloud providers supported by databases, data warehouses or data lakes. An SSBI can consume data from those cloud platforms at any given time and as needed. Despite, many organizations struggle to utilize the potential of SSBI and experience implementation challenges (Lennerholt, Van Laere, & Söderström, 2018).

Nevertheless, data exploration by stakeholders is essential, it may happen a BI solution is deployed, and data specialists provide models without communicating potential data insights. At other times, data specialists supply only a set of charts that may be more or less impactful.

The dashboards and data storytelling stages are gaining attention since when well-done discoveries are communicated effectively as they transmit and highlight insights. As part of the project, effective communication of results should be combined with contextualized narratives for guidance and higher quality insights. Although stakeholders have rich background knowledge, they may not understand how to sculp the data, how to model the data, how to organize layouts and communicate insights effectively. Also, to access and use several data sources for analysis and decision-making is not easy as expected and different challenges arise for SSBI (Alpar & Schulz, 2016; Lennerholt, Van Laere, & Söderström, 2021). It requires technical skills that not all users possess, such as data cleaning, data modelling, knowledge about layouts arrangements and choosing the right charts, among others.

It is considered essential that users with background knowledge in a subject and who wish to analyse data themselves acquire concepts of BI to develop SSBI. In this way, more proactive SSBI projects can be built with more data quality and more impactful decisions. Therefore, a symbiosis between casual users and power users is fundamental, as their roles complement each other - power users with technical skills and casual users with background knowledge about the case under study.

In SSBI the casual users should have minimum knowledge such as capacities to connect to the data sources, clean and transform the data, build a data model, choose the right charts and build dedicated layouts and communicate the data stories. As so casual users should be promoted to a role designated by casual power users. These are users with background knowledge regarding the case study and some technical and theoretical expertise about BI.

Also recently, the paradigm started to be on data visualization and data communication. How can traditional BI methodologies be integrated with the dashboards and data storytelling approaches for easy and flexible data consumption and in a light but stricter manner?

4 THE FRAMEWORK

Authors propose to build a framework to help casual power users to the development more quality SSBI solutions.

4.1 Specification

The framework has 5 constraints each specify the minimum knowledge requirements that they should possess:

1. Knowledge about requirements.
2. Knowledge about modelling.
3. Knowledge about data integration.
4. Knowledge about data visualization.
5. Knowledge about data storytelling.

The constraints have subitems, some of which are interrelated and dependent on each other. The interrelated subitems are developed together due to their interdependence. For instance, the requirements constraint is closely linked to the data visualization and data storytelling constraints. When identifying requirements, is necessary to establish the audience, specify performance indicators, and design the dashboard layouts and charts to be used. Conversely, during dashboard layout design, new requirements may also emerge. Similarly, the integration constraint is strongly connected to the data modelling constraint, as integration, for example, is not feasible without identifying the metadata. Below, the main stages and their subitems are outlined.

In the **knowledge about requirements constraints** casual power users grasp both the context and the audience, along with their profiles. The discovery of relevant questions is crucial, as they influence problem comprehension, leading to problem resolution. For instance, the Specific, Measurable, Achievable, Relevant, and Time-Bound (SMART) criteria (Doran, 1981) may be applied. The goal is to develop sets of relevant questions and to identify performance indicators, as these enable the organization to monitor and control its operations. Every organization has a specific strategy to achieve certain goals and uses these indicators as references for decision-making (Balon, 2024). On the other hand, design the dashboard *mockups* to organize previously the data to display.

In the **knowledge about the modelling constraints** casual power users discover the data source metadata and design an appropriate model for data exploration. Kimball (2016) proposes an approach for designing a multidimensional model. This model is considered significant because it allows flexible combinations when querying the data. The dimensional model and the associated star schema enhance data exploration capabilities, providing the system with a powerful mechanism for data analysis.

The dimensional model is expressed by fact tables surrounded by dimension tables. The fact tables store business measures, while the dimension tables contain axes of analysis describing measures. The Kimball process has the following stages (Kimball, 2016): select the business processes, declare the grain, identify the dimensions, identify the facts, design the star schema, define the data, handle slowly changed dimensions, implement and test the model, iterate and refine.

In the **knowledge about data integration constraints,** it is important to understand how to connect to a diverse group of data sources and how to clean and transform the data. Many SSBI tools come equipped with features that allow connection to various types of sources, along with easy-to-use data cleaning and transformation capabilities.

In the **knowledge about data visualization constraints,** casual power users implement the layouts designed in the first stage, utilizing the identified layouts and charts to convey the appropriate messages.

In the **knowledge about data storytelling constraints,** the narratives are built by identifying the most appropriate episodes for each taking into considerations the audience previously identified. They then express these narratives using guiding threads.

4.2 SSBI Framework

In this section the subitems of each constraint are described.

1. **SSBI_KR** Knowledge about requirements
   1.1. Identify the context and the audience
   1.2. Identify analysis questions
   1.3. Describe performance indicators
   1.4. Gather functional requirements
2. **SBI_KM** Knowledge about modelling
   2.1. Identify metadata from data sources
   2.2. Build a dimensional model
   2.3. Implement the dimensional model
3. **SSBI_KI** Knowledge about data integration:
   3.1. Connect to data sources
   3.2. Infer the data profile
   3.3. Clean and transform the data
   3.4. Load the data tables (dimensions and facts)
4. **SSBI_KV** Knowledge about data visualization:
   4.1. Design the layouts and identify the best charts in agreement with the data visualization objectives
   4.2. Implement the dashboards
5. **SSBI_KS** Knowledge about data storytelling
   5.1. Identify the context
   5.2. Identify narratives
   5.3. Build narratives guiding threads

	1.1	1.2	1.3	1.4	2.1	2.2	2.3	3.1	3.2	3.3	3.4	4.1	4.2	5.1	5.2	5.3
1.1																
1.2		D														
1.3																
1.4																
s 2.1	D	D	D	D												
2.2	D	D	D	D		D										
2.3																
3.1																
3.2									D							
3.3																
3.4					D		D									
4.1	D	D	D	D			D					D				
4.2	D	D	D	D			D				D					
5.1	D											D	D			
5.2	D	D	D	D								D	D		D	
5.3	D	D	D	D								D	D			

Figure 1: Dependence between subitems.

Figure 1 highlights the dependence between its subitems, and Figure 2 displays the graphic representation of the framework. In the framework there are high dependences between the requirements phase and the data visualization and data storytelling phases. In the data visualization dashboards are built as they serve as a support to the data storytelling phase. As so they influence each other.

5 CASE STUDY: CLASS ATTENDANCE

The framework was utilized by a casual power user and applied to a case study in a higher education institution. The institution needs to make decisions regarding the management of the classes. The casual power user is a manager aware of the problem under analysis and uses a SSBI tool (Power BI). Next, the problem is contextualized, and later, the framework is applied to solve the problem.

5.1 Contextualization

A higher education institution has a transactional and operational digital platform to control class attendance. In the school, each course has a set of subjects with enrolled students. Students are divided into groups. A class is a lesson conducted by a teacher for a group of students. After each class the teachers register the number of attending students in the digital platform. There is a need for a data-driven solution to monitor student attendance throughout the semester.

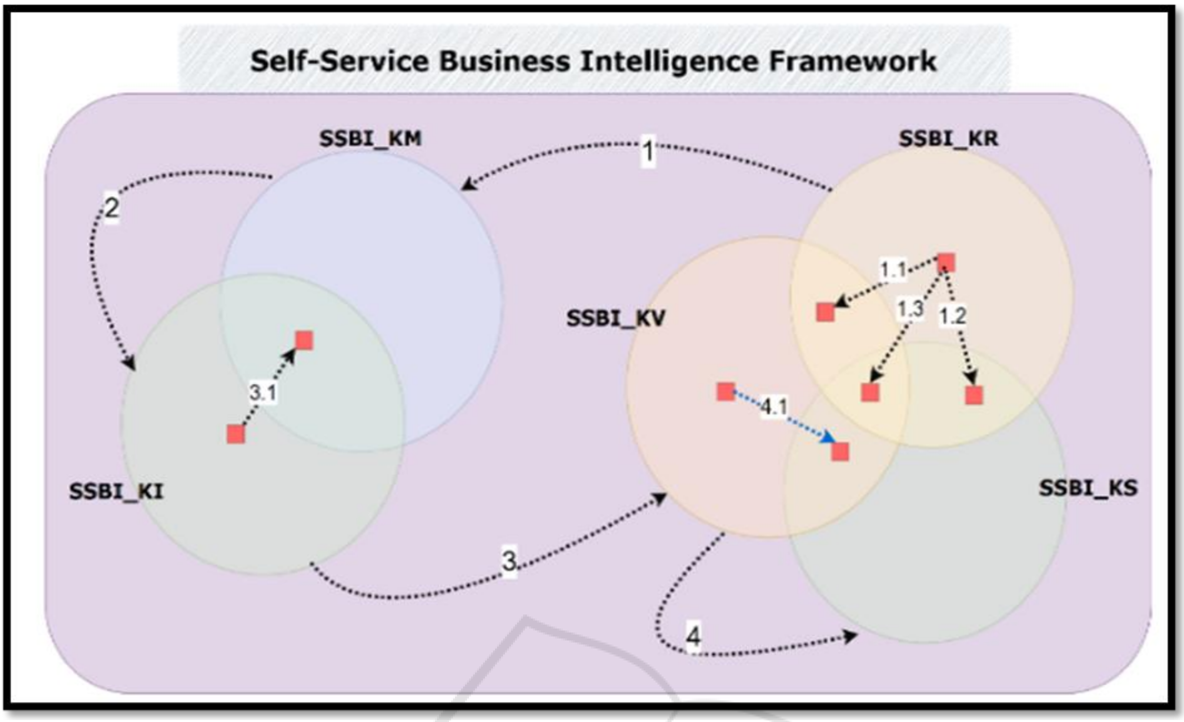

Figure 2: The SSBI framework with interconnected stages.

It has two main objectives: the first is to discourage school dropouts and prevent early course withdrawals, while the second is to identify attendance patterns to support decisions about rearranging classes for students over the semesters. In some cases, classes may have low or high attendance. Low attendance is undesirable, as resources are underutilizing while high attendance is not pedagogically effective.

The objective is to build a small-scale SSBI system to support decision-making regarding the classes rearrangement.

5.2 Applying the Framework

5.2.1 Requirements

In initial meetings with other project sponsors the objectives of the project were identified together with the questions to respond. The project sponsors are the managers who also have the responsibility to rearrange the groups of students. The questions were formulated using the SMART criteria (Table 1).

Table 1: For managers.

Q1	What is the number of courses, subjects, teachers, and enrolled students in the current academic year to assess resource allocation?
Q2	How many students are attending each class over the weeks during the current academic year to help determine necessary adjustments?
Q3	Which classes have the highest and lowest attendance rates over the weeks and may require rearrangement?
Q4	What is the attendance rate for all the classes of a specific subject, both daily and weekly?
Q5	What is the impact on the attendance rate of academic events?

The project main objective is to analyse the student's attendance evolution over the weeks and identify classes that need to be rearranged, more concretely, classes to be closed and classes to split.

5.2.2 Data Modelling

A star model was built resulting from the steps early mentioned in section 4.1. The casual power user contextualize itself with the approach.

The casual power user background knowledge with the problem has facilitate the modelling phase, since the data and the terminology are well-known. The dimensions such as teachers, courses, subjects and classes were identified. Additionally, it was recognized the need for the academic date dimension since the it was considered important to observe the impact of some academic events in the students' class attendance behaviour. The following facts were identified: attendance and enrolment.

Table 2 presents the relationship between the facts and dimensions. In Figure 3 the achieved data model may be analysed.

Table 2: Relationships between facts and dimensions.

	Subjects and Courses Enrolment	Classes Attendance
Course	X	X
Subject	X	X
Teacher		X
Date		X
Academic Date	X	X

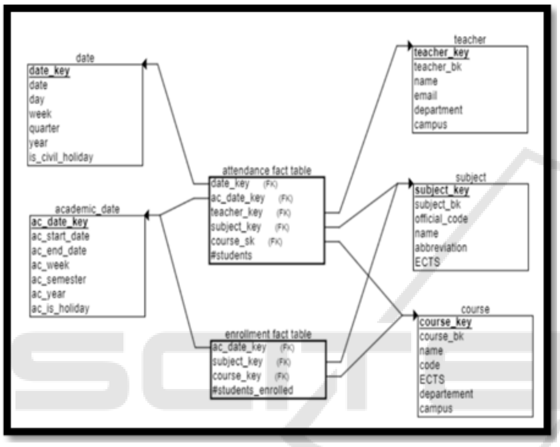

Figure 3: The star schema.

5.2.3 Data Integration

The data sources are consumed using RESTful Web Services. After it, data is visually shaped (cleaned, integrated and transformed) step by step. The result is a group of connected tables. In PowerBI both Power Query and Data Analysis eXpressions (DAX) are used to perform the ETL process. The first to load and accomplish initial transformations and DAX for additional operations and to load data to the final dimension and fact tables.

5.2.4 Data Visualization

All at all dashboards classified as tactical have been developed for decisions. Despite charts being generally used daily it was considered a challenge the identification of the most suitable charts for data display.

5.2.5 Data Storytelling

The narratives were elected. For instances, the narrative of the 4th week semester was told since in that period the identification of classes attendance is a main concern (since it is still the beginning of the semester). The narrative starts to contextualize the courses, the subjects and teachers. Then it highlights the classes with the lowest and highest number of students. The narrative was build using elected frames extracted from dashboards. Additionally, the frames were organized, and context was assigned creating a movie. The audience in this case were the managers.

6 CONSIDERATIONS

The most expensive tasks that the casual power user reported was the development of the dimensional data model and the development of dashboards with an effective layout. However, later the dimensional model was considered fundamental to support data combination and data exploration. Nevertheless, the familiarization with the problem in analysis also has contributed to assist in the development of that model. Additionally, there has been reported some versions of *mockups*. Thinking about the layout and their visual elements was considered fundamental to a more effective design. The casual power user established the requirements and design the layouts in conjunction. In modelling as the data was gathered and its profile obtained from the web services the dimensional model was elaborated. The developed solution enables the understanding of class attendance behaviour during an academic semester, facilitating necessary adjustments. By the 4th week, the casual power users could identify classes to merge and classes to split. The custom solution developed by its own is now capable of telling him and others about the need of changes. Casual power user stated that the model with the appropriate connections were a main resource to build a set of filter segmentation components and to identify the rate attendance in classes.

7 CONCLUSIONS

SSBI aims to enable the agile development of BI solutions using low-code features and facilitating the creation of custom data-driven systems. For casual users, this is useful, as they are the ones who best understand the primary objectives of the analysis and may what to independently build a personalized solution. However, it has been reported that some poor solutions have resulted from these users' lack of conceptual understanding. Although SSBI tools provide visual artifacts, there is still a need to know the underlying concepts. This work introduces the role of casual power users: individuals who are familiar with the case study and have a general understanding of BI concepts. The authors present a framework with five interconnected knowledge constraints for developing SSBI solutions. These constraints were applied to a case study conducted by a casual power user, who uncover insights for decision-making. In the future, the authors plan to apply the framework to additional case studies.

ACKNOWLEDGEMENTS

This work was supported by the Fundação para a Ciência e a Tecnologia (FCT), I.P., under Project UIDB/04524/2020.

REFERENCES

Sharda, R., Delen, D., & Turban, E. (2018). *Business intelligence, analytics, and data science: a managerial perspective*. pearson.

Evelson, B., & Norman, N. (2008). Topic overview: Business intelligence. *Forrester research*, *61*.

Lennerholt, C., Van Laere, J., & Söderström, E. (2018). Implementation challenges of self-service business intelligence: A literature review.

Microsoft. (2024). *Microsoft*. Retrieved July 15, 2024, from *Power BI*. https://powerbi.microsoft.com/

Tableau Software. (2024). *Tableau* Retrieved July 15, 2024, from . https://www.tableau.com/

Qlik. (2024). *Qlik*. Retrieved July 15, 2024, from https://www.qlik.com/

Arnaboldi, M., Robbiani, A., & Carlucci, P. (2021). On the relevance of self-service business intelligence to university management. *Journal of Accounting & Organizational Change*, *17*(1), 5-22.

Suprata, F. (2019). Data storytelling with dashboard: accelerating understanding through data visualization in financial technology company case study. *Jurnal Metris*, *20*(01), 1-10.

Kimball, R., & Ross, M. (2016). *The kimball group reader: Relentlessly practical tools for data warehousing and business intelligence remastered collection*. John Wiley & Sons

Zaghloul, M. M., Ali-Eldin, A., & Salem, M. (2013). Towards a self-service data analytics framework. *International Journal of Computer Applications*, *80*(9).

Lennerholt, C., Van Laere, J., & Söderström, E. (2021). User-related challenges of self-service business intelligence. *Information Systems Management*, *38*(4), 309-323.

Dedić, N., & Stanier, C. (2017). Measuring the success of changes to Business Intelligence solutions to improve Business Intelligence reporting. *Journal of Management Analytics*, *4*(2), 130-144.

Alpar, P., & Schulz, M. (2016). Self-service business intelligence. *Business & Information Systems Engineering*, *58*, 151-155.

Inmon, B. (2006). DW 2.0; Architecture for the Next Generation of Data Warehousing. *Information Management*, *16*(4), 8.

Olaoye, F., & Potter, K. (2024). *Business Intelligence (BI) and Analytics Software: Empowering Data-Driven Decision-Making* (No. 12550). EasyChair.

Shneiderman, B. (2003). The eyes have it: A task by data type taxonomy for information visualizations. In *The craft of information visualization* (pp. 364-371). Morgan Kaufmann.

Chokki, A. P., Simonofski, A., Frénay, B., & Vanderose, B. (2022). Engaging citizens with open government data: The value of dashboards compared to individual visualizations. *Digital Government: Research and Practice*, *3*(3), 1-20.

Zheng, J. G. (2017). Data visualization in business intelligence. In *Global business intelligence* (pp. 67-81). Routledge.

Doran, G. T. (1981). There's a SMART way to write managements's goals and objectives. *Management review*, *70*(11).

Balon, U. (2024) KEY PERFORMANCE INDICATORS (KPIs) IN THE QUALITY MANAGEMENT SYSTEM. *International Journal for Quality Research*, *18*(2), 473-486.

Few, S. (2006). *Information dashboard design: The effective visual communication of data*. O'Reilly Media, Inc.

Schwendimann, B. A., Rodriguez-Triana, M. J., Vozniuk, A., Prieto, L. P., Boroujeni, M. S., Holzer, A., ... & Dillenbourg, P. (2016). Perceiving learning at a glance: A systematic literature review of learning dashboard research. *IEEE transactions on learning technologies*, *10*(1), 30-41.

Shneiderman, B. (2003). The eyes have it: A task by data type taxonomy for information visualizations. *In The craft of information visualization* (pp. 364-371). Morgan Kaufmann.

Sorour, A., & Atkins, A. S. (2024). Big data challenge for monitoring quality in higher education institutions using business intelligence dashboards. *Journal of Electronic Science and Technology*, 100233.

Zhang, Y., Reynolds, M., Lugmayr, A., Damjanov, K., & Hassan, G. M. (2022, September). A visual data storytelling framework. In *Informatics* (Vol. 9, No. 4, p. 73). MDPI.

Dykes, B. (2019). Effective data storytelling: how to drive change with data, narrative and visuals. *John Wiley & Sons*.