Quantitative Economics and Management Studies (QEMS) *ISSN: 2722-6247 (online)*
Vol. 5 No. 4 (2024)
https://doi.org/10.35877/454RI.qems2699

Implementation of Design Science for Developing BI Dashboard Employee Engagement Survey

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Abstract

Organizations are transitioning to become data-driven across all business aspects, including human resource management. The most crucial data managed is from Employee Engagement Surveys (EES). Organizations require process improvements to analyze EES results more quickly and accurately, even at the subsidiary level. This study implements the design science method to develop an artifact in the form of a Business Intelligence (BI) dashboard. The EES BI dashboard is evaluated using the Technology Acceptance Model (TAM) to assess user acceptance within the organization. The results indicate that the EES BI dashboard is well-received, with users demonstrating a high intention to use it. Thus, it is concluded that design science can be implemented to produce artifacts that assist organizations.

Keywords: Design science; dashboard; data-driven; human resource; engagement survey.

Received: 13 March 2024 Revised: 21 June 2024 Accepted: 10 July 2024

1. Introduction

Rapid advancements in technology have significantly transformed business models and processes within organizations. The Fourth Industrial Revolution has compelled various business sectors to evolve their processes using digital technology. The COVID-19 pandemic has further accelerated digital transformation in many organizations (Madsen et al., 2020; Schilirò, 2021; Tregua et al., 2021). The surge of information and the development of digital infrastructure have made data-driven economies one of the most strategic and crucial assets (Sultana et al., 2021).

This digital transformation extends to one of the critical functions within an organization: Human Resources (HR). The HR function plays a vital role in implementing digitalization within an organization, both as a mediator and as a function that transforms using digital infrastructure in its business processes (Nicolás-Agustín et al., 2022; Zehir et al., 2020; Zhang & Chen, 2021).

Digital Human Resource Management (DHRM) is an approach where HR utilizes digital tools and applications to perform its functions (Deloitte, 2017). Current technology makes HR processes faster and easier, from recruitment, selection, training, performance evaluation, to measuring employee engagement. It is essential for organizations to adapt to technological advancements to make HR processes more effective and efficient. Routine and repetitive processes are particularly suited for automation, reducing the need for human interaction (Zehir et al., 2020).

Company X is an organization managing over 200 subsidiaries and is focusing on digital transformation, particularly digital HR. To support this function, Company X has established the Corporate People Analytics (CPA) department under Corporate Human Resources. This department's primary task is to assist subsidiaries in managing people data, especially employee engagement data. As an internal consulting function, the CPA department can facilitate subsidiaries that wish to conduct Employee Engagement Surveys (EES). The diagram below illustrates the EES process at Company X's subsidiaries.

To accommodate the numerous subsidiaries, the CPA Department needs a tool that can assist the subsidiaries of Company X, especially in the follow-up process. In this follow-up process, subsidiaries generally require help to analyze

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the detailed data from the previously provided static EES reports. This tool is expected to empower the EES implementers in Company X's subsidiaries to conduct their analyses independently.

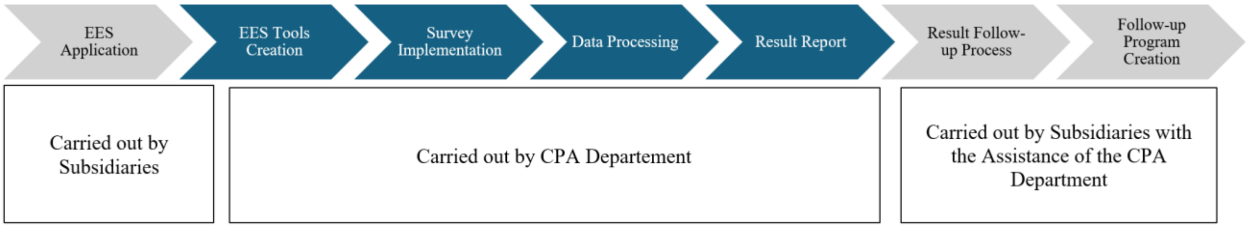

Figure 1. EES Implementation Process

The tool that can help is a Business Intelligence (BI) dashboard. BI dashboard is a visualization that summarizes various data(Matheus et al., 2020). Effective data utilization can aid organizations in the decision-making process. However, if not done correctly, decision-making will be hindered and suboptimal (Franklin et al., 2017; Hansoti, 2010).

The development of this tool can be carried out using the design science method. Design science research aims to develop or build knowledge for the design and realization of artifact creation (Andrias, 2023). The artifact developed by the CPA Department is a BI dashboard. This BI dashboard includes descriptive overviews of EES results as well as predictive analyses using machine learning. The hope is that this BI dashboard will empower the EES implementers in Company X's subsidiaries to independently analyze EES follow-up data.

The BI dashboard will be evaluated using the Technology Acceptance Model (TAM). TAM is a theory that helps understand how a technology can be accepted and utilized by people (Davis, 1989). The validity of the design science results can be seen through pragmatic validity, which is observed when its implementation yields the desired results (Aken et al., 2016). This theory is considered appropriate by the researchers because it can test whether the BI dashboard will indeed be used by the users.

2. Literature Review

2.1. Design Science Research

According to Brocke et al. (2020a), design science is an approach aimed at generating knowledge on how to build innovative solutions to problems in the form of models, methods, constructions, and applications. Simply put, design science seeks to advance technological and scientific knowledge through the creation of innovative artifacts that solve problems and improve the environments in which they are implemented (Brocke et al., 2020b). Design science research addresses relevant real-world issues across various fields, including engineering, medicine, computer science, accounting, and social sciences (Brocke et al., 2020b; Pandza & Thorpe, 2010).

Aken et al. (2016) explains that design science research is a strategy focused on developing knowledge about generic or common actions, processes, and systems to solve field problems or leverage promising opportunities. Aken also emphasizes that the goal of design science research is to make improvements based on a deep understanding of the problem or opportunity. This method is not bound by specific, rigid rules but is a strategy that can be operationalized in various ways.

Aligning with Aken (Brocke et al., 2020b) also state that the design science research process is generally not linear but is an ongoing process of refining both problem understanding and solution development. The research results will document the iterative process of problem and solution, providing explanations from both scientific and practical perspectives. The validity of design science results can be assessed through pragmatic validity, observed when the implementation achieves the desired outcomes (Aken et al. 2016).

Brocke et al. (2020a) highlight various design science research applications across different fields, from information management and information systems development to knowledge management and education, as well as maritime and governmental sectors. Design science is also commonly used in professional fields such as medicine, architecture, and civil engineering (Andrias, 2023). This encourages the application of the design science approach in management research, particularly for Master's in Management students (Andrias, 2023). Andrias (2023) believes that design science will be relevant for Master's in Management students, enabling them to provide practical solutions for their organizations.

2.2. Design Science Cycle

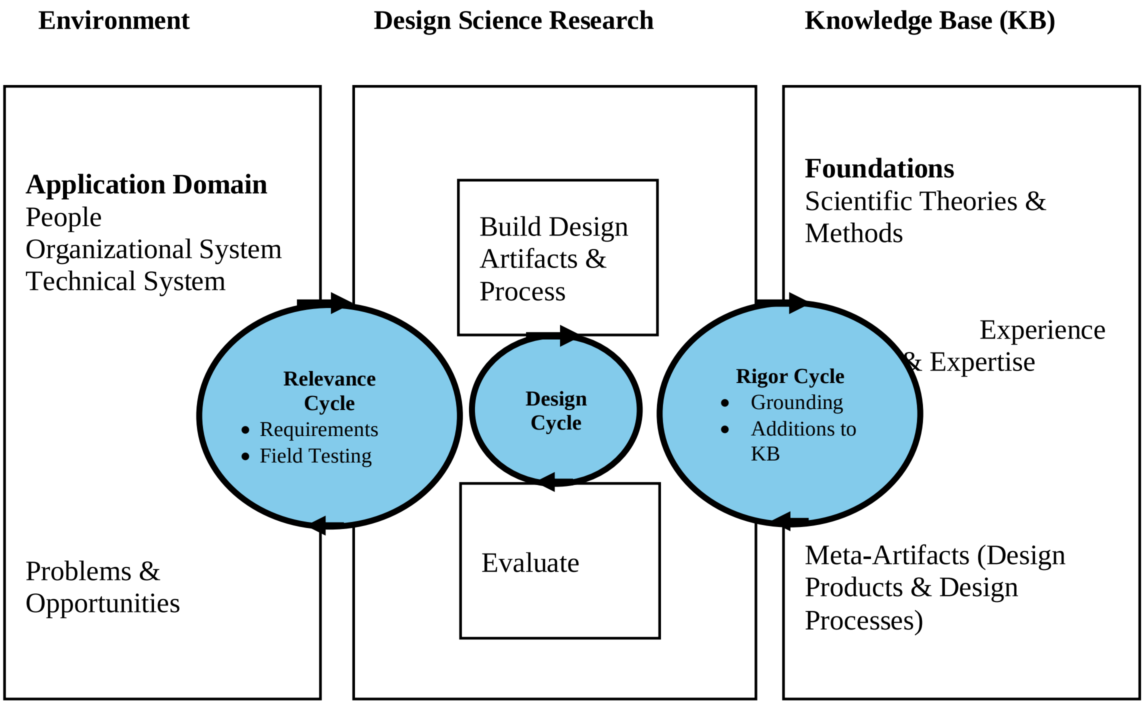

Figure 2. Design Science Cycle (Hevner, 2007)

In conducting research projects using design science, Hevner (2007) explains the cycles that researchers will go through. Hevner's insight is that all projects employing design science will pass through three cycles: the relevance cycle, the design cycle, and the rigor cycle. The relevance cycle bridges the research context with the design science activities. The rigor cycle connects design science activities with the knowledge base of scientific foundations, experience, and expertise that inform the research project. The design cycle iterates the core activities of building and evaluating the artifacts and design processes of the research.

2.3. Design Science Research Guidelines

Hevner and Chatterjee (2010) provide guidelines for researchers to implement the design science method, summarized in Table 1. Andrias (2023) elaborates on the series of design science research guidelines from Hevner et al. (2004), which can be applied in management research.

The first guideline, which distinguishes design science research from other types of research, is the creation of artifacts. Artifacts can take the form of concepts or ideas expressed as models or constructs (Andrias, 2023). The second guideline is to ensure that the developed artifact is relevant to the problem. The third guideline involves beginning the evaluation of the design. Design is a social and incremental activity, so the evaluation phase provides feedback to test the quality of the product being developed (Hevner et al., 2004). Evaluation methods are typically conducted using various existing approaches in the knowledge base (Hevner et al., 2004). Common methods include observation, analytical techniques, experiments, testing, and descriptive analysis (Hevner et al., 2004).

The fourth guideline is research contribution. Design science research must provide a clear contribution in the areas of artifact design, knowledge about design construction, and evaluation of design knowledge (Hevner et al., 2004). Hevner et al. (2004) explain that an important criterion when assessing contribution is the accuracy of representation and the extent to which the artifact can be implemented, as the artifact should accurately represent business needs. The fifth guideline is research rigor. Design science research must be applied with rigorous methods both during the construction and evaluation of the artifact (Hevner et al., 2004). Hevner et al. (2004) emphasize that this stage typically involves the effective use of the knowledge base, which includes existing research theories and methodologies.

The sixth guideline reiterates that the design science approach is iterative, requiring researchers to seek the best and most optimal design to solve business problems (Hevner et al., 2004). The main goal of this stage is to find the most satisfactory solution (Simon, 1996). The next stage is to communicate the research, thereby reaching a broader audience, including both managerial and academic communities (Brocke et al., 2020b; Hevner & Chatterjee, 2010; Hevner et al., 2004).

Table 1. Design Science Research Guidelines (Hevner & Chatterjee, 2010)

Guidelines		Description
1st Guideline:	Design as an artifact	Design science research must produce viable artifacts in the form of constructs, models, methods, or instantiations
2nd Guideline:	Problem Relevance	The goal of design science research is to develop solutions to important and relevant business problems
3rd Guideline:	Design Evaluation	The usability, quality, and effectiveness of the design artifact must be rigorously demonstrated through well-executed evaluation methods
4th Guideline:	Research Contribution	The effective design science research must provide clear and verifiable contributions in the areas of design artifacts, design foundations, and/or design methodology
5th Guideline:	Research Rigor	Design science research relies on the application of rigorous methods in the construction and evaluation of design artifacts
6th Guideline:	Design as a Search Process	Effective artifact search requires utilizing available means to achieve desired goals while satisfying the laws of the problem environment
7th Guideline:	Research Communication	Design science research must be presented effectively to a management-oriented audience

2.4. BI Dashboard as a Tool of Visual Communication

Data is a crucial asset for every organization (Hansoti, 2010). Organizations strive to manage the information and data they possess by leveraging technology, ensuring that this data can provide valid insights for decision-making (Eckerson, 2011). Eckerson (2011) further explains that in data management, organizations use business intelligence (BI) or scorecards to provide data visualizations that help them measure, monitor, and manage data more effectively.

Data visualization is essential for stakeholders to help them understand conditions or even to assist in making business decisions (Kintz et al., 2017; Lawson-Body et al., 2023; Matheus et al., 2020; Zingde & Shroff, 2020). Typically, this data visualization is presented in the form of a Business Intelligence (BI) dashboard, which summarizes various data (Matheus et al., 2020). Effective data utilization can aid organizations in the decision-making process, but if not done properly, decision-making can be hindered and suboptimal (Franklin et al., 2017; Hansoti, 2010).

Zingde and Shroff (2020) summarize various literature findings on BI dashboard studies, creating a framework to help researchers understand the different types of dashboards, as shown in Figure 3.

2.5. Technology Acceptance Model (TAM)

Davis (1989) introduced the Technology Acceptance Model (TAM) as a theory that helps understand how technology can be accepted and utilized by individuals. TAM seeks to explain why individuals choose to adopt or not adopt a particular technology in their work (Wallace & Sheetz, 2014). As a theory developed over a long period, TAM has evolved significantly and has become one of the key models for predicting the potential acceptance or rejection of a technology (Marangunic & Granic, 2015).

Davis (1989) introduced and provided a theory and context to explain the relationship between attitude, intention, and behavior. Turner et al. (2010) provided context within individuals or organizations, where TAM can be used to predict the likelihood of a technology being adopted or used. The Technology Acceptance Model explains that the behavior of using technology can be determined by the intention to perform the behavior, the attitude towards the behavior, and social pressure to exhibit the behavior (Sheldon, 2016).

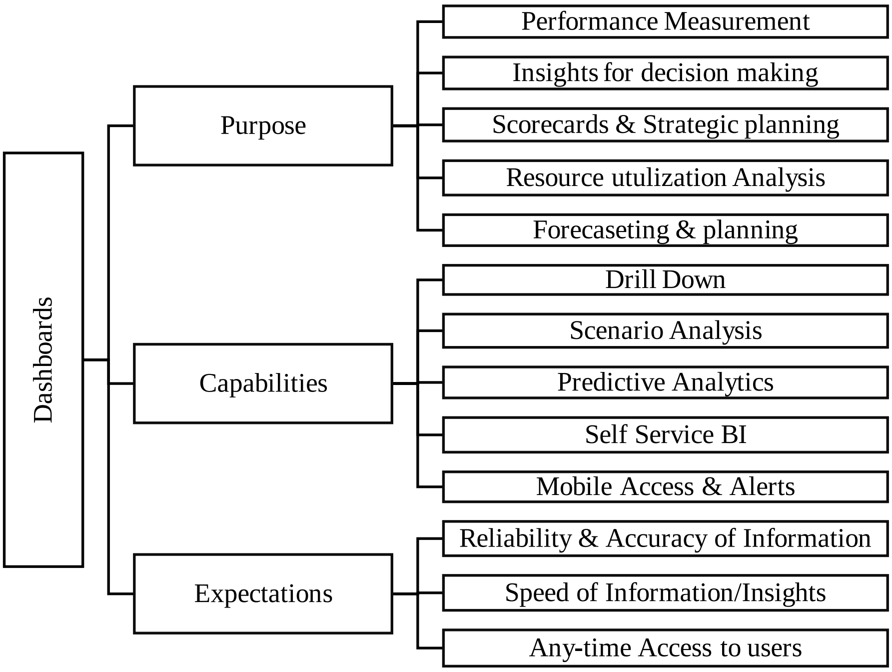

Figure 3. Dashboard: Purpose, Capabilites, Expectation (Zingde & Shroff, 2020)

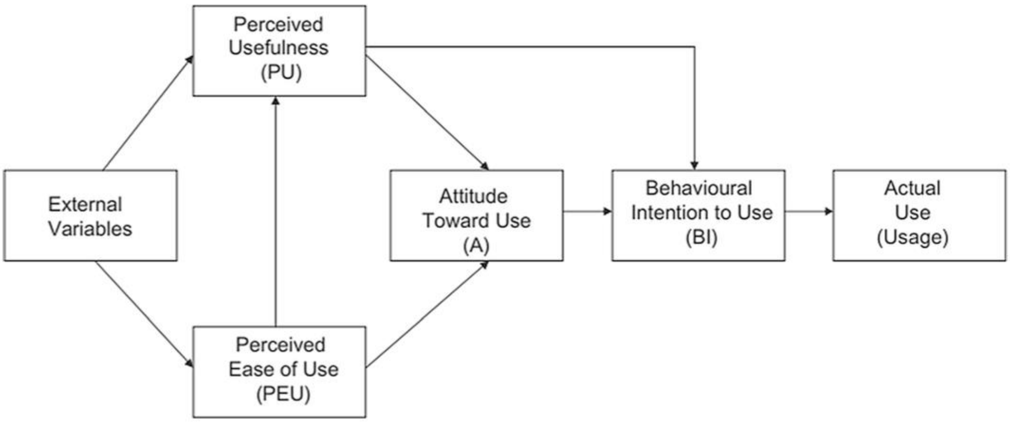

Figure 4. Technology Acceptance Model (Turner et al., 2010)

In general, TAM is a relatively old theory that has been extensively researched. Testing of the TAM model has been frequently conducted with relatively consistent results, and its evolution has provided better explanations for predicting technology use (Marangunic & Granic, 2015; Turner et al., 2010). The use of this theory surged during and after the COVID-19 pandemic because many organizations had to adopt specific technologies to ensure that their operations and goals could continue, making technology acceptance crucial for individuals within these organizations (Han & Sa, 2022; Hong et al., 2021; Papakostas et al., 2023).

Fundamentally, Davis (1989) explains how individuals will utilize technology through four main internal variables: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude toward Use (AT), and Behavioral Intention to Use (BI). PU is the extent to which an individual perceives a technology to be useful and how it can enhance their performance. Perceived Ease of Use (PEOU) refers to the extent to which an individual believes that using a system or technology will be free of effort. Turner et al. (2010) found that PU and PEOU typically do not directly correlate with actual technology use; instead, the variable that directly correlates is Behavioral Intention to Use (BI). Therefore, to predict technology usage, it is not enough to measure only PEOU and PU; BI must also be assessed.

3. Research Method

This study employs a quantitative approach using a case study method. The quantitative approach was selected to quantify the perspectives and experiences of experts and management teams involved in the supply chain business process. Creswell & Creswell (2018) state that the quantitative approach emphasizes precise measurement of a series of variables to address theoretical research questions. In the quantitative approach, one of the techniques used is through surveys. Surveys provide a quantitative or numerical overview of trends, attitudes, or opinions of a population by studying a sample from that population. From a temporal dimension perspective, questionnaires, and structured interviews in data collection with the aim of generalizing from the sample to the population fall into the cross-sectional category.

Based on the design science cycles and the stages of design science research, researchers generally undertake two main processes: the initiation and design of the BI dashboard (lap 1) and the evaluation of the BI dashboard (lap 2). The initiation and design process will cover most of the design cycle and relevance cycle, and will follow steps 1 and 2 of the guidelines. The evaluation process will encompass the rigor cycle and steps 3 to 6 of the guidelines. The implementation process of the research method is summarized in Table 2.

Table 2. Research Process

		Guidelines		Research Implementation
First Phase	Design & Relevance Cycle	1st Guideline	Design as an artifact	Researchers documented the process of artefact development carried out by the Company
		2nd Guideline	Problem Relevance	Researchers link user problems to the artifact being developed
Second Phase	Rigor Cycle	3rd Guideline	Design Evaluation	Researchers evaluate the use of artifacts in accordance with user needs
		4th Guideline	Research Contribution	Researchers test artifacts with theories that already exist in the knowledge base, namely the Technology Acceptance Model theory
		5th Guideline	Research Rigor	Researchers ensure that the process is carried out in accordance with the research guidelines
		6th Guideline	Design as a Search Process	Researchers carry out an iterative process for continuous improvement until the artifact can solve the problems faced by users

3.1. *First Phase*

In first phase, we conducted interviews with three users: EES practitioners at Subsidiary X. These users were selected based on their experience with EES, having engaged in the survey and follow-up processes prior to the development of the BI dashboard. The interview findings will serve as the foundation for developing the EES BI dashboard. Next, the researcher will collaborate with a development team to work on creating a BI dashboard that meets user needs. The first phase iteration will begin in this phase. The development of the BI dashboard starts with establishing data infrastructure, including data collection, storage, analysis processes, and data visualization accessible to users. The visual development begins with creating mockups, processing data using programming languages, and developing data visualizations within the BI dashboard platform. The outcome of Phase 1 will be a BI dashboard ready for user access.

3.2. *Second Phase*

In second phase, we will commence evaluating the developed BI dashboard. The BI dashboard, now a Minimum Viable Product (MVP), will be tested by a sample of users. The researcher will introduce users to the dashboard and encourage them to explore its features for 14 days. This sample will consist of 40 users from 7 business units of Subsidiary X and the headquarters. Users will then complete a survey developed by the researcher based on the Technology Acceptance Model (TAM), which includes 4 dimensions influencing technology adoption, with survey items detailed in Table 3, adapted from Davis (1989). The evaluation results will form the basis for the researcher to determine whether the developed BI dashboard will be adopted by users or not.

Table 3. TAM Measurement Items

	Perceived Usefulness
PU	Using the EES dashboard will improve my job performance. Using the EES dashboard will enhance my effectiveness at work. Using the EES dashboard will increase my productivity at work. I find the EES dashboard beneficial.
PEOU	Learning to operate the EES dashboard feels easy to me. I find it quite easy to display what I want on the EES dashboard. It is easy for me to master the EES dashboard. I quickly understand how to use the EES dashboard.
AT	The EES dashboard is beneficial for assisting my work. Using the EES dashboard has a positive impact on my work. Using the EES dashboard is advantageous for my work.
BI	I am willing to use the EES dashboard to assist my work. I will use the EES dashboard to assist my work. I am likely to use the EES dashboard to assist my work.

4. Results

4.1. First Phase

4.1.1. BI Dashboard Development Initiation with Interviews

As the first step, we interviewed 3 users, they are EES practitioners from different subsidiaries of Subsidiary X. These users were selected based on their experience with EES processes multiple times, ensuring they have gone through the entire cycle from planning to follow-up of results. All users had previously used static EES reports. The interview findings were summarized by the researcher using the categorization framework by Zingde and Shroff (2020), focusing on purpose, capabilities, and expectations as perceived by the users. Here is the summarized breakdown:

In terms of purpose, the primary goal of the dashboard identified by users is to provide insights for decision-making. Users generally need a dashboard interface that helps them gain deeper understanding of survey results. As a data-driven organization, the development priority should be based on valid data, making the process of extracting insights from survey results crucial.

In relation to capabilities, several important features were highlighted by users:

a. Displaying descriptive results similar to those in static EES reports
b. Performing slice and dice operations tailored to the needs of each business unit (e.g., displaying data from specific departments or divisions, filtering data by age, and others)
c. Conducting predictive analysis to assist in planning EES improvements
d. Benchmarking results against other subsidiaries of Subsidiary X
e. Comparing results with previous surveys
f. Facilitating ease of reading reports, thus eliminating the need to refer back to other sheets to find related information.

Based on expectations, the researcher mapped out several desired dashboard features to enhance user usability:

a. Independent accessibility
b. Continuous availability
c. Fast access speeds
d. Support for user hardware devices
e. Real-time data updates

These insights from the interviews provide a comprehensive basis for developing a BI dashboard that meets the specific needs of users and aligns with the data-driven goals of Subsidiary X.

4.1.2. Data Infrastructure Development and BI Dashboard Interface

The artifact development process involves mapping and developing data management from collection, storage, analytics processing, to visualization. Here is the diagram of the data infrastructure for the EES BI Dashboard.

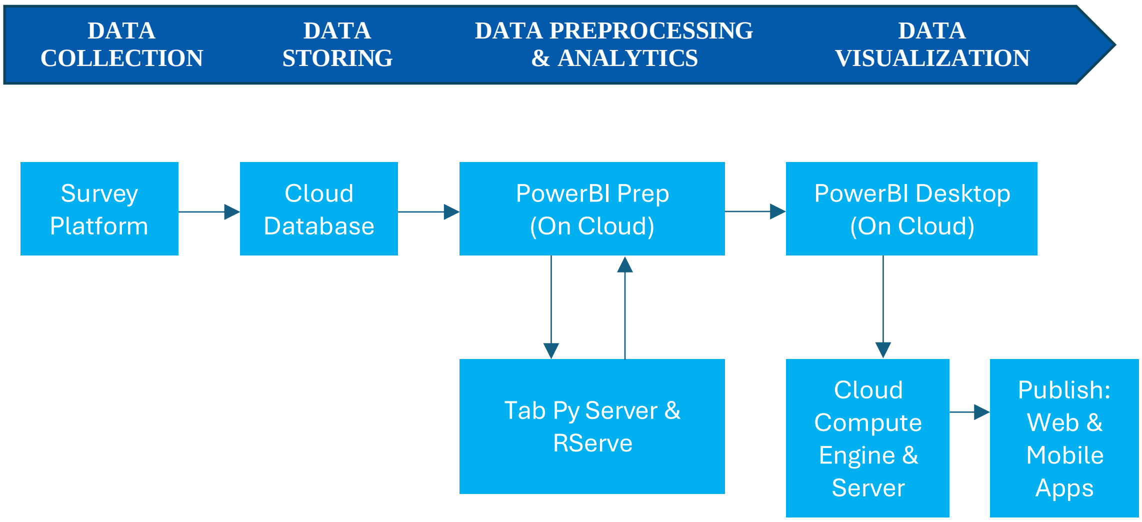

Figure 5. BI Dashboard Data Management Flow

Based on Figure 5, the data management process begins with online survey data collection. The development team utilizes the Alchemer platform (alchemer.com), capable of handling tens of thousands of data entries simultaneously. Collected data is stored within Alchemer and then pulled into a cloud-based database, enabling the BI Dashboard platform to access and process the dataset. Data processing occurs on servers using Python and R. Python is renowned for its versatility and user-friendly nature, offering powerful libraries such as 'pandas', 'NumPy', and 'scikit-learn' for data manipulation, visualization, and implementing machine learning algorithms (Van Rossum & Drake, 2009). Team (2020) describes R as a programming language and software used for computation and graphics. Python and R are considered suitable for processing EES data at PT XYZ, before the processed results are read by the BI Dashboard and published through its interface. This allows business units to access the survey data processing outcomes.

4.1.3. Design Result

To accommodate the needs of users, the development team created the most viable product to be tested on users, namely an executive summary that can help users analyze EES data using Microsoft's BI dashboard platform, namely Power BI. The display that is built can be seen from Figure 6. The BI Dashboard developed by the development team can accommodate several user needs starting from descriptive data, comparison of previous survey results, and predictive analysis results. The BI dashboard that had been developed was then socialized to 40 users and researchers gave users 14 days to be able to use and explore the BI dashboard. After that, test participants are expected to fill out a survey about the BI dashboard being developed.

4.2. First Phase

4.2.1. BI Dashboard Evaluation with TAM

In the evaluation of the BI EES dashboard, 40 users across all subsidiary business lines completed a quantitative survey based on the dimensions developed in the Technology Acceptance Model (TAM) theory. This measuring tool assesses Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Toward Use (AT), and Behavioral Intention to Use (BI). These dimensions aim to predict whether users will accept and use the EES dashboard in the future. According to a systematic literature review by Turner et al. (2010), BI dimensions show stronger correlation with actual technology use compared to PU and PEOU. Therefore, researchers included BI measurement alongside PU and PEOU to provide robust evidence of the EES dashboard's potential for adoption.

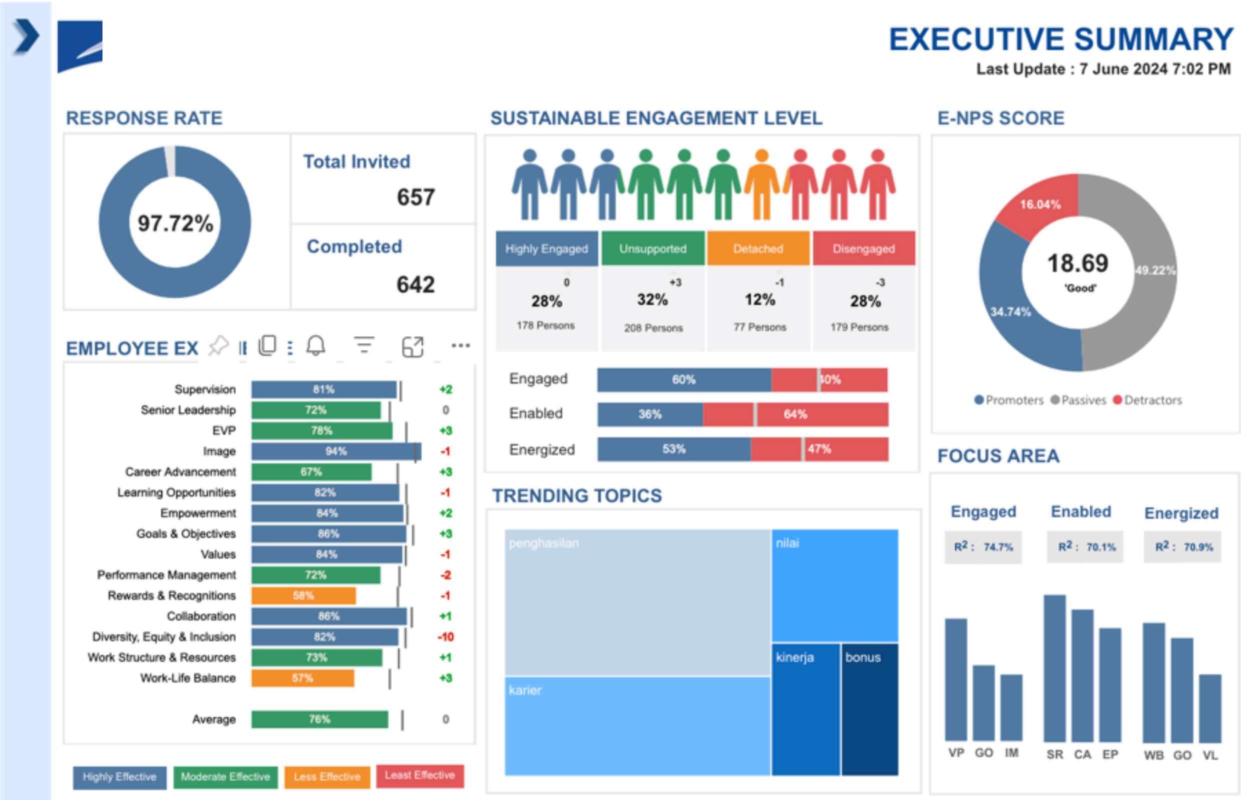

Figure 6. Executive Summary EES

The evaluation included users from various age groups across all subsidiary business lines. Researchers also collected age information to better understand user acceptance of the BI dashboard. Table 4 illustrates that overall, user acceptance ratings for the BI EES dashboard exceed 4, indicating favorable reception across all dimensions (PU, PEOU, AT, BI), placing it in a positive category. This suggests that users perceive the BI dashboard as useful and easy to use, hold positive attitudes toward its use, and intend to use it.

Age-specific analysis revealed consistent results across all demographics, with average ratings for all dimensions hovering around or above 4. Notably, the 21-25 age group showed slightly lower scores in PEOU compared to other age groups, suggesting areas where dashboard usability could be simplified and improved.

These findings underscore the positive reception and potential effectiveness of the BI EES dashboard among users, highlighting areas for refinement to enhance overall usability and user experience, particularly among younger users.

Table 4. Average TAM Dimensions by Age

Age (Year)	n	Average PU	Average PEOU	Average AT	Average BI
21– 25	13	4.02	3.92	4.23	4.18
26 – 30	15	4.00	4.00	4.20	4.22
> 30	12	4.17	4.04	4.25	4.25
Total	**40**	**4.06**	**3.99**	**4.23**	**4.22**

When analyzed by business lines within Subsidiary Company X, the results show minimal variation across all lines, with scores averaging around 4, indicating positive perception across all TAM dimensions. The lowest score was observed in the PU dimension within the logistics business line. Enhancements in dashboard functionality could be implemented to improve user perceived benefits.

Table 5. Average TAM Dimensions by Business Line

Business Field	n	Average PU	Average PEOU	Average AT	Average BI
Automotive	8	4.09	3.94	4.25	4.13
Headquarters	6	4.13	3.92	4.50	4.39
Heavy equipment	6	4.00	3.92	4.00	4.06
Plantation	5	4.05	4.15	4.20	4.27
Financial Services	4	4.38	3.88	4.25	4.50
Infrastructure	4	4.06	3.94	4.25	4.25
Information and Technology	3	3.83	4.00	4.33	4.22
Logistics	2	3.50	4.63	4.00	4.00
Property	2	4.13	3.88	4.00	4.00
Total	**40**	**4.06**	**3.99**	**4.23**	**4.22**

5. Conclusion

From the descriptive results obtained, the researcher concludes that overall, user acceptance of the EES BI dashboard is positive across all TAM dimensions. Generally, users perceive the EES BI dashboard as beneficial, easy to use, met with positivity, and have the intention to use it. This indicates a successful evaluation of the EES BI dashboard, which will be utilized by Subsidiary X to analyze EES outcomes.

These findings demonstrate that the design science method effectively aids in developing BI dashboards for EES processes at Company X. This method provides clear guidelines, enabling researchers to assist the CPA Department in developing BI dashboards that meet field-specific needs and contribute knowledge on BI dashboard utilization in EES implementation.

Based on the TAM evaluation results, the researcher also gained insights for further development. Developers should focus on enhancing the ease of use and usefulness of the developed BI dashboard.

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