Business intelligence application for patient reported experience measures (PREMs) to support performance management analytics

by

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ABSTRACT

Business Intelligence (BI) is a widely known technology that is used to facilitate decision-making processes in many organizations. BI is a collection of decision support technologies that provides information and knowledge from a variety of sources, analyzes them, and presents them in a user-friendly fashion. Research into the adoption, utilization, and success of BI systems has grown substantially over the past two decades. However, despite the growing investments and significant market expansion, evidence suggests that several organizations fail to reap benefits from the implemented BI systems [6]. Nearly 60% to 70% of BI projects fail to yield the expected returns [80] or often result in little or no benefits for organizations [114]. Previous studies report that although user under-utilization and resistance are vital challenges, little empirical research has focused on user-centred issues [102]. From the literature's findings, it is notable that organizational and Information Systems (IS) perspectives were more frequently considered, while a little light has been shed on users' perspectives of BI application [42, 66].

In this thesis, we developed a BI application with interactive visualization based on the Emergency Departments (ED) patient survey data of British Columbia (B.C.) to visualize the important insights for better healthcare decision-making. We also investigated if a BI application can equally benefit both novice and experienced users within an organization. The purpose of this thesis is to develop and understand how BI facilitates the decision-making process for all types of users within an organization regardless of their previous experience with BI application use.

We evaluated our developed tool using a user study which includes an online semi-structured interview followed by survey questionnaires to investigate the effect of the user's prior experience on their performance and perception of BI application. Our study found that BI applications are not equally beneficial to novice and experienced users in terms of performing analytical tasks. We found a significant experience effect in completing the difficult analytical tasks, and experienced users significantly overperformed the novices in performing difficult analytical tasks independently. But interestingly, we found no significant impact of the user's prior experience on their usability perception of a BI application. Based on the interview findings, we also proposed a design recommendation both for novice and experienced users to develop a BI application that can potentially increase BI adoption and success within an organization.

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ACRONYMS

BI Business Intelligence

B.C. British Columbia

DAX Data Analysis Expressions

DW Data Warehouse

ED Emergency Departments

ETL Extract-Transform-Load

EHRs Electronic Health Records

HCI Human-Computer Interaction

IT Information Technology

IS Information Systems

IV Information Visualization

KPI Key Performance Indicators

OLAP Online Analytical Processing

PREMs Patient Reported Experience Measures

QA Quality Assurance

SME Subject Matter Expert

SSAS SQL Server Analysis Service

SSMS SQL Server Management Studio

SQL Structured Query Language

TAM Technology Acceptance Model

VADA Visual and Automated Disease Analytics

1 INTRODUCTION

This research investigated the impact of user's experience on the Business Intelligence (BI) application use. By capturing the user's performance and perceived usability, we tried to show if both novice and experienced users can benefit from a BI application even after having a different level of analytical skills. This research explored if the Business Intelligence applications can equally benefit all types of users in their analytical and decision-making process in light of various success factors. We also proposed a design recommendation that will help to develop a BI application for all types of users so that everybody can take advantage of that for their analytical and decision-making tasks. The findings may aid the organizations in developing a BI system so that all of their users can extract greater value from the existing BI system.

Understanding the experiences of people who use healthcare services from the patient perspective is a key priority for Canadian health systems. In British Columbia, Canada, Patient Reported Experience Measures (PREMs) in healthcare is a provincial strategic objective and provides a means to evaluate progress made towards providing patient-centred care. So, to assist this process, we leveraged the power of BI to process, analyze the raw patient survey data to visualize important insights for better decision making. Although BI has the potential to improve the quality, efficiency, and effectiveness of health services [64] but implementing and succeeding with BI is a complicated process [112], as BI technologies are expensive, given the costs associated with software, licenses, training, and wages [20]. Notably, many organizations fail to realize the expected benefits of BI [20, 39, 83]. Although much attention has been paid to the decision-making benefits of BI adoption, limited research has examined factors that influence user acceptance of BI systems [41]. Still, many healthcare decision-makers have been reluctant to use BI in conjunction with its data because of the complexity of such systems and the data itself [58]. A theoretical issue that has dominated the (BI) system research for many years is BI success [98]. The study on how BI systems are being adopted by end-users needs to be analyzed to identify the factors that impact the successful adoption of BI systems in an organization [81, 87, 102]. The user's perspective e.g, lack of technical skill, perceived usefulness, ease of use, previous experience etc. with regards to the BI system is important for understanding the adoption, use and success of any BI system [102], but little research has been published on the impact of user-centred issues on BI application and their success [47].

Therefore, in this research, we focused on investigating the determinants of users' perceptions to use BI systems and the moderating effects of the user prior experience on the BI application use. Literature [90] proposes that usability guidelines be considered as criteria for the design and evaluation of information visualization tools. This also points to a need for specific context-relevant research into BI tools. Since an increasing number of companies have adopted BI systems, there is a need to understand the factors that influence user perception of BI systems [41]. In this regard, our goal was to investigate the impact of a user's prior experience on BI applications use. In this thesis, we developed a BI application and investigated the effect of the user's prior experience on the BI application use. We have evaluated our BI application with 42 B.C. Ministry of Health employees to see how the prior experience influences the user's performance and perception of BI application. We also suggested some design recommendations based on our interview findings to develop a BI solution for both novice and experienced users regardless of their prior experience so that everyone can be benefited equally.

1.1 OUTLINE OF THESIS

Chapter 2 provides the motivation of this research. The chapter consists of what are the current gap in the BI usability testing and, followed by the research questions we tied to answer through this thesis.

Chapter 3 explains the background literature related to our research. This chapter consists of the literature about the definition of BI, the impact of user adoption on BI success, BI and its importance in healthcare decision making, and finally, the effect of user's skills and experience on the BI technology adoption and use.

Chapter 4 presents the details about the key components of a BI systems. This chapter consists of a detailed description of the traditional BI system and its key components and how BI components work together to build and run a complete BI solution.

Chapter 5 reflects on the detailed implementation pipeline of our BI application. this chapter contains a detailed description of our implementation steps, followed by the implementation challenges we faced throughout the process.

Chapter 6 describes the user study and evaluation results of our BI application. this chapter contains both the quantitative and qualitative analysis, our hypothesis testing and qualitative findings based on our interview, followed by the design recommendation for novice and experienced users.

Chapter 7 reflects on the summary of both quantitative and qualitative analysis results, the possible reasons for our quantitative outcomes, and followed by the thesis contribution.

Chapter 8 is the final chapter which presents a conclusion of the findings together with limitations of the study and suggestions for future research.

2 MOTIVATION

The use of business intelligence applications has become a popular technique to aid users in data analysis and discovery. The increase in the number of BI applications on the market is driven by the expanding end-user population. A wider range of novice users, such as business users with minimal Information Technology (IT) or data science skills, are demanding BI applications that support rapid and easy information access for them as well. But, most of the time this type of BI application benefits the technical and experienced users only [90]. The research problem investigated in this thesis is prompted by the evidence that novice users may not be fully knowledgeable and skilled enough to satisfy the BI and data analysis requirements of their needs [33]. Limited research has been conducted regarding usability criteria specific to BI applications that support novice users as well [48, 95]. The primary aim of this research is to investigate how novice and experienced users experience the usability of BI applications and to capture their performance and perceptions while using them. So we wanted to develop a BI application and investigate the moderating effect of prior experience to see if it influences user's performance and usability perception.

2.1 RESEARCH QUESTIONS

The aim of this research is two-fold. First, we leveraged the benefit of BI technologies to build a decision-making tool that will visualize the most important insights from patient survey data to give an idea of overall patient care in the province of B.C.. Second, We investigated the impact of the users' prior experience on several factors like their analytical performance, perceived clarity, and perceived usability of a BI application. We tried to identify the factors that affect the perception of novice and experienced users and investigated if both novice and experienced users are able to benefit equally from a BI application. Our research questions include:

In a Business Intelligence solution, what is the impact of user's prior experience on:

1. The clarity of the content?
2. Ability to perform analytical tasks of different difficulty levels?
3. The perception of usability on the following aspects?
    - Effectiveness
    - Efficiency
    - Ease of use

3 RELATED LITERATURE

In this chapter, we explained the background literature related to our research to show the gap and motivation for this work. This chapter consists of the literature about the definition of BI, BI and its importance in healthcare decision making, the impact of user adoption on BI success, and the effect of user's skills and experience on the user's perception of BI technology adoption.

3.1 WHAT IS BUSINESS INTELLIGENCE?

BI applications are defined as specialized tools for data analysis, query, and reporting that support organizational decision-making [45]. BI is the ability of an enterprise to collect, maintain, and organize knowledge, and has emerged as an important area of study for both practitioners and researchers, to address data-related problems in contemporary business organizations [15, 36, 88]. BI applications aim at improving business decision-making by implementing data-driven decision-making processes that enable knowledge workers to make better and faster decisions [31, 70, 86]. From the perspective of information systems, BI systems combine data gathering, and data storage with analytical tools to present complex internal and competitive information for planners and decision-makers [31]. Although the name is new, its purpose has been for several decades, characterized under different labels. Largely driven by the need in the business world, business analytics has become one of the most active research areas in academics, and in industry or practice [22]. We also can leverage the broad use of Business Intelligence solutions in healthcare to capture the patient's preference to improve the quality of care. Moreover, BI is a powerful tool for causality analysis and corporate analyses since it provides a data-driven approach to link an organization's strategic goals to tactical policies and operational actions [110].

3.2 business intelligence in healthcare decision making

Business intelligence can help any organization make better decisions by showing present and historical data within their business context. Analysts can leverage BI to provide performance and competitor benchmarks to make the organization run smoother and more efficiently [3, 51, 64]. Nowadays, the implementation of BI systems has become an undeniable imperative in the healthcare industry because it can provide precise information for best decisions [2, 16, 37]. Clinical organizations have used business intelligence to store data in a centralized data warehouse, keep patient data secure, complete, accurate analysis and share reports among departments for a modern, integrated approach to healthcare [96]. BI is important because healthcare organizations generate a lot of data from Electronic Health Records (EHRs), patient feedback, operational data, to financial data. Healthcare BI analytics are used to uncover insights and see a unified view of patient care that is not possible with legacy systems and traditional reporting. BI potential benefits have placed it as a top priority of the health policy agenda in the world [3]. Nowadays, patients should be able to access their health records to self-manage their health status and have an active role in their treatment decisions and overall health. Hospitals need systems that not only help them to manage data but also facilitate extracting information from data. This is where BI systems as a strategic solution come into the picture. BI systems lead to improved patient outcomes and safety, increased revenue, reduced costs, and increased efficiency [5, 12, 16, 62, 75]. Over half of all healthcare organizations plan to replace or buy a new business intelligence system over the next three years, according to a KLAS report [8]. There are many reasons for that. Growth in the healthcare industry is at an all-time high, and healthcare organizations are seeking new ways to improve operating efficiency and reduce costs [8]. The big data revolution has left those in the healthcare industry with massive amounts of information that they have never had access to before. From this seemingly overwhelming mass of information, business intelligence tools can generate key insights to improve patient outcomes, cut expenses, and analyze treatment plans [89].

3.3 EXPERIENCE OF NOVICE USERS WITH BI SYSTEMS

Despite the benefits of Business Intelligence and Analytics systems, the adoption of such systems remains fairly low due to several factors. Research has indicated that required analytical skills shortages among the users are predicted as a moderating factor in the field of Information Visualization (IV) [90]. Additionally, a wider audience of users are participating in data analysis and are not limited to the stereotypical statisticians or technical experts. The field of IV is addressing the need to produce software products that eliminate the technical skills required to operate such software tools. Martin Smuts et al. [90] investigated some of the usability factors hindering BI knowledge transfer and skills in an organization. Several studies have shown that the adoption of BI remains low, particularly amongst organizations with resource constraints [67, 77]. Many of these constraints relate to high failure rates, problems with data irregularities, and lack of compatibility with existing systems [73]. A need exists to increase the knowledge and skills of novice users intending to work in data analysis and BI. Skills in data analysis are especially necessary to improve the socioeconomic status in developing countries and to provide real-time feedback on socioeconomic programs and policies that might require rapid alternations [54]. The low usability of BI tools often makes it difficult for novices to gain the required skills [48]. BI platforms are developed using various software tools from different vendors that require users to have strong technical skills and domain knowledge. So, often the novice users might not have such skills as they are in the process of learning and struggle to develop and interpret moderately complex visualizations of data [33, 52]. Fan and Bifet [27] showed that the main task of data analysis is how to visualize data. Still, it is often difficult to find user-friendly visualizations interpretable by less experienced users. The complexity of the BI systems makes it difficult for new users to interact with these systems fairly easily [26, 76]. As a result, users with less technical knowledge must seek assistance from experts to extract the required data from various applications, apply statistical techniques and present the data accordingly [26].

3.4 USER'S SKILL AS A MODERATING FACTOR OF TECHNOLOGY ACCEPTANCE

Organizational adoption of BI applications is growing rapidly, yet a majority of BI application implementations are failing [84, 115]. According to a survey by Dresner Advisory Services, 59% of BI application implementation projects are not successful. One of the main reasons for the failure is end-user resistance to use the BI application that their organization has chosen [43, 94]. Like most technology adoption projects, resistance to using the BI application must be overcome to realize the promised benefits of BI applications. Whether organizations can realize the promised benefits of technology significantly depends on individuals within the firm who are the ultimate end users [1]. Therefore, it is important to understand how to facilitate individual adoption of BI applications. According to literature, User experience is a key determinant of the choices individuals make to engage in and persist in activities [50, 72].

In addition, we can express that information system success or efficiency can be measured by user satisfaction, which has become a very convincing estimate recently [23]. Hence, user satisfaction impacts a BI system's effectiveness and is influenced by the information and system quality. On the other hand, the key aspects of user satisfaction can be listed as follows: User Skills, Perceived Usefulness, and Technology Acceptance. A study by Torkzadeh and Lee [99] showed that user skills are an important element of user satisfaction. In contrast, there remains a far larger potential population of 'reluctant users', individuals who lack inclination for involvement and have considerable difficulty learning to use any computer system [24]. Further, there is a high probability that user satisfaction varies with user's technical skill, attitudes, anxiety, and use, among other factors that should be considered to better understand user satisfaction [38]. It has been confirmed by numerous studies that Perceived usefulness (PU) is a reliable indicator of users' involvement with the intention to adopt different technologies in different settings. Previous literature defined PU as "the degree to which a person believes that using a particular system would enhance his or her job performance." [18]. On the other hand, usefulness perceptions have their origin in cognitive beliefs of job relevance (i.e. technology is related to the task), output quality (i.e., technology performs the specific task well), and result demonstrability (i.e., results of using a system are observable) [91]. Previous studies recommended that users' continuance motivation is decided by their comfort with information system use and the perceived usefulness of a maintained system. Consecutively, user satisfaction is impacted by their ratification of likelihood from earlier information system use and perceived usefulness [9].

Finally, we need to understand how users accept new and upcoming technology, systems, and applications in view of user satisfaction. Technology systems' acceptability can be defined as a function of three dimensions: (1) utility (the system works as needed); (2) usability (users work with the system successfully); (3) likeability (whether the system is suitable) [69]. Thus, the technology acceptance model (TAM) describes two approaches that influence the acceptance of informatics innovations: perceived usefulness and perceived ease of use [46]. Previous research has found that a user's degree of relevant experience moderates several relationships within the Technology Acceptance Model Technology Acceptance Model (TAM) [57, 107, 109]. For perceived usefulness, research reported that experience significantly moderated the relationship of perceived usefulness and behavioural intention to use [97, 108] with the relationship stronger for experienced users. Moreover, it was also shown that individuals with a more advanced grade of technical expertise were more expected to accept using the newest technology and would not be nearly as difficult for them compared to individuals with an inferior grade of proficiency. Correspondingly, previous studies also suggested the connection between technology acceptance desires, conducts, and background knowledge is connected to a users' perceptions of the computer systems [105] which in turn influences the user participation in the new technology use. User participation has a great deal of significance for the implementation of any successful IS projects, particularly for BI systems [20, 34, 63, 68, 82, 112–114].

3.5 IMPACT OF USER ADOPTION IN BI SUCCESS

The spread of Business Intelligence Systems has had a huge impact on the way firm performance is being measured in organizations. [103] focused on analyzing and evaluating the implementation of systems like BI in large organizations with a strong focus on the technological aspects. They tried to pinpoint the critical success factors of the implementation of BI systems. If the implemented system has been well developed, it can support the organization to transform its plans, goals and strategy into actual tangible operational benefits. The major perks of having such systems in place are that they give decision-makers quick insights and the ability to make swift decisions, they can act on the information they get and re-plan accordingly at any point, and they don't have to go in blind. Integration and infusion of the BI are key. Once the adoption process starts, it is vital that users accept it, start to use it well and regularly, and ultimately, make it an integral part of their jobs and become dependent on it for making decisions. A lot of the time, a decision is made to implement BI in an organization. However, despite success on the technical front, the business users end up not utilizing them, and they lay dormant, which means in the end, it results in failure rather than success. The Technology Acceptance Model [19] provides a basis for measuring user acceptance; it was introduced in 1993 by Fred Davis. Since then, it has been widely used by researchers to determine a software/technology user's acceptance of it. Various studies have also been conducted in order to build a more robust framework in this regard. This is a critical aspect, as the practical success or failure of a system is determined by the user's acceptance. Formally in IT for closing software projects, a document sign-off known as the User Acceptance Testing (UAT) report is required; without it, project closure is not achieved [60]. Trieu [100] suggests most research in the area is focused on how organizations can create opportunities, and tackle hurdles with the help of BI; however, a gap still exists because both users and academics alike are unsure about the real value being generated via BI software usage. There is a need for broad, comprehensive research to understand the issues from the user's perspective for successful BI adoption so that end-users will realize the actual value of a BI system [29].

3.6 ALIGNING BI WITH END-USER TO PROVIDE BETTER VALUE

Over the years, many organizations have invested in Business Intelligence (BI) systems. BI has increasingly been moving into the mainstream of knowledge worker computing [15, 74]. Logi [56] illustrates that 66% of organizations use some sort of BI tool to drive their business, whereas only 6% of organizations do not consider applying such systems. The size of the global BI market is also expected to grow from $15.64 billion in 2016 to reach $29.48 billion by 2022 with a compound annual growth rate of 11.1% (BARC, 2019 [7]). Furthermore, the provisioning of the right information to the right person at the right time is critical to remain competitive and represents a key concern of BI [13]. No longer are BI solutions solely being used by information specialists or analysts. This is reflected in the population of BI end-users, which is becoming increasingly more heterogeneous in both the skills that end-users bring to BI-systems as well as in the demands they place on them [32]. Most of the time, novice business users work with data by collaborating with skilled power or IT users within an organization [4]. Hereby, organizations face the challenge to support different user roles with diverse levels of expertise for various analytical demands ranging from information usage (e.g., access to reports) over information creation (e.g., creation of reports) towards information resources creation (e.g., harnessing of new data sources) [4]. Novice users are associated with scarce knowledge for conducting analytical tasks; Self-reliant novice users are an important factor for the success of BI systems [53] as they have extensive knowledge of their business or engineering domain [92]. Especially negative effects occur for novice users with scarce knowledge of applying BI systems. Unfortunately, according to several authors, many BI projects fall short of their promise to deliver value. According to Raden [78], "business intelligence applications have low adoption rates within organizations." Furthermore, Biere [10] states that "too many organizations take the easy technology-driven route by selecting some tools, hoping the end-users will "magically" emerge with what they want." This approach has diminished the potential benefit of BI systems since it assumes that all users are capable of finding their way around in this 'ocean' of information." In other words, an implementation from a technology-driven perspective does not ensure the adoption and usage of end-users, which constrains organizations from benefiting from the potential of their BI investments. Looking from an end-users perspective, end-users simply want a better way to solve data-related business problems. The end-user perception of the benefits received from a BI solution is dependent on the degree of productivity increase or the number of positive results that they receive. If a BI solution helps them look better and lets them do their job better, they will be more likely to use it [101]. While BI-software enables organization-wide decision support, problems are encountered in the fit between systems' provision and changing requirements of a growing number of end-users [21]. The main reason why this "fit" is missing is that when BI-solutions are implemented in practice, end-users are usually considered (if considered at all) to be equal in their adoption, and usage of the system [10], which is not always the case [11]. If end-users get provided with a BI-solution that does not fit their capabilities or tasks, they will most likely not use it or use it in the wrong manner, or even become negative about the BI-solution, which obviously does not contribute to a positive result. However, if end-users are equipped with a BI system that fits their needs, they will produce better intelligence to support their decisions, and in the end, reduce uncertainty. However, the effect of learning on novice users is still an avenue for future research [55].

4 KEY COMPONENTS OF BUSINESS INTELLIGENT SYSTEM

BI is an umbrella term that combines architectures, tools, methodologies, databases and data warehouses, analytical tools, and applications. The major objective of BI is to enable interactive access to data (and models), to enable manipulation of data, and to provide managers, analysts, and professionals with the ability to conduct the appropriate analysis for their needs [93]. BI analyzes historical and current data and transforms it into information, and valuable insights (and knowledge), which leads to more informed and better decisions [85]. To generate business intelligence, data from business transactions need to undergo an Extract-Transform-Load (Extract-Transform-Load (ETL)) process, which cleanses, transforms and restructures the data into a data warehouse or a data mart. Data warehouses and data marts are essentially databases specially designed for facilitating data analysis and knowledge discovery. The data analyses are guided by the Key Performance Indicators (Key Performance Indicators (KPI)) of the organization, and they vary from business to business. Figure 4.1 summarises the key components of a BI solution.

Following describes the key elements of traditional BI systems:

- Data Staging Area
- Extract-Transform-Load (ETL)

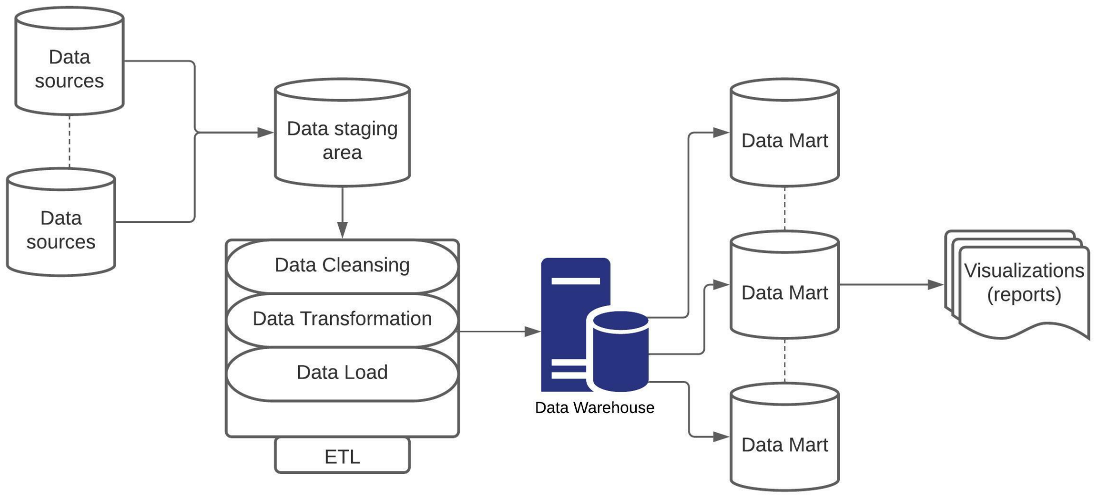


Figure 4.1: Key components of BI

- Data Warehouses
- Data Mart
- Visualization (reports)

4.1 DATA STAGING AREA

The data staging area captures data from the production systems without altering data. Data is then copied from the staging area to the data warehouse after going through cleansing and transformation as part of ETL processing. Data copy rate from staging area to data warehouse most often will not match data change rate in the production data sources. The data staging area would need to keep data around till it is copied into the data warehouse.

4.2 EXTRACT-TRANSFORM-LOAD (ETL)

ETL process theoretically involves moving data from production systems, transforming it before loading it into a target datastore like a data warehouse. But in many deployments, data is first moved into data staging areas, and data is cleansed before it is transformed and loaded into target data stores like data warehouses. Data transformation typically would involve applying business rules, aggregating or disaggregating the data. One important concern regarding ETL is the performance of ETL. Most ETL tools would apply some sort of parallel data fetch and transportation mechanism to improve the speed.

4.3 DATA WAREHOUSE (DW)

A Data Warehouse (DW) is a central repository that stores, cleans and correlates data. The data warehouse is normally a central database that supports Structured Query Language (SQL). Many of these databases employ specialized hardware to accelerate query performance. Data warehouses usually store data for long periods of time, and changes in source data get appended to existing data, thus providing a chronological order of changes. Data warehouse provides some key benefits to the organization:

1. Offloads data analysis workloads from data sources
2. Provides an integrated view of data
3. Provides a consistent view of data
4. Provides a historical perspective on data

DW end up storing large amounts of data, often billions of records running into terabytes. This large data size introduces some unique challenges for executing queries and applying changes to the schema. The organization of the data has a key role to play in query performance and schema flexibility. Over the years, various architectures have evolved for data organization in data warehouses. Some of the important architectural considerations are:

- Normalized Schema
- Denormalized Schema

4.3.1 *Normalized Schema*

Normalization is the process of grouping data attributes that provide a stable structure to data organization. Normalization reduces data duplication and thus avoids data consistency issues. However, for BI applications, normalized schema introduces a challenge. Normalization would group different attributes into different tables; since BI needs to correlate data from different tables, BI applications would have to join data from different tables. Since data warehouses have large data sets, these joint operations tend to be expensive.

4.3.2 *Denormalized Schema*

An alternative strategy is to employ a normalized schema for production systems and a denormalized schema for the data warehouse. In this model, BI apps would avoid costly joins since data is denormalized. There are several denormalization techniques employed by industry; the popular de-normalization techniques include:

- Materialized Views: Materialized View refers to the caching of data corresponding to a SQL query. The cached data is treated as a regular database table, and all operations supported by a regular table are supported on a materialized view. Indexes can be created on the materialized views, just like in a regular table. Materialized Views reduce the load on data warehouse DB as frequently used queries can be cached as materialized views, thus enabling re-usability and reducing workload.
- Star and Snowflake Schema: Star and Snowflake schema follow a dimensional data model, which groups data into the fact tables and dimension tables. The fact table would contain all critical aspects of the business, and the dimension table would contain non-critical aspects of the business. Fact table would be, in general, large data sets and the dimension table would be small data sets.
- Prebuilt Summarization: Data warehouses support multidimensional data structures like Online Analytical Processing (OLAP) cubes, which allow for aggregating data across different dimensions. Once OLAP cubes are created, then multiple analyses could share cubes to analyze data across different dimensions.

4.4 DATA MART

Data Mart can be considered as a subset of data warehouses. Usually, these are created per department. While a data warehouse has a global scope and assimilates all of the data from all information systems, a data mart is focused on a much-limited scope, either contained by the organization or by time.

4.5 visualizations (reports)

A data visualization tool is used to present the results of data analyses to BI users. These results may appear in the form of standard reports based on regular queries or as on-demand reports that show information about business performance and efficiency.

5 IMPLEMENTATION PIPELINE

We developed a BI application using the 2018 Emergency Department patent survey data of British Columbia to assist better decision making. In this chapter, We discussed briefly the British Columbia Emergency Department patient survey data, the complete implementation steps in full detail, and the challenges we faced throughout the implementation process.

5.1 DATA USED TO BUILD THE BI APPLICATION

In this thesis, we used the latest emergency department patient survey data of 2018. Information collected focused on patient appraisals of their experiences and satisfaction with the quality of care and services they received in one of British Columbia's emergency departments. We used the provincial data collected using Patient-Reported Experience Measures (PREMs) only because this indicated the patient's experience that will give us the overall quality of service they received. PREMs capture the patient's views about their experiences while receiving care, are designed to allow comparative performance measurement and to support quality improvement in healthcare services across Canada [14]. Patients who received Emergency Health Services from one of B.C.'s 108 emergency departments, urgent care centers, and diagnosis and treatment centers between January 1, 2018, and March 31, 2018, were eligible to participate in the 2018 Emergency Department Patient Survey. Data from patients in the six health authorities (Fraser Health, Interior Health, Island Health, Northern Health, Provincial Health Services Authority, and Vancouver Coastal Health).

The data consists of:

- Quantitative answers (scores at the item and domain level)
- Qualitative answers (narrative comments provided by respondents)
- Weighting (to correct for oversampling of smaller units)

5.2 steps of implementation

There are different approaches to implementing a BI solution. This could vary significantly based on the IT infrastructure of the company, as well as the company's knowledge in the BI field. However, by considering the organizational structure and business need, we have adopted an iterative, seven-stage implementation process for the Ministry of Health, B.C.

The implementation steps are as follows:

- Planning
- Data Discovery
- Data Cleansing
- Data Transformation
- Semantic Layer Design

- Data Analysis
- Data Visualization

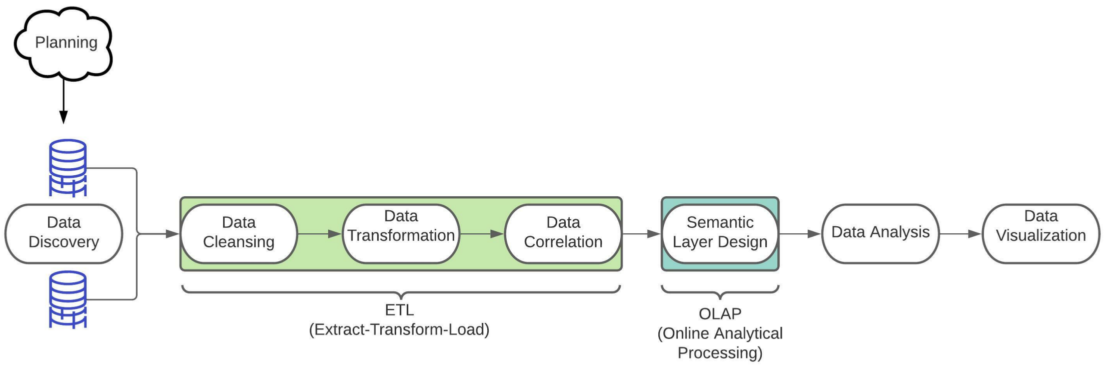


Figure 5.1: Implementation pipeline

5.3 PLANNING

Our BI implementation project starts with the planning phase. In this phase, the management team that would be consuming the intelligence articulate their requirements and establish the KPI required to be measured. This forms the foundation for the subsequent phases. Based on the objectives stated, Microsoft Visual Studio was used for designing the semantic model, and SQL Server Management Studio (SSMS) was used to deploy our Online Analytical Processing (OLAP) cube to the SQL Server Analysis Service (SSAS) for the complete BI solution. In addition, the end-user visualization achieved using Microsoft Power BI was used to generate standard reports. This decision was based on the existing IT infrastructure available in the Ministry. Since the company already uses Microsoft SQL Server 2019 as its back-end database, the Microsoft BI suite was a convenient option to implement this BI project. Microsoft SQL Server 2019 has a database system and other components needed for BI implementation. SQL Server 2019 includes five core server components providing services ranging from data storage, management, and security to specialist tools for data analysis, e.g. OLAP, and data mining.

5.4 DATA DISCOVERY

One of our first problems to tackle for BI and data integration projects are taking inventory of all the available data across the organization that is relevant to the BI project. Due to decentralized information system organizations and due to mergers and acquisitions, business often accumulates a large number of data repositories. The Ministry data warehouse (DW) called Health*Ideas* has a large number of application database tables. Understanding what each of these tables is about and how they relate to other tables was the first task in the data integration process. This is how we discovered the data, what is needed and what is not.

5.5 DATA CLEANSING

The quality of the analysis depends on the quality of the source data. In practice, we observed that source data often contained errors introduced during data entry. Data Cleansing is the process of removing errors from source data. In erroneous data, during data entry into the production system, errors may creep in. These errors need to be recognized and corrected before data can be integrated. According to our investigation, erroneous data we found in data sources can be broadly classified as follows:

- Illegal Values: These are values that violate the boundary conditions for values. Example: Discharge date: 15/01/2012, where the date format is MM/DD/YYYY.
- Dependency Violation: If one attribute of data is true then it would violate some other attribute. Example: age 10, birth date 01/01/1975
- Miss spellings During data entry: spelling mistakes may creep in. For example, in the patient information table, the hospital names were misspelled. We had to write a custom script to correct those.
- Cryptic Values or Abbreviations Example: Facility volume group: LF (instead of Large Facility).

5.5.1 *Phases of Data Cleansing*

Our data cleansing was a multi-phased procedure that typically involved:

- Error Detection: Error detection requires automated and manual inspection of data. Often metadata helped in this error detection process. One of the major sources of the problem was recognizing that two different representations of data are actually describing the same business entity.
- Error Correction: Once data errors are identified and classified then they need to be corrected. Correcting erroneous data entry was a very tedious and manual process. After the error was corrected we had to recheck and verify data with subject-matter experts who know most about the data. The Ministry also has a digital Metadata repository called *Metaspace*, we had to go through the documentation of the *Metaspace* to make everything clear.

- Replacing Source Data: In some cases, like in cases where data was wrong due to data entry problems, data in the source systems needed to be replaced with the corrected data using a custom ETL script before loading the data for analysis.

5.6 DATA TRANSFORMATION

After data was corrected for data entry errors, data was transformed further so that they could be correlated correctly. Data transformation was required primarily due to the following:

5.6.1 *Data Type Incompatibilities*

Usually, data from different sources were filtered and joined together as part of data integration. The equivalence of the data type becomes important when two pieces of data are compared. If data type definitions are different, it will result in data loss. Data type incompatibility primarily arises from the below sources:

- Usage of different data types for the same piece of data: Different facility systems may choose different data types for the same piece of data. For example, patient ID, some departments may choose to store it in a String data type whereas others may store it in an integer data type.
- Data Formatting differences: Data formatting needs to be normalized before integration. Dates and Time Stamps were common sources of such problems. Different facilities may have different formats for these. For example, most

facilities followed the MM-DD-YYYY format, whereas we also found the DD-MM-YYYY format for some facilities.

5.6.2 *Data Correlation*

Once data has been cleansed and normalized, data from different sources are correlated. Typically correlation of data would involve the steps below:

- Filtering: Selected only a subset of available data based on some conditions. For example, patient response for the latest emergency department survey only.
- Joining: Data from different tables that satisfy some criteria were joined together. For example, to find out the distinct number of patients who answered 50% of the survey questions, data from patient responses needed to be joined with the Attribute (question) table using a unique survey definition ID.
- Aggregation: Data needed to be partitioned based on some attributes, and then the calculation of each partition was done. For example, latest Emergency department data, patient satisfaction for specific facility type and then find the level of satisfaction for a particular health authority. Another example of aggregation is ethnic information. First, we aggregated the ethnicity, e.g. people from all Asian countries as the Asian and then calculated the label of satisfaction.

5.7 SEMANTIC LAYER DESIGN FOR REPORTING

The goal of a BI solution is to provide tools that simplify access to information by end-users for analytical and reporting purposes. Because of the complex relational nature, a database is often not user-friendly; therefore, we had to create a layer of data objects to interface between the database and the reporting to use the common business terms rather than data language. One of the most commonly used techniques for designing a semantic layer is dimensional modelling [49]. The main reasons for its popularity are that it results in a database schema that supports fast query performance and allows the presentation of data in a user consumable format. Though the dimensional model holds the same data as the source database, the dimensional model deals with unnormalized tables for extracting summarised and aggregated data. The main building blocks of building a dimensional model are facts and dimension tables. As per Kimball [49], a dimensional model could be designed based on the two kinds of schemata:

- Star Schema usually consists of fact tables linked to dimension tables using primary/foreign key relationships. In Star Schema (Figure 5.2), the data set is divided into facts and its descriptive attributes. Facts are stored in a central fact table and descriptive attributes in several separate tables known as dimension tables. The central fact table would have foreign key references to dimension tables.

- Snowflake Schema consists of hierarchical relationships in a dimension table, with normalized, low-cardinality attributes appearing as secondary tables connected to the base dimension table by an attribute key. Snowflake schema (Figure 5.3) has a central fact table and multiple dimension tables. Each of

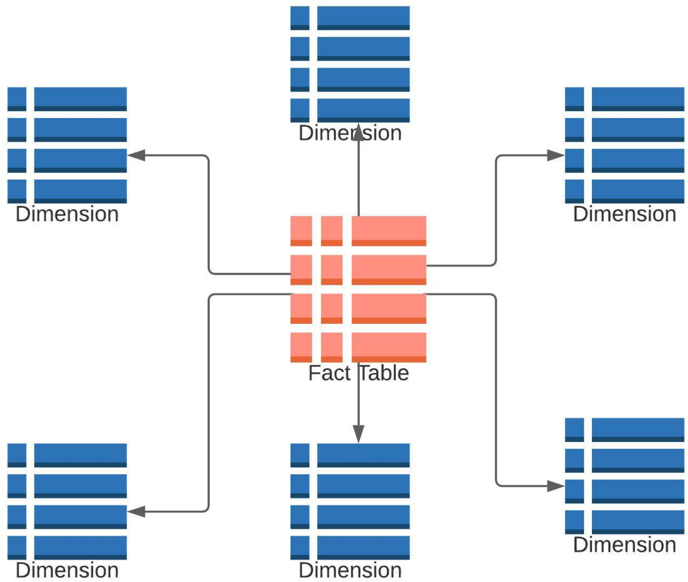


Figure 5.2: Star schema

the dimension tables may have sub-dimensions. The sub-dimensions are the key difference between the Star and Snowflake schema. Compared to the Snow Flake schema, the star schema is easier to implement.

For this research, we have implemented our data model using star schema. As star schema is faster in terms of query and filtering data, it made our report faster. The whole schema has almost 17 Million records for all available surveys, but we had to write a custom ETL script to pull only the required data efficiently. To maintain the data consistency among the dimensions, we have used the star schema approach so that the end-user will not face any significant delay when they filter data by different dimensions.

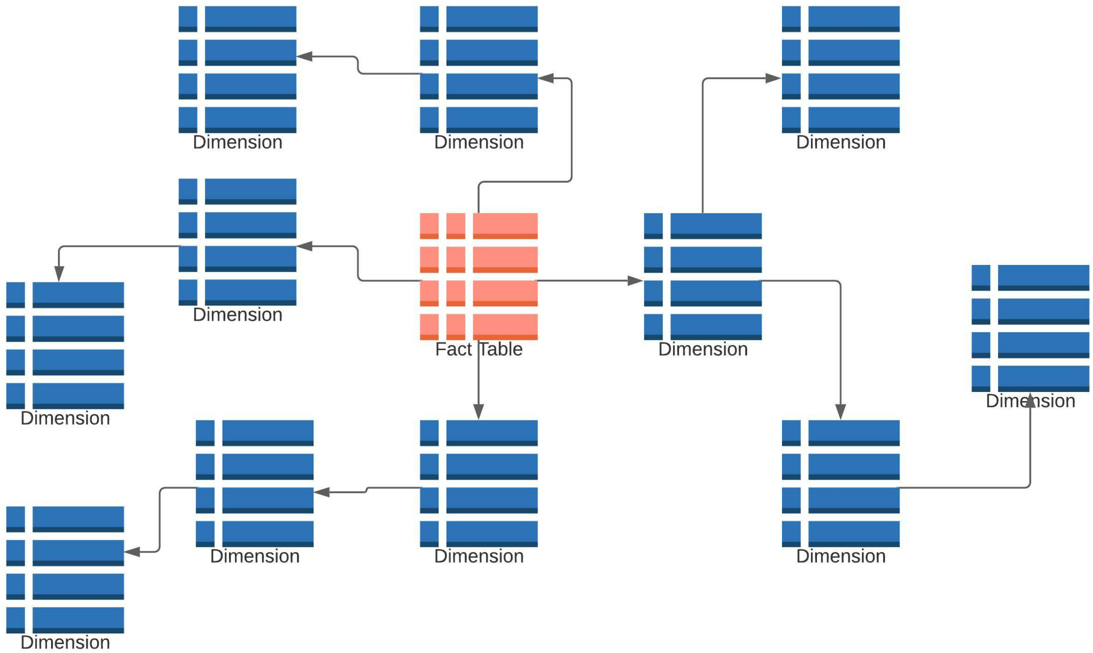


Figure 5.3: Snowflake schema

5.8 BUILDING ONLINE ANALYTICAL PROCESSING (OLAP) CUBE

The Ministry of Health used a relational database to store their data. But with the adoption of relational databases, it was found that relational databases were great at storing data but made it difficult to generate management reports from huge amounts of data. If, for example, you needed to report the data for a specific health authority, the database server would potentially have to loop through millions of records to generate a summary. On the day's hardware, this would often slow down the entire system to the point where it became unusable for critical business operations. Of course, the reports would still be generated eventually, but the whole process will take far too long. So we thought of a solution: OLAP. OLAP refers to a multi-dimensional array of datasets. It is an analysis technique with a variety of functionalities to summarize, aggregate, and consolidate numeric data, as well as the ability to view (slice-and-dice), pivot, sort, and filter data to discover patterns from different angles [44, 111]. The idea behind OLAP was to pre-compute all of the totals and subtotals needed for reporting. At night or the weekend, when the database server was normally idle. The totals are stored in a special database, called an OLAP Cube. An OLAP Cube doesn't have to loop through any records to do the calculations because totals are all pre-calculated, providing instant access.

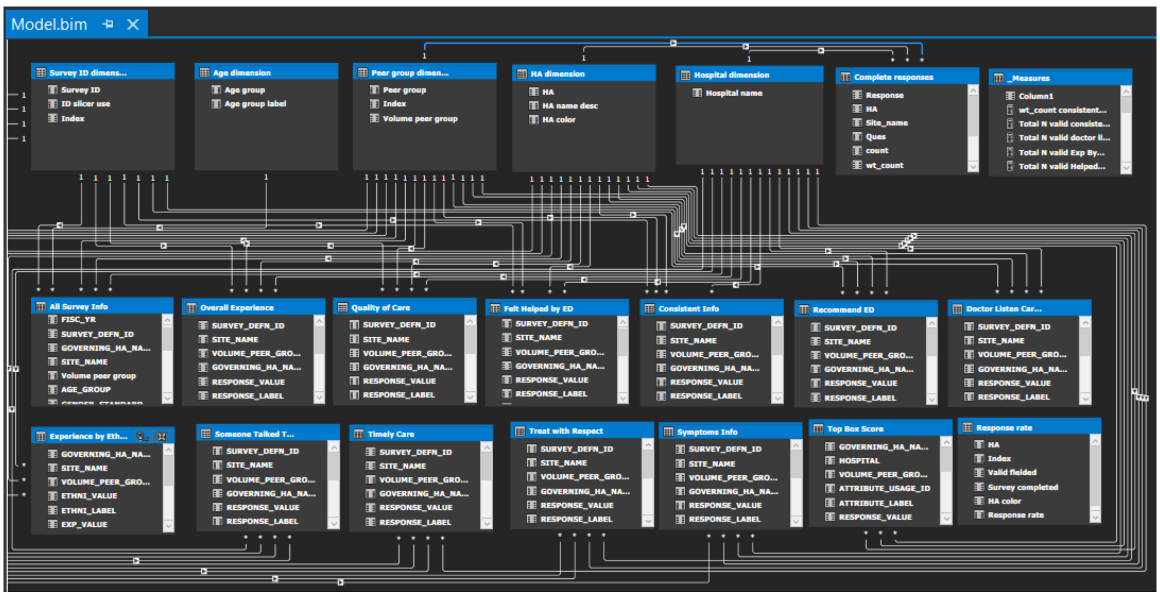


Figure 5.4: Semantic layer that will work as the OLAP cube for reporting

Figure 5.4 shows the partial view of our semantic layer, which will act as the middle layer between the complex DW schema and the visualization for the end-users. It's generally very difficult to query data out of the data warehouse directly which is a relational database system. One of the critical goals that the OLAP has to achieve is to minimize the amount of on-the-fly processing needed while the user is navigating the data. This was achieved by pre-processing and storing every possible combination of dimensions, measures, and hierarchies before the user started their analysis. This allowed the data to appear instantaneously when the user investigated the information. In Business Intelligence, the analysis and presentation of data, stored in an OLAP Cube. In this research, we have used Microsoft Visual Studio to design and extract data into the OLAP Cubes and the SQL Server Management Studio SSMS to deploy it to SQL Server Analysis Service (SSAS).

5.9 DATA ANALYSIS

5.9.1 *Key Performance Indicators*

We addressed a list of questions through our analysis so that stakeholders/health authority users would be able to get the answers to the following broad questions from the BI dashboard we developed. Below are the KPI we investigate through our analysis and reporting.

1. What is the overall Emergency Department (ED) experience in different hospitals?
2. What is the overall quality of care according to patients?
3. How are the patients treated and supported by doctors and nurses regarding courtesy, respect, and consistent information in different hospitals?
4. What are the strengths of the Emergency Departments in terms of quality?
5. What are the areas for improvements in the health sector in terms of quality?

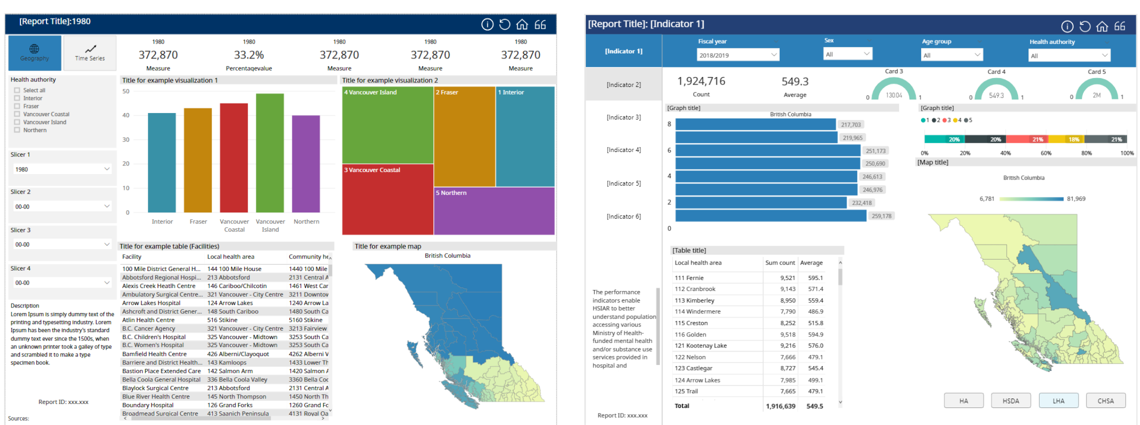
Once data has been correlated, and the OLAP cube has been built, it is ready for analysis. Once the semantic layer (OLAP cube) is designed, it is populated with data from different health authorities and facilities from the data warehouse. This is known as an ETL process. After building the data staging area and a multidimensional OLAP cube, data from all different sources must be extracted and brought to the BI platform. Microsoft Power BI (Microsoft, 2020) provides business users with useful data analysis and rich visualization to facilitate informed decision-making. The desktop version of Power BI provides the ability to create powerful data connections, models, and reports for data analysis. In this research, we have used the Power BI desktop version to connect live to the OLAP cube, which was deployed in SQL Server Analysis Service. Once we have connected to the data source, we can adjust the data to meet our needs. We did some transformations using the query editor in Power BI, such as renaming column headers and changing the text to numbers. It is important to note that the original data source is not affected; only this particular view of the data is modified. We have also created new measures using Data Analysis Expressions (DAX) queries (Microsoft, 2020) to provide aggregated data.

5.10 DATA VISUALIZATION

Results of the analyses need to be captured visually so that findings can be easily communicated. The common focus of visualization is on information presentation. The output of the data analysis process is presented as business intelligence to the end-users. Visualization depends on the information that needs to be presented and should convey the most important message to the end-users efficiently [28, 106].

5.10.1 *Mock-up Designs*

In this phase, we brainstormed and came with two mock-up designs (Figure 5.5) according to the design standard of the Ministry of Health B.C. to decide what are the most efficient way to present the patient survey data. The goal of the design standard is to make the BI applications consistent throughout the departments so that the end-users will experience better support in their analytical tasks. Based on our data and its results, we finally decided on our final visualization layout after consulting with the quality assurance team and subject matter experts of the Ministry. As we designed a BI solution for the Ministry of Health B.C., we had to consider the inputs from the Quality Assurance (QA) team and the SME to make an effective visualization for the Ministry's end users.



(a) Mock-up design1 (b) Mock-up design2

Figure 5.5: Initial mock-up designs of our BI dashboard

5.10.2 *Final Visualization*

Finally, we decided our layout for producing the final visualization where bar graphs, column charts, tables, and matrices were mainly used to visualize the analysis results of the patient survey data. These were the most appropriate visuals for the data to convey the key message to the end-users efficiently. Figure 5.6 shows our interactive visualization created using Power BI.

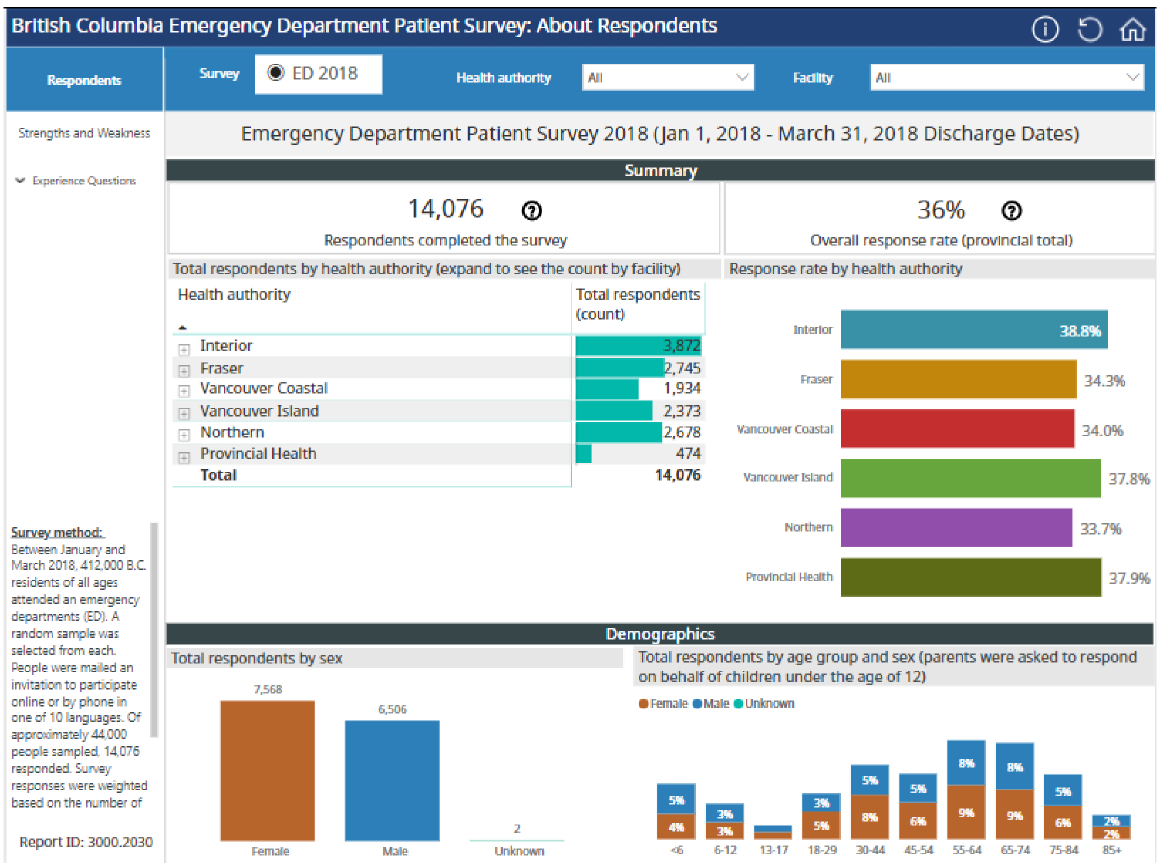


Figure 5.6: Final visualization created in Power BI

We utilized the latest cloud-based version of Power BI to disseminate the results of data analysis to the Ministry users. Users can quickly find the answers to some important questions and export data to generate their own reports. Below is the first page of our business intelligence report.

5.11 REASON TO CHOOSE POWER BI

We have chosen Power BI over the other self-service BI options available in the market mainly because Power BI is fairly easy to use even for non-IT experts, and it has the ability to integrate with Office 365. Any Excel user who is familiar with using pivot tables and charts could be a potential user of Power BI because the learning curve is not steep. With some basic training, we found that the end-users were generally able to generate required business intelligence using Power BI without much technical assistance. Our Power BI users can edit their own reports, but they cannot edit the underlying data. This helps ensure data integrity.

5.12 IMPLEMENTATION CHALLENGES

There are certainly some things that are quite different for patient surveys compared to other data. The ED 2018 survey had some challenging factors that were really tricky for us to handle during implementation. We have tried to summarize below:

- Each survey question has a different number of responses. The most common way to report on them is focusing on the 'most positive' response option(s).
- Survey results need to be weighted (concept like age/sex standardizing) as the surveys are set up to get responses from each emergency department, so there are more responses from small/rural ED than would be expected if

randomly sampling across B.C. Weighting makes sure each ED contributes to the B.C. result based on its total volume of ED visits (ex. If ED had 2% of ED visits, weighted total respondents would be 2% of total respondents).

- Non-standard survey responses (not applicable, multiple response options).
- Lack of visible/developed business rules (e.g. what is a performance question? what is a most positive category? what are exclusions? etc.).

6 EVALUATION: USER STUDY

In this chapter, we define the purpose of our study, its design and methodology in detail. This study consisted of two conditions: novice and experienced BI users. We recruited forty-two participants from the Ministry of Health, B.C. for our study as they are the intended users of this developed BI application.

6.1 PURPOSE OF STUDY

From the literature review (Chapter 3), we found the research gap to investigate the issues of failing a BI project from the user's perspective. We also found the user's experience and expertise are important factors of BI technology adoption, which in turn influence the successful BI implementation. Also, in the motivation section (Chapter 2) we provided our rationale to conduct this study. The goal of this study was to investigate the impact of users' experience on the perception of a BI application in terms of usability. We wanted to see if all types of users (novice or experienced) can take benefit of a BI application regardless of their prior analytical experience. It will help to know how we can develop a BI application that will serve all types of users equally.

6.2 STUDY PROCEDURE

This study employed a mixed-method design to evaluate the usability of the BI dashboard we developed. The study design included a set of semi-structured interviews using a think-aloud protocol and scale-based questionnaires to capture the user's perceived usability. This study design followed the format of multiple usability studies used in the areas of health informatics, and interactive visualizations [25, 35, 40, 71].

At first, the research assistant invited participants to take part in our study through the email that was collected from the B.C. Government directory. The research assistant sent the study poster along with a brief description of the study. After getting the response from the interested participants, the research assistant sent the consent form along with more information, including to see if they qualify, what participation involves, and more information about the online interview. The research assistant also let the participants know that this study received ethics approval from the University of Manitoba and the Ministry of Health, British Columbia. On the day of the interview, after getting the signed consent form from the interested participant, the research assistant provided the zoom link, dashboard link, and the online survey link to the participant through email and requested to join the meeting timely. After starting the meeting, the research assistant elaborated the study procedure briefly and requested the participants to open the dashboard in a browser using the link provided through email. When Participants were ready, they were told that the entire meeting session would be recorded and stored in a local computer for qualitative analysis. After getting their oral consent, the research assistant started recording the session. In the beginning, the participants were asked some open-ended questions about themselves, their general perception of the BI dashboard, and their previous experience of using BI dashboards. After that, participants were asked to answer the questions from the task list (Section 6.5) using our dashboard (e.g., finding the best facility based on patient's rating, category of the hospital doing good or bad, strengths and weaknesses of the current healthcare system, etc.). After completing the tasks, participants were asked some more questions about their browsing experience in terms of effectiveness, efficiency, and ease of use. After the interview session, based on their browsing experience, the participants were requested to provide their valuable feedback using an online survey on the features of the dashboard they liked, did not like, and any suggestions for improvements. We also allowed our interested participants who wanted to browse our dashboard for a bit longer before answering the online questionnaires to get their more accurate ratings. Turning the camera on was not mandatory if some participants were not comfortable with that. Each interview session took up to 45 minutes, 30 minutes for Interview and 15 minutes for online questionnaires ($M = 43.67, SD = 4.37$). During the interview, participants were encouraged to think aloud [104] and vocalize their thoughts. They were given as much time as they desired, and the research assistant guided them where it was necessary. Finally, the participant was debriefed and thanked for their time. As all our participants were government employees, they were not allowed to receive compensation for this study. This research (HE2021-0082) was approved by the Research Ethics Board at the University of Manitoba, Fort Garry campus, and the Ministry of Health, British Columbia, Canada.

6.3 STUDY DESIGN

Our study had a within-subjects design with two conditions (novice and experienced) with twenty-one participants in each condition. For each condition, we tested the following effects:

1. The clarity of the content: To test if there is a difference of perception on the clarity of contents between the novice and experienced BI users. It helped us to know if the clarity of a BI tool is impacted by the prior BI application use experience. We asked the following 7 points Likert scale question to capture their rating.

   On a scale of 1-7, how do you rate the clarity of the content of the dashboard you visited?

   Where '1' represents 'Not clear at all' and '7' represents 'Very clear.'

2. Ability to perform analytical tasks of different difficulty levels: To test if both the novice and experienced BI users can perform the analytical tasks of different levels of difficulties using a BI application. It will help us to know if the prior BI use experience has an impact on their performance. We measured it by calculating the percentage of accuracy based on the number of correct answers each participant provided for both easy and difficult tasks. We provided seven easy tasks followed by six difficult tasks to all participants with a fixed order to perform using our dashboard and calculated the number of correct and wrong answers they provided for both types of tasks.

3. Perceived usability: To test how a BI application helps both novice and experienced users in terms of usability. It will help us to know if the BI application is serving both the novice and experienced equally.

    - Effectiveness: To test if the BI application is effective for decision-making for both groups. We asked the following 7 points Likert scale question to capture their rating.

      On a scale from 1 to 7, please rate the effectiveness of this dashboard in terms of potential to help in decision making.

      Where '1' represents 'Not effective at all' and '7' represents 'Very effective.'

    - Efficiency: To test if the BI application helps both groups to find the required information efficiently. We asked the following 7 points Likert scale question to capture their rating.

      On a scale from 1 to 7, please rate the efficiency of this dashboard in terms of finding the answers to the questions in the task list.

      Where '1' represents 'Not efficient at all' and '7' represents 'Very efficient.'

    - Ease of use: To test if the BI application is easy to use for both groups. We asked the following 7 points Likert scale question to capture their rating.

      On a scale from 1 to 7, please rate the overall ease of use of this dashboard.

      Where '1' represents 'Not easy at all' and '7' represents 'Very easy.'

6.4 participants

Forty-two participants (24 males, 18 females) were recruited through the email invitation from the B.C. Ministry of Health consists of Programmers, Analysts, Managers, and employees with non-technical roles from various levels who will use our BI application. At the beginning of our survey, we asked a question (*Did you use any Business Intelligence dashboard before for getting useful information? (yes/no question))* to assess participant's BI experience to assign them into two conditions (novice or experienced). Twenty-one of them were **novice** and had no previous experience of BI dashboard use, and the other twenty-one were **experienced** and had previous knowledge of BI dashboard use. Participant's ages ranged from 24 to 56 years old (M = 37.53, SD = 9.95). Experience with Business Intelligence technology use was not necessary to participate in this study.

6.5 task

Below (Table 6.1) is the list of tasks we asked our participants to perform as quickly and accurately as possible using our dashboard. These tasks are aligned with the business requirements to guide our analysis and reporting for this project. We have ten different pages in our developed BI dashboard. We divided our tasks into easy (only required visual search to find the answers) and difficult (required additional navigation and filtering to find the answers) tasks. Below is the list of tasks we asked the participants to perform during the interview session. Participants had to visit all pages of our dashboard to perform these tasks. We tried to measure the performance of both groups (novice and experienced) to see how correctly they could find the answers to the questions using the BI dashboard.

Difficulty level	Task description
Easy	1. What is the number of male and female respondents in the Emergency Department (ED) 2018 survey? 2. Which health authority has the most respondents? 3. What are the top 03 provincial strengths of B.C. emergency departments? 4. Which volume peer group (e.g., Extra-small, Small, Medium, Large) is doing the best in terms of overall good experience? 5. Find top 03 large facilities where patients got care within 30 minutes of getting to the emergency departments. 6. What are the top 03 large facilities patients will definitely recommend to others? 7. In which health authority, most patients get the written information about symptoms or health problems to look out for after they leave the emergency department?
Difficult	1. Which ethnic group tends to have the most positive emergency department experience? Is that true for all health authorities? 2. Which health authority is doing worst in terms of Good quality of care?
	Continued on next page

Table 6.1 – continued from previous page

Difficulty level	Task description
Difficult	3. What are the top 03 small facilities in Fraser where doctors always listened to the patients carefully? 4. What are the top 05 large facilities where patients waited less than 5 minutes before someone talked to them to know the reason for the emergency department visit? 5. Which health authorities are doing better than the B.C. average where patients were helped by emergency department visits? 6. What are the bottom 05 small facilities were patients most likely to say they always got consistent information from doctors and nurses?

Table 6.1: List of tasks to perform during the interview session

6.6 QUANTITATIVE RESULTS

In this section, the results for novice and experienced users are organized by; 1) The clarity of the content, 2) Task completion accuracy, and 3) Usability (effectiveness, efficiency, and ease of use). After doing the Shapiro-Wilk normality test, we found our data was not normally distributed, so we decided to conduct a non-parametric test like the Mann-Whitney U test as we have two groups of independent random samples to compare for each dependent variable.

- **The clarity of the content**

  Goal 1: To test if there is a difference of perception on the clarity of contents between the novice and experienced BI users. We used a 7-points Likert scale question (*On a scale of 1-7 how do you rate the clarity of the content of the dashboard you visited? where 1 denotes 'Not clear at all' and 7 denotes 'Very clear'*) to capture participant's perceived clarity of content based on their browsing experience.

  Ho: There is no difference between the novice and experienced users in terms of the clarity of content of a BI application.

  H1: There is a difference between the novice and experienced users in terms of the clarity of content of a BI application.

  Two groups of users were tested using the Mann-Whitney U test to investigate the potential difference in their perception. No significant experience effect was found between novice (Median = 6.00 , n= 21) and experienced (Median = 6.00 , n= 21) users on the perception of their clarity of content, $U = 169.50, Z = -1.418, p = 0.156 (> .05)$ (2-tailed), with a small effect size $r = 0.219$ [17], hence we failed to reject the null hypothesis. So, we can conclude that there is no significant impact of the user's prior experience on the clarity of the content of a BI application.

- **Ability to perform analytical tasks of different difficulty levels**

  Goal 2: To test if there is a difference in the performance of novice and experienced BI users in performing the easy and difficult tasks (discussed in Table 6.1). We measured the performance of two groups by calculating the percentage of accuracy based on the number of correct answers each participant provided during the interview session. We tested the performance for both types of tasks. We provided 07 easy tasks followed by 06 difficult tasks to all participants with a fixed order to perform using our dashboard and calculated the number of correct and wrong answers they provided to find the accuracy for both types of tasks. The summary results are presented in Table 6.2 for both novice and experienced users in case of easy and difficult tasks.

Ho: There is no difference between the novice and experienced BI users in performing easy and difficult analytical tasks using a BI application.

H1: There is a difference between novice and experienced BI users in performing easy and difficult analytical tasks using a BI application.

	U	Z	P VALUE (2-TAILED)	R (EFFECT SIZE)* [17]
Accuracy (easy tasks)	173.0	-1.251	0.211 (> 0.05)	0.193 (small effect)
Accuracy (difficult tasks)	94.0	-3.327	< 0.001 (<0.05)	0.513 (large effect)

Table 6.2: The summary statistics of accuracy for easy and difficult tasks

Two groups of users were tested using the Mann-Whitney U test to investigate the potential difference in their performance for easy and difficult tasks. No significant experience effect on the performance was found between novice ($n = 21$) and expert ($n = 21$) users for easy tasks ($p - value > 0.05$, with a small effect size $r = 0.193$), but there is a statistically significant experience effect between novice and experienced in performing difficult tasks ($pvalue < 0.001$, with a large effect size $r = 0.513$), hence we rejected the null hypothesis and accepted the alternative hypothesis. So, we can

* Effect Size r less than 0.3 means small effect, r between 0.3 and 0.5 means medium effect, and r greater than 0.5 means large effect. [17]

conclude that novice and experienced users can perform easy tasks with almost the same accuracy. But, there is a significant difference between them while performing difficult tasks using a BI application. Experienced users significantly overperformed the novices in performing the difficult tasks. In summary, using a BI application, both types of users can perform the easy analytical tasks with equal accuracy but experienced significantly overperform the novices in terms of performing difficult analytical tasks, which requires additional navigation and filtering.

- **Perceived usability**

  Goal 3: To test if there is a difference between the novice and experienced BI users on the perception of the usability (effectiveness, efficiency, and ease of use) of a BI application. We used three 7-points Likert scale questions (*1. On a scale from 1 to 7, please rate the effectiveness of this dashboard in terms of potential to help in decision making, 2. On a scale from 1 to 7, please rate the efficiency of this dashboard in terms of finding the answers to the questions in the task list, 3. On a scale from 1 to 7, please rate the overall ease of use of this dashboard.*) to capture participants' perceived effectiveness, effectiveness, and ease of use based on their browsing experience.

  Ho: There is no difference between the novice and experienced BI users in terms of the perceived usability of a BI application.

  H1: There is a difference between the novice and experienced BI users in terms of the perceived usability of a BI application.

  Two groups of users were tested using Mann-Whitney U test to investigate the potential difference of their perceived effectiveness, efficiency, and ease of use of a BI application. No significant experience effect was found between novice and experienced users on their perceived usability of a BI application. we evaluated usability for three aspects, that is

1. Perceived effectiveness between novice ($Median = 6.00, n = 21$) and expert ($Median = 7.00, n = 21$)
2. Perceived efficiency between novice ($Median = 6.00, n = 21$) and expert ($Median = 6.00, n = 21$)
3. Perceived ease of use between novice ($Median = 6.00, n = 21$) and expert ($Median = 6.00, n = 21$)

Table 6.3 shows the summary of the test for all three aspects of perceived usability between novice and experienced users.

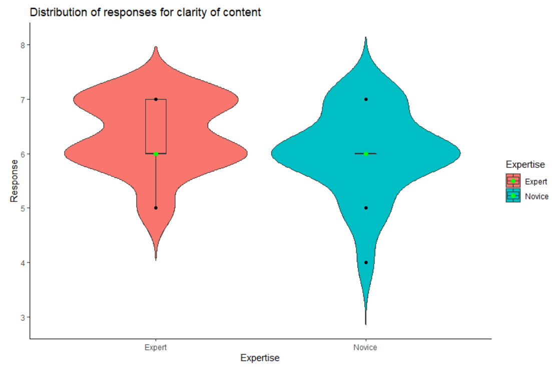
	U	Z	P VALUE (2 TAILED)	R (EFFECT SIZE)* [17]
Effectiveness	186.5	- 0.932	0.351 (> 0.05)	0.144 (small effect)
Efficiency	207.5	- 0.363	0.717 (> 0.05)	0.056 (small effect)
Ease of use	164.5	- 1.552	0.121 (> 0.05)	0.239 (small effect)

Table 6.3: The summary statistics of usability aspects

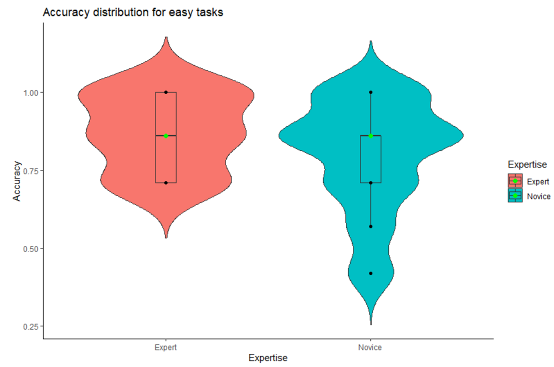
Based on the test result, we failed to reject the null hypothesis for all the aspects. So, we can conclude that there is no significant impact of users' prior experience on their perceived usability of a BI application.

Finally, in Figure 6.1 we showed the distribution of the responses for novice and experienced users for all of our evaluation criteria.

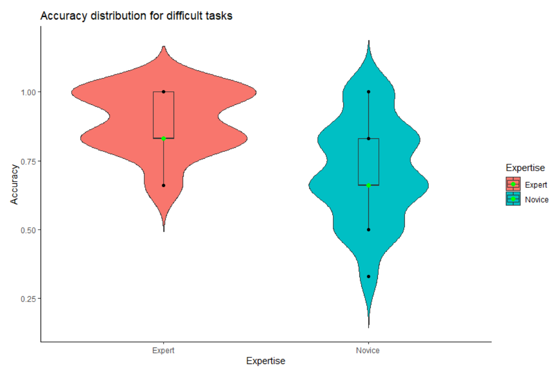
* Effect Size r less than 0.3 means small effect, r between 0.3 and 0.5 means medium effect, and r greater than 0.5 means large effect. [17]



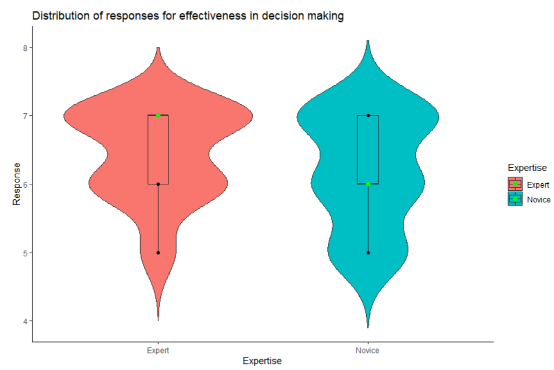
(a) The clarity of content



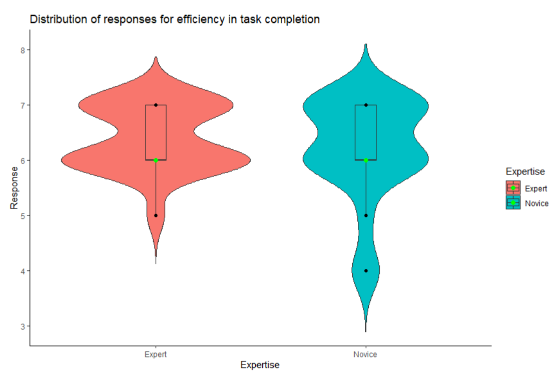
(b) Accuracy for easy analytical tasks (%)



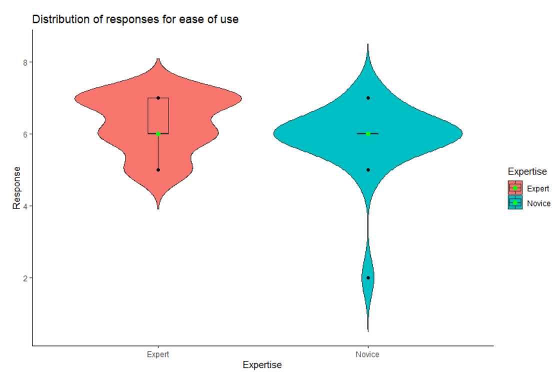
(c) Accuracy for difficult analytical tasks (%)



(d) Effectiveness



(e) Efficiency



(f) Ease of use

Figure 6.1: The distribution of responses of the evaluation criteria for novice and experienced users

6.6.1 *Interpretation of the Results*

In this section, we interpreted the data distribution and quantitative results for all the evaluation criteria.

- The clarity of content:

  In Figure 6.1(a), We see that the overall response distribution and interquartile range for clarity are similar for novice and experienced users, but there are some outliers in the case of novices. At the same time, it is clear from the plot that both expert and novice gave their rating in a similar range (6 or 7 out of 7), which means the contents were clear for both of them. We also found it in our statistical finding (Section 6.6). So, the contents of the BI dashboard were equally clear for both novice and experienced users. A user's prior experience in using BI technology does not affect the perception of clarity of the content of a BI application.

- Accuracy to perform easy analytical tasks:

  Figure 6.1(b) shows that the response distribution for the accuracy in performing easy analytical tasks is not quite similar for novice and experienced users, but the medians are the same for both groups. We can see more variability and outliers in the case of novices. But the performance of experts and the novices are the same with similar density distribution, and most participants from both groups performed the easy tasks with between 75% to 100% accuracy. The overall performance of experienced is slightly better than the novices, but that is not significant. The novice and experienced performed almost equally to find easy information correctly from our BI application which is also found in our statistical test (Section 6.6). So, in conclusion, there is no significant experience effect between novice and experienced users in performing the easy analytical tasks; they both can perform with almost equal accuracy.

- Accuracy to perform difficult analytical tasks:

  From Figure 6.1(c), We see that the response distribution of performing comparatively difficult analytical tasks is quite different for novice and experienced users. The interquartile range and the median of the two groups are also different. We can also see that experts significantly outperformed the novice in performing the difficult analytical tasks, which we also found from our statistical result (Section 6.6). Most experienced participants performed between 85% to 95% accuracy, whereas the most novices performed between 60% and 75% accuracy. So, the experienced can better perform comparatively difficult analytical tasks than the novice. The user's prior experience has a significant effect on performing the difficult analytical tasks using a BI application.

- Effectiveness: In Figure 6.1(d), we see that the response distribution and interquartile range are similar for both novice and experienced users in terms of effectiveness. The responses are also distributed to a similar range for both groups. Both experienced and novice gave similar ratings (mostly 5 to 7 out of 7) in terms of the effectiveness of the BI application which is aligned with our statistical finding (Section 6.6). So, the user's prior experience of BI technology use does not affect the perceived effectiveness of a BI application in terms of decision making.

- Efficiency: Figure 6.1(e) shows the response distribution for the efficiency is similar for both novice and experienced users except for some outliers for novice users. We got similar ratings (mostly 6 or 7 out of 7) from both groups in terms of efficiency to find the answers to the tasks using the BI application which also supports our statistical finding (Section 6.6). So, the BI application can equally help both groups to find the answers to the important questions; users' previous analytical experience does not affect their perceived efficiency of a BI application to find useful information.

- Ease of Use: From Figure 6.1(f), We see that the overall response density for the ease of use is similar for both novice and experienced users with the same interquartile range. It is also clear that both novice and experienced rated almost similarly (mostly 6 or 7 out of 7) in terms of ease of use of the BI application. Our statistical finding (Section 6.6) also supports this fact. So, the BI applications are equally easy to use for both novice and experienced users; their previous BI use experience does not affect their perception of ease of use.

6.7 QUALITATIVE ANALYSIS

The data collected during the 30 minutes semi-structured interviews were transcribed verbatim and analyzed qualitatively using thematic analysis [59]. From our interview, we got some important insights both from novice and experienced users.

6.7.1 *Interview Findings*

We reported the following key findings that were identified from our interview sessions. Afterwards, based on their suggestions and feedback, we came with a design recommendation to develop a BI application for healthcare decision-makers that will potentially benefit all users within an organization.

- **The consistent design increases the overall satisfaction and makes users more efficient to get useful information (mentioned by 16 participants)**

  Both the novice and experienced users were happy with the pages with the consistent design and easy navigation. An easy and user-friendly layout is very effective for a good browsing experience.

  "I liked the consistent layout [of the dashboard] and the presentation of information in each page, it made the navigation easy for me" - P01 (experienced)

  "I liked the overall design of the dashboard, it is simple and yet very informative." - P13 (experienced)

  "I think the overall and consistent layout helps with finding information, even if you haven't used the dashboard before." - P38 (novice)

  Consistency in design will increase the efficiency of a dashboard, and users are more likely to find the information they need. Users feel helped if they find information quickly and easily from a dashboard.

  "I found the consistency of the layout between the different response pages. Once you have visited one [page], you are immediately familiar with the others. "- P26 (novice)

  "I liked the simple, clean layout. All pages were similar in design, and that created efficiency in finding the relevant information." - P01 (experienced)

User-friendly design can better help new users to get benefits and even requires no tutorial to get used to it.

"The overall layout [of the dashboard] is simple. I was able to understand what to look for without having training."- P39 (novice)

- **Users get lost with too much information and crowded interface on a single page (mentioned by 10 participants)**

  We found both the novice and experienced participants continuously emphasized the information overload while designing the user interface; both types of users faced problems due to the crowded interface and high volume of information on some pages.

  "Some navigation and clicks are confusing to me, not sure where to click, less intuitive design. I was lost sometimes" - P05 (novice)

  "Understanding the link between the questions took a little bit of time. Too busy and too much info on a single tab" - P23 (novice)

  "Some of the tabs are quite busy. For an end-user, it [data interpretation] may be as effective or easy to navigate as the other tabs" - P25 (novice)

  Novice participants struggled more with this problem; they think it creates a cognitive load on the new users, and users lose their interest in visiting other pages.

  We also found that both types of users, especially novices, struggled with the pages busy with information. They simply can not process the information on a busy page even if the design is very simple. Both types of users suggested keeping the pages less crowded with a lot of information.

"A person looking at the first time might find the number of pages overwhelming" - too many pages is sometimes overwhelming for novice users.- P19 (novice)

"Crowded user interface will make a tool tough for users even if the content is very simple " - P17 (experienced)

We found that especially novice users are very reluctant to read the description and side notes. They are not always interested in reading all the descriptions. It imposes a more cognitive load on them, so it's better to design in a way that information will pop up only with click/ hover over.

"I felt more cognitive load to read the text and questions, it was time-consuming for me to find the answers " - P33 (novice)

- **Proper documentation can enhance the trust of novices in background data (mentioned by 03 participants)**

  We found that proper documentation may improve users' trust in the data used in a dashboard. Users feel more confident while browsing a dashboard when it has adequate documentation of the back-end data. As new users generally don't have the context of the BI applications, they feel more helped while finding the clear documentation and resources to validate the data themselves. It increases their trust in the data shown in the dashboard.

  "I'm very impressed with the background information. Most dashboards I've seen don't tell you the source of the data, how or why that data has been cleaned, how metrics are calculated, etc. Here, I have to trust the information presented [in the dashboard], because you've given me the tools I need to go and verify it for myself. "- P11 (novice)

- **Descriptive analysis is useful and easy to interpret for novices but does not always satisfy experienced users (mentioned by 04 participants)**

  Interestingly we found some participants who preferred more details and complex analysis besides conveying the descriptive information. They were interested to know the statistical methods used for calculation besides only the overview.

  "No overall visual distribution of facility results to see the range from low to high. Challenging to know the variability/confidence interval around some estimates with small N." - P13 (experienced)

  "I would love to see some detailed analysis of this type of data, error bars/ variability /confidence interval around estimates will make more sense to me" - P15 (experienced)

- **Intuitive flow is an important factor for an effective BI application, It is better to start with the low-level overview and eventually drill down to show the details (mentioned by 06 participants)**

  We found that especially novice users struggle if an application does not have a nice flow to follow or it has a complex flow of information.

  "The organization of pages is problematic to me. I'm not sure which audience this is intended to serve. The dashboard does not have an intuitive flow." - P12 (novice)

  "I think having to click between different questions to see the statistics might be missed by first-time users" - P03 (experienced)

  Our interview findings also showed that both novice and experienced users prefer to convey the most important and aggregated information on the first page, then drill down eventually to visit other pages with detailed information if only they are interested.

"I think on the Respondents page, a description of what the study was would be a bit more useful. I felt like I didn't fully understand what the data was until I was a few pages in. A short summary somewhere would have been good." - P06 (experienced)

"Summary pages should be early in the layout. The good and bad responses should be earlier, and depending on my need, I would drill down from there.[...]" P32 (novice)

- **Colour combination and the proper order of visuals are the important factors for good browsing experience (mentioned by 07 participants)**

  Choosing the right colour is one of the most important factors of visualization; it has a significant impact on the successful conveying of information. Users are distracted by too many colours and sometimes fail to find the most important takeaway message from a dashboard.

  'I was distracted by too many colours, colours need to be visually neutral for better visual perception.'- P38 (novice)

  "Due to colour combination some pages are cluttered so a bit difficult to read/interpret." - P41 (novice)

  We also found that some participants suggested maintaining the order from top left to bottom right to visualize the important information. The most important information should be placed at the top left of the page and eventually the less important visualizations towards the bottom right.

  "Generally, the human brain is trained to scan from left to right and top to bottom. I found some important information is misplaced, that should be placed at the top left corner of the page to capture user's eye at the very beginning." - P29 (experienced)

6.7.2 *Recommendations from Novice*

In this section, we have included the design recommendations especially for novice users to consider while building a BI application that will potentially help novice users in terms of better user experience.

1. Improved information flow, and easy navigation is important factor of successful dashboards; it should be easy yet organized and should follow an intuitive flow (mentioned by 7 participants).

2. Use text with icons instead of only icons because new users may not know what that icon means without clicking that and hence the chance of missing valuable information (mentioned by 4 participants).

3. Make the fonts and colour in a way that is clearly visible and easy to understand; new users might struggle with inappropriate text and font style. Too many colours might overwhelm new users even if the dashboard looks good (mentioned by 3 participants).

4. Provide enough details of the information where possible to improve the level of trust of the dashboard users. Make sure there is a short introduction for the user with a low-level or no data analytics experience (mentioned by 3 participants).

5. Make more pages with less information instead of making fewer pages with a lot of information. Novices can not process a lot of information on a single page and fail to get the most important message (mentioned by 2 participants).

6.7.3 *Recommendations from Experienced Users*

In this section, we have included the design recommendations especially for experienced BI users to consider while building a BI application which will potentially make the application more useful for the experienced users.

1. Proper layout and the order of visuals are important for an efficient BI dashboard, so follow an appropriate order from left to right based on their importance (mentioned by 6 participants).

2. Always provide high-level information first to convey the most important message to the users, don't overwhelm them with a lot of detailed information at the beginning! Otherwise, they might lose interest in visiting other pages (mentioned by 5 participants).

3. Use varieties of visuals where appropriate to convey the message in an interesting way which will improve the user experience (mentioned by 3 participants).

4. Design Standardization is an important consideration to reduce the complexity of BI applications. Design should not put more cognitive load on the users; they will lose interest otherwise (mentioned by 3 participants).

5. The tool is only useful when users find their answer within 5 to 10 sec on a page; it should not take more than that if the design is efficient (mentioned by 1 participant).

7 SUMMARY AND CONTRIBUTION

In this chapter, we briefly summarized the results of the study conducted with novice and experienced BI users on their perceptions. We observed and discussed the performance, similarities, and differences between the two groups. Furthermore, we mentioned the potential causes of the quantitative results and suggested further research scope based on our findings.

7.1 SUMMARY OF QUANTITATIVE RESULTS

We statistically analyzed our data to find any significant effect of users' prior BI experience on their performance and perception of a BI application. We found a significant difference in their performance in performing the difficult analytical tasks but no difference in their perceived usability of a BI application. Our results showed that both novice and experienced users can perform the easy analytical tasks equally but not the difficult ones. Experienced significantly overperformed the novices in performing comparatively difficult analytical tasks. But, interestingly, we found no experience effect in their perception regarding the clarity and perceived usability of a BI application. So the further investigation is required to find other important factors which might also affect the perceptions of both types of users.

7.2 potential causes of our quantitative results

Interestingly, our quantitative results didn't find any statistically significant difference between the novice and experienced users regarding clarity and perceived usability. But we found a significant difference between them in performing difficult analytical tasks. We think that our quantitative results of their perception can potentially point towards the following couple of causes:

1. Firstly, perception might also depend on the user's personal capabilities and organizational environment; both groups of users are educated enough as the Ministry employees. That could be a potential reason for not getting a difference in their perception. This might be a future scope of research to investigate personal capability in broad.

2. Secondly, our participants are working in a very technical environment where BI is widely used. So, even our novice users might have little familiarity with BI technology to some extent. They all had a level of technical literacy, unlike a *true novice* and that could be another reason why we did not find any significant difference in their perception.

7.3 summary of qualitative findings

From our qualitative analysis, we found that both novice and experienced users emphasized some common factors that need to be considered to build an application for all. From the interview, we captured the perception of both groups of users to see the similarities and differences between them based on their browsing experience. We reported the summary below.

7.3.1 *Similarities*

- Both preferred the consistent design and easy navigation for a better user experience.
- Both advised to present less information on a single page.
- Both advised to avoid overcrowded user interfaces for a better experience.
- Both advised to maintain a good intuitive flow of information to better understand the contents of a BI application.
- Both advised to start with conveying only the most important information on the landing (first) page and eventually going for details.

7.3.2 *Differences*

- Novices struggle more with many options and functionalities in a single page than the experienced.
- Visual perception of novice users is more problematic than an experienced if the colour is not chosen properly. Neutral colours are good, especially for novice users.
- Experienced users are not always satisfied with the simple and aggregated information; some prefer to see the detailed analysis instead. On the other hand, novices are lost with a lot of information and prefer to keep the pages less crowded with information.

- More text works as noise, especially for novice users; they can not easily interpret the information if it requires more reading. It imposes a more cognitive load on them.
- Proper documentation can enhance the level of trust of novice users, as new users generally do not have the context of the BI applications; they feel more helped while they find the clear documentation and resources to validate the background data themselves. It increases their trust in the data shown in the dashboard.

In summary, our study found that there are still some gaps in building a common BI platform that can serve both novice and experienced users. There is more scope of research in this area to find out if other confounding variables like relative advantage, requisite skills and resources, and organizational learning climate also have indirect effects on the individual's perception of a BI application.

7.4 CONTRIBUTION

Our research provides important contributions to BI technology adoption literature. While several studies have examined factors influencing organizational adoption of BI applications [79, 112], factors associated with individual adoption (technical literacy, personal ability, or previous experience) of BI applications have not received much attention [42, 66, 102]. This thesis attempts to close this literature gap. This research developed a BI dashboard that will work as a useful tool to facilitate better decision-making by visualizing the insight of patient survey data. Then it also investigated if a business intelligence application can help both novice and experienced BI users equally in the decision-making process. Specifically, We investigated the impact of the prior BI experience on the user's performance (accuracy), and perception of the usability (effectiveness, efficiency, and ease of use) of a BI application. In addition to making these contributions to the literature, the qualitative findings of this research also provided some design recommendations that can help to develop a BI application that will equally help both novice and experienced users.

8 LIMITATION AND FUTURE WORK

8.1 LIMITATIONS AND FUTURE DIRECTION

In this section, we highlighted a couple of limitations of our study that should be addressed in future research.

1. First, this study is based on a government organization, and we developed a BI application based on their needs. We recruited participants from the Ministry of Health, B.C., as this dashboard is not accessible outside their organizational network right now, so the result could have been different if we could run the study using the lay people outside the B.C. Government.

2. In addition, it may be relevant to investigate other variables such as technical literacy, personal ability, level of education, etc., to see the impact of those factors on the overall perception of the BI application use. As this was an online study and it was tough for us to manage Ministry employees due to their busy schedule, we could not measure other concrete variables (e.g., eye movement) for a stronger conclusion. But using both the interview and online survey, we captured the performance and most of their perceptions of BI application use.

3. Finally, this study presented cross-sectional research that measures users' perceptions and intentions at one point in time. However, users' perceptions may change over time as they gain more experience of using BI systems [61]. Hence, future research should consider conducting a longitudinal approach to gain a deeper understanding of the user's perception of BI application use.

8.2 FINAL WORD

The usage of BI solutions in healthcare decision-making is yet to be sufficient and still lower than that in other business organizations. Studies show that health organizations appreciate the importance of streamlining their information resource to help them make important healthcare decisions [3, 30, 65]. However, the technical expertise required to select and deploy the right combination of BI solutions that can benefit everyone is not readily available. It was confirmed that adapting BI systems interfaces to the end-user is of significant importance since the users' skills in information technology and analytics can be varying [47]. This is an important factor for providing a good user experience. In light of this thesis, we have described how a health organization can reap the benefits of BI application, which will help both novice and experienced users within an organization. We developed a business intelligence application and investigated the impact of users' prior experience on their performance and usability perception. Our research will work as the catalyst to investigate if other variables like technical literacy, personal ability, or level of education have any impact on the user's performance and overall perception of BI application so that any organization can develop a common platform to serve all types of users. Finally, we provided a design recommendation that should be considered while developing a BI application so that both novice and experienced users can get benefit from a single platform.

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