INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN ECONOMICS & MANAGEMENT SCIENCES

OPEN ACCESS JOURNAL

Vol 13, Issue 3, (2024) E-ISSN: 2226-3624

# Knowledge Representation of Supply and Demand Through Data Visualization: Assessing Usability Using Dual Method

Siti Salwa Salleh

College of Computing Sciences, Informatics and Mathematics University Technology MARA, Negeri Sembilan Branch, 63000 Seremban Campus, Negeri Sembilan, MALAYSIA

Corresponding Author Email: ssalwa@uitm.edu.my

**To Link this Article:** http://dx.doi.org/10.6007/IJAREMS/v13-i3/21899 DOI:10.6007/IJAREMS/v13-i3/21899

**Published Online:** 05 July 2024

**Abstract**

Data visualization plays a crucial role in helping business decision-makers comprehend supply and demand dynamics within business operations. Despite its importance, there is a notable gap in methods used to assess the usability of the knowledge presented through visualizations. To address this gap, a study has been conducted with a focus on tourism industry data stories. The study aims to achieve three primary objectives: to demonstrate how to identify and process data attributes, design data stories that link these attributes to uncover relational patterns, and evaluate the usability of these data stories on a dashboard. The study methods consist of three main stages: data gathering and treatment, iterative exploratory data analysis (EDA) to uncover significant patterns, and the development of data story design and knowledge modeling, followed by usability evaluation. Usability was measured in terms of learnability, efficiency, memorability, error rate, and user satisfaction. A dual method was used, incorporating both the “evaluating communication through visualization” technique (CTV) and a generic usability approach. This was done to measure whether the storytelling narration gives meaning to the visuals and to determine the relevance, consequences, and conclusions of the supply and demand data stories. The findings show that the usability scores ranged from 4.0 to 4.4 on a five-point Likert scale, indicating that respondents generally agreed or strongly agreed that the dashboard represented usable knowledge. The relationships between supply and demand in market segments were illustrated using a Sankey chart. The overall mean usability score was 4.61, with a usability evaluation score of 92%, indicating that the data stories and dashboard were significantly comprehensible to users. Future work involve integrating advanced mathematical models with real-time data visualization and usability assessment to optimize decision-making processes in supply chain management.

**Keywords:** Knowledge Representation, Data Stories, Supply and Demand, Tourism, Visualization

## Introduction

Data science (DS) combines computer science, mathematics, and statistics with domain-specific knowledge, for example, tourism knowledge, to gain insights from large sets of data (George et al., 2016). To represent the knowledge and insight, data visualisation has been used to aid comprehension to decision makers, and it can be represented in a two-dimensional or three-dimensional graph (Salleh et al., 2021). The visual representations in a form of charts simplify, accentuate, and quickly communicate important information stories (Khalid et al., 2020). These charts are typically displayed on a screen and integrated into an interactive page for operational purposes, as a dashboard. Despite just depicting a subset of the data, it reflects the whole set of stories of actionable data to facilitate users' gaining knowledge and making quick decisions (Few, 2006; Tableau.com, 2021).

Vsualization techniques play a crucial role in identifying usability issues (Buono et al., 2020). Relating to that, research highlights the significance of Usability Evaluation Methods (UEMs) in improving the usability of computer objects (Hertzum & Jacobsen, 2001). To effectively evaluate visualization usability, appropriate evaluation methods are essential. Specifically, methods tailored for assessing dashboard visualizations have successfully pinpointed both information visualization-specific and general usability issues (Dowding & Merrill, 2018). Adapting usability methods to dashboard visualizations has also proven advantageous in their evaluation and enhancement (Laurent et al., 2020).

Evaluation of visualization usability can be based on factors such as task completion time, task completion correctness, and user satisfaction. However, in this study, we employ another method that focuses on user satisfaction, encompassing overall user opinions regarding visualizations (Onyimbi et al., 2018). Additionally, we integrate testing on end user interpretation of the visuals. This integration of usability techniques can facilitate early identification of usability problems during development and enhance the validity of electronic assessments (Turner-Bowker et al., 2011). Given the relatively recent emphasis on data visualization, decision makers are still navigating this terrain, revealing a knowledge gap that needs attention. Thus, this article provides guidance to fill the knowledge gap, presents how data can be explored using a data science approach, and explains how to present the data stories in a visual form through dashboard design and essential visuals and presents on how the usability could be assessed.

This study uses an empirical approach with a prototype to demonstrate its findings. It focuses on the supply chain as a case study domain, where hotel booking, and demand datasets have been used in this study. It has been selected as the hotel needs to increase its business performance and provide excellent customer service using a technological approach, specifically by using data science analytics. Some of the hotel's customers are repeat customers. They make early reservations, and some of them stay in the hotel for long periods of time. The hotel business planners need to identify these customer booking behaviors as well as the business's performance on a monthly and yearly basis. Therefore, they require a dashboard to fulfill the customer's demands and improve business performance. In addition, as empirical social research methods have gradually professionalised tourism research, and DS methodologies are going to be utilised more frequently to further comprehend and resolve tourism challenges (Gretzel, 2022).

This study's objectives are: first, to present how to identify a data attribute and treatment; second, to identify and design data stories that establish a link between attributes to reveal patterns of the relationship; and third, to assess the usability of the data stories on the dashboard. The presentation of this paper is in the following format: it starts with the knowledge gap in the data science approach and the study objectives. Sections 2 and 3 present the literature review, methodology, and materials, respectively. Section 4 covers analyses and discussions, while the final section covers conclusions and future work.

**Review of Literature**

Data science, a powerful discipline at the forefront of extracting valuable patterns and knowledge from large datasets in the field of information and insights, employs advanced techniques. Data visualization is a component of data science that improves overall performance and transforms complex analytics into understandable insights. The goal is to effectively convey the outcomes, bridging the gap between technical competence and broader stakeholders (Salleh et al., 2021). Integrating charts on a single dashboard is a common and effective practice in data visualization, providing a comprehensive and centralized view of various aspects of data. A dashboard typically includes multiple charts and visualizations to convey diverse insights cohesively. The visual objects in it must assist users in comprehending the significance of the data by presenting it in a logical manner and allowing the user to select the level of data information needed (Costa, 2019). Dashboards are straightforward front ends for monitoring, analyzing, and optimizing important business processes, empowering users at all organizational levels to make better decisions (Jinpiang, 2020; Alwi, 2019).

Analysis of the supply chain of a hotel is important. With enough rooms available, the accommodation supply could have experienced the escalating pattern when the tourism sector was acknowledged (Mohamad et al., 2020). In addition, Azmadi et al (2023) also mentioned the importance of embracing smart tourism initiatives, which can significantly enhance tourist satisfaction, happiness, and revisiting intention, ultimately benefiting the tourism industry. Antonio (2019) examined hotel booking cancellations in his research, focusing on the impact of hotel demand and forecasts. The purpose is to understand the booking and demand as well as reduce cancellation uncertainty. He showed a machine learning model that predicts booking cancellations, and a prototype was constructed for field tests. However, no data visualization was undertaken in this investigation.

To analyze hotel bookings and demand using data analytics and visualization, it is essential to consider various factors that influence customer behavior and booking patterns. The study by Vives et al (2018) provides insights into a demand function model for resort hotels, measuring own-price elasticities and seasonal demands across booking horizons. This model can be utilized to understand the price sensitivity of customers and optimize pricing strategies. Furthermore, Wang (2021) presents an intelligent passenger flow prediction method for hotel operations using a deep learning model based on historical booking demand datasets. This approach can be valuable in forecasting the number of monthly arrival bookings, aiding in capacity planning and resource allocation. According to Suman's (2021) tourism research, internet purchases of travel-related products and services via web channels have grown at an unparalleled rate. He conducted a study that exami'ed how the quality of information provided on hotel websites influences consume's' online booking intentions and how trust as a mediator influences customer online bo'king intention. The results revealed a significant and positive relationship between information quality and users' online hotel booking intentions, while the relationship between source credibility and on'ine hotel booking intentions was found to be insignificant. Satu et al (2020) did a study on hotel booking cancellation and found that it has a significant impact on demand management decisions in the hospitality industry. The purpose of this research is to investigate the effects of various machine learning approaches on the cancellation of hotel reservations. Dowding & Merrill (2018) introduce a heuristic evaluation checklist tailored for assessing systems generating information visualizations. Drawing from Nielsen's heuristics and prior research on information visualization, the checklist amalgamates principles to effectively evaluate such systems. They highlighted that the usability heuristic checklist for evaluating information visualization systems holds significant promise in ensuring the high quality of electronic data systems developed for healthcare.

**Materials and Methods**

There were five steps involved in this study: understanding the nature of the business, data gathering and treatment, visualization design and development, and usability evaluation. Figure 1 depicts the overall steps. The dataset used in this study is a hotel booking and demand dataset obtained from Kaggle.com (Kaggle.com, 2021). For this study, the scope of the data has been reduced by focusing on four countries that are less than 2,000 kilometers away from Portugal, namely Ireland, Italy, Spain, and France. The original dataset consisted of 119,390 records with 32 attributes. After a thorough cleaning, only 26,124 records were used from four countries for the years 2015–2017, and from the 32 attributes, only 29 relevant attributes have been selected, including 3 attributes that have been merged. Attributes used in this project are as follows: types of hotels that are available; countries selected; customer types of booking; date of expected arrival for the customer; room type reserved; type of meal booked; market segment; and booking distribution channel.

The first step began with understanding the nature of the data set, the business process, and the data profile by identifying data types and their descriptions. Data types such as numerical, categorical, ordinal, and nominal require different handling and visualization approaches depending on their nature.

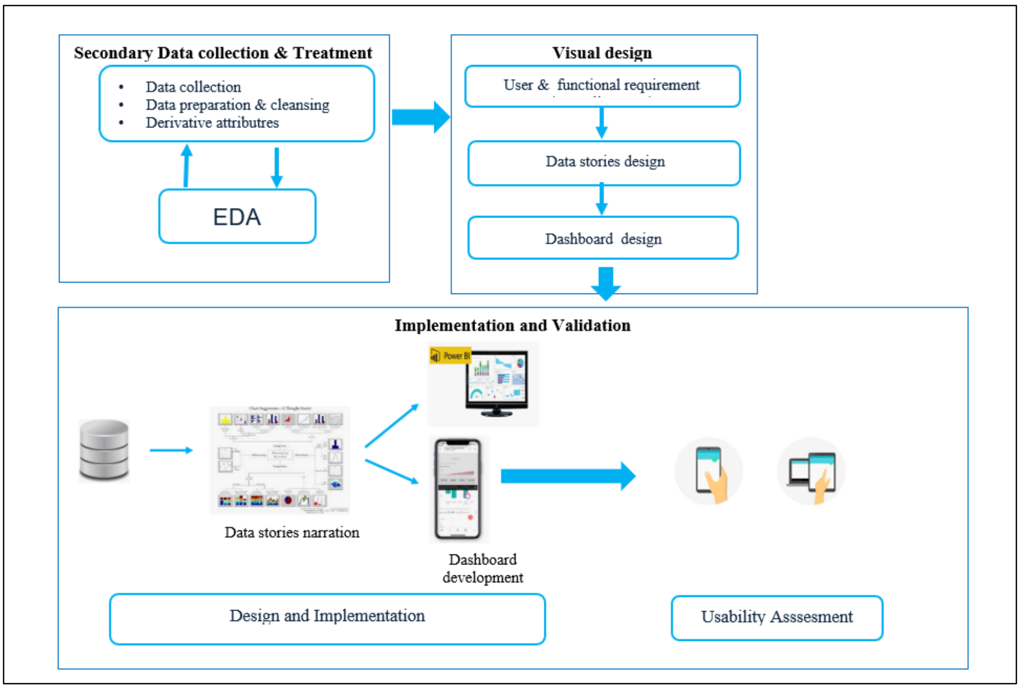


Figure 1. Research Flow

Based on this, the exploration's objectives have been defined as identifying the customer category of two hotels, plotting a pattern of relationship between the meal and the reserved room type, and identifying market segments based on booking channels. Next, an exploratory data analysis (EDA) task has been executed with the purpose of identifying basic data patterns for each attribute. At the same time, it also helps in finding outliers, missing values, and errors in data values. In addition, the relevance of the data value of certain attributes may also be better understood by researchers with the help of simple charts, such as line or bar charts.

The second step was data preparation, which included cleansing and treatment as well as combining, structuring, and organising the data. In this process, data has been cleaned up by removing unnecessary or null values. It also includes resolving errors if data value errors are encountered, as that will improve the quality of the visuals. At this stage, the EDA needs to be done repeatedly, some relationships can be projected, and thus derivative attributes need to be generated. At the same time, data issues were identified, such as the attribute arrangement becoming fuddled and disorganized, as well as missing values when no value was recorded for the variable. Irrelavant attributes were removed, and a new derivative attribute was added to the dataset. The function of derivative attributes is to provide additional insights, enhance the models, or simplify the representation of the data.

Continuing with the third step, which imposed datastory design and modeling, this involves the creation of visual objects, as the selection of the right charts is very important in giving an accurate representation of the data. For example, only the important attributes that contribute to a single narrative that relates to the datra story objectives should be displayed on a dashboard.

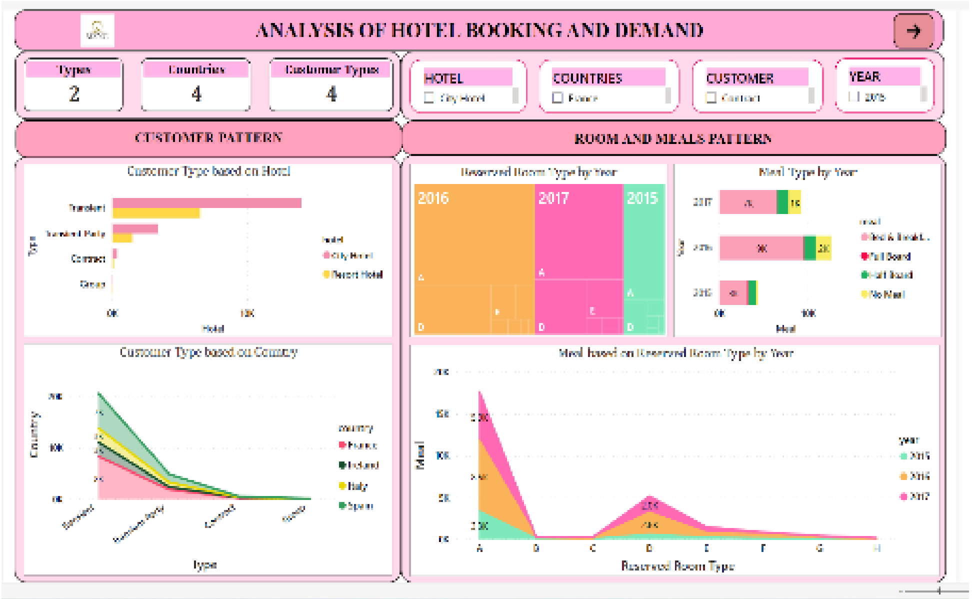


Figure 2. Screenshot of the dashboard

Objects in the dashboard were arranged based on Gestalt principles on each page, as this was done to avoid jumpy flow and misinterpretations (Mungan, 2020; Paceko, 2022). The descriptive statistics of the supply chain transaction are indicated by booking and demand transactions were visualize by four charts that correspond to them, whereas the market segment analysis is presented by the Sankey chart. Narration of each visual are described in Table 1.

Table I

*Purpose and Narration of Sankey Chart*

| No | Title of Charts | Narration | Purpose |
|---|---|---|---|
| 1 | Customer type based on hotel | This chart contains two attributes: customer type and hotel. There are four different types of customers: contract, group, transient (temporary), and transient party. | To display the types of customers that have made bookings based on two different types of hotels. |
| 2 | Customer type based on country | This chart contains two attributes: customer type and country. There are four different types of customers: contract, group, transient (temporary), and transient party. | To show the types of customers who have made the booking based on four types of countries. |
| 3 | Reserved Room Type by Year | In this chart, there are two types of attributes: reserved_room_type and arrival_date. There are eight different reserved room types, which consist of A, B, C, D, E, F, G, and H. | To analyze which type of room has been reserved by customers for three years. |

| | | | |
|---|---|---|---|
| 4 | Meal Type by Year | This chart contains two attributes: meal and arrival_date. Several types of meals can be booked by the customers and come with the packages, which are bed and breakfast (BB) and full board (FB). | To show the type of meal that has been booked based on three different years, which are 2016, 2017, and 2018. |

The final step is the assessment of the usability and comprehension of visual objects. The prototyped dashboard has been used in the usability evaluation exercise, and the screenshot of the prototype is shown in Figure 2. This has been carried out by conducting a post-study system usability assessment adapted from Khalid et al (2020) combined with a technique namely "evaluating communication through visualization" (CTV) (Enrico, 2011; medium.com, 2021). The main goal of any storytelling narration is to give meaning to the visuals and figure out the relevance, consequences, and conclusions. The test used a Likert scale on a 5-point scale, where 0 to 5 indicates strongly disagree, neutral, agree, and strongly agree, respectively. The respondents had been given a set of questionnaires, and in the last part, there were three writing tasks chosen at random on storytelling narration. The usefulness of a system is defined as its ability to be easy to use and discover, as well as its ability to execute tasks productively and effectively. In this study context, usability refers to the degree of user-friendliness and effectiveness in interacting with the dashboard. It encompasses factors such as learnability, efficiency, memorability, error rate, and user satisfaction. There were 30 respondents who were familiar with data visualization and dashboard operations who took part in the evaluation. Apart from providing feedback on the usability features, they were given three activities to complete. One of the interesting findings illustrated in the Sankey chart, as shown in Figure 3, It shows the relationship between the market segment related to the distribution channel and two types of hotels.

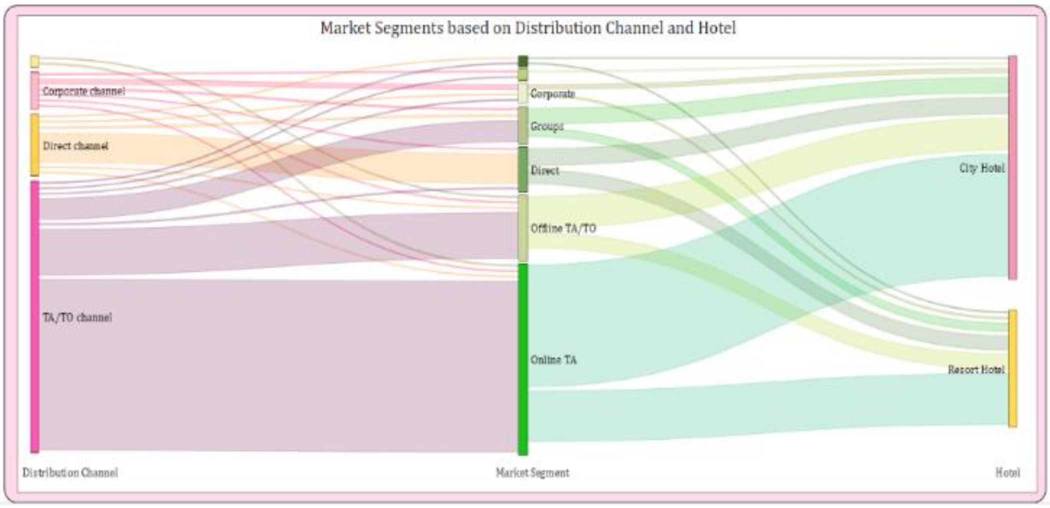

Figure 3. Relationship between the market segment and two types of hotels

The thickness of the stream represents the number of records it contains within the flow. A market segment is a collection of individuals grouped based on marketing objectives. There are four types of distribution channels where the customer supplies: the GDS channel, direct channel, corporate channel, and travel agent or tour operator (TA/TO) channel, while there are seven types of market segments: complementary, aviation, corporate, groups, direct, offline TA/TO, and online travel agent (TA). The sankey chart shows that the TA/TO channel supplies the most customers, followed by the direct channel and the corporate channel. The GDS channel supplies the least number of customers. Next, online TA is the highest in the market segment, while complementary is the least compared with others. Thus, the city hotel has the highest demand compared with the resort hotel. It can be concluded that the customers from TA/TO are the most likely to be from the online TA market segment, and most of them book the city hotel. For the CTV exercise, this sankey chart has been used as task no. 3 in the usability exercise. The result of the evaluation shows that almost every respondent described the storytelling narration comprehensively, as the score is 4.9. A highly usable design ensures that users can easily understand, navigate, and accomplish tasks with minimal effort, reducing errors and enhancing overall satisfaction. Usability evaluation has been conducted and is aimed at measuring the satisfaction, learnability, memorability, efficiency of users as well as the error rate.

TABLE 2
*Result of the usability test*
(Adapted from Khalid et. al and CTV approach (adapted from Bertini et. al and Salleh et. al )

| No | Constructs | Item | | n = 30 | | | |
|---|---|---|---|---|---|---|---|
| | | | | Mean | Std Dev | Min | Max |
| 1 | Satisfaction | The dashboard is necessary and beneficial for identifying the booking pattern. | | 4.2 | 0.8 | 3 | 5 |
| 2 | Learnability | The dashboard has been clearly designed in achieving the goal of analysis. | | 4.1 | 0.8 | 3 | 4 |
| 3 | Satisfaction | I am satisfied with the design and features. | | 4.1 | 0.6 | 3 | 5 |
| 4 | Learnability | The data visualisation in the dashboard was clear and straightforward. | | 4.5 | 0.7 | 3 | 4 |
| 5 | Learnability | The data visualisation assists users in understanding pattern and issues. | | 4.3 | 0.7 | 3 | 4 |
| 6 | Memorability | User can complete the given task by utilising the information depicted in the visuals. | | 4.3 | 0.7 | 3 | 4 |
| 7 | Efficiency | It was easy to find the data/information required by given task. | | 4.5 | 0.5 | 2 | 4 |
| 8 | Memorability | The interface was pleasant to use. | | 4.2 | 0.8 | 3 | 4 |
| 9 | Efficiency | It includes all the features and capabilities necessary. | | 4.2 | 0.7 | 3 | 4 |
| 10 | Satisfaction | In general, I'm pleased with the dashboard. | | 4.1 | 0.8 | 3 | 4 |
| 11 | Error Rate | There are fewer than three errors made while using this dashboard. | | 4.0 | 0.5 | 2 | 2 |
| 12 | Efficiency | The features works very well and functioning as it is. | | 4.6 | 0.5 | 4 | 4 |
| | | Usability Average | | 4.3 | 0.7 | - | - |
| 13 | Usability using CTV approach | Can useful information be extracted from a casual information visualization ? | Task 1: Tree map | 4.9 | 0.3 | 4 | 5 |
| | | | Task 2: Area chart | 4.9 | 0.2 | 4 | 5 |
| | | | Task 3: Sankey chart | 4.9 | 0.2 | 4 | 5 |
| | | CTV Average | | 4.96 | 0.2 | - | - |
| | | Overal Mean | | 4.61 | 0.4 | - | - |

The evaluation is iterative to enhance the user experience, increase satisfaction, and ensure that the final design aligns effectively with user needs and expectations. The following results are obtained from the third cycle of the evaluation. The summary of the usability result is shown in Table 2. Figure 4 shows the overall result, where the average score is between 4.0 and 4.4, signifying that the respondents' answers were between agree and strongly agree. The average score for error rate, satisfaction, memorability, learnability, and efficiency is 4.0, 4.1, 4.3, 4.3, and 4.44, respectively.

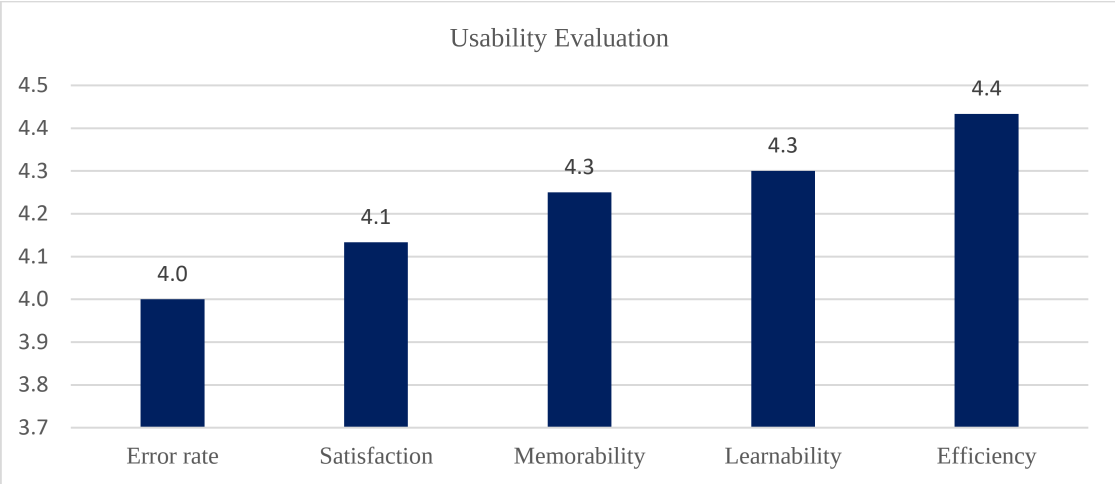


Figure 4. Overall Result for Usability Evaluation

This indicates that the data stories presented fulfill the usability requirements. The overall value for the standard deviation of 0.7 represents the datapoint's variations over a wide range of values. The overall mean that combined usability and CTV average is 4.5, nearing 5 points, indicating that respondents agree and strongly agree that the dashboard is usable in identifying hotel demand and booking patterns. The next assessment that adopted CTV shows an overall mean score of 4.97 with a standard deviation of 0.20, and this significantly shows that the respondents strongly agree that the visual objects can communicate the stories. Thus, the outcome of the story-telling narration tasks indicated that the users were able to comprehend the data stories. The overall mean score of both sections is 4.5, and this significantly shows that the dashboard provides the required features and that visual objects, or charts, communicate the stories. And overall, the outcome of the story-telling narration tasks indicated that the users were able to comprehend the data stories. With an overall mean of 4.61, approaching the maximum of 5 points, and a usability evaluation score of 92%, it is evident that users find the data stories and dashboard comprehensible and user-friendly.

The provided data presents the results of a user satisfaction survey and usability evaluation for a dashboard designed to analyze booking patterns. The constructs assessed include Satisfaction, Learnability, Memorability, Efficiency, and Error Rate. Overall, users reported high levels of satisfaction with the dashboard, with an average rating of 4.3 out of 5. Specific aspects contributing to satisfaction included the dashboard's necessity and benefit for identifying booking patterns, satisfaction with design and features, and general satisfaction with the dashboard. Learnability also scored well, with users finding the dashboard to be clearly designed for analysis purposes. Additionally, the data visualization was reported to be clear, straightforward, and assisting us'rs in understanding patterns and issues. Users also felt confident in completing tasks using the information depicted in the visuals.
Efficiency ratings were particularly high, with users finding it easy to locate the required data/information and stating that the dashboard included all necessary features and capabilities. The features were reported to work well and function as expected, contributing

to overall efficiency. Error rate was relatively low, with users reporting fewer than three errors while using the dashboard. Additionally, usability was assessed using the Cognitive Task Analysis (CTA) approach, which yielded positive results. Users found it easy to extract useful information from different types of information visualizations, with high ratings across tasks. Overall, the dashboard received positive feedback across various usability constructs, indicating its effectiveness in assisting users with analyzing booking patterns.

## Conclusion

This study stresses insightful data stories from extensive datasets and presenting them visually, business planners gain valuable insights. The construction and evaluation of a dashboard focused on hotel bookings and demand demonstrated a high level of usability. The findings affirm strong agreement among respondents regarding the dashboard's usability. Notably, the study's Sankey chart effectively illustrates significant relationships between supply and demand in different market segments. This underscores the effectiveness of data science-driven visualization tools in providing actionable insights for business planning in the dynamic landscape of the tourism industry. Future work includes integrating a machine learning module for precise supply chain predictions in tourism. This enhancement, maintaining the current dashboard's visual format, ensures user-friendly access to advanced analytics. The addition empowers business planners with real-time insights, fostering proactive decision-making and staying at the forefront of data-driven advancements in the industry. A comprehensive approach to evaluating visualization usability is imperative. This approach provides another perspective on usability evaluation, addressing the research gap in methodology. We contend that evaluation should incorporate specific usability evaluation methods that measure satisfaction and interpretation of users interacting with visualized data.

## References

Alper, S., Michael, C., Lyn B., Melanie T., & Danyel F. (2019). What Do We Talk About When We Talk About Dashboards? IEEE Transactions on Visualization and Computer Graphics, 25(1), January 2019. Https://Doi.Org/10.1109/Tvcg.2018.2864903

Azmadi, A. S. A., Abdul Hamid, M., Hanafiah, M. H., Hariani, D., & Shariffuddin, M. N. S. (2023). Measuring Tourist Preferences and Behavior Toward Smart Tourism Destination Planning. Planning Malaysia, 21(30). Https://Doi.Org/10.21837/Pm.V21i30.1405

António, N. M. C. (2019). Hotel Revenue Management: Using Data Science to Predict Booking Cancellations, Phd Thesis, Iul School of Technology and Architecture Department of Information Science and Technology).

Bertini, E., Lam, H., Perer, A. (2011). Summaries: A Special Issue on Evaluation for Information Visualization. Information Visualization, 10(3), 161-161.

Buono, P., Caivano, D., Costabile, M., Desolda, G., & Lanzilotti, R. (2020). Towards the detection of ux smells: the support of visualizations. Ieee Access, 8, 6901-6914. https://doi.org/10.1109/access.2019.2961768

Costa, C. J., & Aparicio, M. (2019). Supporting The Decision on Dashboard Design Charts. Proceedings of The 254th The Iier International Conference, Saint Petersburg, Russia, 10-15.

Dowding, D., and Merrill, J. (2018). The development of heuristics for evaluation of dashboard visualizations. Applied Clinical Informatics, 09(03), 511-518. https://doi.org/10.1055/s-0038-1666842

Few, S. (2006). Information Dashboard Design: Effective Visual Communication of Data. O'reilly Media.

George, G., Osinga, E. C., Lavie, D., & Scott, B. A. (2016). Big Data and Data Science Methods for Management Research. Academy of Management Journal, 59(5), 1493–1507. Https://Doi.Org/10.5465/Amj.2016.4005

Hertzum, M., and Jacobsen, N. (2001). The evaluator effect: a chilling fact about usability evaluation methods. International Journal of Human-Computer Interaction, 13(4), 421-443. https://doi.org/10.1207/s15327590ijhc1304_05

How To Efficiently Evaluate Information Visualization. (2022). Medium. Retrieved From Https://Medium.Com/Visumd/How-To-Efficiently-Evaluate-Information-Visualization-69bece7b30b1

Jianping, C., Ximeng, L., & Yingjie, W. (2020). Svm Learning for Default Prediction of Credit Card Under Differential Privacy. Workshop On Privacy-Preserving Machine Learning in Practice, 2020, 3 Pages.

Kaggle.Com. (2022). Retrieved From Https://Www.Kaggle.Com

Khalid, A. S., Hassan, N. H., Razak, N. A. A. B., & Baharuden, A. F. (2020). Business Intelligence Dashboard for Driver Performance in Fleet Management. Conference On E-Education, E-Business, E-Management, And E-Learning, 2020, P. 347-351.

Laurent, G., Moussa, M., Cirenei, C., Tavernier, B., Marcilly, R., & Lamer, A. (2020). Development, implementation and preliminary evaluation of clinical dashboards in a department of anesthesia. Journal of Clinical Monitoring and Computing, 35(3), 617-626. https://doi.org/10.1007/s10877-020-00522-x

Lawrence, K. D., Kudyba, S., & Klimberg, R. K. (2007). Data Mining Methods and Applications (1st Ed.). Crc Press.

Mohamad, D., Jaafar, M., & Ismail, M. M. (2020). Socio-Economic Carrying Capacity Assessment for Bukit Tinggi. Planning Malaysia, 18(13). Https://Doi.Org/10.21837/Pm.V18i13.779

Mungan. (2020). Gestalt Kuramı: Bir "Nazariye" Nin Mazisi, Akameti Ve Akibeti (Gestalt Theory: Its Past, Stranding, And Future). Nesne, 8(18), 585-618. Doi: 10.7816/Nesne-08-18-15.

Nik Alwi N. N. A., Hassan N. H., Baharuden F., Abu Bakar N. A., & Maarop N. (2019). Data Visualization of Supplier Selection Using Business Intelligence Dashboard. Proceeding Book: Advances In Visual Informatics, 6th International Visual Informatics Conference, Ivic 2019, Bangi, Malaysia, November 19–21, 2019.

Núñez-Pacheco, C. (2022). Applying Gestalt Laws Through Somatic Sensibility. Diseña, (20), Article.6. Https://Doi.Org/10.7764/Disena.20.Article.6.

Onyimbi, J., Koeva, M., & Flacke, J. (2018). Public participation using 3d web-based city models: opportunities for e-participation in kisumu, kenya. Isprs International Journal of Geo-Information, 7(12), 454. https://doi.org/10.3390/ijgi7120454

Salleh, S. S., Mohamed, N. S, & Shah, N. A. S. (2021). Simulating Data Stories of Clients' Credit Card Default, Application of Modelling and Simulation, Vol 5, 184 – 190.

Satu, M. S., Ahamed, K., & Abedin, M. Z. (2020). Performance Analysis of Machine Learning Techniques to Predict Hotel Booking Cancellations in Hospitality Industry. 23rd International Conference on Computer and Information Technology (Iccit).

Salleh, S. S., Shukri, A. S., Othman, N. I., & Saad, N. S. M. (2023). Data Stories and Dashboard Development: A Case Study of An Aviation Schedule and Delay Causes. Iop Conf. Ser.: Earth Environ. Sci. 1151 012049.

Lata, S. (2021). What Determines Tourist Adoption of Hotel Websites for Online Hotel Bookings? An Empirical Analysis by Taking E-Trust as A Mediator. International Journal of Asian Business and Information Management, 12(3), 1-17. Doi: 10.4018/Ijabim.294101

Tourism On the Verge. (2020). Electronic Issn 2366-262x, Print Issn 2366-2611, Series Editor Ulrike Gretzel.

Turner-Bowker, D., Saris-Baglama, R., Smith, K., DeRosa, M., Paulsen, C., & Hogue, S. (2011). Heuristic evaluation and usability testing of a computerized patient-reported outcomes survey for headache sufferers. Telemedicine Journal and E-Health, 17(1), 40-45. https://doi.org/10.1089/tmj.2010.0114

Vives, A., Jacob, M., & Aguiló, E. (2018). Online Hotel Demand Model and Own-Price Elasticities: An Empirical Application in A Mature Resort Destination. Tourism Economics, 25(5), 670-694. Https://Doi.Org/10.1177/1354816618800643

Wang, T. (2021). An Intelligent Passenger Flow Prediction Method for Pricing Strategy and Hotel Operations . Complexity, 2021, 1-11. Https://Doi.Org/10.1155/2021/5520223