A STUDY ON IDENTIFYING THE RELATIONSHIP BETWEEN PERSONALITY DIFFERENCES AND USER PREFERENCES IN VISUALIZATION TYPES FOR STORYTELLING REPORTING

BY

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ABSTRACT

The growth of big data analytics has led to the widespread use of data or information visualization (InfoVis) and storytelling in various industries, such as finance, sports, and education. This process involves turning data, information, and knowledge into interactive visual representations that can effectively communicate a meaningful story. Successful InfoVis reports in big data analytics should be both technically accurate and useful for decision-makers. Previous research has found that a person's personality can influence their preference for InfoVis. While InfoVis tools have become more user-friendly over the years, they have often followed a one-size-fits-all approach, ignoring individual differences. There is limited research on how individual characteristics and visualization-type preferences for storytelling can be considered InfoVis tools. This study aims to explore the relationship between personality and preferences for different visual elements in visualizing and storytelling, such as hierarchical visualization, changes over time, and comparison visualization, among university students in one institution. These visual designs are commonly used in modern research and may be related to personality. The study will use a personality trait test to measure the participants' personalities and a questionnaire to assess their preferences in visualization types for information visualization and data storytelling. This study reveals a significant association between individual personality traits and the specific sorts of visualizations favored by users for narrative purposes. The results of this research may help to address the one-size-fits-all problem in InfoVis tools and provide insights that can be used in the design process to help analysts or designers select the best graphical visualizations for specific target groups, improving understanding and decision-making.

ABSTRACT IN ARABIC

لقد أدى نمو تحليل البيانات الكبيرة إلى استخدام واسع لتصور البيانات أو المعلومات (InfoVis) وفن السرد في مختلف الصناعات، مثل التمويل والرياضة والتعليم. تتضمن هذا العملية تحويل البيانات والمعلومات والمعرفة إلى تمثيلات مرئية تفاعلية يمكنها أن تحكي قصة ذات معنى بشكل فعال. يجب أن تكون التقارير الناجحة في تصور البيانات (InfoVis) في تحليل البيانات الكبيرة دقيقة من الناحية الفنية ومفيدة لصناع القرار. أظهرت الأبحاث السابقة أن شخصية الفرد يمكن أن تؤثر في تفضيله لتصور البيانات (InfoVis). في حين أن أدوات تصور البيانات أصبحت أكثر سهولة في الاستخدام على مر السنين، إلا أنها غالبًا ما اتبعت نهجًا واحدًا يناسب الجميع، متجاهلة عن الاختلافات الفردية. هناك أبحاث محدودة حول كيفية النظر في خصائص الأفراد وتفضيلات نوع التصور لسرد القصص في أدوات InfoVis. تهدف هذه الدراسة إلى استكشاف العلاقة بين الشخصية وتفضيلات العناصر البصرية المختلفة في التصور والسرد القصصي، مثل التصور الهرمي، والتغيرات مع مرور الوقت، وتصور المقارنة، لدى طلاب الجامعة في مؤسسة واحدة. تُستخدم هذه التصميمات المرئية بشكل شائع في الأبحاث الحديثة وقد تكون مرتبطة بالشخصية. ستقوم الدراسة باستخدام اختبار السمات الشخصية لقياس شخصيات المشاركين واستبيان لتقييم تفضيلاتهم في التصور لتصور المعلومات وسرد البيانات. تكشف هذه الدراسة عن ارتباط كبير بين سمات شخصية وأنواع معينة من التصور المفضلة لدي المستخدمين لأغراض السرد. قد تساعد نتائج هذا البحث في التعامل مع مشكلة نهج "مقاس واحد يناسب الجميع" في أدوات InfoVis وتوفير رؤى يمكن استخدامها في عملية التصميم لمساعدة المحللين أو المصممين على اختيار أفضل التصورات الرسومية لمجموعات مستهدفة محددة، مما يحسن الفهم واتخاذ القرار.

APPROVAL PAGE

I certify that I have supervised and read this study and that, in my opinion, it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Master of Computer Science Technology.

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DECLARATION

I hereby declare that this dissertation is the result of my own investigations, except where otherwise stated. I also declare that it has not been previously or concurrently submitted for any other degrees at IIUM or other institutions.

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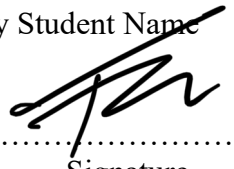

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3/1/2024 …….. Date

This thesis is dedicated to my parents for laying the foundation of what I turned out to be in life.

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All glory is due to Allah, the Almighty, whose Grace and Mercies have been with me throughout my programme. Although it has been challenging, His Mercies and Blessings on me ease the herculean task of completing this thesis.

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LIST OF ABBREVIATIONS

FFM	Five Factor Model
HCI	Human Computer Interaction
InfoVis	Information Visualization
MBTI	Myers-Briggs Type Indicator
UI	User-Interface

LIST OF PUBLICATION

TITLE	PUBLISHER	PAPER
A Review on The Visual Design Styles in Data Storytelling Based on User Preferences and Personality	IEEE	2022 IEEE 7th International Conference on Information Technology and Digital Application (ICITDA)
Human Factors Visualization and Storytelling Design Questionnaire: Validity and Reliability Tests	RMP Publication	Journal of Engineering and Science Research 6 (6)
Visual Design Elements for Data Storytelling Based on Personality Traits: A case of Undergraduate	JATI Asia Pacific University	Journal of Applied Technology and Innovation vol. 7, no. 1
Personality Differences and User Preferences in Visual Design Styles for Data Storytelling: A Work in Progress	MyHCI-UX	Conference: Proceedings of 3rd National Symposium on Human-Computer Interaction
Investigating User Preferences Towards Visualization Types with a Focus on Neuroticism and its Implications on Mental Health	Cosmos Scholars Publishing House	International Journal of Membrane Science and Technology

CHAPTER ONE

INTRODUCTION

1.1 INTRODUCTION

The first chapter of this thesis explains the research issue, including the study's history and an explanation of the notion of data storytelling for information visualization. It also looks at the connection between personality qualities and information visualization. The chapter then covers the issue statement, research goals, research questions, research hypotheses, and the study's importance and limits. Finally, the chapter finishes with a summary of how the remainder of the thesis is organized.

1.2 BACKGROUND OF THE STUDY

In today's society, when the value of information is deemed similar to that of gold, the usage of information visualization has grown more crucial (Tripp, 2019). This approach is used in many fields, including business, education, engineering, and technology, and educational institutions must adopt it in order to adapt to the changing landscape of information communication and technology (Petrovich, 2020). Bakken (2007) defines information visualization as the gathering, analysis, and comparison of data in order to effectively explain complicated concepts and uncover relevant patterns.

The ubiquitous availability of information has substantially risen in the digital age, prompting firms to take a data-driven strategy and often use visualization methods to present information (Knaflic, 2016). These efforts, however, may be ineffectual if the target audience does not comprehend the visualization or if it promotes bias via the use of colors or style. Understanding the users and their psychology is required to successfully interpret information offered via visualization (Zanan M. & Sheikh Abdul Aziz, 2022). This study looks at the user's personality and preferences in terms of visualization types, as well as the relationship between visualization and storytelling, as well as the effects of personality, to gain insight into how people with different personalities approach and interpret visual information.

Despite a lengthy history of information visualization research, few studies have looked at the association between personality qualities and information visualization (Gonc, 2020). The majority of personality study in this topic has taken place in other fields, such as engineering (Capretz & Ahmed, 2010; Cruz, Silva, & Capretz, 2015; Schmidt, Wittmann, & Wolff, 2019; Shameem, Kumar, & Chandra, 2017). For example, Russo and Stol (2020) used the HEXACO model, which is an updated version of the Five Factor Model (FFM) that incorporates an extra characteristic, Honesty-Humility (Lynam & Crowe, 2020), to perform a survey research to evaluate gender differences in the personality traits of software engineers. The study's findings revealed that women scored higher in honesty and humility, a quality that is favorably associated to work and team performance, as well as Emotionality and Openness to Experience. These results may assist software firms forecast new employee job and team performance based on gender and personality, as well as advise judgements about whether personnel are most suited for new endeavors (Russo & Stol, 2020). Unlike earlier studies, this study looks at the link between users' personalities based on the FFM model and their preferences for information visualization and storytelling.

A substantial amount of study has been conducted on personality and its influence on numerous sectors such as engineering, architecture, education, and others. These results, however, may be applicable to the domains of information visualization and narrative. Ferreira and Langerman (2014), for example, performed research on the link between personality type and individual performance on an information technology project. To investigate this association, they employed the Myers-Briggs Type Indicator (MBTI) personality evaluation and the Belbin Team Roles assessment instrument. The Belbin Team Roles evaluation yields findings based on responses to questions that highlight the strengths and weaknesses of individual team members (Vaida, 2019). According to the findings of the research, most business analysts have similar personality qualities, while developers have distinct ones. Business analysts and developers share comparable personality qualities in certain circumstances (Ferreira & Langerman, 2014). This study reveals that individuals have varied personality types depending on their work environment, but there may be certain common trends, such as business analysts being more extroverted and developers having distinct personality features, that are relevant to the current study. Another research was done to study the

relationship between players' personality and game behavior (Wang, Sapienza, Culotta, & Ferrara, 2019). The research find out personality and behavior in role-base are heavily correlated with each other.

Understanding users may help with information visualization analysis and the design of the narrative process. The ability to tell stories with data is becoming increasingly valuable in the world of data-driven decision-making, as effective information visualization can significantly influence the success of communication efforts such as presenting impactful research findings, raising funds for non-profit organizations to help the needy, or presenting data or information to a company board (Knaflic, 2016). Stories, in addition to being an efficient method of presenting facts, can offer an effective means of packaging knowledge and expertise in a manner that others can grasp (Kosara & MacKinlay, 2013).

The purpose of this research is to investigate the relationship between people's personalities and their preferences in information visualization and data storytelling. Data storytelling enhances visualization by providing context, engaging in audience with relatable narratives, simplifying complex information and evoking emotions and understanding this link allows business intelligence tool software makers to better customize their offerings to various sorts of consumers. Furthermore, this study might help professionals and academics in psychology and data analytics understand how personality characteristics and preferences effect information visualization and storytelling. The findings of this research may also aid analysts in selecting the most effective graphical depiction for a certain audience in order to improve comprehension of the material.

1.3 STATEMENT OF THE PROBLEM

In order to quickly analyze and make decisions based on large amounts of information, data visualization has become increasingly popular due to the proliferation of data production (Gatto, 2015). However, in order to successfully transmit information, visualization must be adapted to the target audience. Poorly constructed visualizations, which may be deceptive or confusing owing to the usage of color schemes or layout, might obstruct the audience's comprehension of the contents being delivered. The

purpose of this study is to investigate the link between users' personalities and their preferences for visualization forms in order to better understand how various personalities approach and interpret visual information.

Researchers have resorted to information visualization as a technique of efficiently presenting this information to people as the volume of digital information continues to expand (Tong et al., 2018). Toker et al. (2013) state that information visualization helps people grasp and make sense of enormous volumes of data, transforming it into knowledge and understanding. While there are numerous information visualization solutions on the market, these systems sometimes suffer from a "one-size-fits-all" approach that ignores diversity in user personalities (Gonc, 2020). This may result in a lack of customization for customers, the provision of unnecessary services, and the loss of custom design potential. Furthermore, the uniform approach sometimes overlooks the importance of personality in information visualization and narrative, resulting in a gap between consumers and designers. Personalized visualizations, on the other hand, offer the ability to mitigate some of the reported detrimental consequences of dashboards and visual analytics (Echeverria et al., 2018). According to research in this visualization field, individual users' cognitive styles and the kind of visualization are crucial aspects in determining its success (Ziemkiewicz et al., 2012). However, the use of individualized visualization tools is still in its early stages and has not been generally accepted.

Previous research has attempted to address the issue of personalized visualization by studying the memorability of users' visualizations (Borkin et al., 2013, 2016; Bryan et al., 2020) and using eye-tracking tools to classify users' characteristics, task difficulty, and visualization types (Blascheck et al., 2014; Bryan et al., 2020; Echeverria et al., 2018; Lallé et al., 2015; Toker et al., 2013). However, research on how personality preferences impact information visualization and narrative choices from a design standpoint is lacking. While performance measurements like speed and accuracy are crucial, human variables like personality are equally important since they persist throughout adulthood. Some intriguing studies on the association between personality characteristics and information visualization (Gonc, 2020) and narrative might be investigated further.

This study will look at how personality influences user preferences for different styles of information visualization and storytelling. This involves investigating the influence of personality on preferences for various forms of graphical representations, such as hierarchy, development through time, and comparison contexts, which have recently been extensively employed in research (Gonc, 2020; Liu et al., 2020). Furthermore, this work extends earlier research by investigating how narrative aspects might be included into graphical representations as a novel approach of visualizing knowledge. As a result, this study looks at a broader spectrum of visualization design approaches associated to narrative.

1.4 RESEARCH QUESTION

The research questions for this study are designed to help understand the differences in personality types of users and their preferences for visualization types in information visualization and storytelling reporting. These research questions are:

1. What are the visualization types preferred by the users for information visualization and storytelling reporting?
2. Do personality factors connect with user choices in information visualization and narrative reporting visualization types?
3. How to create more compelling data visualization and narrative reporting for users?

1.5 RESEARCH OBJECTIVES

The primary purpose of this study is to look at the link between personality factors and user preferences for different styles of visualization in information visualization and storytelling. The goal is to discover how personality impacts preferences for meaningful, effective, and efficient visualizations and narrative reports that help people make informed choices.

The specific objectives of this study are threefold:

1. To discover the visualization types preferred by the users for information visualization and storytelling reporting.

2. To investigate the personality differences that may influence user preferences when choosing visualization types for information visualization and storytelling reporting.
3. To provide a set of criteria for visualization designers to follow in order to create relevant information visualization and narrative reports for users.

1.6 SIGNIFICANCE OF STUDY

This study has the potential to solve the shortcomings of the "one-size-fits-all" approach that is now prevalent in many visualization tools. Personalization of information visualization has been found to increase user experience and satisfaction by adapting it to individual requirements, abilities, and preferences (Lallé & Conati, 2019). According to research, personality influences how people engage with visualizations (Gonc, 2020). This study may assist to incorporate personality-based customization into InfoVis and storytelling tools, boosting their efficacy and efficiency, by analyzing the link between personality and user preferences for visualization styles in information visualization and storytelling.

This study may also lead to a better understanding of personality differences and user preferences for information visualization and narrative in the user interface (UI) design of visualization tools. This knowledge may be valuable to software developers from firms such as Microsoft Power BI and Tableau, as well as other visualization tool providers, in modifying their services to respond to the personality peculiarities of their consumers. Developers may make their software more versatile and avoid the "one-size-fits-all" approach by offering a variety of features and settings that cater to diverse personalities. Because visualization is often used to help complicated thinking and decision-making, developing such flexible visualization systems may be difficult. A successful adaptive solution, on the other hand, may considerably increase a user's capacity to accomplish a range of activities (Liu et al., 2020).

This study has the potential to bridge the gap between personality and visualization-type approaches, especially in terms of user preferences. It outlines many study gaps in personality type, information visualization, and data storytelling. Much of

the research in this area has been focused on other fields, such as engineering (Celiktutan & Eyben, 2014; Pieterse et al., 2018; Salleh et al., 2011; Yilmaz & O'Connor, 2012), management (Wu, Zhou & Chen, 2011), education (Alhathli et al., 2017; Rocha et al., 2018; Yan, 2010), and gaming (B This research seeks to address this void by studying the link between personality type and new information visualization and storytelling methodologies, as well as how personality type influences choices while engaging with information visualization and storytelling activities.

Finally, this study might have ramifications for design education. The interpretation of visualizations is critical to their effectiveness, and there is growing interest in the human factors of learning analytics visualizations, particularly given evidence that teachers may struggle to interpret them due to differences in perspective between designers and instructors. Learning dashboards have also been shown to be demotivating for students (Echeverria et al., 2017). Teaching and learning activities that use visualizations may be made more successful by knowing personality characteristics and preferences. Instructors, for example, may develop visualizations for teaching reasons that cater to the preferences of various personalities, and designers can include customization capabilities in their tools to assist instructors and students better comprehend visualizations and achieve meaningful outcomes.

1.7 Limitations of the Study

There are a multitude of possible restrictions inherent in this scientific endeavor. One notable limitation is the dearth of prior scholarly investigations pertaining to the subject matter. As previously stated, conventional visualization tools have always adhered to a uniform design paradigm, disregarding the inherent diversity in user personalities and preferences. Personality plays a significant role in influencing user conduct, and integrating personality traits into visualization tools might potentially address the issue of a standardized approach. Nevertheless, there exists a dearth of scholarly investigations pertaining to the correlation between personality traits, the field of information visualization, and the practice of storytelling.

Another major constraint is the restricted availability of data. The ongoing COVID-19 epidemic has presented challenges in doing in-person data collecting,

necessitating a transition to online methodologies by researchers. This might potentially lead to some samples encountering challenges related to internet connectivity or communication while doing data collecting. Furthermore, it is plausible that the ongoing epidemic has had an impact on the behavior and preferences of the participants, thus introducing a confounding factor that might alter the outcomes of the study.

1.8 MOTIVATION OF STUDY

The existing body of literature on the correlation between users' personalities and their preferences for information visualization and narrative strategies is currently minimal. The comprehension of this correlation has the potential to yield significant ramifications for the human-computer interface (HCI) sector, enabling designers to develop visualization reports that are more efficacious in facilitating decision-making throughout diverse sectors, such as business and education. This study has significant potential for enhancing the businesses of mobile and web developers. Additional investigation in this domain has the potential to provide significant knowledge about the development of customized visualization tools that effectively address the specific requirements and inclinations of users. For instance, the government may use this study as a point of reference for their official web development endeavors, with the aim of tailoring the user experience to align with individual personalities.

1.9 ORGANIZATION OF THE THESIS

This thesis is divided into five chapters. Chapter 1 serves as an introductory section that elucidates the contextual framework of the study, while also expounding upon the research aims, research questions, and the consequential importance of the study. In Chapter 2, an extensive examination is conducted on the existing body of research pertaining to personality, specifically focusing on the Five-Factor Model (FFM). Additionally, the literature on information visualization and narrative is thoroughly reviewed. In Chapter 3, an account is provided of the study design and methodology used to examine the research hypothesis. This encompasses the sampling strategy, questionnaire development, data collecting procedures, and the technique adopted for data analysis. In Chapter 4, the focus is on the validation of the questionnaire and reliability testing, along with the procedures involved in data collecting and processing.

In Chapter 5, the findings of the data collection are presented and an analysis is conducted to examine the correlation between individual personality variations and the various styles of visualization. Additionally, the article addresses the constraints of the study and offers suggestions for future investigations.

CHAPTER TWO

LITERATURE REVIEW

2.1 INTRODUCTION

This chapter examines the relevant literature and research on personality using information visualization and narrative strategies. The chapter begins with a description on the information visualization, data storytelling and personality which further explain the Five-Factor Model (FFM) and the approaches employed in the prior study.

2.2 INFORMATION VISUALIZATION

Data are facts, statistics, and other bits of information that are gathered and evaluated to derive useful insights and guide decision-making. Data analysis, according to Fei (2017), entails using analytical approaches to identify possible hints, reliable facts, and probable results from data. The importance of data analytics in today's digital era has led to the creation of information visualization, which includes the graphical depiction of data and information (Zanan M., Sheikh Abdul Aziz, 2023). Examples of data visualization date back to ancient maps such as the Ptolemy map (200 AD) and the Homero map (900 BC) (Tripp, 2019). The use of visualization to transmit information can be traced all the way back to World War II, when propaganda operations in the form of comic books targeted young adults and teenagers with heroic characters such as Captain America, Superman, and Batman (Scott, 2007).

Visualization is often used to improve analytical thinking via the introduction of interactive visual interfaces (Green & Fisher, 2010). In today's world, it is a commonly used technique with diverse applications in disciplines like as economics, education, and storytelling. Humans tend to put a high value on what they see, which leads to a belief in the veracity of visual information (Hepworth, 2016). As a consequence, the area of information visualization, which includes using powerful computer graphics to analyze and display complicated data sets through the human visual system, has grown in importance (Laramee, 2014). Furthermore, HCI research

has shown that personality factors may strongly impact people's choices for visual interface design (Ziemkiewicz, Ottley, Crouser, Chauncey, Su, & Chang, 2012). The findings reveal that the usefulness of visualization is affected by both the cognitive type of the person and the visual design. Cognitive characteristics such as perceptual skills, spatial abilities, linguistic ability, and working-memory capacity, which vary greatly across people, may have a substantial influence on reasoning.

Information visualization provides four primary functions. The first is to convey a general knowledge of a dataset, so that the viewer is aware of what is and is not known about the data. Ziemkiewicz, Ottley, Crouser, Yauilla, Su, Ribarsky, and Chang (2013) investigated the association between visualization structure and locus of control, as well as other personality factors, in a study. Participants were instructed to explore and infer questions regarding data provided in four distinct hierarchical display frameworks. Participants with an internal locus of control performed slower on inferential tasks but just as quickly on search tasks as those with an external locus of control. The study has shown that visualization may be effective in distinguishing between internal and external locus of control, as well as the difficulties that people may have when utilizing various visualization interfaces.

The second goal of information visualization is to find patterns in a dataset. Individuals may uncover what they are looking for and perhaps find new insights by studying patterns, frequencies, and structures within the data. Doshi, Nadkarni, Ajmera, and Shah (2017), for example, used TweetAnalyzer to extract real-time Twitter data and show trending hashtags and active users on a bar graph in a research on Twitter trends. The findings demonstrated that the tool was capable of identifying patterns and trends in Twitter activity, which may be used to a variety of real-world situations such as news, job hunting, and career counselling (Doshi et al., 2017).

The third goal of information visualization is to modify the degree of abstraction of a dataset in order to vary the angle from which it is seen. For example, previous study resulted in the development of ElectrAus, a tool that shows publicly available information from the Australian energy sector. According to the researchers, making complicated financial market data more understandable for the general public may make

it simpler for individuals to get knowledge and information (Lugmayr, Lim, Hollick, Chan, & Khuu, 2019).

The fourth goal of information visualization is to connect the visual representation of a dataset with the viewer's mental model. This may be accomplished via the use of metaphors, which allow for a precise mapping of facts to the viewer's prior knowledge and understanding. Schreder, Windhager, Smuc, and Mayr (2016) discovered that political information visualization can potentially be misused to distort the interpretation of reality, beyond the well-known "lie factor" that measures the manipulation of data effects, in a study examining the theory of mental models and their implications for the design and development of InfoVis interfaces. Mental models, which are dynamic representations of a system's goal, form, function, and state (Jones et al., 2011), are used to define and explain domain-specific learning and understanding processes. They are not fixed, but rather allow for system prediction and explanation.

Data exploration and analysis have been a key focus of visualization tools in recent years (Segel & Heer, 2010). Spreadsheet and visualization tools may aid in the analytical process and make visual encoding easier. Information visualization is often advertised for its capacity to reveal hidden insights and data tales, and it is intended to allow for a broad variety of findings and viewpoints.

Previous research has largely focused on performance indicators such as speed and accuracy in the use of visualization tools, according to Alves, Ramalho, Goncalves, Gama, and Henriques-Calado (2020), but user preferences have also been identified as an important factor in improving visualization software interfaces (Alves et al. 2020). User preferences may be used by visualization tool developers to guide the design and setup of visualization interfaces (Ko & Liu, 2019). Alves et al. (2020) discovered that individuals with Neuroticism disliked line charts with points, whereas those with high and medium extraversion preferred sunburst visual designs in the hierarchy category in a study examining the relationship between user preferences and personality type concerning visual design. Those with high conscientiousness chose line charts with points, but those with low conscientiousness preferred sunburst charts. These results imply that including personality traits into the design of visualization frameworks might aid in the development of user-friendly interfaces.

Yang, Zhou, and Li did research in 2014 to create an automated visualization framework that assists users in combining numerous knowledge visualizations into an integrated perspective and serves as a basis for creating the system. The researchers collected data from 50 people in 10 distinct settings including varied combinations of data, topics, and factors via 10 online questionnaires, each having 4 pages and 3 pairs of open-ended questions. Crossbars were consistently ranked as the most preferred option, stacked bars were widely considered the least preferred, and nested lines were generally viewed as preferred (Yang et al., 2014).

Lallé, Conati, and Carenini (2017) investigated the interaction between visual working memory, user expectations, and gaze behavior within the context of a real-world information visualization framework designed to assist individuals in deciding how to engage. Visual working memory, which combines visual memory and working memory, is a cognitive quality that comprises, in addition to visual memory, spatial capacity, visual speed, and associative memory (Liu et al., 2020). Visual memory is the capacity to remember an object's shape, position, location, and alignment (Sperling, 1963), while working memory is the ability to remember information for immediate application (Baddeley, 1992). The study's results revealed that individuals with greater visual working memory preferred charts over maps and focused more on the chart area (Lallé et al., 2017). Toker, Conati, Carenini, and Haraty (2012) discovered a statistically significant negative association between working memory and preferences for evaluating bar charts and radar plots in a separate investigation. Participants with superior visual memory preferred radar graphs, whereas those with worse visual memory chose bar graphs (Toker et al., 2012). These findings have aided visualization technologies in achieving high levels of usefulness and utilization, as well as improving people's knowledge of data and how to communicate via visualizations. They also emphasize the need of taking into account the constraints of a "one-size-fits-all" visualization interface, as well as the influence of human variation on the usage of information visualization systems (Liu et al., 2020).

Visualization types in information visualization include the use of suitable photos, typography, space, style, and colour to improve the visual appeal and usability of a design or product (Guney, 2019). Understanding the link between visual aesthetics and personality may help designers modify the user interface to better meet the demands

of diverse users (Kennedy, 2020). Hierarchical, change with time, and comparative visual designs will be used in this research. These visual designs may be utilized to develop more adaptable and customised user interfaces that cater to diverse users' demands and preferences.

Ottley, Yang, and Chang (2015) used an indented tree and a dendrogram in their research to evaluate the link between personality and hierarchical visual designs. An individual's view of whether they have control over events (internal LOC) or if they are controlled by external occurrences (external LOC) is referred to as their locus of control (LOC) (Ziemkiewicz et al., 2013). A dendrogram is a diagram that shows a hierarchical relationship between objects using a classic node-link structure, whereas an indented tree is an ontology visualization in which indentation is used to show super/sub-class relationships and there is only one path between any pair of nodes (Fu, Noy, & Storey, 2013). External LOC users were almost twice as quick when using the indented tree as opposed to the dendrogram, according to the researchers (Ottley et al., 2015). The authors recruited 54 participants using the Mechanical Turk service to explore how LOC influences user search tactics. They discovered that external LOC users did better with the indented tree, whereas internal LOC users performed better with the dendrogram. This research contributes to a better understanding of how personality characteristics affect visualization use and how designers may construct visualizations that better correspond with users' cognitive demands.

Green and Fisher (2010) investigated the impact of personality characteristics on user involvement and learning performance behaviors in an interactive visualization and a menu-driven online table. The visualization style utilized by the researchers was circular packing, and participants were required to perform many procedural learning tasks at each interface. The participants engaged with two interfaces: the web-based NCBI MapViewer for genetic information and the interactive data visualization (GVis) of genomic interactions. The research found that participants interacted more with the visualization than with the web table, and that internal LOC users interacted quicker with both the interactive and web-table interfaces. External LOC users, on the other hand, completed inferential tasks faster than internal LOC users (Green et al., 2010). This research demonstrates how intrinsic personality variations may impact engagement with visualization approaches, and it gives a platform for changing to

match user demands and preferences, as well as a foundation for recognising comparable variances within a community.

Alves, Ramalho, Goncalves, Gama, and Henriques-Calado (2020) investigated if personality influences user choices for various forms of visualizations. According to the research, external LOC users chose a treemap type of visualization over a sunburst, whereas internal LOC users preferred a line chart with points (Gonc, 2020). This study expands on prior work by concentrating on several styles of information visualization and including a storytelling-reporting component. This study seeks to give insights into the impact of personality in visualization choices in order to assist designers construct more effective and user-friendly visualizations.

2.2.1 Visualization Types Under Information Visualization

With the advent of digitalization of everything and everything, the success of a website, application, or product is strongly reliant on the success of its visual design. It is critical to the success of any design project. A strong visual design may successfully communicate information while also eliciting the desired emotional reactions from customers (Bach et al., 2017). Visual design must be assessed based on its concepts and aspects, as well as the sort of design used. There are several design styles available, each with its own specific feature, such as maximalist, minimalist, and skeuomorphic design. The visualization type represents facts or information via information visualization. There are many other forms of visualizations, such as bar graphs, scatter plots, line charts, heat maps, and many more. The sort of visualization used is determined by the data being shown, the narrative being told by the data, and the audience being addressed.

Hierarchy visualization is a sort of information visualization that uses a visual format to depict hierarchical data structures, such as an indented tree or a dendrogram. These visualizations are often used to show interactions between distinct elements or categories in fields such as computer science, biology, and social science (Fu, Noy, & Storey, 2013). One advantage of hierarchy visualization is that it helps users to quickly perceive the hierarchical connections between distinct entities, which may aid in understanding the underlying structure of the data and allowing them to make better

educated choices (Kennedy, 2020). A dendrogram, for example, may be used in a biological setting to show the evolutionary links between various species, letting researchers to observe how different species are connected to one another (Ottley et al., 2015). However, there are significant drawbacks to employing hierarchical visualization. If the hierarchy is too deep or complicated, these visualizations might become crowded or difficult to read (Green & Fisher, 2010). Furthermore, depending on their personality features or cognitive style, certain users may prefer various sorts of visualizations (Lallé, Conati, & Carenini, 2017). External LOC users, for example, may prefer indented trees to dendrograms, but internal LOC users may prefer the converse (Ottley et al., 2015).

Overall, hierarchy visualization is an effective technique for visualizing hierarchical data structures and comprehending connections between various components. However, while selecting an acceptable visualization style, designers must consider the constraints of various visualizations as well as the preferences of their target audience.

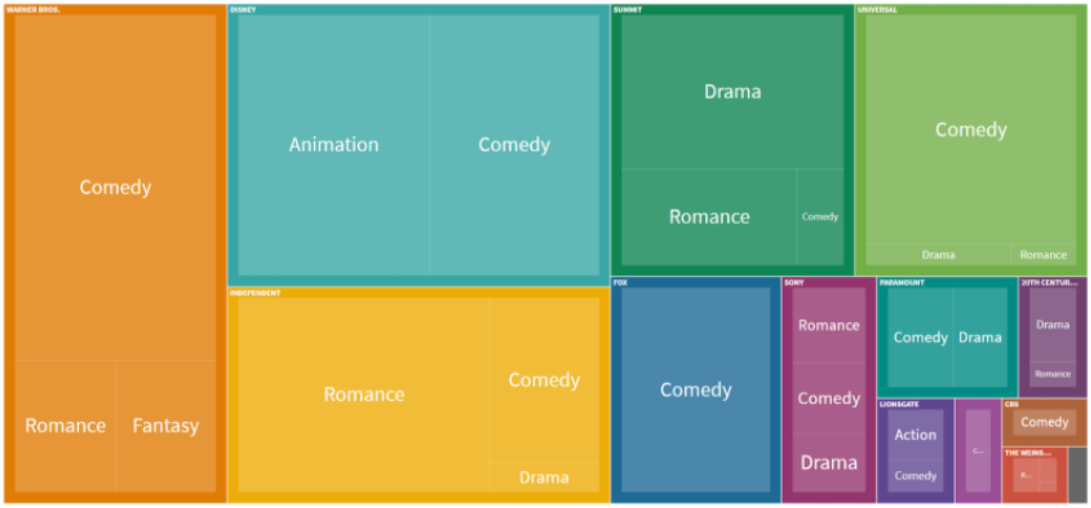


Figure 2.1 Example of Hierarchical Visual Design, The Tree Map.
The design shown the visualization of movie studios and their genres. The image above was an original design by the author of this thesis.

Changes over time visualization is a sort of information visualization that depicts how data attributes and states change over time as well as the moments at which

data states abruptly shift (Fang, Xu, & Jiang, 2020). Line charts and area charts are examples of this style of visualization, which are widely used to highlight trends or patterns in data across time. In a previous study, Sheidin, Lanir, Conati, Toker, and Kuflik (2020) investigated the effects of six user characteristics on the effectiveness of these visualizations, which had not previously been investigated in the context of personalizing information visualization. Previous study on the effect of user variations on processing visualizations has mostly focused on non-temporal data visualizations such as basic and layered bar graphs, radar charts, hierarchical visualizations, tables, and others (Sheidin et al., 2020). The research involved 40 university students who performed tasks given to each visualization and scored their preferences for each visualization, using four separate data sets based on real-world data obtained from Twitter and discussing pertinent events from 2015. One of the six user attributes chosen was locus of control (LOC). The study's findings revealed that high-LOC users outperformed low-LOC users in stream visualization (Sheidin et al., 2020). This research backs up the necessity for customized and adaptable visualization, and the results may be used to design personalized and adaptive visualization systems that take such user preferences into account.

One advantage of using changes over time visualization is that it allows users to quickly and easily see how data has changed over a specific time period, which can be especially useful for identifying trends or patterns that may not be immediately apparent in other types of visualizations (Sheidin et al., 2020). This is particularly valuable for decision-making because it enables users to understand the context in which the data was acquired and make better educated judgements based on that context. However, adopting change-over-time visualizations has significant drawbacks. One difficulty is that these visualizations might become crowded or difficult to read if there are too many data points or the period displayed is too lengthy (Green et al., 2010). Furthermore, user preferences for various kinds of changes over time visualizations might differ based on personality factors or cognitive style (Lallé et al., 2017). Sheidin et al. (2020), for example, discovered that high-LOC users did better with stream visualization, whilst other users may prefer alternative forms of changes over time visualizations.

Overall, change-over-time visualization is an effective method for depicting data changes and detecting trends and patterns over time. However, while selecting an

acceptable visualization style, designers must consider the constraints of various visualizations as well as the preferences of their target audience.

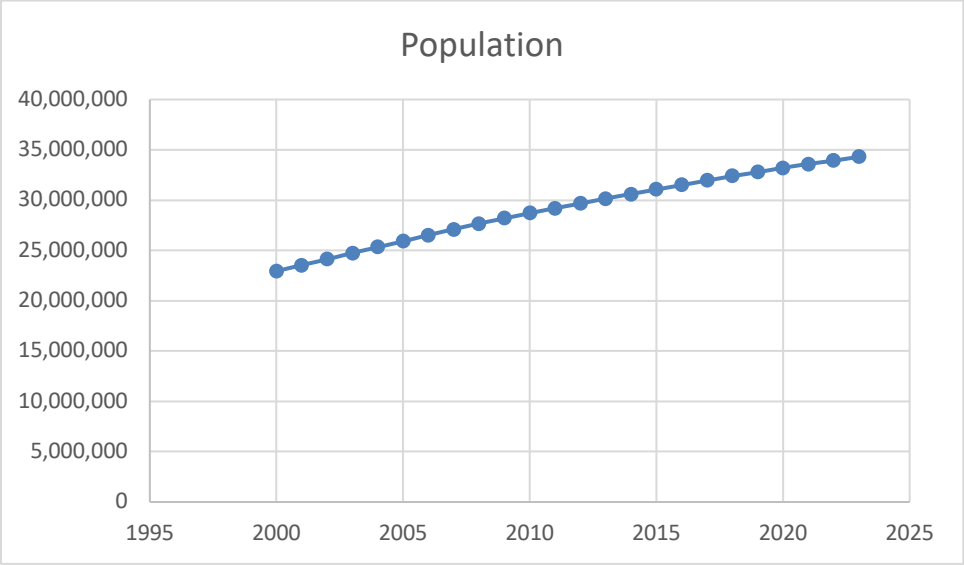


Figure 2.2 Visualization of Change Over Time Illustration.

The population of Malaysia depicted on the graph. The author of this thesis is the image's creator, and the information was taken from www.macrotrends.net

Data comprehension and analysis benefit greatly from comparison visualization. It entails comparing values or quantities and identifying patterns or trends in data using graphical or visual representations. Comparison visualization is typically used to highlight the differences or similarities between groups or categories of data, and it may also be used to depict discrepancies or correlations between values at a finer level of detail. There are several comparison visualizations available, including bar charts, pie charts, scatterplots, and line graphs. Each style of visualization may be used to depict different sorts of information, with each type better suited to certain types of data. Pie charts, for example, are often used to illustrate percentages of a whole, and bar charts are regularly used to compare the values of multiple categories. Line graphs may be used to show trends over time, whilst scatterplots can be used to show correlations between two variables.

Comparison visualization, according to Gonc (2020), is an excellent way for emphasizing differences or correlations between data at a certain degree of detail. Some examples of comparison visualization include pie charts, bar graphs, and word clouds.

Cashman et al. (2019) conducted an experiment to evaluate visualizations and visual analytics tools. The experiment featured six tasks, one of which was a control quest task and another for each visualization. The researchers examined two types of visualization, including a traditional cross-coordinated visualization for tabular data and visualizations for studying hierarchical data, and the findings were based on the users' mouse clicks or mouse movements. According to the researchers, inferential tasks are more complicated and may result in more encounters across longer durations of task completion. They observed that inferential activities led in more participant behaviors than data-collection tasks. In a research setting, the use of inferential tasks in comparative visualization may increase the community's ability for analysis and understanding.

Additionally, a comparison visualization is a great tool for analyzing and evaluating data. It may be used to identify patterns and trends, as well as to highlight differences and correlations between values. The use of inferential tasks in comparison visualization may increase the community's understanding and analysis of visual analytics programmes, resulting in more interactions across longer job completion timeframes.

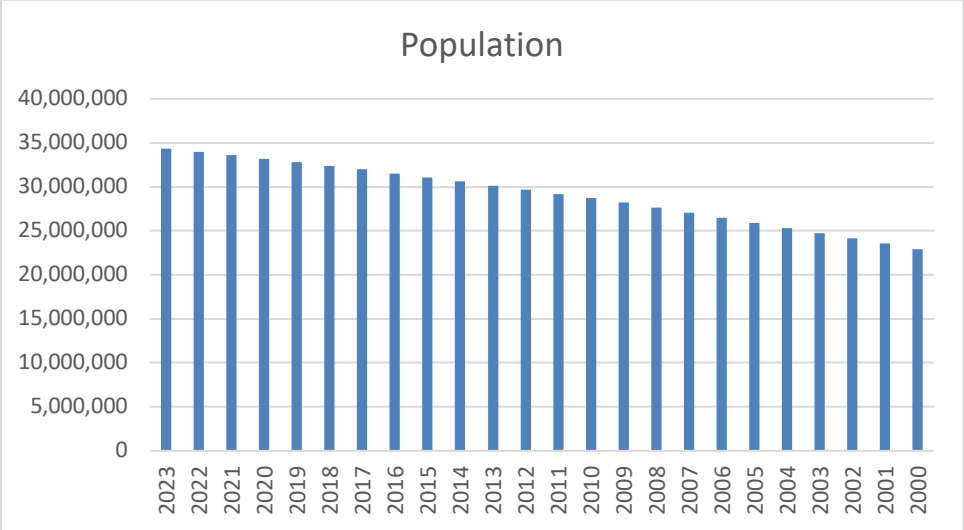


Figure 2.3 Example of Comparison Visualization- Bar Chart.
The population of Malaysia depicted on the graph. The image was created by the author of this thesis.

2.3 DATA STORYTELLING

Data storytelling is the art of using data or statistics to tell a story in a way that helps the audience understand complex data. Graphs and charts are two prominent visualization approaches used to improve the story and assist the audience grasp the facts. In professional contexts, data storytelling has taken numerous forms, including posters, slide shows, and budget presentations.

Data storytelling, according to Echeverria et al. (2018), is an excellent technique to employ information visualization since it may boost the communication potential of the information being presented. Data storytelling aids in bringing data to life and making it more relevant to the audience, allowing them to better grasp and recall the information offered. Individuals and organizations may successfully convey complicated concepts and data sets to a broad variety of people by using data storytelling approaches.

Moretti, Chiara, and Napolitano (2018) performed study in Italy on the use of data storytelling to promote openness in the Italian government. The researchers aimed to make data sharing online more engaging and interactive in order to make it more accessible to the general audience. Although the government makes data accessible to the public, the aim of accountability has not yet been completely realized. This is due, in part, to a lack of established data distribution methods. The researchers observed that employing data storytelling allows a bigger audience to grasp complicated data by recognizing trends over time and showing patterns that would otherwise be hidden in tables of data.

Moretti et al. (2018) contend that employing data storytelling approaches to create visual representations of data might assist overcome the constraints of both static human-readable versions of data and sophisticated machine-readable forms. The researchers think that by utilizing data visualization to deliver information in a more engaging and dynamic manner, they can promote openness in the public sector and make data more accessible to the public.

There are five fundamental guidelines for excellent data storytelling, according to Echeverria et al. (2017). The first criterion is to define a specific aim for the

visualization. To produce good data storytelling, it is necessary to first understand the environment in which the visualization will be given, which includes the audience, their career, educational background, and perception of the presenter and the data visualization. The direction of the narration may be lost if there is no clear aim.

Data visualization makes unseen data visible by using graphical representations. In order to successfully convey information via data visualization, it is critical to choose a representation that suits the data and is simple enough for the audience to grasp (Bach et al., 2017). The selected visualization should correctly depict the data and effectively explain the information being shown. By following these criteria, it is feasible to generate compelling and effective data storytelling that aids in the communication of complicated concepts and data sets to a broad variety of people.

The second guideline of excellent data storytelling is to remove any superfluous information. To make the data visualization more understandable, any data that does not offer value or contribute to the overarching story should be removed. This might assist the reader in focusing their attention on the most relevant information inside the visualization.

A pilot research investigating the use of data storytelling components in education discovered that removing extraneous information and decluttering visualizations might increase readability and attention on the tale, according to Echeverria et al. (2018). It is feasible to emphasize the most significant features and make the visualization more successful at expressing the desired message by deleting extraneous data. Overall, removing unneeded information is a critical step in developing great data storytelling that is simple to grasp and engaging for the reader. It is possible to produce clear and attractive visualizations that successfully represent complicated concepts and data sets by concentrating on the most relevant facts and avoiding distractions.

The third guideline of good data storytelling is to utilize narrative sparingly. This entails carefully choosing and labelling material in order to clarify key points and show facts descriptively. It is critical to ensure that the visualization is consistent with the project's aims or objectives, as well as to offer clear direction on what must be conveyed and what may be left out. However, researchers and designers often make

blunders in this area. To build a successful data visualization that effectively delivers the desired message, it is critical to analyze the information being shown and how it fits into the larger story. It is feasible to produce clear and captivating data storytelling that helps the audience grasp and recall the information being given by employing narrative judiciously.

The fourth criterion of good data storytelling is to direct the viewer's attention by using pre-attentive characteristics that highlight the most significant components of the visualization. Use design elements such as curves, forms, proportions, colors, and contrasts to call attention to crucial features of a certain emphasis. Digital and audio story components may also be employed to provide context and assist the viewer in interpreting the visual aspects. Narrative text may also be utilized to give further explanation and assist the audience in comprehending the facts being displayed. It is feasible to construct data storytelling that successfully conveys complicated concepts and data sets in a manner that is engaging and accessible to the audience by driving attention in this way. Overall, the purpose is to employ data visualization to direct the viewer's attention and aid in understanding and retention of the information given.

The last guideline of great data storytelling is to motivate people to take action. It is critical to employ suitable colors, lines, and forms to direct the viewer's attention while creating a clear and simple visualization that successfully conveys the narrative to the audience. Some visualization approaches are more successful than others for different objectives. A linked scatterplot or a slope graph, for example, may not be appropriate for research but may be highly useful as a narrative tool (Kosara & MacKinlay, 2013).

In order to successfully tell the narrative, it is critical to use the appropriate visualization approach for the desired goal. If the visualization is not done correctly, the spectator may get lost or confused when studying the data without understanding the narrative's emphasis. It is feasible to build compelling and accessible visualizations that help the viewer comprehend and recall the information being given by adhering to the guidelines of successful data storytelling.

Understanding the context in which the data visualization will be presented is critical for effective data storytelling (Echeverria et al., 2017). This involves taking into

account audience characteristics such as their career, educational background, impression of the presenter, and data visualization. It is also critical to examine the precise information that the audience is looking for in order to develop a visualization that fits their requirements while successfully communicating the desired message.

Bach (2017) proposes utilizing data comics to communicate information and data. Other visual styles that emphasize variation and sequence may be an effective technique to interest the audience and communicate complicated concepts via data visualization. It is possible to develop successful data storytelling that effectively conveys complicated concepts and data sets in a manner that is engaging and accessible to a broad variety of audiences by taking the context and audience characteristics into account.

To produce successful data storytelling, consider the human component, which includes the efficacy of the visualization, the visual style, and the audience's degree of attractiveness and visualization literacy. Aesthetics, design principles, audience involvement, and visual discourse must all be balanced.

Another critical part of effective data storytelling is the production assistance given, which includes visualization integration, templates, editing tools, and design patterns. By taking these variables into account and ensuring that the data visualization is at its best, it is possible to improve storytelling and successfully convey complicated concepts and data sets in an engaging and accessible manner to the audience.

Storytelling is gaining popularity in the realm of visualization, especially when connecting with audiences. According to Chen et al. (2020), communicating complex information to viewers who lack sophisticated analytic abilities may be difficult, particularly when utilizing visualization approaches that combine extensive algorithmic, graphic, and interactive features. To solve this problem, the researchers presented a paradigm that connects information processing and result display through narrative synthesis. This entails creating and structuring narrative material in a systematic manner, as well as extracting discoveries from the source data and storing them in a dedicated workspace utilizing tools such as tale slices.

Analysts may bridge the gap between information visualization and storytelling by including a narrative synthesis step into the visual analytics process and integrating it to storytelling. This method broadens the visual analytics process and contributes to making complicated information more accessible and interesting to a broader audience.

There are now five forms of narrative designs that are actively disputed in the area of data visualization, according to Aydin and Am (2020). The first is the magazine style, which includes combining data images with explanations written in flowing text in the manner of a magazine. In recent years, the magazine style has grown in popularity as a means of presenting static visualizations, since it is distinguished by the use of data visualizations supplemented with descriptive text that follows the structure of a typical journal or magazine (Aydin & Cam, 2020). This approach is often used in the development of data stories that are meant to be written by a particular person or group (Kwon, Stoffel, Jackel, & Lee, 2014).

Magazines can readily provide information and entertainment to a big audience. They have been used in a variety of different research, including media impact studies, consumer behavior studies, and cultural studies. This style of storytelling, which is articulated as transmedia storytelling and feeds on the codes of the moment, allows consumers to change media material and media as they see fit by developing a sophisticated, broad, and engaging storyline, vocabulary, and narration model (Gürel, E., & Tl,., 2014). When opposed to previous eras, today's communication technologies, which are formed by postmodern imagery, signify more than merely being means for communication.

Although this style is widespread in static visualization, it has not been used as extensively in interactive visualization (Segel & Heer, 2010). One possible difficulty with the magazine format is that readers may struggle to link the text and the visualization since visualizations may be provided without specific instructions, leaving it up to the reader to decide how to interpret them. To address this issue, Kwon et al. (2014) created a system that uses ordered visualization to offer readers with easy access to the authors' selected point of view while also enriching the visualization with features such as highlighting, annotation, and animation. According to Kwon et al.'s (2014)

research, this method enhances magazine-style articles and allows authors to go farther with their intended data narrative.

Figure 2.4 Example of Magazine Styles – Sunglasses at night – nay or yay? Created by the author of this thesis.

An annotated chart is a visualization in which particular data is highlighted or contextual annotations are included. Endnotes and summary boxes may be used to provide further information in the sentences or paragraphs that follow by annotating data in the chart (Aydin & am, 2020). Endnotes may assist presenters in explaining and emphasizing key ideas or features, while annotations urge the audience to concentrate on certain areas of the charts (Lee et al., 2013). The positioning of annotation boxes, by offering additional context, may also make the material simpler to interpret and enhance aesthetic appeal (Borkin et al., 2013).

The annotations enable presenters to emphasize and clarify significant points or information and assist viewers concentrate on certain areas of the charts. Annotation charts are often used to arrange and interpret data in qualitative research. They let researchers to find patterns and themes within a dataset by grouping comparable information and emphasizing key aspects.

Current charting tools, on the other hand, only provide a few restricted frameworks for making annotations (Ren et al., 2017), and the visualization research community is unfamiliar with the role of annotation in information storytelling. To solve this problem, Ren and colleagues (2017) created a platform that allows users to quickly and simply add annotations to charts utilizing a variety of annotation interactions that support both manual and automated annotation. They established a design area for chart annotations based on a review of 106 annotated charts produced by six notable news visual departments. The researchers want to incorporate their annotation experiences into multiple charting platforms, and the tools offer a unique technique for discovering and using information annotations.

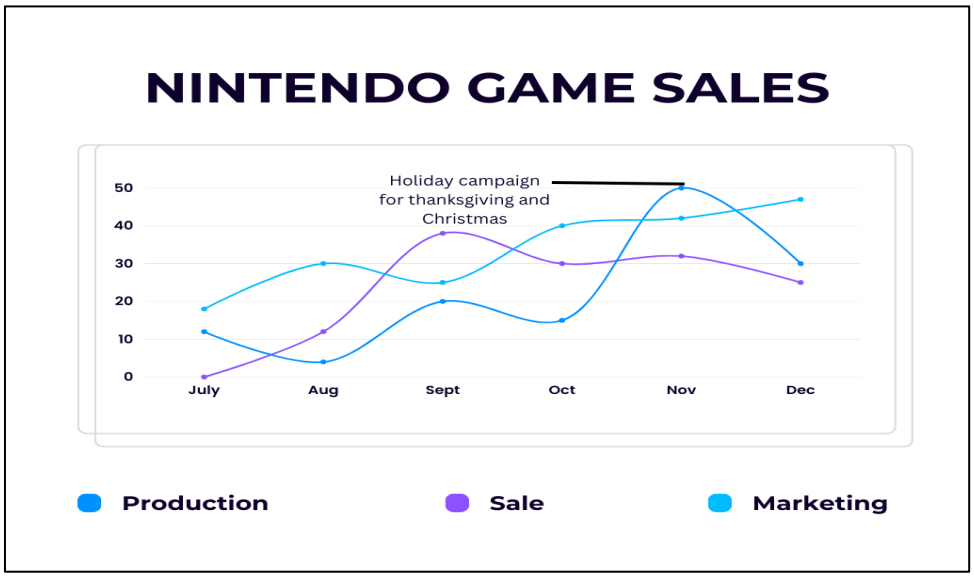


Figure 2.5 Example of Annotated Charts.
The image was created by the author of this thesis.

Flowcharts-infographics is the third data storytelling design, which involves utilizing flowcharts to convey the tale of a system or machine on a hierarchical plane and infographics to graphically display data or numbers in a compact, accurate, and

substantive way (Aydin & am, 2020). Using flowchart-infographics, processes, workflows, or systems may be portrayed in a visually attractive and easy-to-understand format for the user and audience. Complex concepts, procedures, and data may be communicated simply and logically in domains such as business, education, and technology.

Flowcharts are used in a variety of sectors to study, create, record, or manage processes or programmes (Ren & Tobias, 2017) and are a basic tool for conveying procedures and decision-making (Knaflic, 2016). To depict the tale schematically, they blend components connected to boxes and arrows. Infographics, on the other hand, are visual representations of facts or numbers that try to communicate information simply and effectively. They are typically used to convey complex material in a more accessible and exciting manner by merging text, graphics, and visual components to communicate the essential message. By combining flowcharts with infographics, it is possible to effectively convey complex information and processes in a manner that is easy for the audience to grasp and remember.

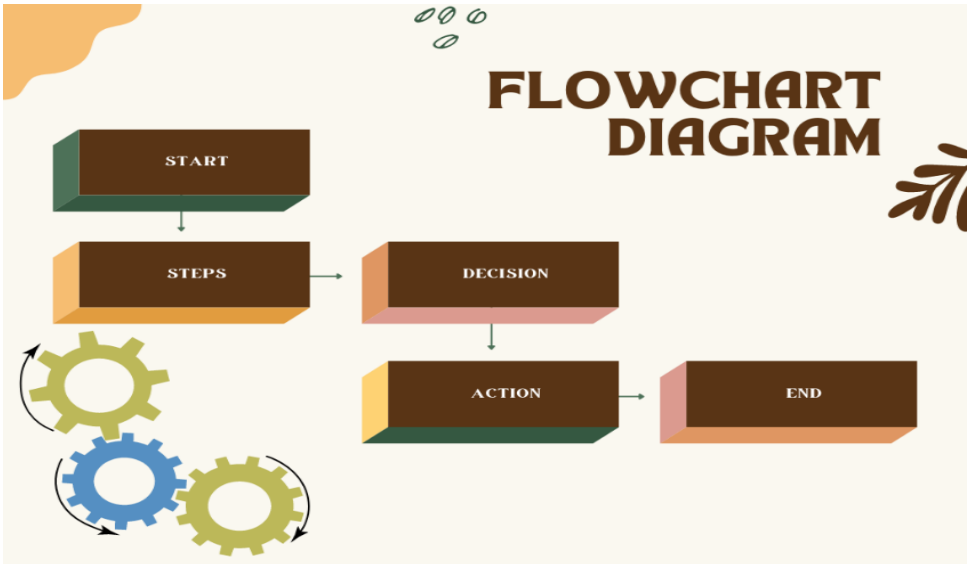


Figure 2.6 Example of Flowchart-Infographics Style.
The image was created by the author of this thesis.

The fourth data storytelling style incorporates the use of partitioned posters, a kind of infographic that is separated into many frames to display different but related

groupings of data (Aydin & Am, 2020). These posters are planned as a series of design frames, with the design area divided into at least two frames and the data interconnected (Segel & Heer, 2010). Partitioned posters enable the display of complicated data sets in a structured and understandable manner for the audience. It is feasible to deliver a clear and unified message to the audience by splitting the material into discrete frames and tying them together. This style is very effective for displaying enormous quantities of data in a succinct and aesthetically attractive manner.

Partitioned posters serve as a venue for subject distribution and discussion, which helps users improve their presenting and communication abilities (Newsome, Miller, & Chesson, 2021). The poster is a recognized informative medium that is simple to interpret, ethically and artistically teaches the audience, and has an emotional and environmental influence on people without demanding any mental effort on his side (Vasilenko, E., Vasilenko, P., Pallotta, Barsukoba, & Sichkar, 2021).

ith the global trend towards digitalization, the conventional poster has transformed into something more interactive. While the foundations of traditional poster design may seem to have remained unchanged, the variety brought forth by modern communication technologies has converted the poster into a platform for interactive digital displays (Köksal & Aluç, 2022). In a recent research, student chemists were asked to explain their perceptions on the use of posters as a teaching tool, as well as their preference for digital versus printed posters for presentation and review (Newsome, Miller, & Chesson, 2021). The researchers split the class into two cohorts by comparing the students' pre- and post-activity surveys. According to the results, digital posters are a more practical, cheap, and desirable presenting medium for pharmacy students than printed posters.

Figure 2.7 Example of Partitioned Poster Style.

The author of this thesis created the image.

The fifth and final design of data storytelling includes employing visual media with scene transitions similar to those found in fictional films or comic strips (Aydin & am, 2020). Comics enable the construction of tales via the use of cartoon depictions of scenes that combine both photographic and live animation aspects, allowing the visuals and text parts to portray the final narrative in a hierarchical sequence (Zhao et al., 2015). In today's media-rich society, comic books have the potential to be a visually captivating and cutting-edge teaching tool. For example, comics and animation may be used to educate patients about diseases such as cancer and AIDS while simultaneously promoting a healthy lifestyle (Muzumdar, 2016).

Bach and colleagues (2016) did research on the use of graphic comics as a method for explaining changes in complicated networks, employing comics' visual eloquence and familiarity to introduce and show spatial dynamics in networks to an audience. The researchers generated three comics with graphics and comments and

invited respondents to report their thoughts and conclusions (Bach et al., 2016). The research discovered that when given little textual annotation and little training, the audience could quickly grasp dynamic temporal transitions using graph comics. Overall, using comics, cartoons, and animation to convey complicated information in a visually attractive and engaging manner may be helpful. It is feasible to deliver a clear and captivating story that is simple for the audience to grasp and follow by employing various mediums.

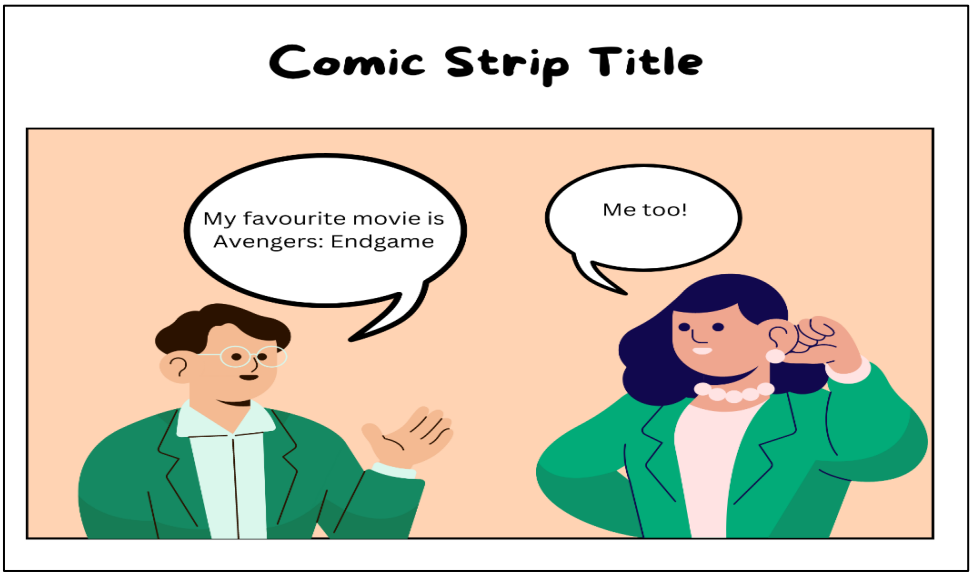


Figure 2.8 Example of Animation Style.
The author of this thesis created the image.

2.4 PERSONALITY

Personality is described by Kaushal and Patwardhan (2018) as "variations in human characteristic patterns of thought, feeling, and behavior" (p. 102). Personality is a complex and multifaceted concept that encompasses an individual's unique patterns of thought, emotion, and behavior. It has traditionally been studied in two main areas: the analysis of individual differences, particularly characteristics such as sociability or irritability, and the understanding of how an individual's various parts come together to form a whole. Personality is frequently defined by a person's individual actions, emotional states, temperament, and mental characteristics (Durupinar et al., 2011).

Personality is typically steady over time, yet it may alter to some degree when a person encounters new things, meets new people, and goes through new life events (Vaida, 2019). Numerous markers, such as the Myers-Briggs Type Indicator (MBTI), the Five-Factor Model (FFM), and the Enneagram of personality, have been established by researchers to assist them better understand personality. However, in the area of personality study, there is considerable disagreement over how many personality characteristics stay constant over time (Durupinar et al., 2011). These tools may assist people in better understanding their personalities.

2.5 Five-Factor Model (FFM)

The Five-Factor Model (FFM), also referred to as the Big Five, is an extensively recognized and extensively studied model of psychology that delineates five overarching aspects of personality: openness, conscientiousness, extraversion, agreeableness, and neuroticism (Costa, 2018). Each of these dimensions consists of a compilation of unique features that pertain to more intricate facets of personality. The Five-Factor Model (FFM) was selected as the personality indicator for this study due to its extensive establishment in the fields of research and clinical psychology. The Five-Factor Model (FFM) utilizes the acronym OCEAN to denote the five expansive dimensions of personality, namely openness, conscientiousness, extraversion, agreeableness, and neuroticism. Additionally, it discerns three fundamental needs that align with these dimensions, specifically the need for influence, the need for security, and the need for tranquilly (Schmidt et al., 2019).

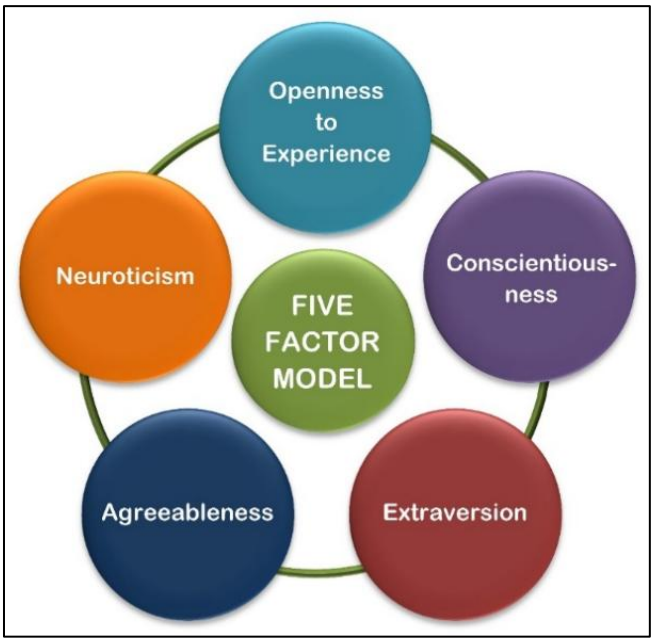


Figure 2.9 The Five-Factor Model.
The image is an original design by the author.

The first FFM element is openness to experience, which relates to an individual's desire to try new things and welcome change (Abyaa et al., 2018). Individuals with high openness tend to be curious, creative, and imaginative, and they are more likely to participate in a variety of activities rather than cling to a routine (Wang et al., 2019). Individuals with high degrees of openness may also make better judgements, both individually and as part of a team, according to research (Harb & Alhayajneh, 2019). In a research evaluating the relationship between personality, beliefs, and attitudes, it was discovered that software engineers with high degrees of openness were more inclined to assume responsibility for a whole project (Feldt et al., 2010). Low levels of openness, on the other hand, are marked by more conservative and traditional qualities (Peever et al., 2012). Individuals with low openness are practical, detest change, and prefer known, repeated actions and surroundings. They may be resistive to learning difficult or analytical concepts, as well as to new ideas (Abyaa et al., 2018). Salleh et al. (2011) discovered that openness had a substantial influence on academic performance of students who performed pair programming in higher education in their study on openness. Students with high degrees of openness were often regarded as "foresightful, intelligent, and resourceful" by the authors (Salleh et al., 2011).

"Conscientious people are highly organized and goal-oriented, and they value discipline and achievement in their work" (Salleh et al., 2010). They are well-known for their dependability and efficiency, often prioritizing their obligations and tasks (Mirza et al., 2015). Those with lesser conscientiousness, on the other hand, may show a lack of care or attention to detail and may be hostile to authority (Peever et al., 2012). This personality attribute has been associated to both academic accomplishment (Salleh et al., 2011) and success with corporate intelligence tools (Harb & Alhayajneh, 2019). As a result, it is not unexpected that conscientiousness is extensively evaluated in research and therapeutic contexts. Harb and Alhayajneh (2019) discovered that people with high degrees of conscientiousness were more inclined to actively seek out and use technologies that may improve their professional performance." Conscientiousness is often seen as a predictor of success in a variety of contexts, including academia and the workplace. According to a research done by Barrick and Mount (1991), conscientious persons had greater levels of work performance and job devotion than those with lower levels of conscientiousness. Furthermore, research has shown that conscientiousness is associated with improved physical and mental health outcomes, including a decreased chance of acquiring chronic illnesses (Furnham & Cheng, 2016). Conscientious people are also more likely to participate in healthy activities like frequent exercise and eating a nutritious diet (Furnham & Cheng, 2016). Conscientious people tend to be more structured, responsible, and driven, which leads to greater grades and academic success (Salleh et al., 2011). Overall, it is obvious that conscientiousness is an important personality attribute that may contribute to success in a variety of aspects of life.

Extraversion, one of the five personality characteristics in the Five Factor Model (FFM), refers to a person's proclivity for sociability, assertiveness, and talkativeness (Acua et al., 2015). Extraverts are often gregarious, lively, and self-assured (Harb & Alhayajneh, 2019; Garrido, Bernard, & Davidson, 2013). They like being among other people and exhibiting pleasant sentiments (Hu & Pu, 2014). Individuals with high degrees of extraversion may be especially helpful in fields that demand contact with others and cooperation, such as engineering and architecture (Weilemann, 2019). Those with low levels of extraversion, on the other hand, tend to be more introverted, exhibiting attributes such as silence, shyness, and timidity.

Extraversion and academic and learning performance have a high association (Zeng et al., 2016). A research of medical university students indicated that individuals with greater extraversion scores had superior learning results (Zeng et al., 2016). This shows that FFM, of which extraversion is a component, is a significant issue for educators and other professionals. Extraversion has also been connected to good leadership (Judge & Bono, 2001). Judge and Bono discovered that people with high degrees of extraversion tend to be more successful leaders in a meta-analysis of over 500 research. They are more aggressive and confident, which may inspire and drive their followers (Judge & Bono, 2001). Furthermore, extroverted leaders are frequently more at ease speaking with people and creating connections, which may aid in the development of a healthy work culture (Judge & Bono, 2001).

Agreeableness, one of the five personality factors in the Five Factor Model (FFM), refers to a person's proclivity for cooperation and conscientiousness, as well as an understanding for the viewpoints of others (Gulati et al., 2016). People who are pleasant tend to be cheerful, kind, and compassionate (Costa & McCrae, 2018). They may be described as selfless and sympathetic, and they are often seen as friendly and concerned with the needs of others (Purdioux, 2016). Individuals with low levels of agreeableness, on the other hand, may be sceptical, aggressive, and egotistical, as well as viewed as disinterested in the needs or events of others (Peever et al., 2012).

Agreeableness is often used to assess team performance and climate (Acua et al., 2015). Acua et al. (2015) discovered that high agreeableness was connected with more efficient teams in a research that looked at the connection between personality, team environment, product quality, and satisfaction in software development teams. This implies that agreeableness is a significant consideration in team dynamics and productivity. Relationship satisfaction and stability have also been connected to agreeableness (Kavanagh, Kenny, & Dolan, 2015). Kavanagh et al. discovered that people with high levels of agreeableness had more happy and stable relationships in a meta-analysis of over 100 research. They are more inclined to cooperate and regard their partner's wants and emotions, which helps promote a healthy and harmonious relationship (Kavanagh et al., 2015).

Neuroticism, one of the five personality factors in the Five Factor Model (FFM), refers to an individual's proclivity for negative emotions such as despair and anxiety (Ziemkiewicz et al., 2012). Those who have high degrees of neuroticism may be more emotionally reactive and struggle to deal in stressful circumstances (Wiesche & Krcmar, 2014). Individuals with low degrees of neuroticism, on the other hand, tend to be more emotionally stable, calm, confident, and secure (Wiesche & Krcmar, 2014).

There has been much discussion on the effect of neuroticism in academic achievement and productivity. Some research, however, have revealed either little or no relationships between neuroticism and performance (Salleh et al., 2011). This implies that people with high degrees of neuroticism, such as those suffering from depression or anxiety, may be able to create high-quality work despite their mental instability. Physical health consequences have also been connected to neuroticism. According to a meta-analysis of over 300 research, people with high levels of neuroticism had worse physical health, including greater rates of cardiovascular disease, immune system dysfunction, and all-cause mortality (Furnham, Cheng, & Drennan, 2010). This might be attributed to the harmful consequences of prolonged stress on the body, since those with high neuroticism are more likely to experience stress and unpleasant emotions (Furnham et al., 2010). Furthermore, neuroticism is linked to drug abuse and addiction. A meta-analysis of more than 80 research showed that people with high levels of neuroticism are more likely to develop drug use disorders and are more likely to relapse following treatment (Slane, Tarter, Kirisci, & Reynolds, 2013). This might be because they are more vulnerable to stress and unpleasant emotions, which may prompt them to seek comfort via drug use (Slane et al., 2013).

Table 2.1 The Summary of the FFM

PERSONALITY TRAIT	**LOW SCORER**	**HIGH SCORER**
OPENNESS	Favors conservative values, and judges in conventional terms.	Values intellectual matters, rebelling, non-conforming
CONSCIENTIOUSNESS	Self-indulgent, engages in daydreams	Behaves ethically, dependable, and responsible

PERSONALITY TRAIT	LOW SCORER	HIGH SCORER
EXTRAVERSION	Avoids close relationships, over-control of impulses	Talkative, socially poised, behave assertively
AGREEABLENESS	Critical, skeptical, behavior is condescending	Sympathetic, considerate, warm, compassionate
NEUROTICISM	Calm, relaxed, satisfied with self	Thin-skinned, anxious, irritable, guilt-prone

2.6 MYERS BRIGGS TYPE INDICATOR (MBTI)

The Myers-Briggs Type Indicator (MBTI) is a personality diagnostic instrument based on Carl G. Jung's philosophical theory (Wu, Zhou, & Chen, 2011). Jung felt that human conduct is predictable and follows certain patterns, and that different people receive information and make judgements in various ways (Gorla & Chiravuri, 2013). He defined four psychological functions that govern how individuals see and understand the world (Usman & Minhas, 2019). These functions are sensation, intuition, emotion, and reasoning. Based on the combination of these four functions, the MBTI divides people into 16 distinct personality types (Luo, Chiu, & Tsau, 2018). An ENFJ (Extroverted, Intuitive, Feeling, and Judging) personality type, for example, is defined by extroversion, intuition, feeling, and judging. An ISTP (Introverted, Sensing, Thinking, and Perceptive) personality type is defined by its introversion, sensing, thinking, and perception. Each personality type is distinct and shows distinct attitudes, actions, and worldviews.

The MBTI has been extensively utilized in a broad range of contexts, including education, work, and therapy. It is often used in companies as a technique for self-discovery and personal development, as well as team building and conflict resolution (Myers & McCaulley, 1985; Kostere & Ogunmokun, 2007; Lussier & Achua, 2010).

The Five-Factor Model (FFM) will be used as the major assessment of personality in this study. The FFM, often known as the Big Five, is widely used in a number of sectors, including academic study on personality (Furnham, 1996). Extraversion (sociable vs. shy), neuroticism or emotional stability (secure vs. neurotic),

agreeableness (friendly vs. unfriendly), conscientiousness (organized vs. careless), and openness to experience (insightful vs. unimaginative) are the five bipolar scales assessed by the FFM (Celli & Lepri, 2018). These personality qualities may be classified as "bright" or "dark," with high scores indicating bright traits and low scores indicating dark ones (Russo & Stol, 2020). The FFM is a reliable and accurate measure of personality that has been frequently utilized in research.

The Five-Factor Model (FFM) has been proven to be a reliable and accurate assessment of personality in a number of circumstances, in addition to its extensive usage and acceptance in academic research. The FFM has a good predictive value in predicting crucial outcomes such as work performance, academic success, and health behaviors, according to research (Digman, 1990). Individuals who score high in conscientiousness, for example, are more organized, responsible, and trustworthy, and have better levels of academic and vocational achievement (Furnham, Cheng, & McManus, 2016). Similarly, Gosling et al. (2003) found that extroverts had more favorable interactions with others and better levels of well-being. Agreeableness, which is defined by a proclivity for cooperation and empathy, has been connected to improved social connections and leadership abilities (Van Lange et al., 2013).

According to studies, the Five-Factor Model (FFM) may be a more accurate personality predictor than tests like the Myers-Briggs Type Indicator (MBTI). This is because FFM ratings have superior control over class distribution and interpretation, making prediction tasks easier (Celli & Lepri, 2018). Furthermore, the FFM is statistically reliable, with each feature displaying significant "constructive validity," which means it fits Adam Grant's four requirements for a valid personality trait (David, 2019). Unlike the MBTI, the FFM has been shown to have significant predictive value in a range of situations. Overall, the FFM has shown to be a reliable and accurate measure of personality, and its application in research and applied contexts has greatly improved our knowledge of individual variations and their influence on behavior and outcomes.

2.7 Chapter Conclusion

In conclusion, personality, information visualization, and data narrative are all intertwined. Personality may affect how people approach and perceive data visualization and data storytelling, and the approaches used to visualize and tell stories can impact the efficacy of the information being given.

According to research, using data visualization and data storytelling to convey complicated facts and ideas to audiences may be beneficial (Echeverria et al., 2017). It is possible to create compelling and effective data stories that are engaging and easily understood by the audience by following certain rules, such as stating a clear goal, eliminating unnecessary information, using narrative wisely, driving attention, and calling for action (Echeverria et al., 2018).

Magazine style, annotated charts, flowcharts, infographics, partitioned posters, comics, cartoons, and animation are all examples of data storytelling techniques (Aydin & am, 2020). Each approach has advantages and disadvantages and may be employed successfully in various settings, based on the audience's requirements and preferences as well as the aims of data storytelling.

Overall, personality, information visualization, and data storytelling are all interrelated and play important roles in communicating complicated information and ideas. It is feasible to successfully transmit data-driven tales and engage people in meaningful ways by recognizing these links and using relevant strategies.

This chapter examined all of the essential topics and theoretical literature in personality characteristics, data visualization, and data storytelling. This review influenced the formulation of the study technique and how to collect data for the next chapter.

CHAPTER THREE

RESEARCH METHOD

3.1 INTRODUCTION

The emphasis of this chapter will be on outlining the methodology used in the research. There are four parts in this chapter. The first part will offer a summary of the study's research design. The second portion will go through the study's demographic and sample. The third portion will define the methodologies and processes used, and the fourth section will discuss the data analysis process. Additionally, the ethical issues and actions taken to assure the study's trustworthiness will be presented.

3.2 DEFINITION OF METHOD

According to Polit and Hungler (2013), the term "method" refers to how data is collected, organized, and evaluated. The method employed in a study may differ based on the research issue being addressed. The word "method" in this study refers to the actions performed and the logical sequence in which the research was carried out. For example, Moustakas (2011) observes that a research aimed at exploring and describing the experiences of registered nurses who have participated in abortion operations would most likely use a qualitative method.

A study's approach encompasses the design, setting, sample, methodological constraints, and data gathering and analysis tools. The technique is described by the framework of ideas and concepts on which methods and processes are founded.

3.3 RESEARCH DESIGN

Akhtar (2016) posits that the research design serves as the comprehensive framework or structure that directs the acquisition and analysis of data inside a research endeavor. The concept may be conceptualized as the cohesive element that unifies all the constituent parts of the investigation. The research design serves the purpose of

assessing the suitability of the research topic, offering a comprehensive depiction of the investigation, and formulating anticipations about the research procedure. There are two primary categories of research designs, namely qualitative and quantitative. The selection of a research design is contingent upon the particular aims and objectives of the study, as well as the nature of the data that is being gathered and examined.

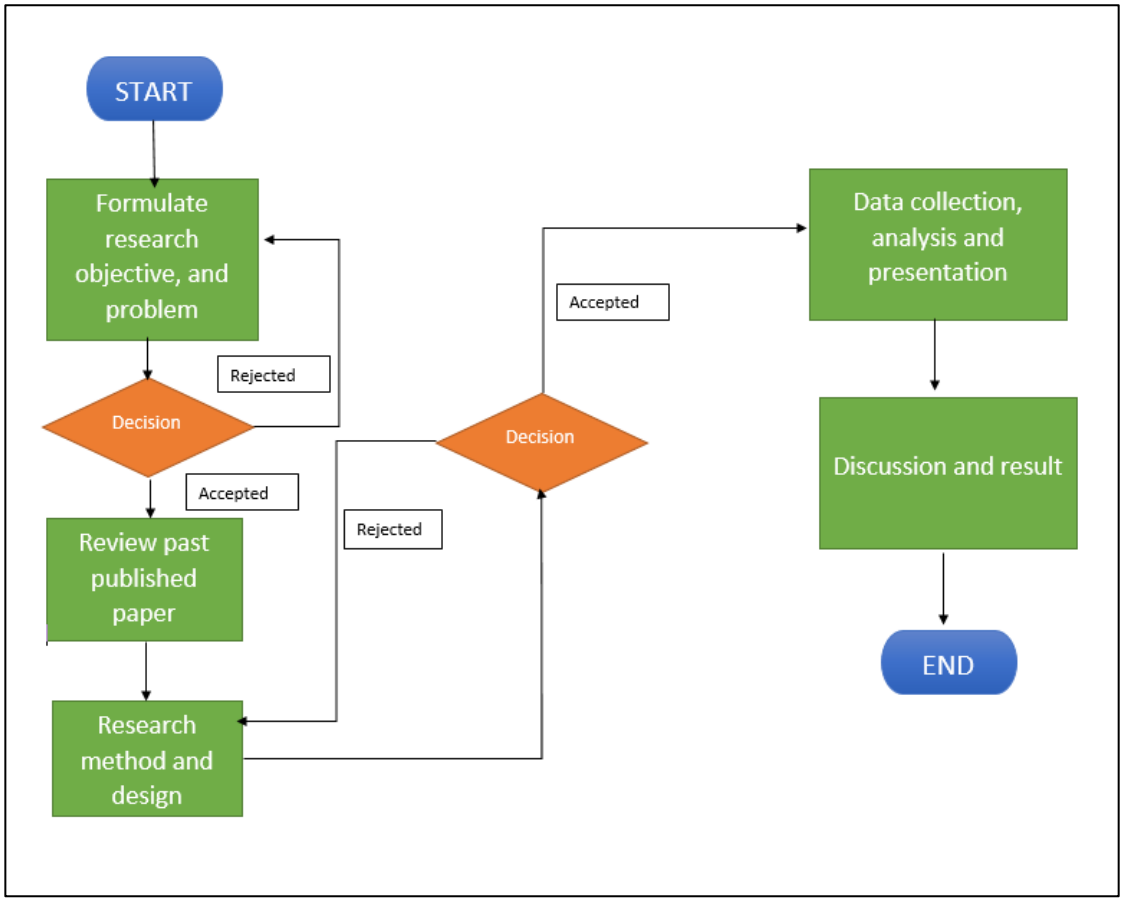


Figure 3.1 Flow Chart of the Overall Research.

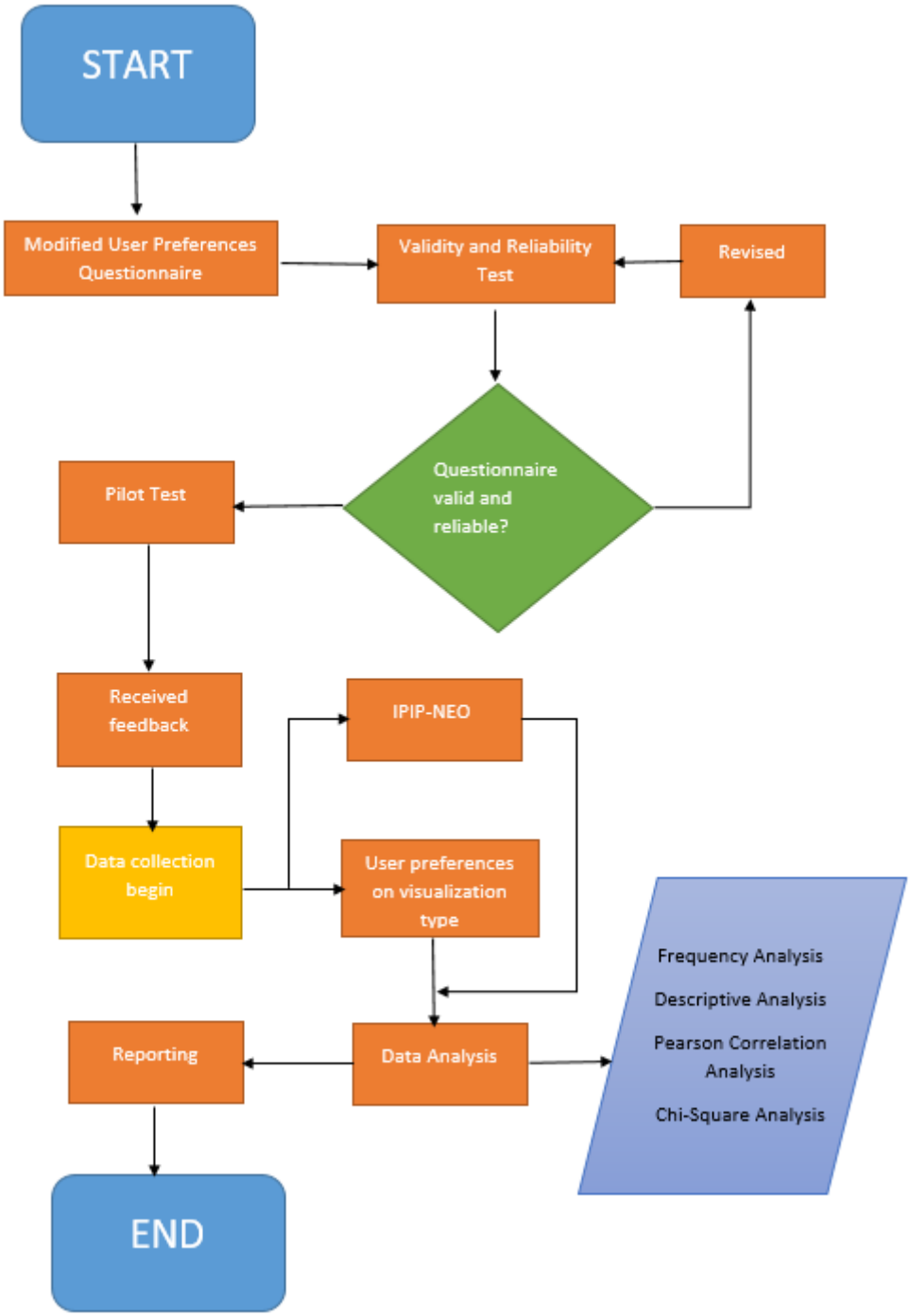


Figure 3.2 Flow Chart of Quantitative Research

In this study, a quantitative research technique was used. Quantitative research entails the collecting and analysis of numerical data, which is often accomplished via the use of surveys, questionnaires, or statistical analyzes of pre-existing data (Ingham-Broomfield, 2014). One of the primary advantages of this technique is that it allows for

the investigation of cause-and-effect interactions between variables as well as the assessment of the link between independent and dependent variables within a population (Polit and Hungler, 2013; Moxham, 2012). A quantitative technique also allows for a more extensive study with a larger number of participants, boosting the generalizability of the findings, and offering better objectivity and accuracy in the research.

A similar sort of quantitative study employing the Myers-Briggs sort Indicator (MBTI) personality test, but with a different emphasis on investigating the link between Judging and Perceiving, two of the MBTI's four dichotomies (Li, Shih, & David, 2018). However, in the proposed study, the researcher intends to employ the Five Factor Model (FFM) as the key personality indicator rather than the MBTI. The MBTI is a popular personality assessment that assesses four cognitive functions: sensing, intuition, reasoning, and emotion (Usman & Minhas, 2019). However, for this research, the FFM was selected over the MBTI because it has better control of class distribution and more interpretable prediction tasks (Celli & Lepri, 2018). Furthermore, the FFM has good statistical validity, with each feature displaying high "constructive validity" and predictive power (David, 2019). Descriptive research design is a style of study that seeks to describe and summarize phenomena, often utilizing numerical and graphical approaches to display data (Dangal, 2021). This method is effective for presenting an accurate and thorough description of a specific occurrence and for exploring patterns, trends, and linkages in data. Descriptive research is often undertaken through surveys, observations, or other data gathering techniques, and it may be conducted using either qualitative or quantitative methodologies.

In descriptive research designs, survey research is a frequent approach. It entails gathering information from a sample of people using a structured questionnaire or survey instrument (Müller, Sedley, & Ferrall-Nunge, 2014). Surveys may be done in a number of methods, including online, via phone, or in person, and are effective for assessing attitudes, beliefs, behaviors, and other aspects of a population. Surveys are often used in descriptive research because they are a simple and efficient approach to gather data from a large number of individuals and may be beneficial for establishing an overall perspective of a population or making temporal comparisons.

Finally, the study's research design and procedure are critical for assuring the reliability and validity of the findings. A well stated research design and technique give a clear and transparent knowledge of how the research was carried out and enable others to duplicate the study if necessary. The research design and technique used will be determined by the precise aims and objectives of the study, as well as the sort of data being gathered and processed. Descriptive research designs, such as surveys, are often used to offer an accurate and thorough account of a certain occurrence and may be carried out using either qualitative or quantitative methodologies (Dangal, 2021). Survey research, in particular, is an effective approach for evaluating a population's attitudes, beliefs, behaviors, and other traits, and it may be conducted in a number of forms (Müller, Sedley, & Ferrall-Nunge, 2014). To give a clear and transparent picture of the research process, it is critical to thoroughly analyze and define the research design and technique employed in a study.

3.4 POPULATION AND SAMPLE

In a research study, the population refers to the group of persons or organisations that the researcher is interested in examining (Babbie, 2017). Creswell and Creswell (2018) define the sample as a subset of the population chosen to participate in the research. The sample size is an essential factor to consider in research since it might impact the reliability and validity of the findings.

The population for this study included undergraduate students from a nearby institution. The sample size was 112 people. The choice to concentrate on undergraduate students as the target sample was designed to decrease sample variability owing to educational level variations, reduce administrative expenses, and maybe reduce response bias. This method enables the researcher to concentrate on a more homogenous and easier-to-study group (Babbie, 2017).

When establishing the optimal sample size for a study, numerous aspects must be considered, including the size and characteristics of the population, the research aims, the accuracy of the estimates needed, and the available resources (Trochim, 2006). To guarantee the generalizability of the findings, it may be required in certain circumstances to pick a sample that is typical of the population (Yin, 2014). To

guarantee the validity and reliability of the study results, the sample size and selection method must be carefully considered.

This study included a non-probability sampling strategy as well as convenience sampling approaches. Convenience sampling is a non-probability sampling approach in which participants are chosen based on their availability or accessibility (Babbie, 2017). When a researcher is unable or unwilling to commit the time and resources required to pick a sample using a probability sampling technique, this strategy is often utilized. When a researcher has limited resources or time and wants to collect data quickly, convenience sampling is often employed. The major benefit of convenience sampling is that it is quick and simple to execute, but it may be biassed since the sample may not be representative of the population (Babbie, 2017).

Non-probability sampling is a sample approach in which the researcher does not use a random or systematic process to pick participants from a community (Babbie, 2017). As a consequence, the sample may not be representative of the total population, and the study's findings may not be generalizable to a wider group. Purposive sampling, convenience sampling, and snowball sampling are all examples of non-probability sampling approaches.

This method has been employed in personality study and with undergraduate students. Ismail, Basharirad, and Ismail (2018), for example, employed convenience sampling to identify undergraduate students who were having trouble deciding on a university curriculum. The researchers employed the Myers Briggs Type Indicator (MBTI) to investigate the elements that impacted the students' decision-making process, and the sample was chosen based on availability and accessibility.

Another research, Li, Shih, and David (2019), employed convenience sampling to choose a sample of 421 undergraduate students to investigate the link between Judging and Perceiving, two components of the Myers-Briggs Type Indicator (MBTI). The sample was chosen based on availability and accessibility, and the researchers employed the MBTI to assess the individuals' personality characteristics.

3.5 INSTRUMENTATION

3.5.1 The Questionnaire

Participants were recruited among undergraduate students. Before the experiment, participants were told of the objectives of the research and the number of surveys to be completed. They can also leave the survey session at any time.

3.5.1.1 The International Personality Item Pool) IPI-NEO

The FFM IPIP-NEO form was used to evaluate the five personality traits (Goldberg, 1999). This test was used to assess the kids' personalities. The questionnaire findings offered estimations of the individual's level of each of the five FFM personality categories, including their subdomains (McCrae & Costa, 2008). In the extraversion domain, for example, subdomains include friendliness (the extent to which an individual genuinely likes and projects positive feelings towards others), gregariousness (the extent to which an individual genuinely enjoys the company of others), assertiveness (the extent to which an individual exhibits leadership and confidence when interacting with others), and activity level (the extent to which an individual leads an active and busy life versus a more passive life).

The IPIP-NEO was given in a truncated version of 120 items in this research. According to the instrument's website (Goldberg, 1999), the abridged version was created to measure the same personality traits as the full version but with fewer items for efficiency. Despite this, the website claims that the original, complete version is more trustworthy. The shorter version was selected for use in this research to eliminate possible concerns with participant boredom and attention span, as well as owing to time restrictions.

It should be noted that using shorter versions of personality tests may result in decreased reliability and validity when compared to complete versions (McDonald, 2015). Because shorter versions may not effectively capture the complete range of qualities and features being assessed, the findings will be less accurate. When determining the version of a personality assessment to utilize in research, it is critical to carefully analyze the trade-off between efficiency and accuracy (McDonald, 2015). The

use of a reduced version of the IPIP-NEO, such as the 120-item form used in this study, may be more practical and efficient to administer in research settings (Goldberg, 1999). This is particularly valuable when time or resources are limited, or when a large number of participants must be evaluated. Shorter versions of personality tests may also be more attractive to participants since they take less time and effort to complete (Goldberg, 1999). This may result in better participation rates and more representative samples. Furthermore, the possible influence of participant characteristics on the outcomes of personality tests should be considered. Individuals who are more intellectually capable, for example, tend to score higher on measures of openness to experience and lower on measures of conscientiousness (Furnham, Cheng, & Cheng, 2015).

Participants in this research were needed to input their nickname or a made-up name, sex, and age on the website to complete the personality evaluation. It is vital to highlight that the assessment replies are fully secret, albeit they may be stored in a database for the purpose of developing the instrument. As a result, participants were cautioned not to use their full name as a nickname. Following the disclosure of this information, participants were given a 120-item personality test. Participants completed the first 60 tasks before going on to the second set of 60 items. The poll employed a five-point Likert scale ranging from "very inaccurate" to "very accurate," and participants were asked to identify themselves using words like "I would never cheat on my taxes." 1999 (Goldberg).

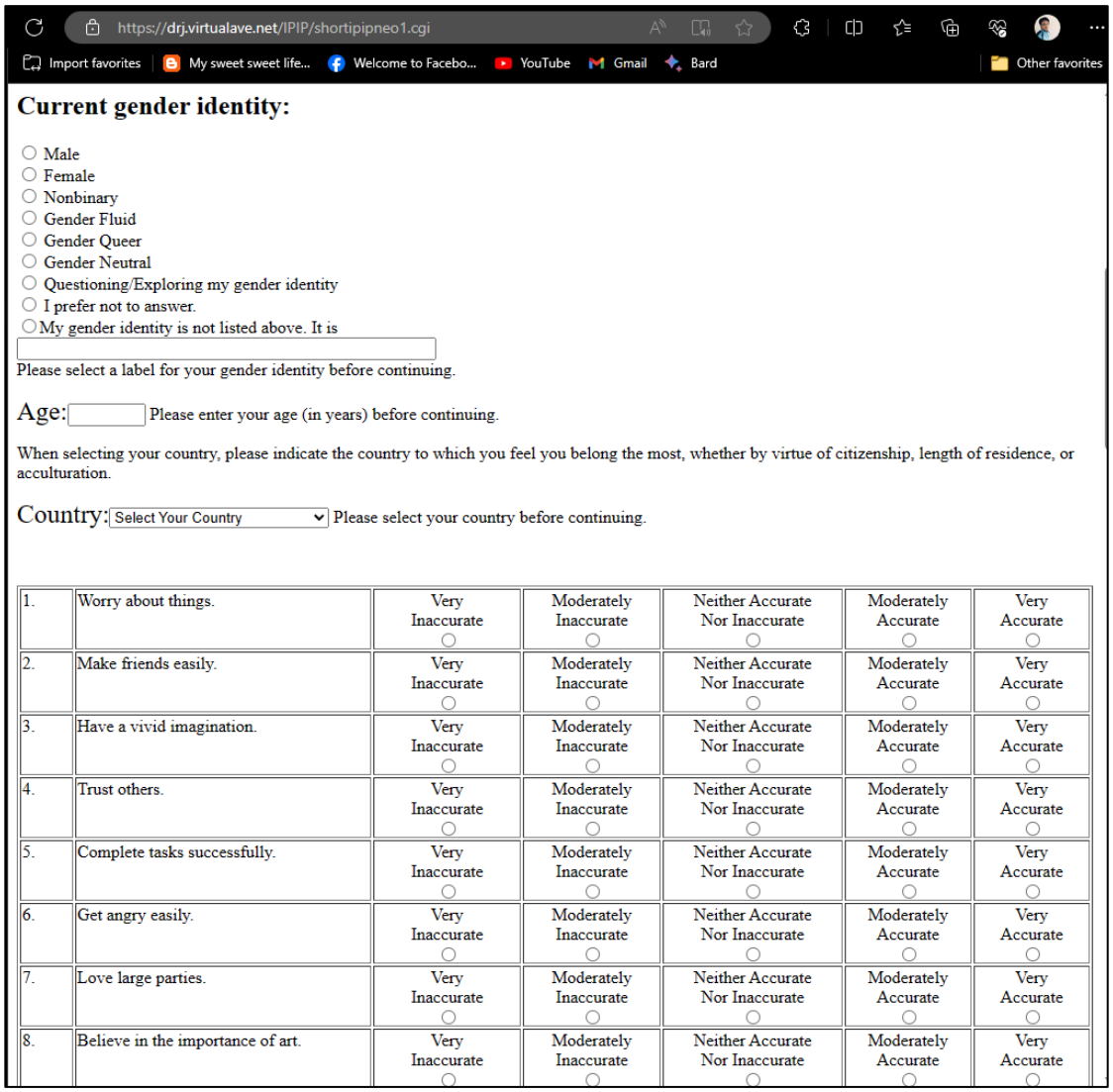


Figure 3.3 The Website Page of IPIP-NEO Test Including Some of the Questions.

3.5.1.2 User Preference on Visualization and Storytelling Questionnaire

The questionnaire utilized in this research was based from a study conducted by Gonc et al. (2020) on the influence of user preferences on idioms used for hierarchy, development through time, and comparative contexts. The questionnaire provided visual samples of several visual designs organized into three settings, and participants were asked to rank their preferences for each design on a seven-point Likert scale, with one being the least preferred and seven being the most preferred. Participants were asked to read the questions and then complete the Likert scale to indicate their preferences for the visual designs.

This research employed a modified version of the questionnaire since it would contain a new part on data narrative techniques that will meet this thesis aim. User context, typeface, buttons, and icons; information density; navigation bar location; hierarchy visualization; change over time visualization; comparison visualization; and narrative style options were all included in the revised version. Participants were asked to identify which category their score fits into for each of the five key personality characteristics (Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness to Experience) in the user context section. For example, if a person scored 45 on the extraversion scale, their score would lie between 40 and 59. In the user context section, there were two extra questions concerning the participants' favorite gadgets and whether or not they were colorblind.

Participants were prompted to choose their desired font style and size in the font section. The section on buttons and icons asked participants to choose their favorite kind of information button. Participants were asked to score their preferences for the density of information regarding the screen size of each interface in the information density section. Participants were able to choose their desired location for the navigation bar in the navigation bar position area.

Participants were asked to pick their favorite form of visualization to depict movie studios and the amount of films produced by each studio depending on genre in the hierarchy visualization section. Data about movie studios and their films was gathered from numerous sources and utilized to build visualizations in the questionnaire's hierarchy visualization section. The data on movie companies and their films may have been used to investigate trends or patterns in the film business, such as genre distribution or the productivity of various studios. To acquire a more thorough picture of the film business, data on movie studios and their films may have been evaluated in combination with other factors such as audience score or profitability.

Film	Genre	Lead Studio	Audience score %	Profitability	Rotten Tomatoes %	Worldwide Gross	Year
27 Dresses	Comedy	Fox	71	5.3436218	40	160.308654	2008
(500) Days of Summer	Comedy	Fox	81	8.096	87	60.72	2009
A Dangerous Method	Drama	Independent	89	0.44864475	79	8.972895	2011
A Serious Man	Drama	Universal	64	4.382857143	89	30.68	2009
Across the Universe	Romance	Independent	84	0.652603178	54	29.367143	2007
Beginners	Comedy	Independent	80	4.471875	84	14.31	2011
Dear John	Drama	Sony	66	4.5988	29	114.97	2010
Enchanted	Comedy	Disney	80	4.005737082	93	340.487652	2007
Fireproof	Drama	Independent	51	66.934	40	33.467	2008
Four Christmases	Comedy	Warner Bros.	52	2.022925	26	161.834	2008
Ghosts of Girlfriends Past	Comedy	Warner Bros.	47	2.0444	27	102.22	2009
Gnomeo and Juliet	Animation	Disney	52	5.387972222	56	193.967	2011
Going the Distance	Comedy	Warner Bros.	56	1.3140625	53	42.05	2010
Good Luck Chuck	Comedy	Lionsgate	61	2.36768512	3	59.192128	2007
He's Just Not That Into You	Comedy	Warner Bros.	60	7.1536	42	178.84	2009
High School Musical 3: Senior Year	Comedy	Disney	76	22.91313646	65	252.044501	2008
I Love You Phillip Morris	Comedy	Independent	57	1.34	71	20.1	2010
It's Complicated	Comedy	Universal	63	2.642352941	56	224.6	2009
Jane Eyre	Romance	Universal	77		85	30.147	2011
Just Wright	Comedy	Fox	58	1.797416667	45	21.569	2010
Killers	Action	Lionsgate	45	1.245333333	11	93.4	2010
Knocked Up	Comedy	Universal	83	6.636401848	91	219.001261	2007
Leap Year	Comedy	Universal	49	1.715263158	21	32.59	2010
Letters to Juliet	Comedy	Summit	62	2.639333333	40	79.18	2010
License to Wed	Comedy	Warner Bros.	55	1.9802064	8	69.307224	2007
Life as We Know It	Comedy	Independent	62	2.530526316	28	96.16	2010
Love & Other Drugs	Comedy	Fox	55	1.817666667	48	54.53	2010
Love Happens	Drama	Universal	40	2.004444444	18	36.08	2009
Made of Honor	Comedy	Sony	61	2.64906835	13	105.962734	2008
Mamma Mia!	Comedy	Universal	76	9.234453864	53	609.473955	2008
Marley and Me	Comedy	Fox	77	3.746781818	63	206.073	2008
Midnight in Paris	Romance	Sony	84	8.744705882	93	148.66	2011
Miss Pettigrew Lives for a Day	Comedy	Independent	70	0.2528949	78	15.173694	2008
Monte Carlo	Romance	20th Century Fox	50	1.9832	38	39.664	2011
Music and Lyrics	Romance	Warner Bros.	70	3.64741055	63	145.896422	2007
My Week with Marilyn	Drama	The Weinstein Company	84	0.8258	83	8.258	2011
New Year's Eve	Romance	Warner Bros.	48	2.536428571	8	142.04	2011
Nick and Norah's Infinite Playlist	Comedy	Sony	67	3.3527293	73	33.527293	2008
No Reservations	Comedy		64	3.307180357	39	92.60105	2007
Not Easily Broken	Drama	Independent	66	2.14	34	10.7	2009
One Day	Romance	Independent	54	3.682733333	37	55.241	2011
Our Family Wedding	Comedy	Independent	49		14	21.37	2010
Over Her Dead Body	Comedy	New Line	47	2.071	15	20.71	2008
P.S. I Love You	Romance	Independent	82	5.103116833	21	153.093505	2007
Penelope	Comedy	Summit	74	1.382799733	52	20.741996	2008
Rachel Getting Married	Drama	Independent	61	1.384166667	85	16.61	2008
Remember Me	Drama	Summit	70	3.49125	28	55.86	2010
Sex and the City	Comedy	Warner Bros.	81	7.221795791	49	415.253258	2008
Sex and the City 2	Comedy	Warner Bros.	49	2.8835	15	288.35	2010
She's Out of My League	Comedy	Paramount	60	2.4405	57	48.81	2010
Something Borrowed	Romance	Independent		1.719514286		60.183	2011
Tangled	Animation	Disney	88	1.365692308	89	355.08	2010
The Back-up Plan	Comedy	CBS	47	2.202571429	20	77.09	2010
The Curious Case of Benjamin Button	Fantasy	Warner Bros.	81	1.78394375	73	285.431	2008
The Duchess	Drama	Paramount	68	3.207850222	60	43.305978	2008
The Heartbreak Kid	Comedy	Paramount	41	2.129444167	30	127.76665	2007
The Invention of Lying	Comedy	Warner Bros.	47	1.751351351	56	32.4	2009
The Proposal	Comedy	Disney	74	7.8675	43	314.7	2009
The Time Traveler's Wife	Drama	Paramount	65	2.598205128	38	101.33	2009
The Twilight Saga: New Moon	Drama	Summit	78	14.1964	27	709.82	2009
The Ugly Truth	Comedy	Independent	68	5.402631579	14	205.3	2009
Twilight	Romance	Summit	82	10.18002703	49	376.661	2008
Twilight: Breaking Dawn	Romance	Independent	68	6.383363636	26	702.17	2011
Tyler Perry's Why Did I get Married	Romance	Independent	47	3.7241924	46	55.862886	2007
Valentine's Day	Comedy	Warner Bros.	54	4.184038462	17	217.57	2010
Waiting For Forever	Romance	Independent	53	0.005	6	0.025	2011
Waitress	Romance	Independent	67	11.0897415	89	22.179483	2007
WALL-E	Animation	Disney	89	2.896019067	96	521.283432	2008
Water For Elephants	Drama	20th Century Fox	72	3.081421053	60	117.094	2011
What Happens in Vegas	Comedy	Fox	72	6.267647029	28	219.367646	2008
When in Rome	Comedy	Disney	44		15	43.04	2010
You Will Meet a Tall Dark Stranger	Comedy	Independent	35	1.211818182	43	26.66	2010
Youth in Revolt	Comedy	The Weinstein Company	52	1.09	68	19.62	2010
Zack and Miri Make a Porno	Romance	The Weinstein Company	70	1.747541667	64	41.941	2008

Figure 3.4 Hierarchy Visualization Data

In the change over time visualization section, participants were asked to choose their preferred type of visualization to represent data on the number of mass shootings. The data on the number of mass shootings in the United States from 1980 to 2021 was used to create visualizations in the change over time visualization section of the questionnaire. The data on mass shootings may have been used to explore trends or patterns in the incidence of mass shootings over time, such as any changes in frequency or severity, analyzed in conjunction with other variables, such as the location or motive for the shootings, to gain a more comprehensive understanding of this issue and to inform policy or advocacy efforts related to gun violence prevention.

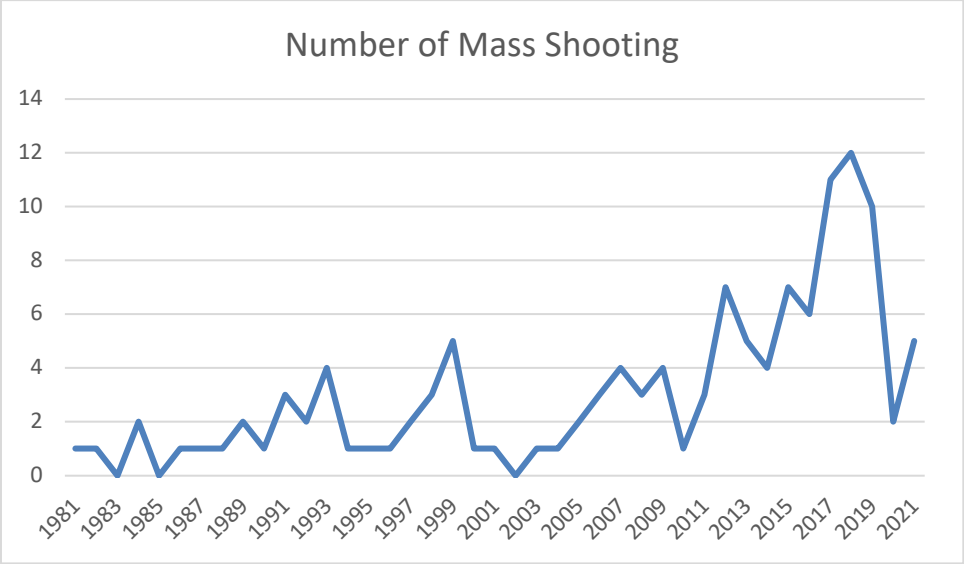


Figure 3.5 Change Over Time Visualization Data.
Sources from Statista.com

Participants were invited to pick their favorite visualization methods to depict data on the number of World Cup victories for eight different nations in the comparative visualization section: England, Italy, France, Brazil, Argentina, Germany, Spain, and Uruguay. The data on World Cup victories may have been used to investigate patterns or trends in various nations' performance in this international football competition, such as the dominance of specific countries or the rise and fall of different teams over time. To acquire a more full knowledge of the World Cup, the comparative visualizations may have been evaluated in combination with other factors such as the performance of particular players or the tactics utilized by various teams.

Table 3.1 Comparison visualization. The number of World Cups won by FIFA.

Country	**Number of World Cup win**
Argentina	2
Brazil	5
England	1
France	2
Germany	4
Italy	4
Spain	1
Uruguay	2

In the storytelling styles preferences section, participants were asked to choose their preferred type of visual storytelling design. This may have included various options for the layout, organization, and presentation of information in a visual format, such as using charts, graphs, maps, or infographics. The selected storytelling styles may have been used to communicate complex or nuanced information in a more engaging and accessible way or to highlight specific patterns or trends in the data.

The author completed the design on the Canva website in the context of the current study, which used the magazine style. The information for the magazine-style presentation was from the World Health Organization's website, with the focus being on the global COVID-19 pandemic.

Figure 3.6 Magazine Style Visual Type.

The image was created by the author and the information in the image was obtained from the World Health Organization (WHO) website.

A flowchart-infographic is a visual representation that incorporates components from both flowcharts and infographics. Flowcharts employ boxes and arrows to illustrate the flow of information inside a system or process, while infographics use graphic visualizations to communicate data or information in a succinct and correct manner (Aydin & Cam, 2020).

In the present investigation, a flowchart-infographic depicting the connections between several characters was built utilizing material from the 1983 film Star Wars: Return of the Jedi. The author created the flowchart-infographic, which included endnotes and summary boxes, which are annotated charts that give extra context and explain the information provided in the graphs. Smith, Lee, and Kazi (2013).

Figure 3.7 Flowchart-Infographic Visualization of Star Wars Characters' Relationship. The image is an original design by the author.

In this research, the author designed the partitioned poster, and the contents were taken from the equilibrium concept.

Figure 3.8 Visualization of Partition Equilibrium.

The image is an original design by the author.

The data for the annotated chart was taken from Statista.com and showed the unemployment rate in the United States from 2000-2020.

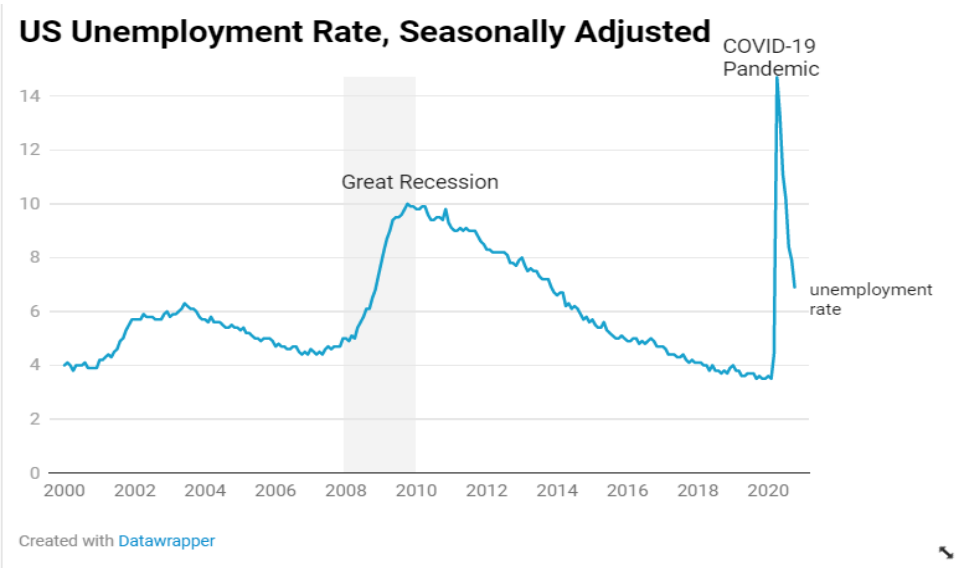


Figure 3.9 Annotated Chart Visualization of the US Unemployment Rate.

The image is an original design by the author

The comics and animation used in this research are based on information about China's investments in India over the years. The illustrations for the comic and animation were created using drawing software and designed by the author.

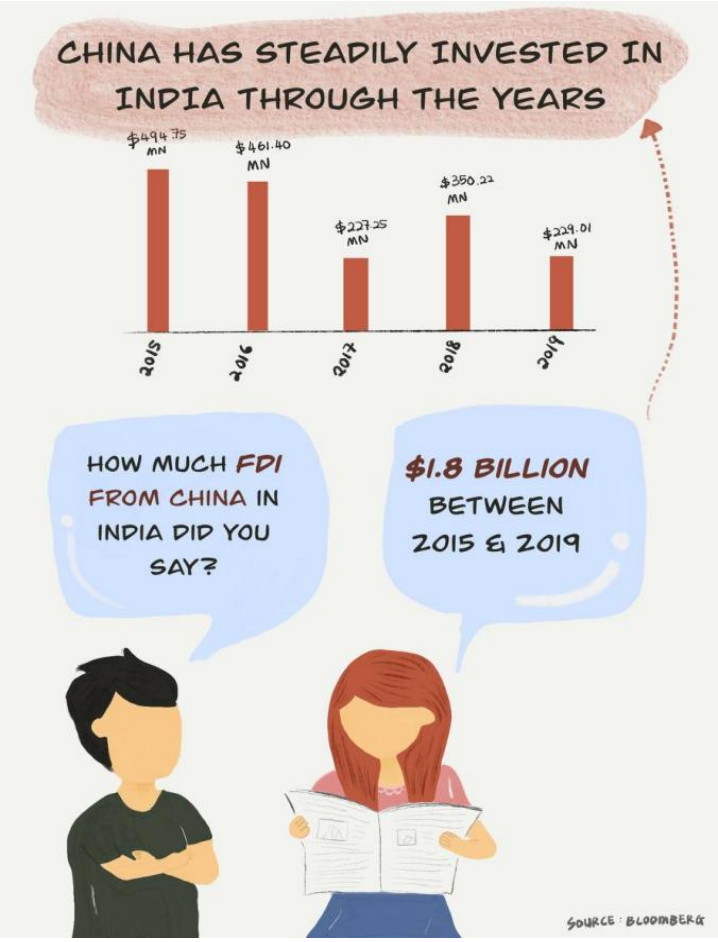


Figure 3.10 Comic and Animation Visualization Type of China Investment in India. The image is an original design by the author.

3.6 CONTENT VALIDATION AND RELIABILITY

The questionnaire used to gather information on user preferences for visualization types was divided into two categories: information visualization and storytelling techniques. The items included in the questionnaire were based on a review of relevant literature and adapted from an existing questionnaire created by Gonc et al. (2020).

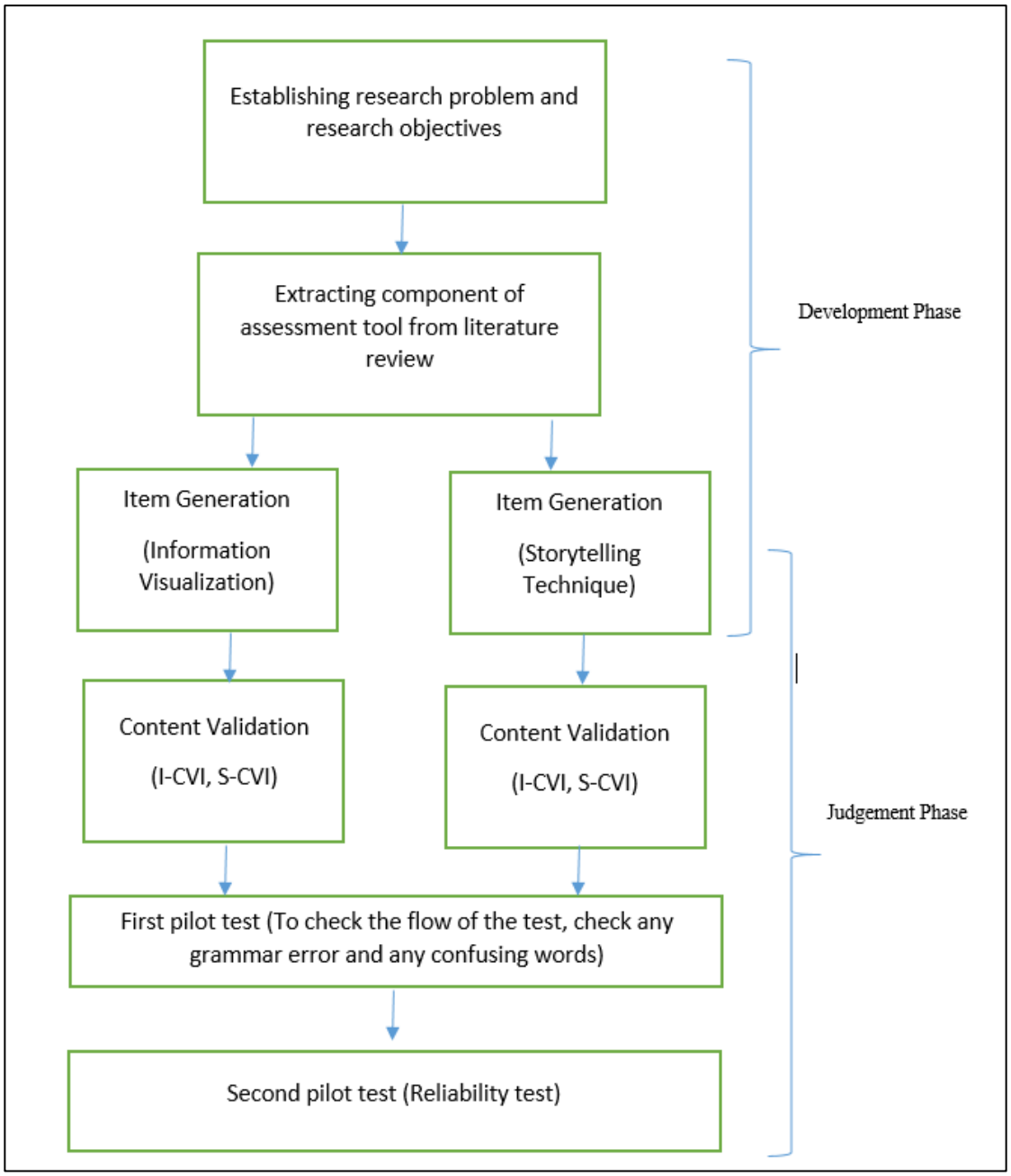


Figure 3.11 The Flowchart of Development and Validation of User Preferences on Visualization and Storytelling Techniques Questionnaire.

The process of developing and validating the User Preference on Visualization and Storytelling questionnaire, which aims to investigate the relationship between personality traits and user preferences for visualization types in terms of effective, efficient, and meaningful visualization and storytelling, is depicted in Figure 1. The questionnaire was modified from one produced by Gonc et al. (2020), which focused on the influence of user preferences on the usage of idioms in the hierarchy, their

progression over time, and comparative settings (Gonc, Alves, Ramalho, & Gama 2020). The questionnaire also contained a section on several styles of narrative visualization.

The poll contained visual samples of several design styles, which were organized into categories. Participants were asked to read the questions and then use a 7-point Likert scale to indicate their preferences for each design type, with 1 being the lowest and 7 being the greatest.

3.6.1 Validity Test

The content validity index (CVI) and inter-rater reliability tests were conducted on each item in the questionnaire to assure its accurate and adequate measurement of the intended notion. The concept of content validity pertains to the degree to which a measurement tool encompasses a representative subset of the overall domain of the specific attribute being assessed (Venkitachalam, 2003). In order to assess the content validity of the questionnaire, a panel consisting of seven specialists specializing in data analysis and visualization from both academic and industrial backgrounds was convened. The experts assessed the pertinence and inclusiveness of each topic using a Likert scale that ranged from 0 (indicating lack of relevance) to 4 (indicating high relevance). The questionnaire underwent revision in accordance with the suggestions provided by the panel, and subsequent analysis of the panel's raw scores was conducted using Microsoft Excel. The researchers manually computed the item-level content validity index (I-CVI), scale-level content validity index (S-CVI), universal agreement calculation method (S-CVI/UA), and averaging calculation methodology (S-CVI/Ave) in order to assess the overall content validity of the questionnaire.

Ebeling and Nitzl (2019) argue that content validity has significant importance in the context of measuring instruments, since it guarantees the true representation of the intended notion. Prior to using the instrument for data collection, it is vital to verify content validity, as it serves to guarantee the reliability and validity of the obtained findings (Messick, 1989).

The content validity index (CVI) may be categorized into two distinct types: item-level CVI (I-CVI) and scale-level CVI (S-CVI). There are two ways available for

calculating the Scale Content Validity Index (S-CVI). The first approach involves obtaining the average of the Item Content Validity Index (I-CVI) scores for all items on the scale, which is referred to as S-CVI/Ave. The second method involves determining the percentage of items on the scale that get a relevant value of 3 or 4 from all experts, known as S-CVI/UA (Yusoff, 2019). In order to compute the CVI, it is necessary to document the relevance ratings as either 1 (indicating a relevance scale of 3 or 4) or 0 (indicating no relevance, on a relevance scale of 1 or 2) (Mohamad Marzuki et al., 2018). The data presentation takes into account both individual item judgements and the average of each item. The inclusion of the supplementary calculation for universal agreement serves to evaluate the degree of consistency among raters, known as inter-rater dependability. The calculation of S-CVI/Ave may be performed by using the following formulas:

I-CVI = (agreed item) / (number of raters)

S-CVI/Ave = (summation of all I-CVI) / (number of items)

There are two ways to calculate S-CVI/Ave. The first method entails adding up all I-CVI values and dividing them by the number of elements. The second method is to compute the average percentage of agreement for each rater. S-CVI/UA is determined by dividing the total number of items in the domain by the number of things with 100% agreement. According to Mohamad Marzuki et al. (2018), for a measuring instrument to be regarded satisfactory in terms of content validity, it must attain at least 80% agreement.

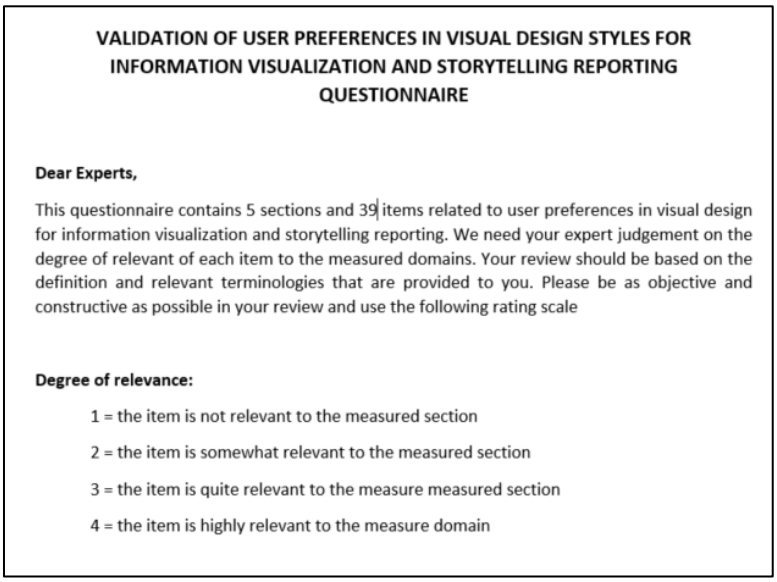
The constancy of a measurement device over time is referred to as its reliability. It assesses how well an instrument score represents an individual's genuine talents or qualities (Price, Jhangiani, & Chiang, 2015). For example, if a set of students regularly performs well on two English language exams given by the same teacher over the course of a term, this would imply that the test questions are reliable assessments of the students' English language ability. In other words, the student's test results are a good predictor of their genuine English language ability.

Reliability testing is essential because it evaluates the consistency of items inside a measuring device (Huck, 2007). The scale is considered to have strong internal

consistency and reliability if the items on it measure the same concept and are consistently connected to each other. The Cronbach's Alpha coefficient is the most often used internal consistency metric. Cronbach's Alpha is regarded as the best acceptable measure of reliability when employing a Likert scale (Taherdoost, 2018). This test entails computing the average of all correlations between all conceivable combinations of the instrument's divided halves. This exam may use instruments with multiple-choice questions. Cronbach's Alpha is a number between 0 and 1, with 0.7 deemed good (Heale & Twycross, 2015).

The questionnaire's content validity was tested from July 5th to July 14th, 2021. For the testing, seven specialists were recruited: four from business and three from academics. Initially, 15 specialists were sought, but only seven accepted the offer. For content validation, the non-face-to-face technique was employed, which included giving an online content validation form to the experts along with explicit instructions to aid the procedure. When a systematic follow-up is in place to raise the response rate and duration, the non-face-to-face technique may be extremely efficient (Yusoff, 2019). An online poll was used to conduct the expert evaluation procedure.

The questionnaire has 39 questions. The validation form contained instructions and a grading scale to assist verify that the intended respondents (the panel of experts) understood the questionnaire and had clear expectations for completing it.



VALIDATION OF USER PREFERENCES IN VISUAL DESIGN STYLES FOR INFORMATION VISUALIZATION AND STORYTELLING REPORTING QUESTIONNAIRE

Dear Experts,

This questionnaire contains 5 sections and 39 items related to user preferences in visual design for information visualization and storytelling reporting. We need your expert judgement on the degree of relevant of each item to the measured domains. Your review should be based on the definition and relevant terminologies that are provided to you. Please be as objective and constructive as possible in your review and use the following rating scale

Degree of relevance:

1 = the item is not relevant to the measured section

2 = the item is somewhat relevant to the measured section

3 = the item is quite relevant to the measure measured section

4 = the item is highly relevant to the measure domain

Figure 3.12 The Validation Form for the Experts

After reviewing the domain and items, the experts provided scores for each item individually using the provided scale. Once all items had been scored, the experts submitted their responses to the researcher. The results of the content validation process are presented below.

Item/Expert	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7		Expert in Agreement	I-CVI	UA
Q1	1	1	1	1	0	1	1		6	0.86	0
Q2	1	1	1	1	1	1	1		7	1	1
Q3	1	1	1	1	1	1	1		7	1	1
Q4	1	1	1	1	0	1	1		6	0.86	0
Q5	1	1	1	1	0	1	1		6	0.86	0
Q6	1	1	1	1	1	1	1		7	1	1
Q7	0	1	1	0	1	0	0		3	0.43	0
Q8	1	0	1	0	0	1	0		3	0.43	0
Q9	0	1	0	1	0	0	0		2	0.29	0
Q10	1	1	1	1	1	0	0		5	0.71	0
Q11	1	1	0	1	0	1	1		5	0.71	0
Q12	1	1	0	1	0	1	1		5	0.71	0
Q13	1	1	1	1	0	1	1		6	0.86	0
Q14	1	1	1	1	1	1	1		7	1	1
Q15	1	1	1	1	0	0	1		5	0.71	0
Q16	1	1	0	1	1	1	1		6	0.86	0
Q17	1	1	1	1	0	1	1		6	0.86	0
Q18	1	1	1	0	0	0	1		4	0.57	0
Q19	1	1	1	0	0	0	1		4	0.57	0
Q20	1	1	1	1	0	0	1		5	0.71	0
Q21	1	1	1	1	0	1	1		6	0.86	0
Q22	1	1	1	1	0	1	1		6	0.86	0
Q23	1	1	1	1	1	0	1		6	0.86	0
Q24	1	1	0	1	0	1	1		5	0.71	0
Q25	1	1	0	1	1	1	1		6	0.86	0
Q26	1	0	1	1	1	1	1		6	0.86	0
Q27	1	1	1	1	1	1	1		7	1	1
Q28	1	1	1	1	0	1	1		6	0.86	0
Q29	1	1	1	1	1	1	1		7	1	1
Q30	1	1	1	1	1	1	1		7	1	1
Q31	1	1	1	1	1	1	1		7	1	1
Q32	1	0	1	1	1	1	1		6	0.86	0
Q33	0	1	0	0	0	1	1		3	0.43	0
Q34	1	1	0	1	0	0	1		4	0.57	0
Q35	1	1	1	1	0	1	1		6	0.86	0
Q36	1	1	1	1	1	1	1		7	1	1
Q37	1	1	1	1	0	0	0		4	0.57	0
Q38	1	1	1	1	0	0	1		5	0.71	0
Q39	1	1	1	1	0	1	1		6	0.86	0
Propotion Relevance	0.92	0.92	0.79	0.87	0.41	0.72	0.87		S-CVI/Ave	0.79	
Sum of Proportion	5.5								S-CVI/UA	0.230769	
S-CVI/Ave	0.79										

Figure 3.13 The Original Content Validation Data

Based on the data presented, it appears that the questionnaire did not meet the threshold for content validity. The acceptable value of 0.83 for a panel of six to eight experts according to Lynn (1986) is below the S-CVI/Ave score of 0.79. To improve the content validity of the questionnaire, the researcher removed the sections on colors (items 7-9) and storytelling tactics (items 32–34), resulting in an improved CVI score of 0.84.

Item/Expert	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7		Expert in Agreement	I-CVI	UA
Q1	1	1	1	1	0	1	1		6	0.86	0
Q2	1	1	1	1	1	1	1		7	1	1
Q3	1	1	1	1	1	1	1		7	1	1
Q4	1	1	1	1	0	1	1		6	0.86	0
Q5	1	1	1	1	0	1	1		6	0.86	0
Q6	1	1	1	1	1	1	1		7	1	1
Q10	1	1	1	1	1	0	0		5	0.71	0
Q11	1	1	0	1	0	1	1		5	0.71	0
Q12	1	1	0	1	0	1	1		5	0.71	0
Q13	1	1	1	1	0	1	1		6	0.86	0
Q14	1	1	1	1	1	1	1		7	1	1
Q15	1	1	1	1	0	0	1		5	0.71	0
Q16	1	1	0	1	1	1	1		6	0.86	0
Q17	1	1	1	1	0	1	1		6	0.86	0
Q18	1	1	1	0	0	0	1		4	0.57	0
Q19	1	1	1	0	0	0	1		4	0.57	0
Q20	1	1	1	1	0	0	1		5	0.71	0
Q21	1	1	1	1	0	1	1		6	0.86	0
Q22	1	1	1	1	0	1	1		6	0.86	0
Q23	1	1	1	1	1	0	1		6	0.86	0
Q24	1	1	0	1	0	1	1		5	0.71	0
Q25	1	1	0	1	1	1	1		6	0.86	0
Q26	1	0	1	1	1	1	1		6	0.86	0
Q27	1	1	1	1	1	1	1		7	1	1
Q28	1	1	1	1	0	1	1		6	0.86	0
Q29	1	1	1	1	1	1	1		7	1	1
Q30	1	1	1	1	1	1	1		7	1	1
Q31	1	1	1	1	1	1	1		7	1	1
Q35	1	1	1	1	0	1	1		6	0.86	0
Q36	1	1	1	1	1	1	1		7	1	1
Q37	1	1	1	1	0	0	0		4	0.57	0
Q38	1	1	1	1	0	0	1		5	0.71	0
Q39	1	1	1	1	0	1	1		6	0.86	0
Propotion Relevance	1	0.97	0.85	0.94	0.42	0.76	0.94		S-CVI/Ave	0.84	
Sum of Proportion	5.88								S-CVI/UA	0.272727	
S-CVI/Ave	0.84										

Figure 3.14 The New Data After Removing Not Relevant Sections

3.6.2 Reliability Test

Reliability testing was carried out with the help of 12 target users who completed the questionnaire online through a URL link. The majority of the intended users were Malaysian university students with at least a bachelor's degree.

Table 3.2 Listwise Deletion Based on All Variables in the Procedure.

		N	%
Cases	Valid	12	100.0
	Excludeda	0	.0
	Total	12	100.0

Table 3.3 Cronbach's Alpha value

Cronbach's Alpha	N of Items
.910	33

Table 3.4 Item Statistics

	Mean	Std. Deviation	N
1. Arial	6.08	1.165	12
2. Calibri	5.58	1.443	12
3. Calibri Light	5.08	1.782	12
4. Small font size	3.08	1.505	12
5. Medium font size	4.33	1.303	12
6. Large font size	5.58	1.165	12
10. Button with icon only.	4.17	1.697	12
11. Button with text	4.58	1.084	12
12. Button with icon and with text	4.42	1.881	12
13. Low density	4.75	1.545	12
14. Average density	5.00	1.206	12

	Mean	Std. Deviation	N
15. High density	5.08	1.443	12
16. Top position of the navigation bar	5.33	1.497	12
17. Bottom position of the navigation bar	4.50	1.834	12
18. Right position of the navigation bar	3.75	2.006	12
19. Left position of the navigation bar	3.67	1.826	12
20. Representation through a Treemap.	4.83	1.115	12
21. Representation through a Circular Packing diagram.	4.58	1.240	12
22. Representation through a Sunburst.	4.83	1.992	12
23. Representation through a Radial diagram	3.83	1.850	12
24. Representation through a Line chart.	4.58	.900	12
25. Representation through a Line chart, with points.	4.92	1.782	12
26. Representation through an Area chart.	5.08	1.621	12
27. Representation through a Radar chart	5.25	1.288	12
28. Representation through a Word Cloud	4.67	1.435	12
29. Representation through a horizontal bar chart	4.83	.937	12
30. Representation through a vertical bar chart	5.33	.985	12
31. Representation through a Pie Chart.	5.33	1.723	12
36. Magazine Style	5.17	.937	12
37. Annotated Chart	5.25	1.485	12
38. Flowchart-Infographic	5.67	1.155	12
39. Partitioned Poster	4.75	1.288	12
40. Comic & Animation	5.58	.996	12

Table 3.5 Total Items Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
1. Arial	153.42	559.356	.794	.904
2. Calibri	153.92	549.902	.775	.903
3. Calibri Light	154.42	527.902	.896	.900
4. Small font size	156.42	584.083	.249	.911
5. Medium font size	155.17	584.515	.290	.910
6. Large font size	153.92	578.992	.430	.908
10. Button with icon only.	155.33	637.152	-.415	.922
11. Button with text	154.92	575.356	.537	.907
12. Button with icon and with text	155.08	546.447	.619	.905
13. Low density	154.75	573.659	.384	.909
14. Average density	154.50	570.636	.562	.907
15. High density	154.42	554.265	.708	.904
16. Top position of the navigation bar	154.17	561.424	.575	.906
17. Bottom position of the navigation bar	155.00	558.909	.486	.908
18. Right position of the navigation bar	155.75	538.932	.660	.904
19. Left position of the navigation bar	155.83	553.242	.557	.906
20. Representation through a Treemap.	154.67	587.697	.287	.910
21. Representation through a Circular Packing diagram.	154.92	580.083	.382	.909

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
22. Representation through a Sunburst.	154.67	546.788	.576	.906
23. Representation through a Radial diagram	155.67	537.515	.740	.903
24. Representation through a Line chart.	154.92	576.629	.625	.907
25. Representation through a Line chart, with points.	154.58	561.720	.468	.908
26. Representation through an Area chart.	154.42	545.174	.748	.903
27. Representation through a Radar chart	154.25	568.568	.557	.907
28. Representation through a Word Cloud	154.83	598.152	.060	.914
29. Representation through a horizontal bar chart	154.67	597.697	.128	.911
30. Representation through a vertical bar chart	154.17	596.152	.153	.911
31. Representation through a Pie Chart.	154.17	558.879	.523	.907
36. Magazine Style	154.33	569.697	.757	.906
37. Annotated Chart	154.25	561.841	.574	.906
38. Flowchart-Infographic	153.83	591.606	.205	.911
39. Partitioned Poster	154.75	590.023	.204	.911

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
40. Comic & Animation	153.92	585.902	.364	.909

IBM SPSS was used to perform the reliability analysis. Table 3.1 presents the outcomes of listwise deletion, demonstrating the impact of removing cases with missing values across all variables in the research procedure. In Table 3.2, Cronbach's Alpha values are showcased, providing an indication of the internal consistency reliability of the research instrument. Table 3.3 delves into the item statistics, offering insights into the performance of individual items in the research instrument and their contribution to overall reliability. Table 3.4 outlines the total-items statistic, summarizing key reliability metrics and providing a comprehensive view of the overall reliability of the research instrument. The questionnaire is trustworthy, according to Table 3.2, with a Cronbach's Alpha value of 0.91 for 33 questions, which is more than the minimum acceptable value of 0.7 (Mohamad Marzuki et al., 2018; Taherdoost, 2018; Venkitachalam, 2003). Finally, the researcher employed content validity to evaluate the questionnaire and Cronbach's Alpha to assess its reliability. The questionnaire was confirmed to be valid after being revised based on the content validation findings, with a CVI value of 0.84, which satisfies the acceptable CVI value of 0.83. The questionnaire was also determined to be trustworthy, with a Cronbach's Alpha score of 0.91, which is more than the acceptable threshold of 0.7.

3.7 PILOT STUDY

A pilot test was carried out on June 7, 2021, utilizing the WhatsApp programme. The researcher created a WhatsApp group and all instructions were given there. The pilot test entailed administering a small-scale version of the full survey to eight persons aged 25 and above from various origins, education levels, and genders. The researcher sent the survey link through a WhatsApp group and discussed the project's goals and processes, as well as the quantity of participants required for the study.

The individuals were asked to participate in the research and given enough time to determine whether or not to participate. They were then given the questionnaire, which sought information on personality characteristics and user preferences in information visualization and narrative reporting visualization forms. The measuring instrument (a questionnaire) asked participants to complete it on their own. The questionnaire's comprehensibility, appropriateness, and consistency of question wording and presentation were also reviewed throughout the pilot test.

There were three components to the questionnaire: user context, information visualization, and narrative. The questionnaire took participants an average of 10-15 minutes to complete, with one person spending 20 minutes. All feedback from the pilot test were taken into account, and problems were fixed.

Some participants gave comments and recommendations for enhancing the questionnaire during the pilot test. The size of the check boxes on the personality test was complained about by four out of eight participants, and it was suggested that the questionnaire be completed on a computer rather than a mobile device for a better experience. The directions for filling in scores were perplexing to all participants, thus the researcher changed the format from adding scores to picking a range for personality ratings. Participants were asked to choose which groups their scores belonged to after obtaining their results for each personality trait and aspect. One participant complained that the questionnaire (which included both the personality test and questions on user preferences) had too many questions.

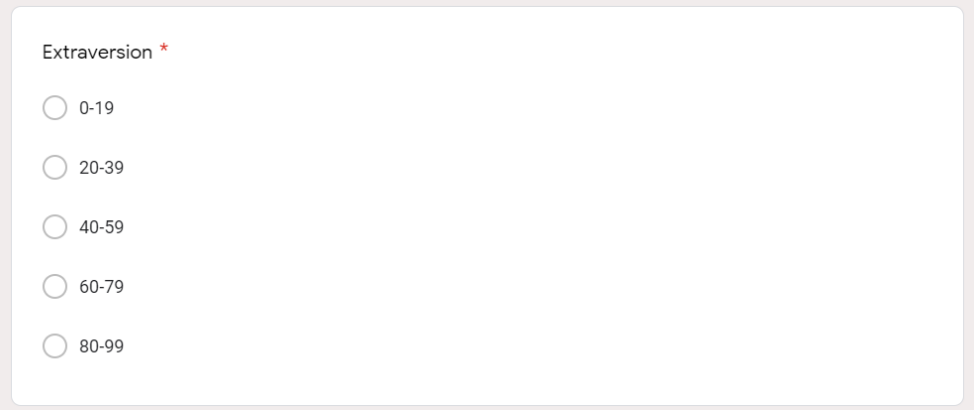


Figure 3.15 The New Format of the Score

3.8 SURVEY COLLECTION PROCEDURES

The survey was carried out online with the use of a web-based survey application. This approach will describe how to recruit participants, distribute the survey, and manage the data gathering process.

This survey's participants were drawn from a pool of undergraduate students from a nearby institution. Social media platforms such as Facebook, Twitter, Telegram, and WhatsApp are used in the recruiting process. The proper survey instrument was employed, which enables for online data gathering. The authors additionally verified that the survey was operational and that all questions were legitimate.

The survey tool's gathered replies were exported into a spreadsheet. The information was validated for completeness and correctness. This document's online survey collecting technique is intended to verify that the data obtained is trustworthy and legitimate. The authors expect that by following these protocols, they can reduce possible sources of bias and guarantee that the data obtained delivers relevant insights into this study..

3.9 DATA ANALYSIS PROCEDURES

The Statistical Package for the Social Sciences (SPSS) was used to analyze the data gathered in this research. Pearson's correlation approach was utilized to investigate the association between personality traits and user preferences. This approach is often used to evaluate the strength and direction of linear relationships between two continuous variables (Field, 2009). The degree to which personality traits were connected to user preferences might be determined using Pearson's correlation approach. It should be noted that Pearson's correlation approach is best suited when the variables under consideration are continuous and regularly distributed (Hinkle, Wiersma, & Jurs, 1988). Furthermore, Pearson's correlation coefficient is susceptible to the existence of outliers, which may affect the analysis's conclusions (Zhang & Ying, 2011). To solve this problem, it may have been essential to eliminate extreme scores or alter the data in order to limit the impact of outliers (Zhang & Ying, 2011).

The descriptive analysis approach was then used to get a better understanding of the link between personalities, information visualization, and narrative preferences. The purpose of descriptive statistics was to identify the mean and standard deviation of each variable and to investigate variations in personality and visualization kinds (Russo & Stol, 2020). At this point, a correlation between the variables was also evaluated to assess the degree and direction of any relationships. Descriptive analysis may give useful insights into the properties of the data and the connections between variables, which can help understand the findings and lead additional research (Russo & Stol, 2020).

Following the completion of the descriptive study, frequency and chi-square analyzes were performed to better understand the link between personalities, information visualization, and narrative preferences. Frequency analysis, which entails counting the number of occurrences of each category or value inside a variable, may give insights into the data's distribution and relative proportions (Field, 2009). Chi-square analysis, on the other hand, is used to examine the link between two categorical variables and may reveal if the variables have a significant correlation (Field, 2009). Both frequency analysis and chi-square analysis may give useful insights into the properties of the data and the connections between variables, which can help understand the findings and lead additional study (Field, 2009).

3.10 ETHICAL CONSIDERATION

The participants were given information about the research both verbally and in writing, and their participation was entirely voluntary. The research only included students who provided informed consent. The surveys for the FFM and user preferences were conducted anonymously. The participants had the option to leave the study at any time.

3.11 CHAPTER CONCLUSION

This chapter outlines the methodological aspects of this study, including the design of the research, the population, the study sample, the data collection process, the data analysis, and the ethical considerations.

CHAPTER FOUR

RESULTS

4.1 INTRODUCTION

This chapter covers the results of the data analysis, which is divided into four sections. The first section discusses the questionnaire's validity and reliability. The pilot study is discussed in the second section. The third section explains the data gathering procedure, while the last section offers data analysis techniques such as correlation and descriptive statistics.

4.2 DATA ANALYSIS

4.2.1 Frequency Analysis

Frequency analysis was used to view the demographic distribution of the personalities and the visual designs. Frequency analysis is used to predict how often certain values of a variable phenomenon may occur and to assess the reliability of the predictions (Oosterbaan, 2002). Frequency analysis is useful to see the class division for each piece of data presented (Sutrisno et al., 2020).

According to the figure 4.1, the majority of the individuals exhibit low or moderate extraversion. People with low extraversion tend to be more reserved and consider things over before speaking. Low and moderate scores had 36 and 35 frequencies. With 4 frequencies the lowest score is extremely strong extraversion.

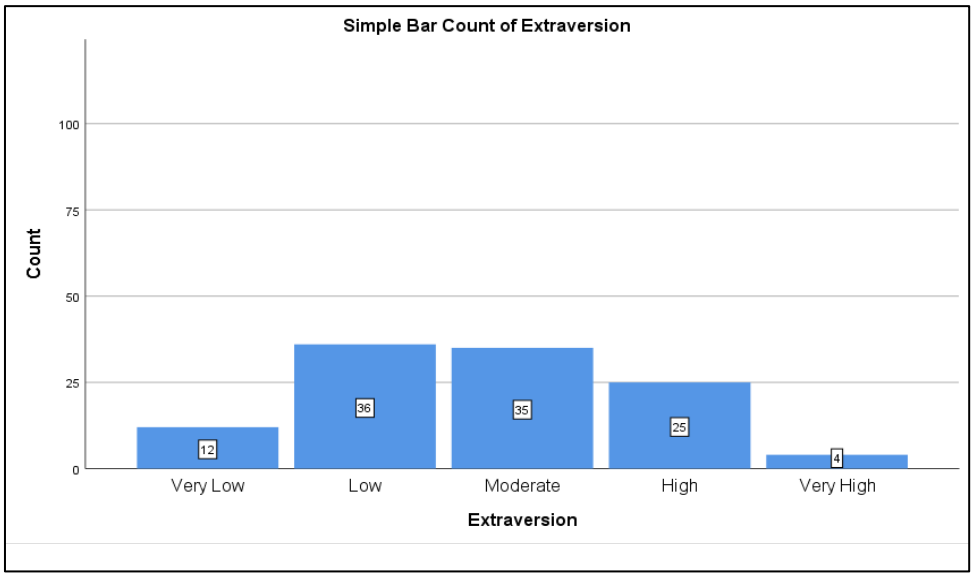


Figure 4.1 Horizontal Bar of Extraversion Personality Trait

In figure 4.2, individuals with moderate to high agreeableness ratings is the highest number. People with a high agreeableness score care deeply about other people and love assisting and contributing to their pleasure. Both moderate and high scores had 35 frequencies. With 9 frequencies, the lowest agreeableness score is quite high.

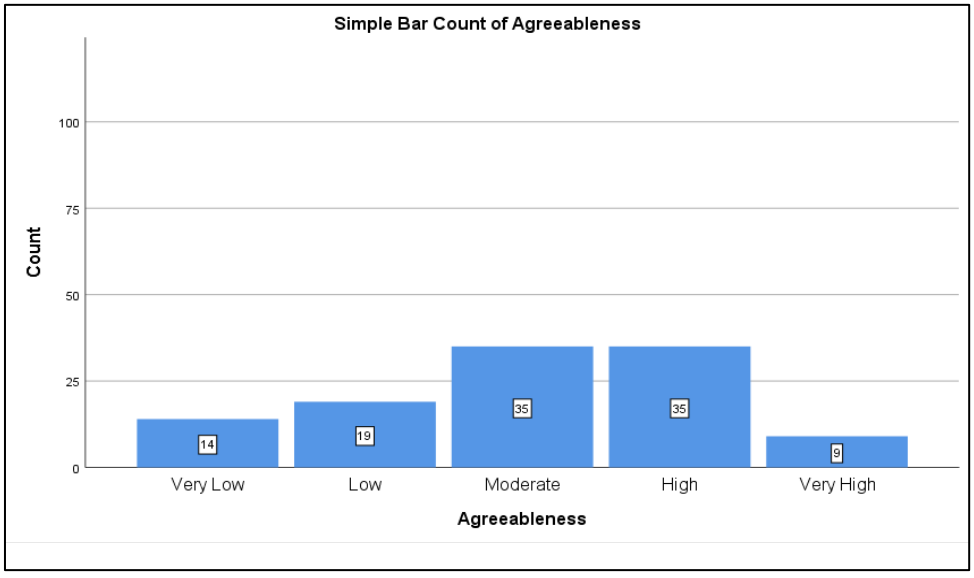


Figure 4.2 Horizontal Bar of Agreeableness Personality Trait

According to the figure 4.3, the highest number of participants have a high conscientiousness score with 36 frequencies. People with a high level of

conscientiousness tend to be organized and mindful of details. A very high conscientiousness score is the lowest, with 10 frequencies.

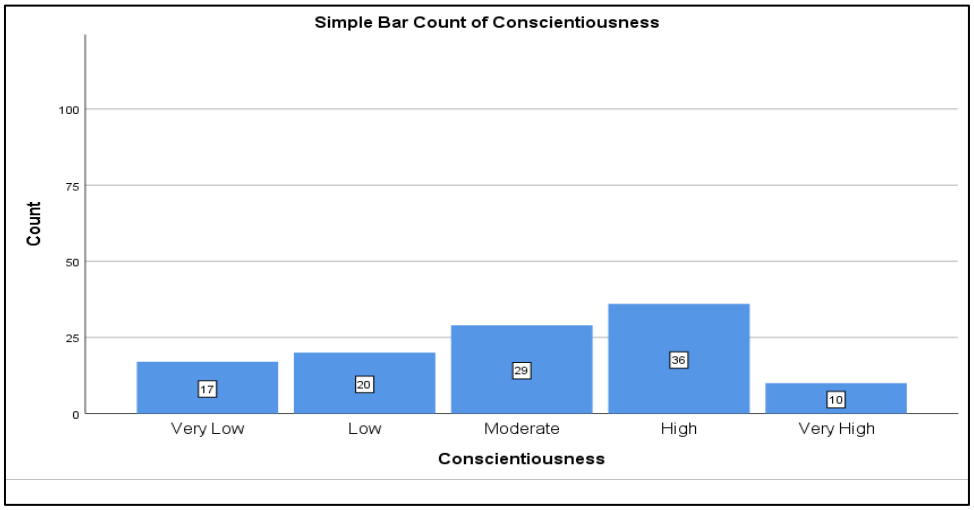


Figure 4.3 Horizontal Bar of Conscientiousness Personality Trait

Figure 4.4 reveals that the highest number of individuals had a moderate neuroticism score of 39 frequency points. Sadness, moodiness, and emotional instability are characteristics of neuroticism. In terms of emotions and mental health, the participants are fairly balanced. A very low neuroticism score is the lowest, with 4 frequencies.

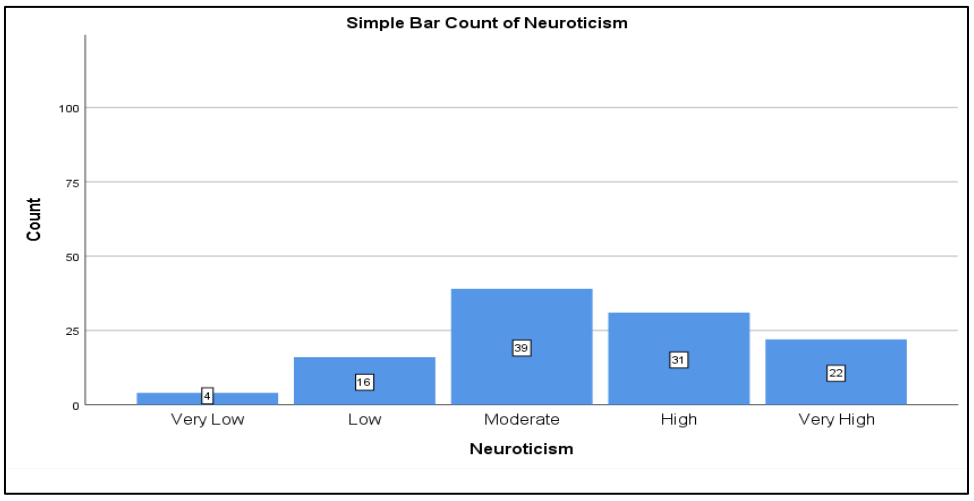


Figure 4.4 Horizontal Bar of Neuroticism Personality Trait

The highest number of individuals had a low openness score with 29 frequencies, as shown in Figure 4.5. Participants with low openness detest change and are resistant to new ideas. With 16 frequencies the lowest openness score is quite high.

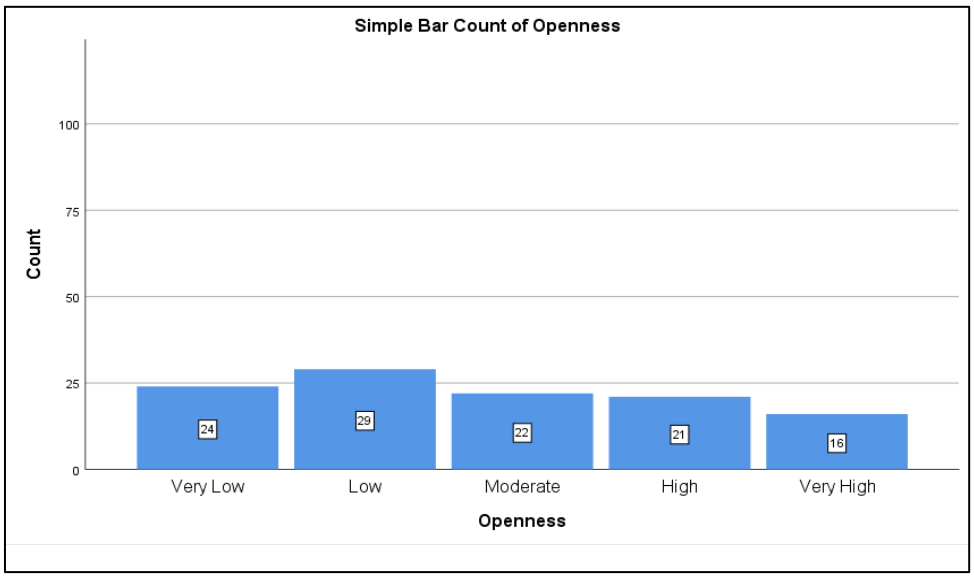


Figure 4.5 Horizontal Bar of Openness Personality Trait

Figure 4.6 show the highest number of the individual's exhibit moderate to low extraversion, moderate to high agreeableness, high conscientiousness, moderate neuroticism, and low openness. The findings indicate that the individuals are more guarded towards themselves and prefer a life of seclusion. They are also resistive to new ideas and usually oppose them. They do, however, like assisting those in need and have empathy and compassion for others. They are also thoughtful, have strong impulse control, and engage in goal-directed behavior. They also have a moderate emotional capability. Their mood may change significantly based on the day and their state of mind, making them a realist. Figure 4.7 show the lowest frequency of the personality among the participants.

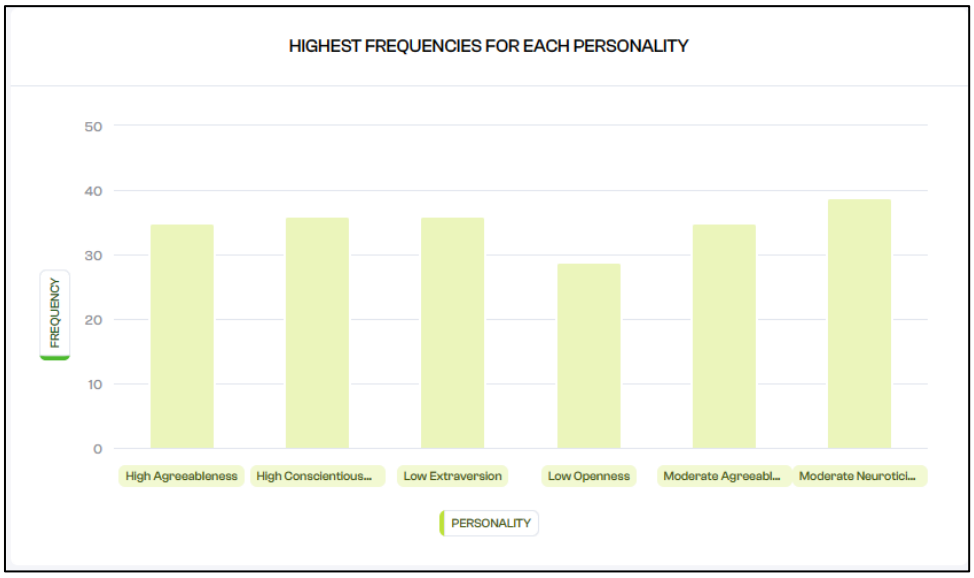


Figure 4.6 Highest Frequencies for Each Personality.

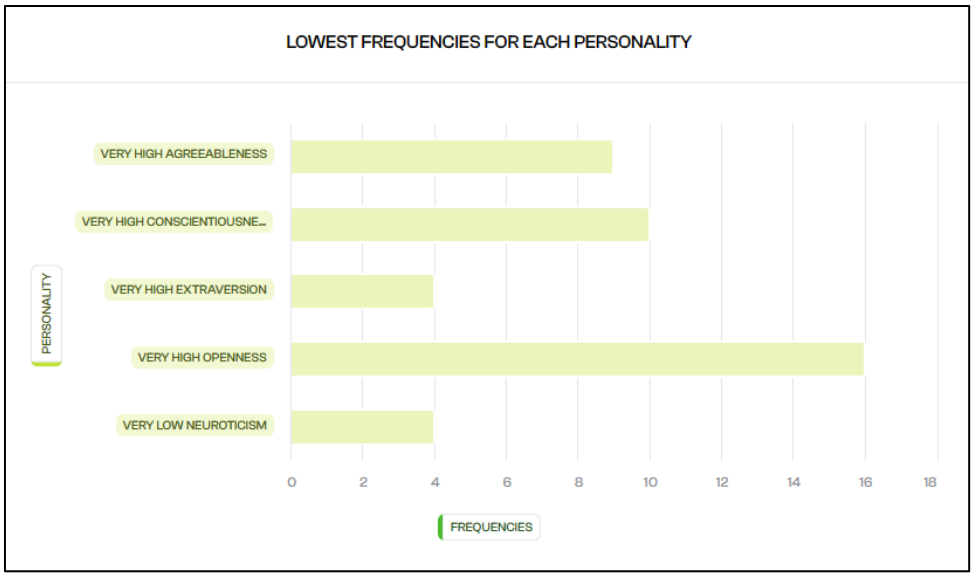


Figure 4.7 Lowest Frequencies for Each Personality.

Figure 4.8 shows that the majority of participants chose the highest preference using Arial font with a 30 frequency, while somewhat preferring options with a 29 frequency, which comes in second. With 3 frequencies, the lowest preferences and low preferences are the least popular options.

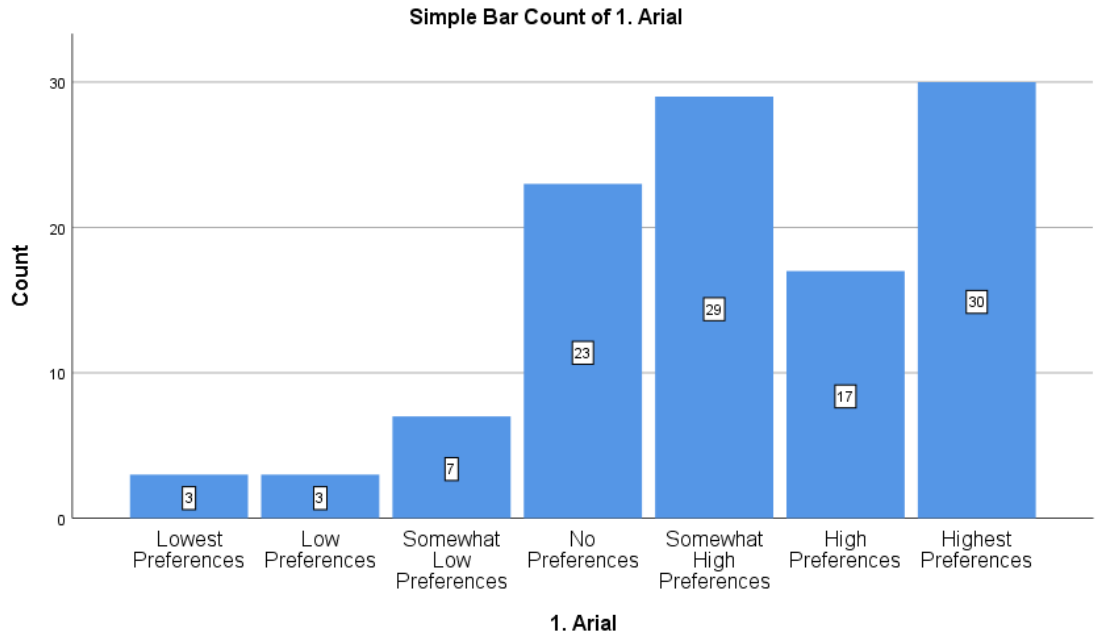


Figure 4.8 Vertical bar of Arial Font

This is Arial

Figure 4.9 Image of Arial font

Figure 4.10 reveals that the majority of participants (33 frequencies) prefer the Calibri typeface. The low preference choice has the lowest frequency, only 1 out of all participants picking it.

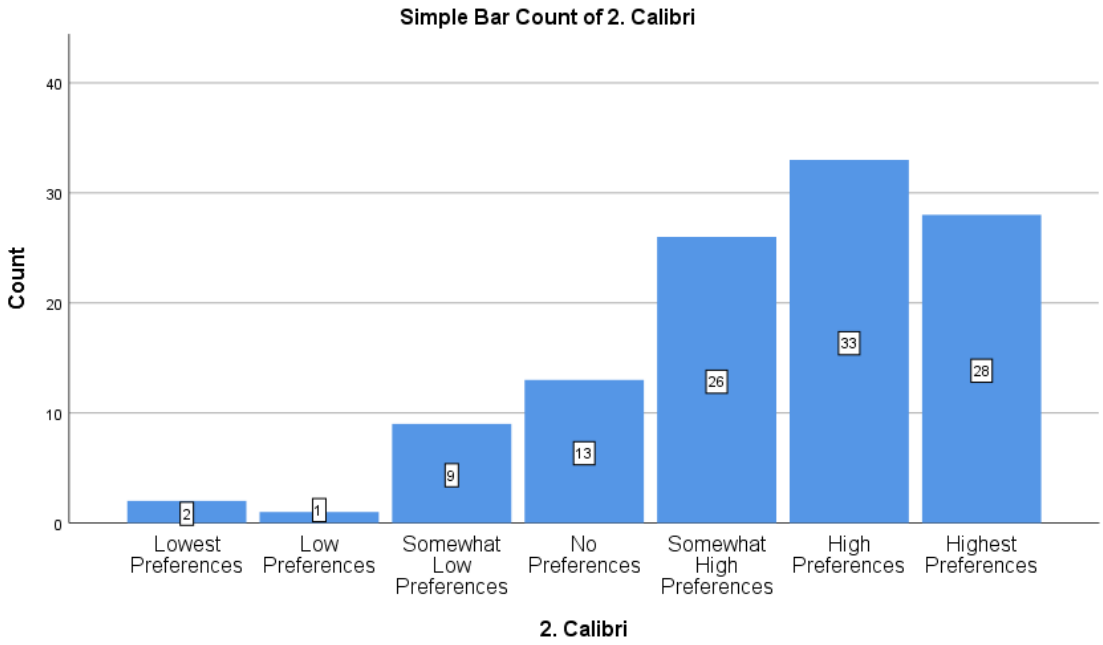


Figure 4.10 Vertical bar of Calibri Font

This is Calibri

Figure 4.11 Image of Calibri font

According to Figure 4.12, the majority of participants used Calibri Light at 33 frequencies to choose their top choices. The choice with the lowest preferences is the least popular.

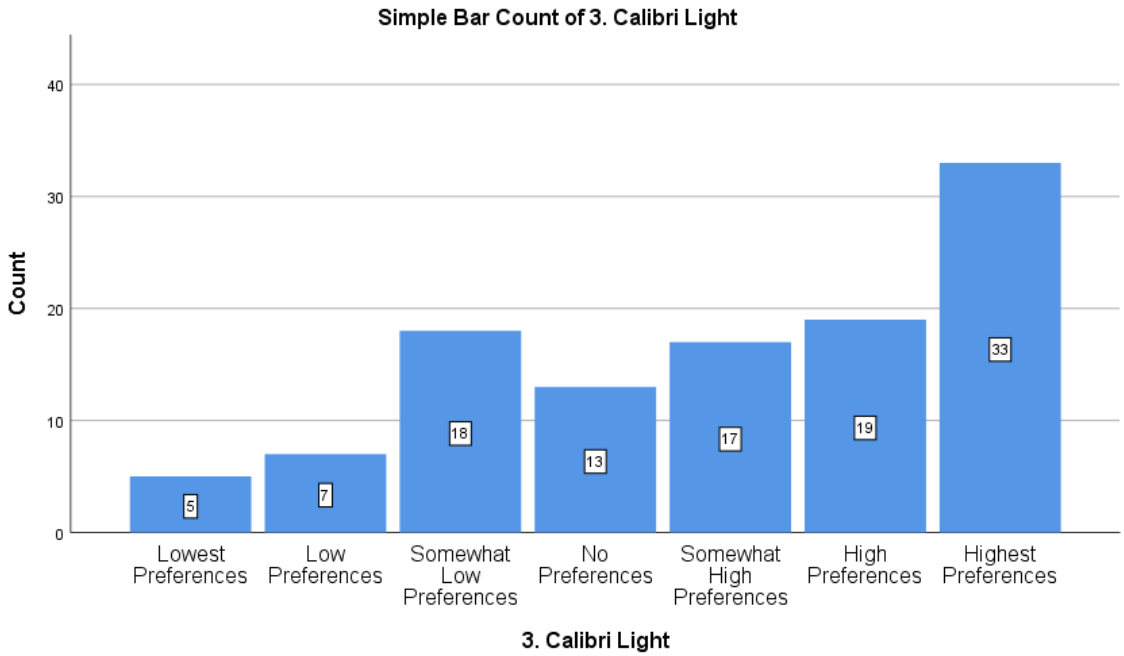


Figure 4.12 Vertical bar of Calibri Light Font

This is Calibri Light

Figure 4.13 Image of Calibri Light font

Figure 4.11 shows that the majority of participants chose low preferences using small font sizes with 34 frequencies. High preferences and highest preferences options are the least popular, with only six frequencies each.

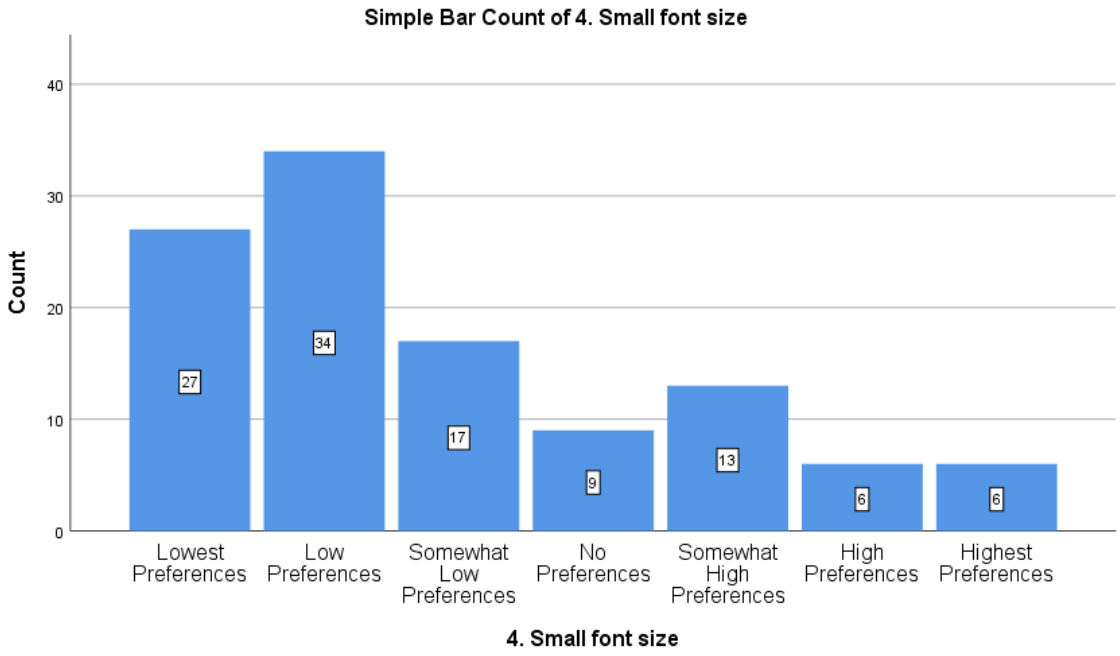


Figure 4.14 Vertical bar of Small Font Size

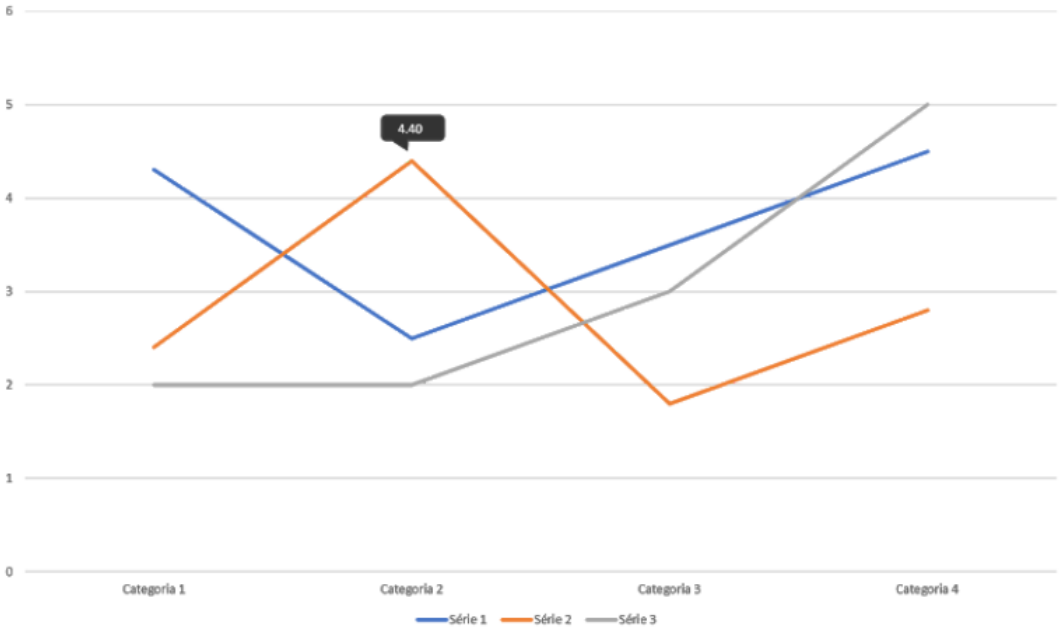


Figure 4.15 Image of small font

Figure 4.16 demonstrates that the majority of participants picked fairly low preferences with a 28 frequency using a medium text size. With a frequency of 5 respectively, the alternatives of low preferences and lowest preferences are the least popular.

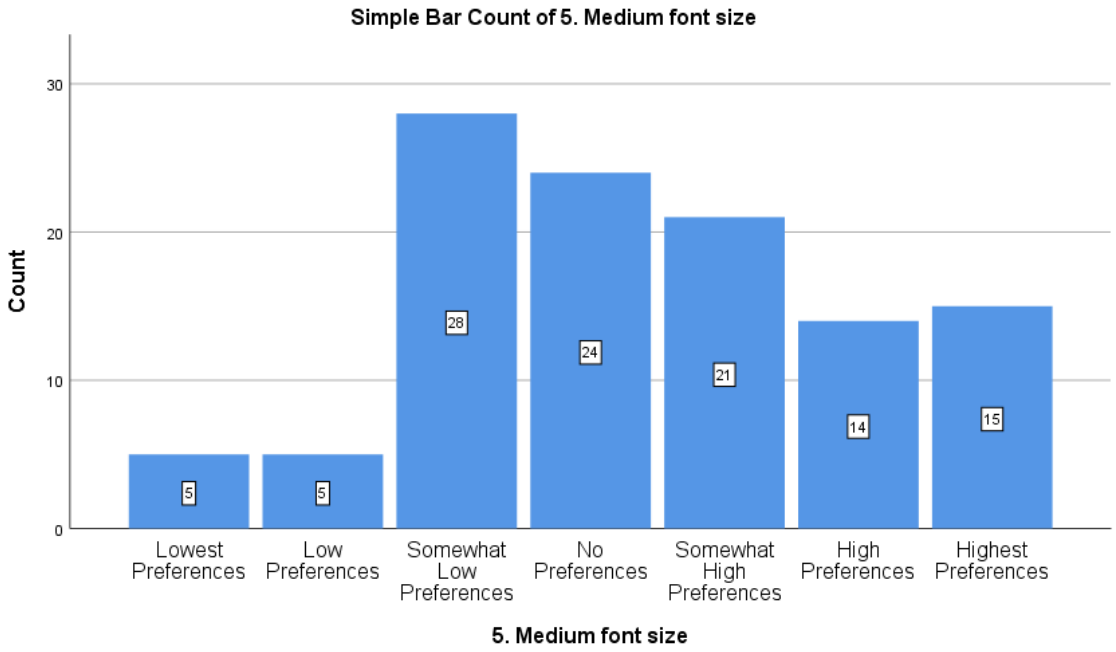


Figure 4.16 Vertical bar of Medium Font Size

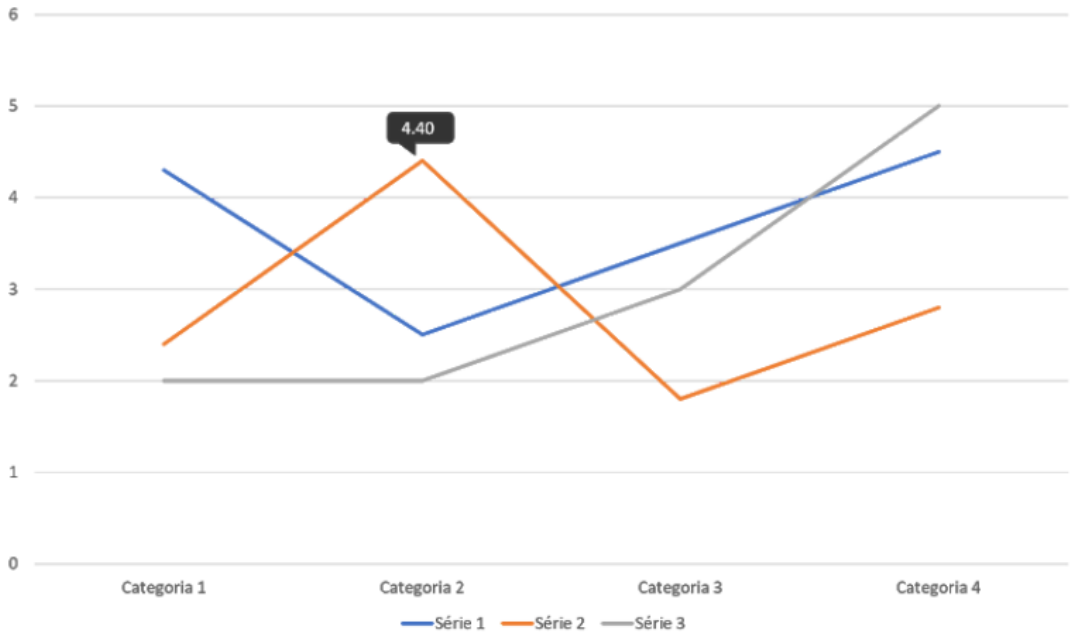


Figure 4.17 Image of Medium Font Size

Figure 4.18 shows that the majority of participants (32 percent) chose the largest font sizes. With 3 frequencies, the reject and lowest preference options are the least popular.

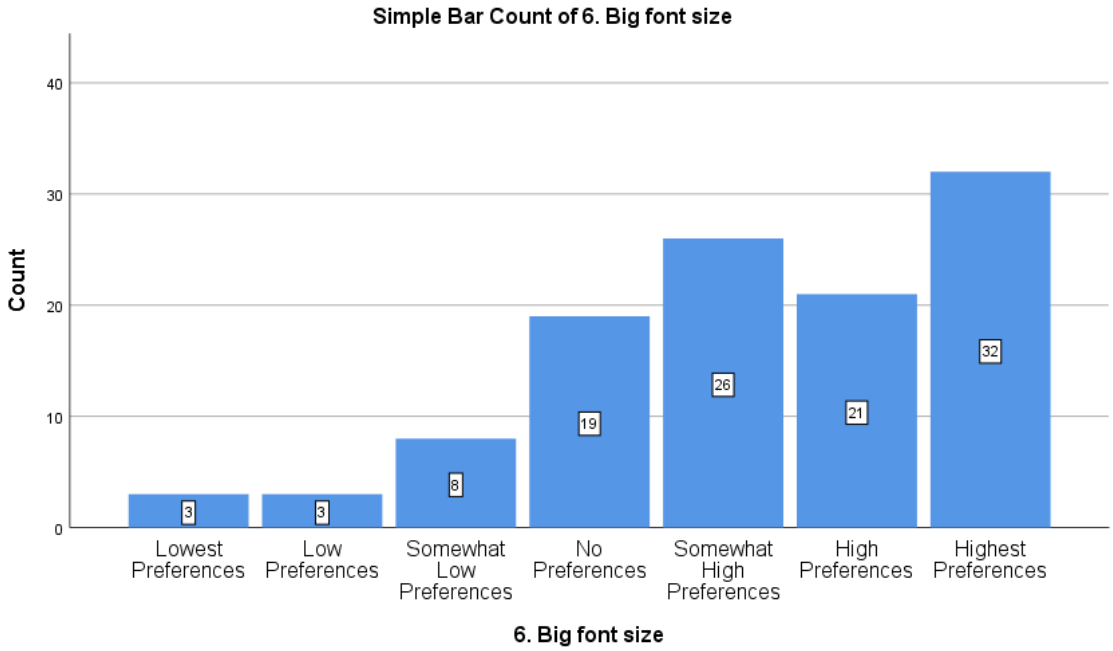


Figure 4.18 Vertical Bar of Big Font Size

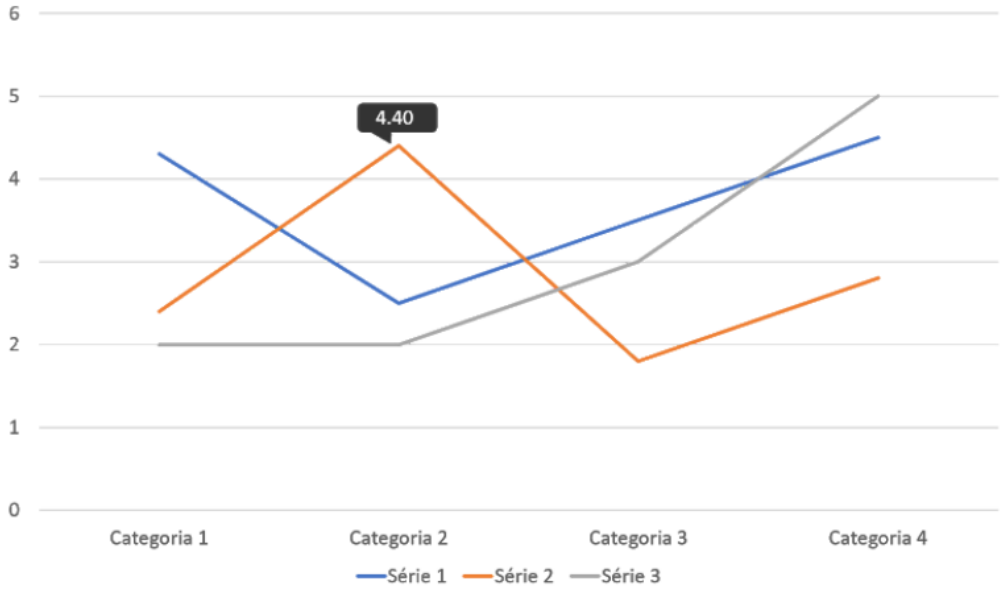


Figure 4.19 Image of Big Font Size

Figure 4.20 shows the majority of participants selecting the greatest preference choice using buttons with 25 frequencies. The lowest preference alternatives are the least prevalent, with a frequency of 7 respectively.

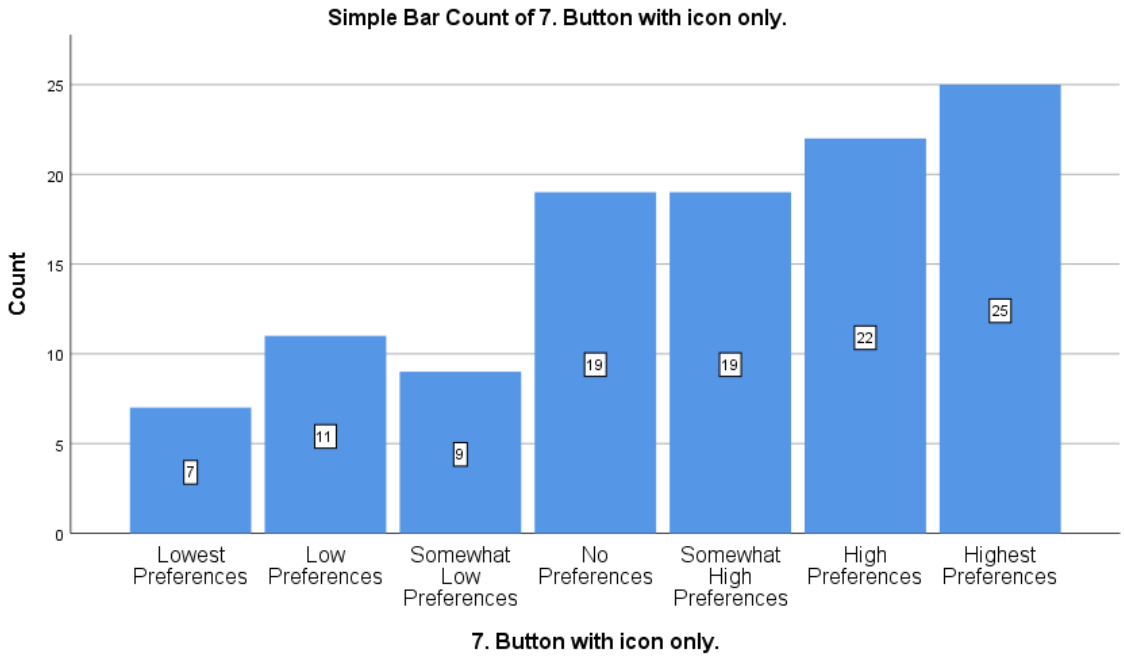


Figure 4.20 Vertical Bar of a Button with Icons

Figure 4.21 Image of Button with Icons

Figure 4.22 reveals that the majority of participants had no preference for utilizing simply text buttons at 24 frequencies. However, with 23 frequencies each, alternatives with relatively high preferences, high preferences, and highest preferences are second in number. With three occurrences of all participants, the low preference choice is the least prevalent.

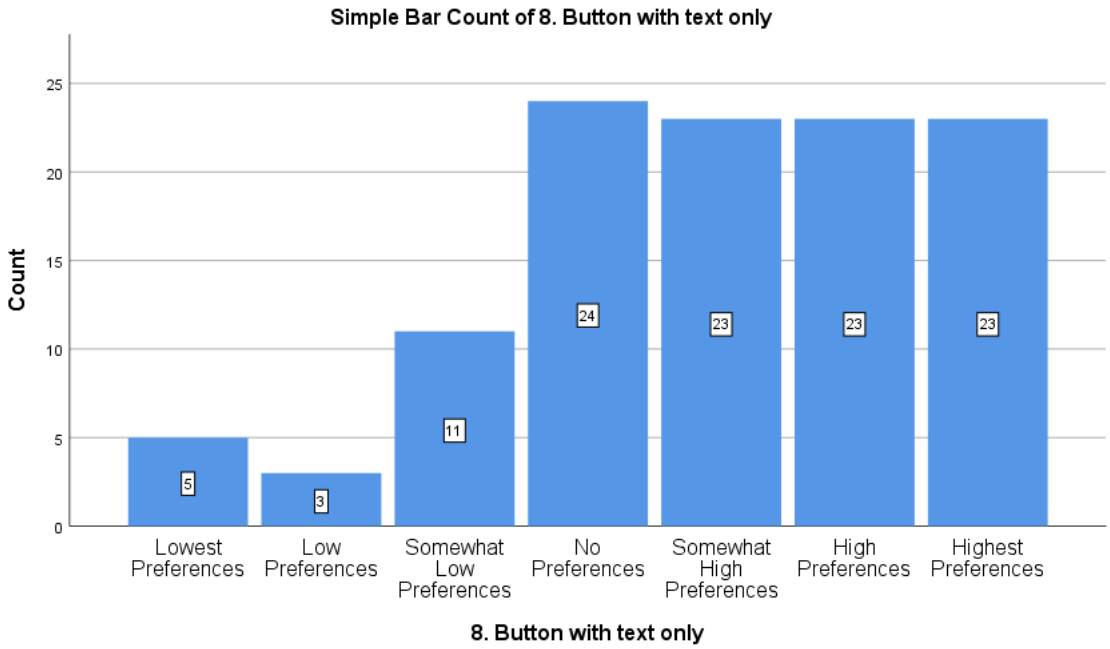


Figure 4.22 Vertical Bar of a Button with Text

Figure 4.23 Image of Button with Text

According to Figure 4.16, the majority of participants (41 frequencies) selected the greatest preferences using buttons with icons and text. The fairly low preference choice is the least popular, with a frequency of 5.

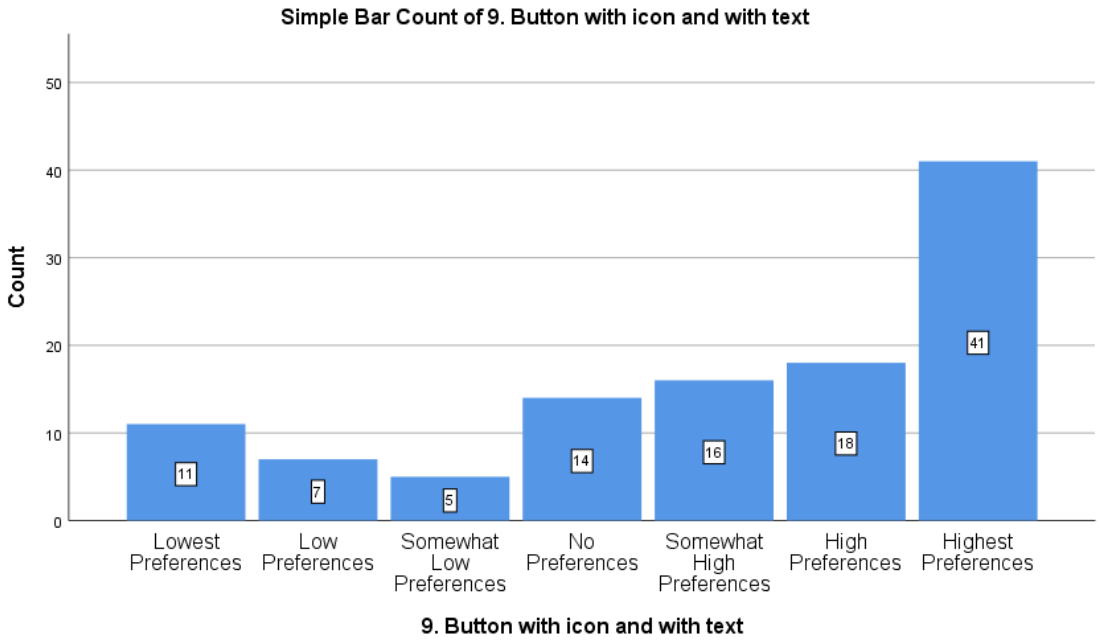


Figure 4.24 Vertical Bar of a Button with Icon and Text

Figure 4.25 Image of Button with Icon and Text

Figure 4.26 shows that the majority of the participants have no preferences for using low-density information with 27 frequencies. However, the somewhat high preference option comes in second with 26 frequencies. Lowest preferences and low preference options are the least with 5 frequencies.

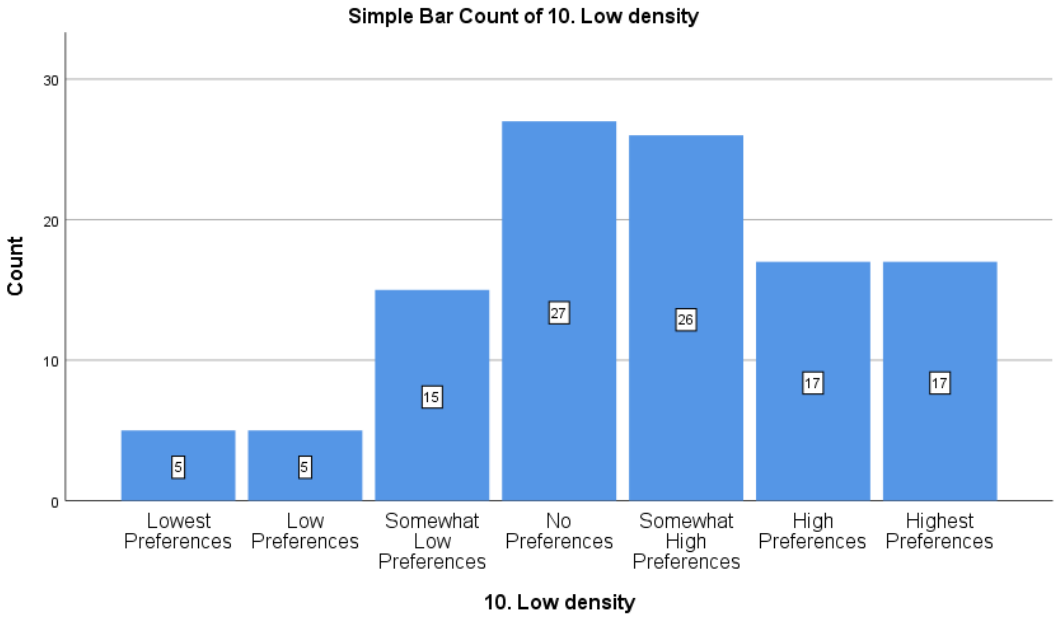


Figure 4.26 Vertical Bar of Low-Density Information

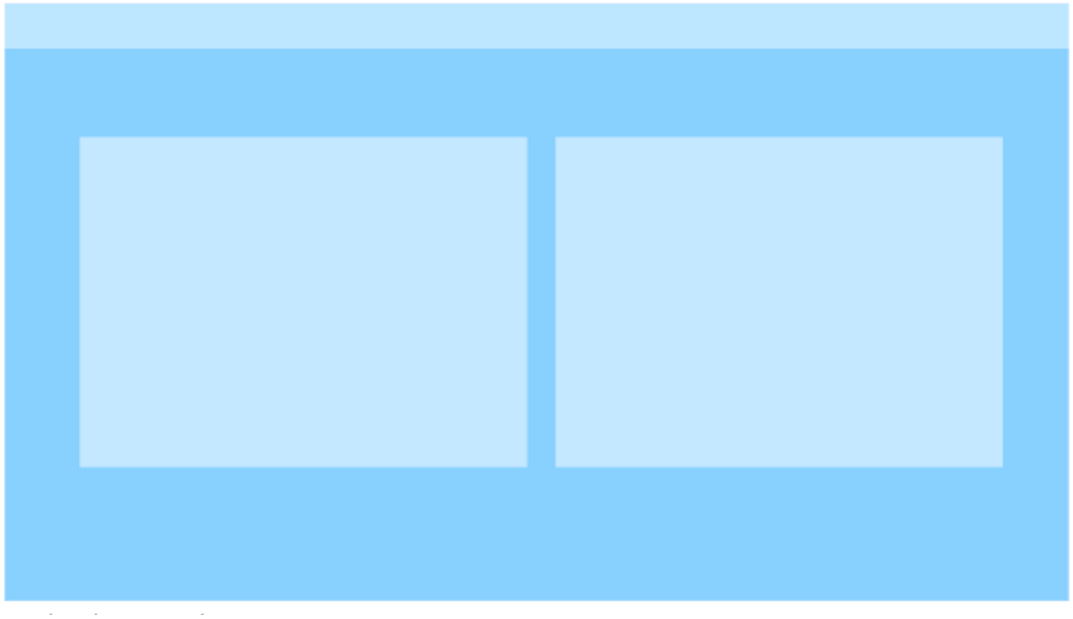


Figure 4.27 Image of Low-Density Information

According to Figure 4.28, the majority of participants, prefer utilizing average density information with 35 frequencies. The lowest preference alternatives are the least common, accounting for only 1 participant.

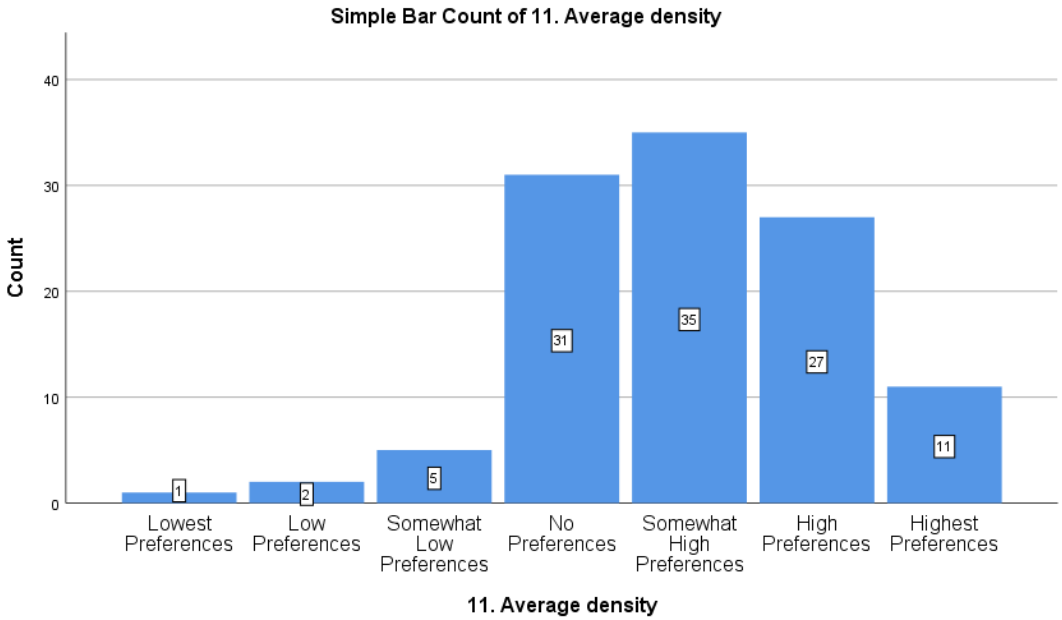


Figure 4.28 Vertical Bar of Average-Density Information

Figure 4.29 Image of Average-Density Information

Figure 4.30 shows that the majority of the participants, neither reject nor prefer using high-density information with 20 frequencies. However, high- and low-preference options come in second with 19 frequencies. The lowest preference is the least, with 8 frequencies.

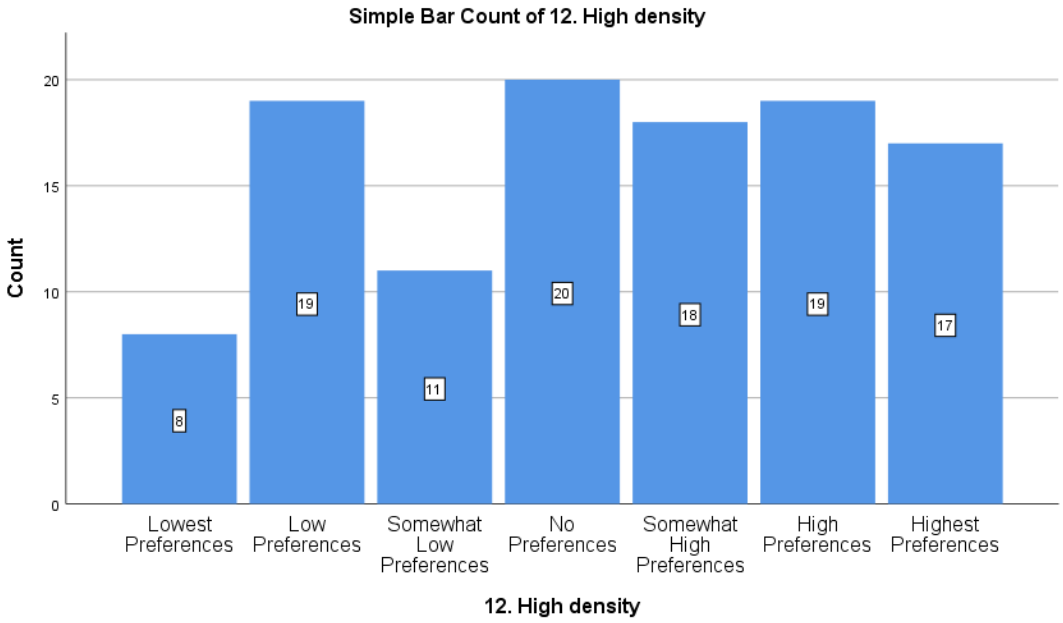


Figure 4.30 Vertical Bar of High-Density Information

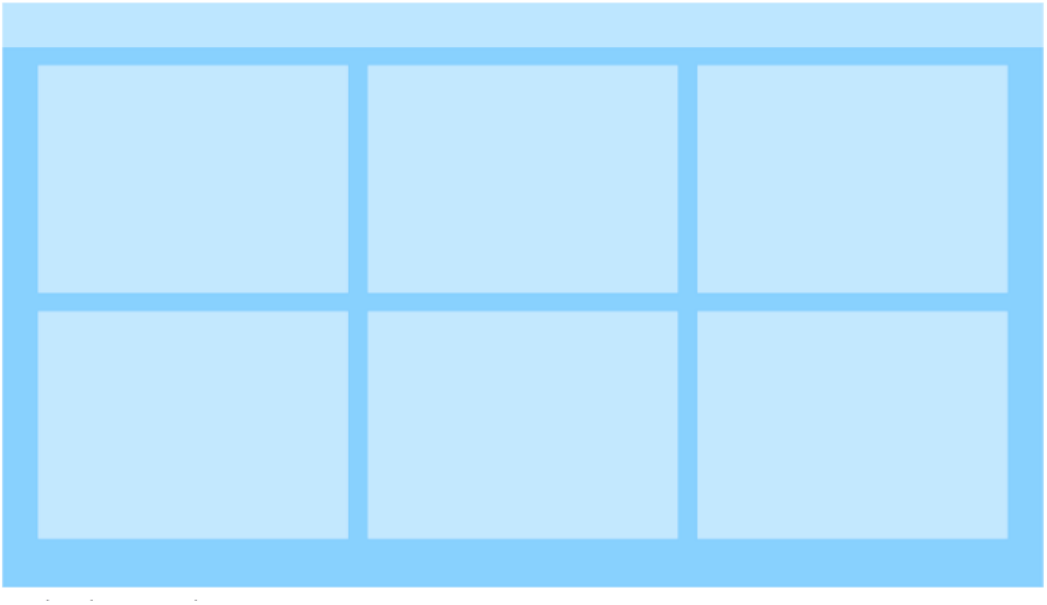


Figure 4.31 Image of High-Density Information

Figure 4.20 shows that the majority of the participants, chose the highest preferences using the top position of the navigation bar with 45 frequencies. Low preferences are the least common, with 3 frequencies.

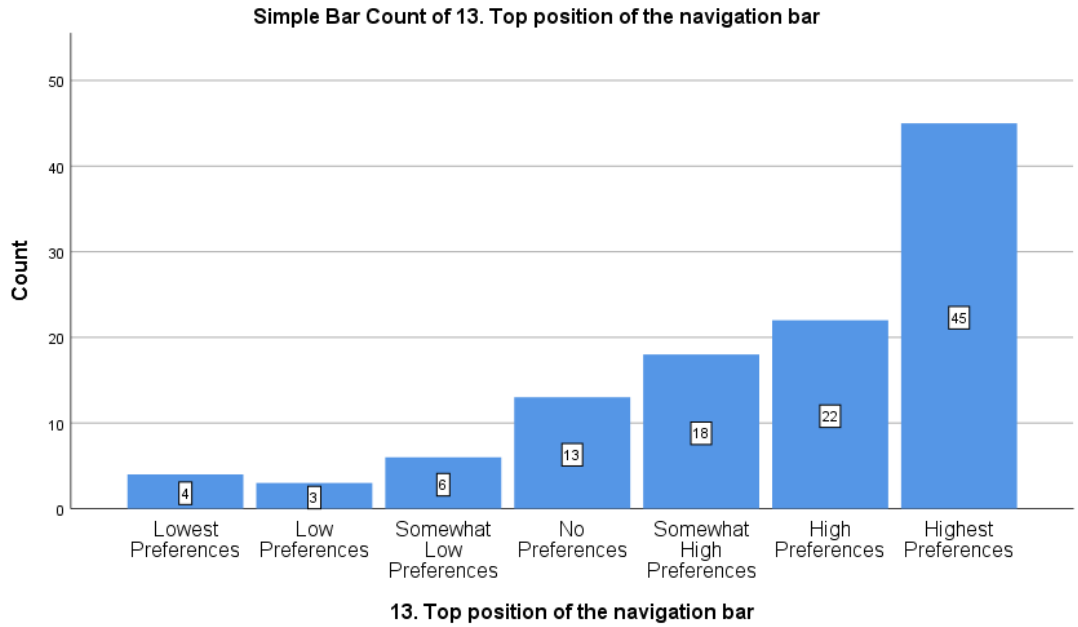


Figure 4.32 Vertical Bar of the Top Position of the Navigation Bar

Figure 4.33 Image of Top Position of the Navigation Bar

Figure 4.34 shows that the majority of the participants, chose high preferences using the bottom position of the navigation bar with 23 frequencies. Low preferences are the least common, with 10 frequencies.

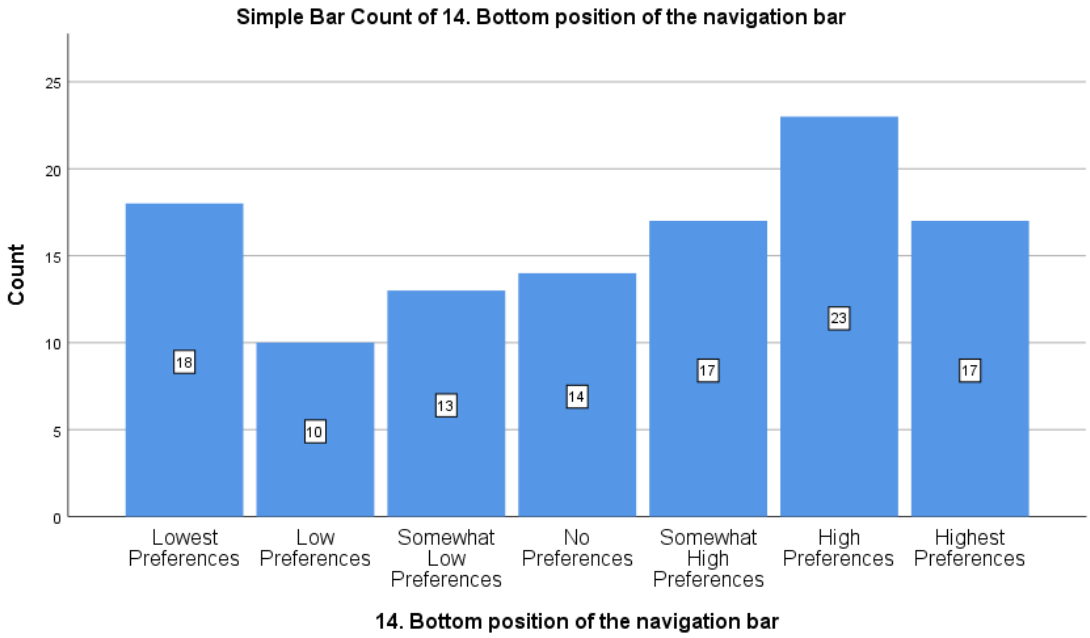


Figure 4.34 Vertical Bar of the Bottom Position of the Navigation Bar

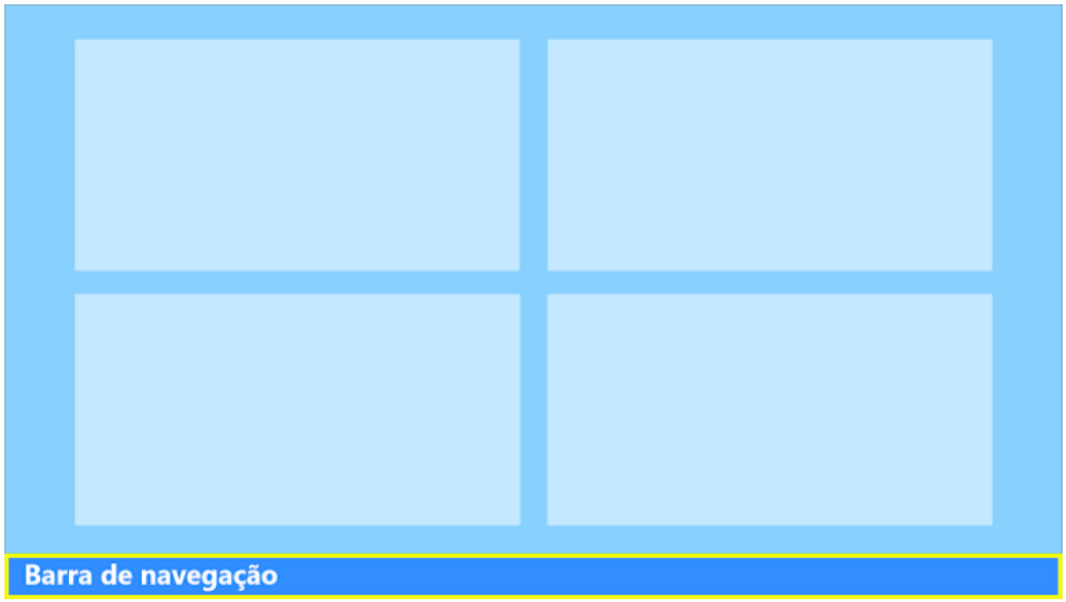


Figure 4.35 Image of Bottom Position of the Navigation Bar

According to figure 4.36, the majority of participants, selected the lowest preferences utilizing the right position of the navigation bar with 39 frequencies. With 7 frequencies the highest preference is the least.

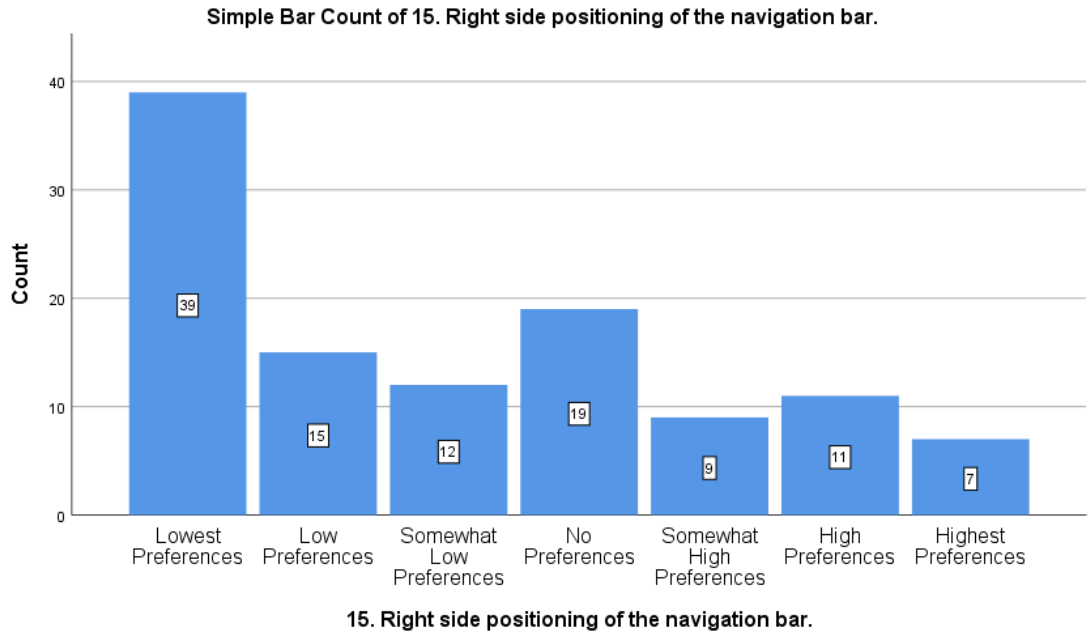


Figure 4.36 Vertical Bar of the Right Position of the Navigation Bar

Figure 4.37 Image of Right Position of the Navigation Bar

Figure 4.38 shows that the majority of the participants, chose the lowest preferences using the left position of the navigation bar with 31 frequencies. Somewhat high preferences are the least with 5 frequencies.

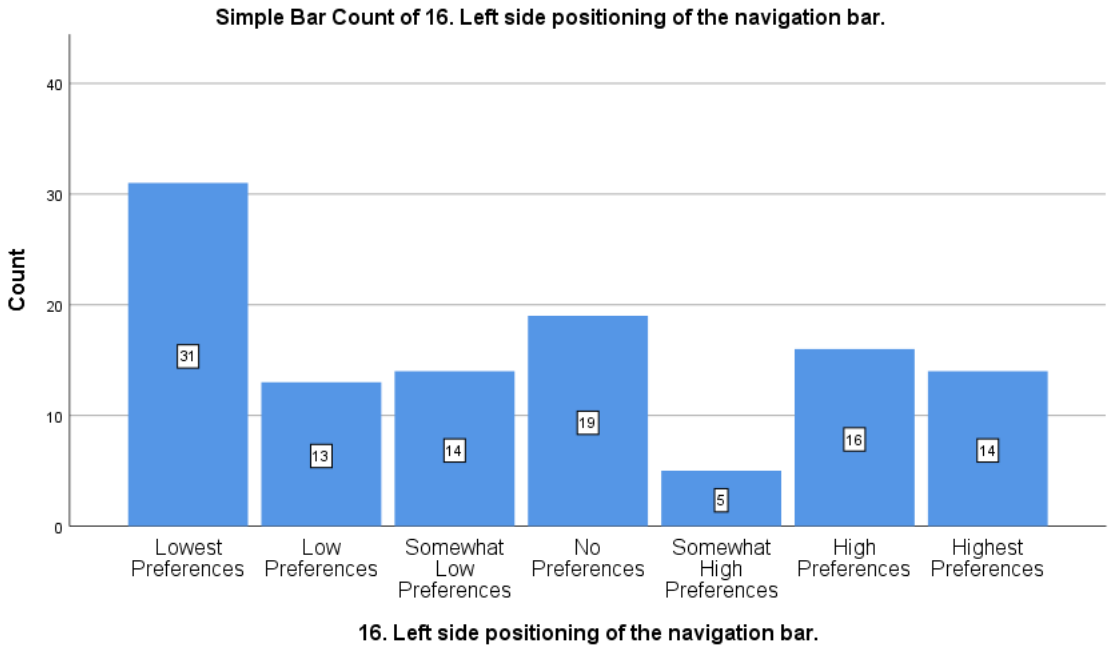


Figure 4.38 Vertical Bar of the Left Position of the Navigation Bar

Figure 4.39 Image of Left Position of the Navigation Bar

Figure 4.40 demonstrates that utilizing a Treemap with 22 frequencies, the majority of participants, selected rather high preferences. With 11 frequencies, those with quite low preferences are the fewest.

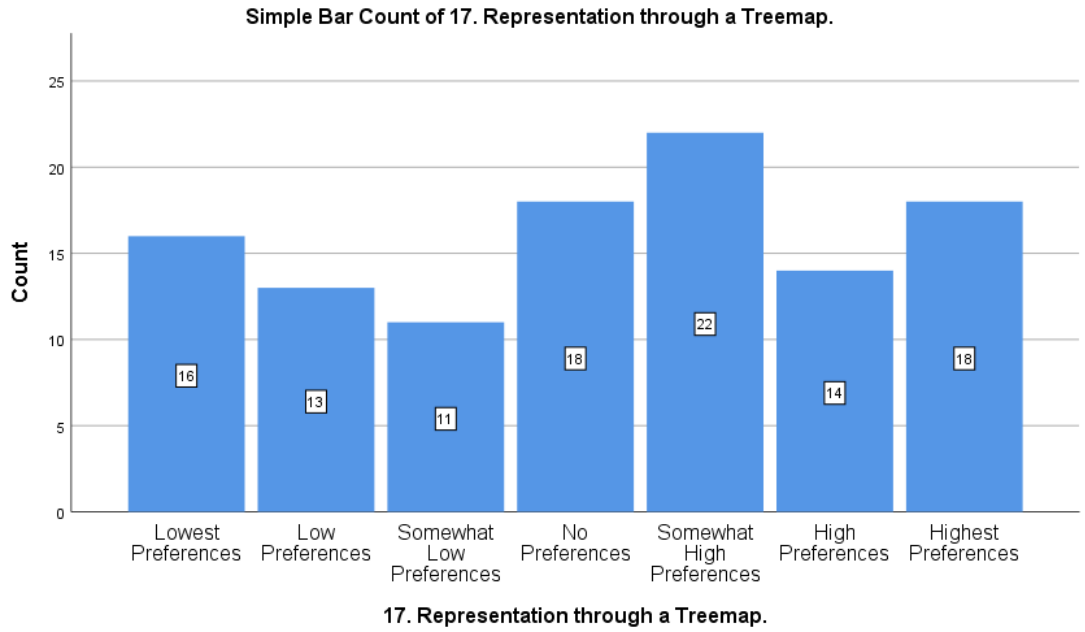


Figure 4.40 Vertical Bar of the Tree Map

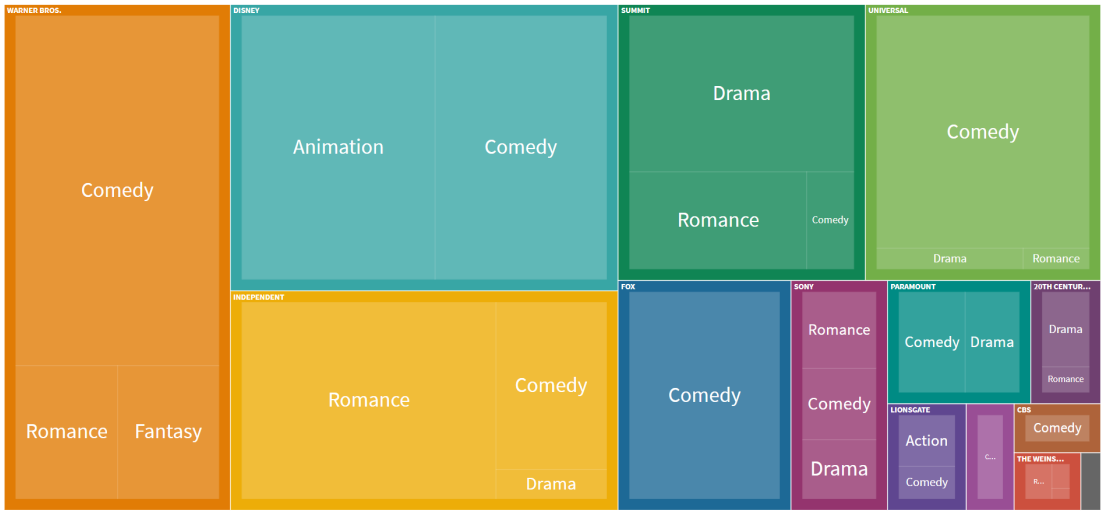


Figure 4.41 Image of Tree Map

According to Figure 4.42, the majority of participants, selected high preferences using the circular packing model with 24 frequencies. The somewhat higher preference choice, on the other hand, comes in second with 23 frequencies. Low preferences are the least prevalent, accounting for 4 frequencies.

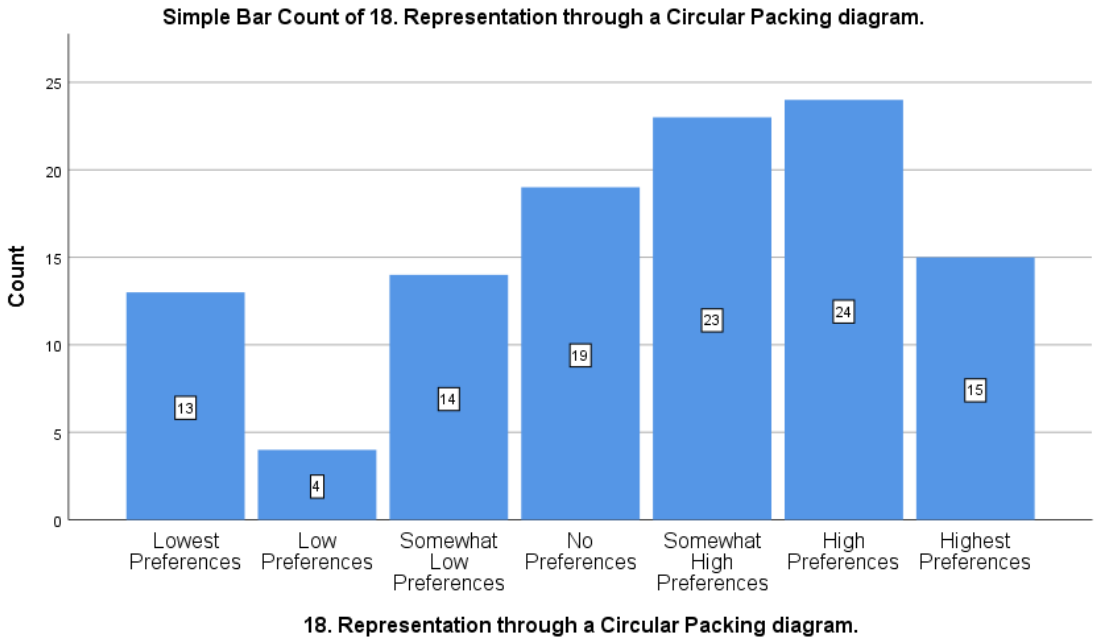


Figure 4.42 Vertical Bar of a Circular Packing

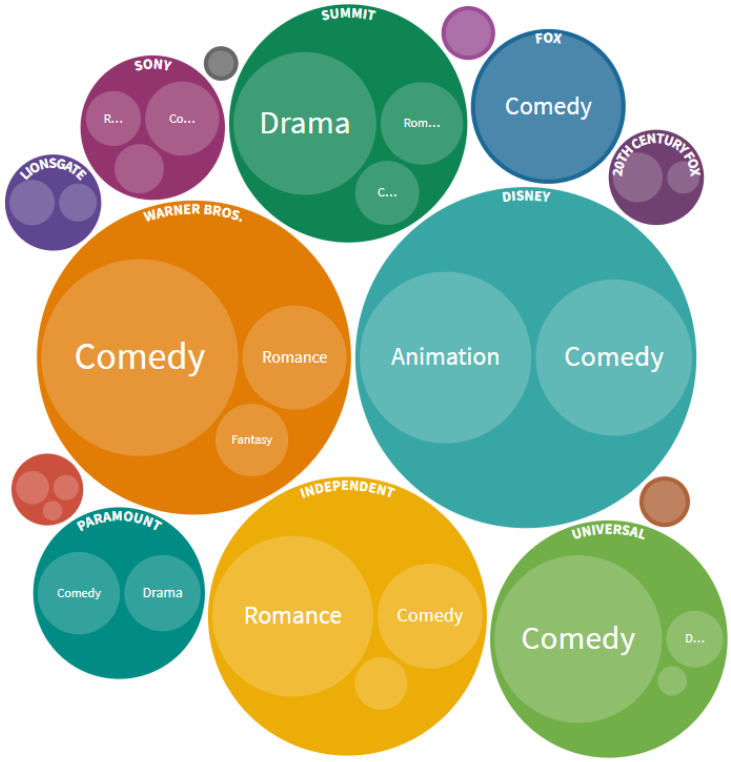


Figure 4.43 Image of Circular Packing

Figure 4.44 shows that the majority of the participants, chose somewhat high preferences using Sunburst with 28 frequencies. Low preferences are the least with 8 frequencies.

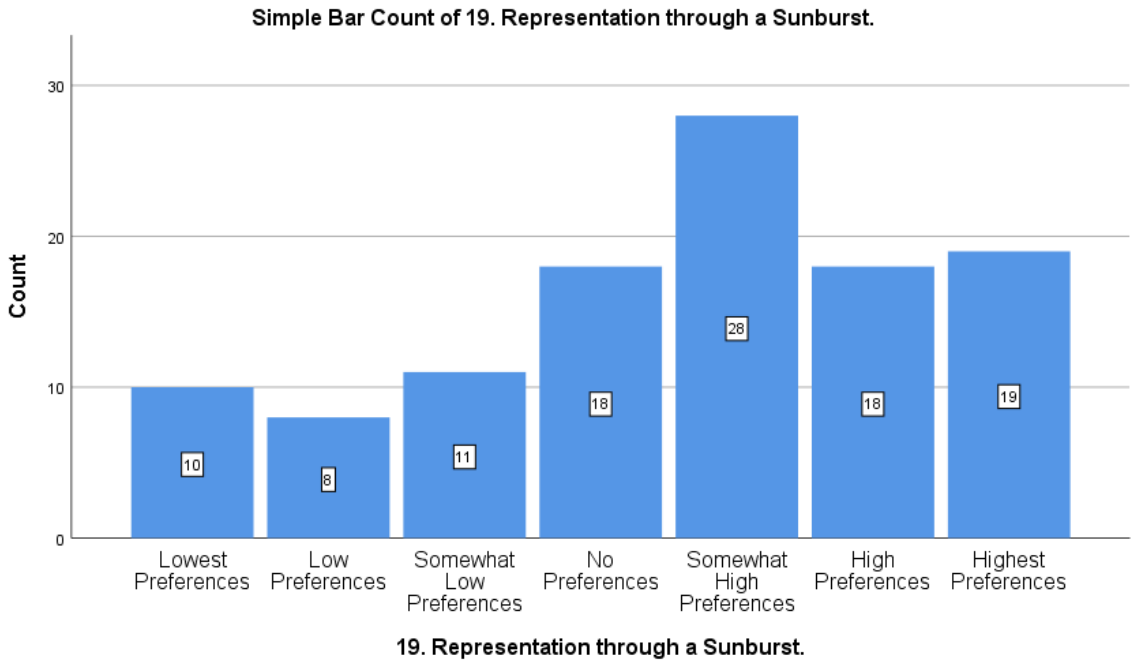


Figure 4.44 Vertical Bar of Sunburst

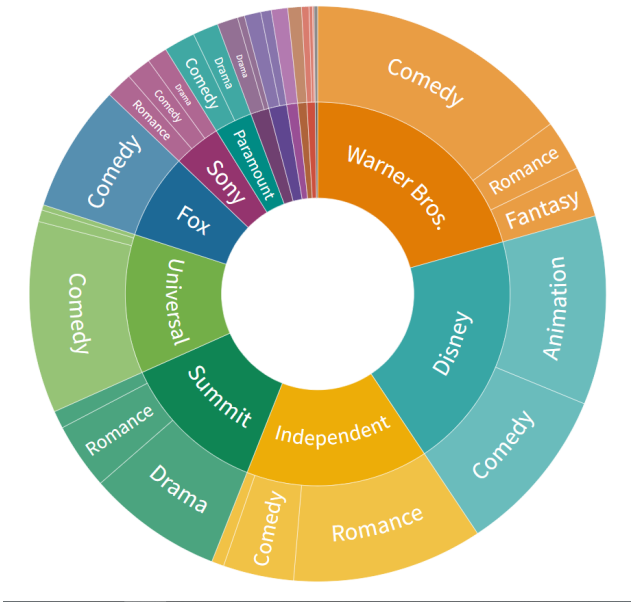


Figure 4.45 Image of Sunburst

Figure 4.46 shows that the majority of the participants, chose the lowest preferences using a Radial diagram with 24 frequencies. The highest preference is the least, with 6 frequencies.

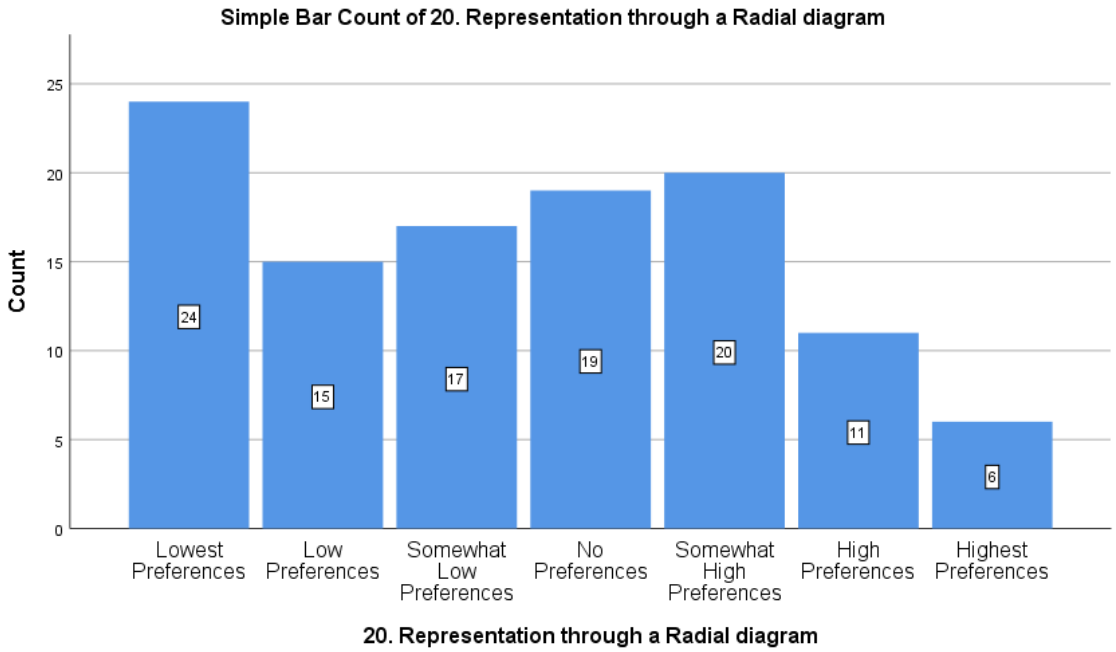


Figure 4.46 Vertical Bar of a Radial Diagram

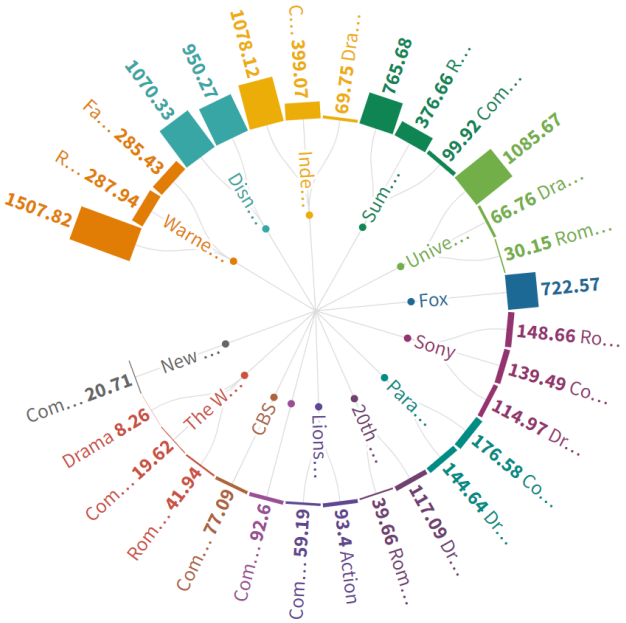


Figure 4.47 Image of Radial Diagram

Figure 4.48 shows that the majority of the participants, chose somewhat high preferences using a line chart with 30 frequencies. The lowest preference is the least with a frequency.

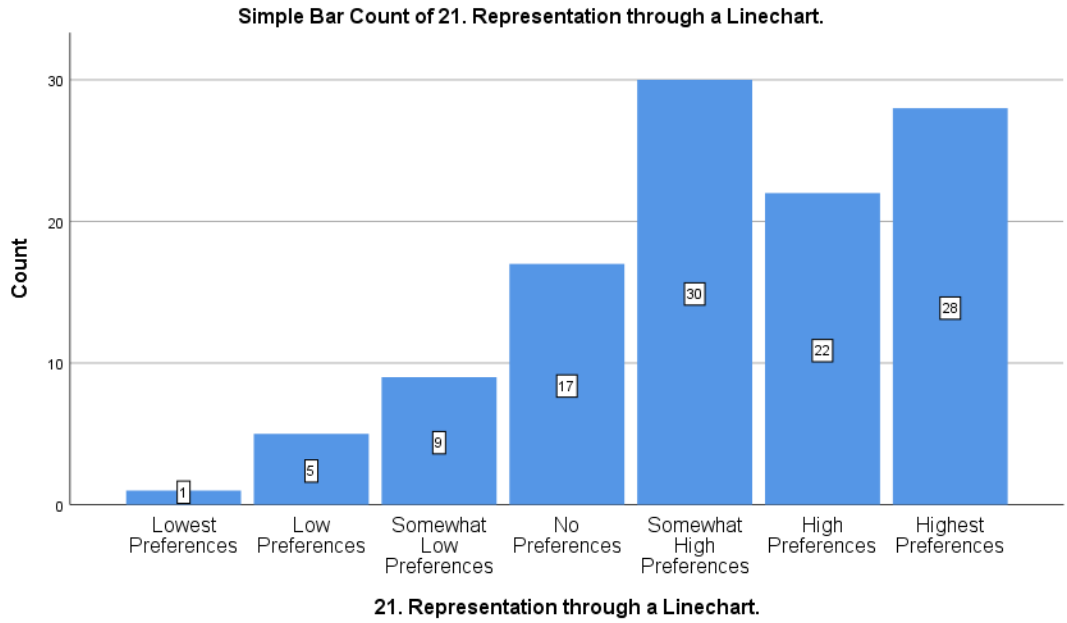


Figure 4.48 Vertical Bar of a Line Chart

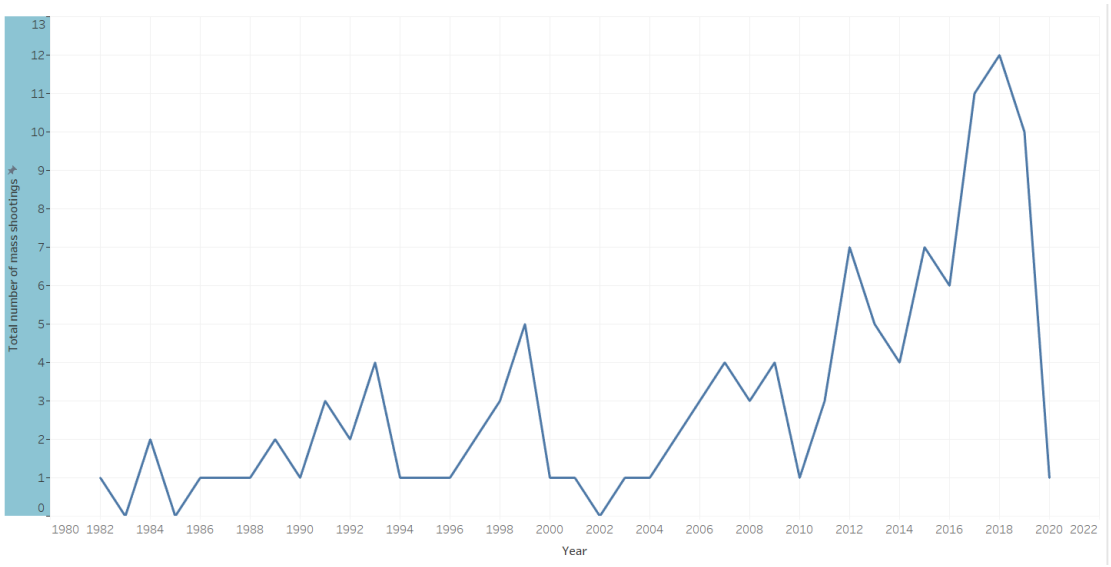


Figure 4.49 Image of Line chart

Figure 4.50 demonstrates that utilizing a line chart with points with 31 frequencies, picked rather high preferences. The least preferred option has 5 frequencies.

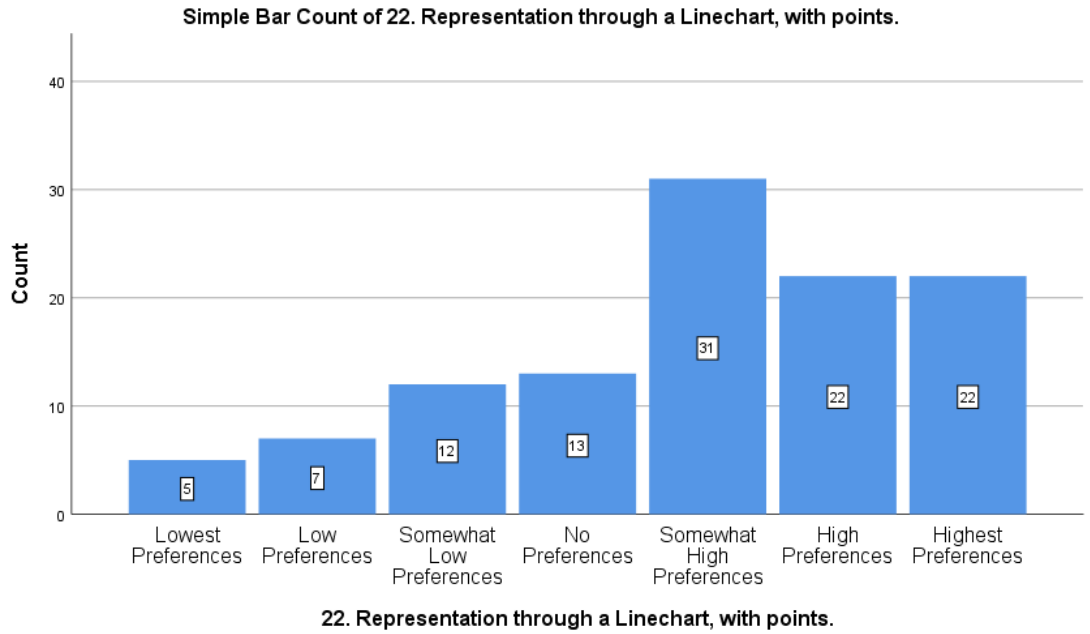


Figure 4.50 Vertical Bar of a Line Chart with Points

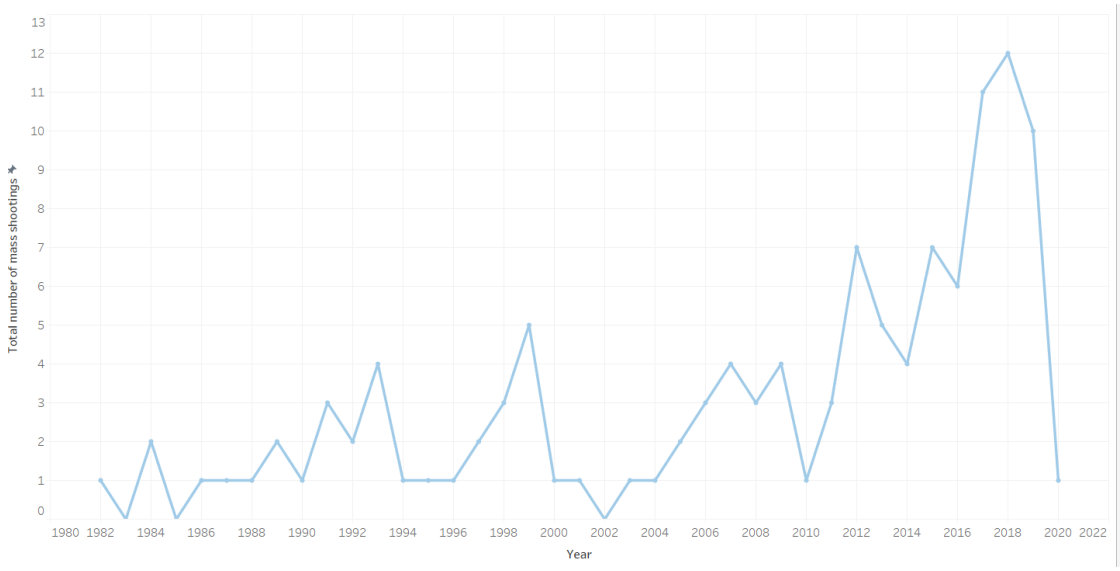


Figure 4.51 Image of Line Chart with Points

Figure 4.52 shows that the majority of the participants, chose high preferences using an area chart with 26 frequencies. However, the highest preference option comes in second with 25 frequencies. Low preference is the least with 4 frequencies.

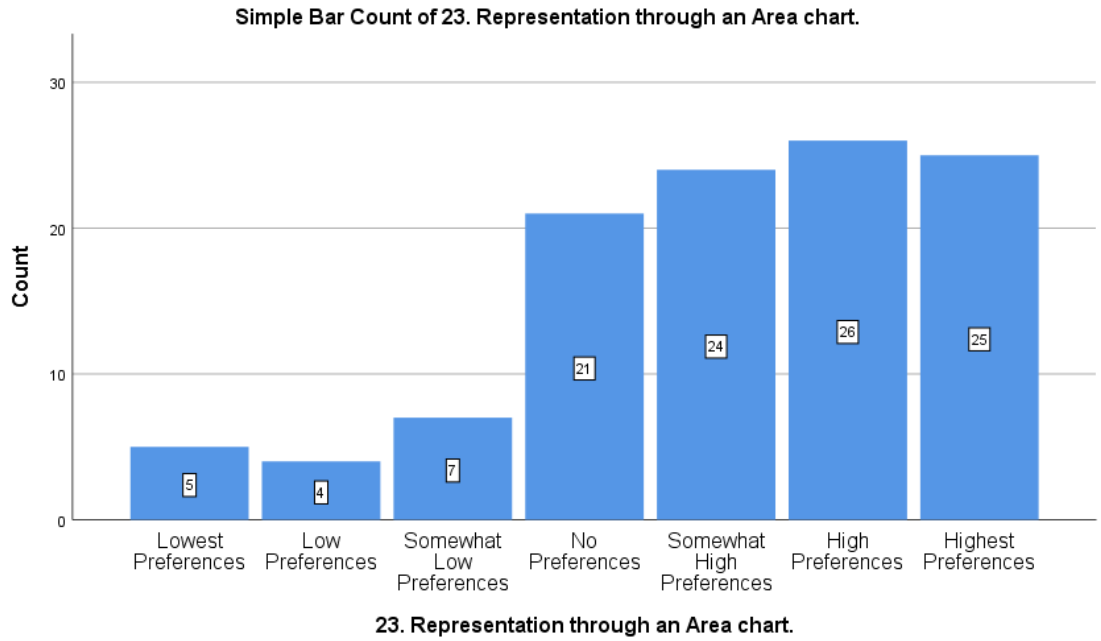


Figure 4.52 Vertical Bar of Area Chart

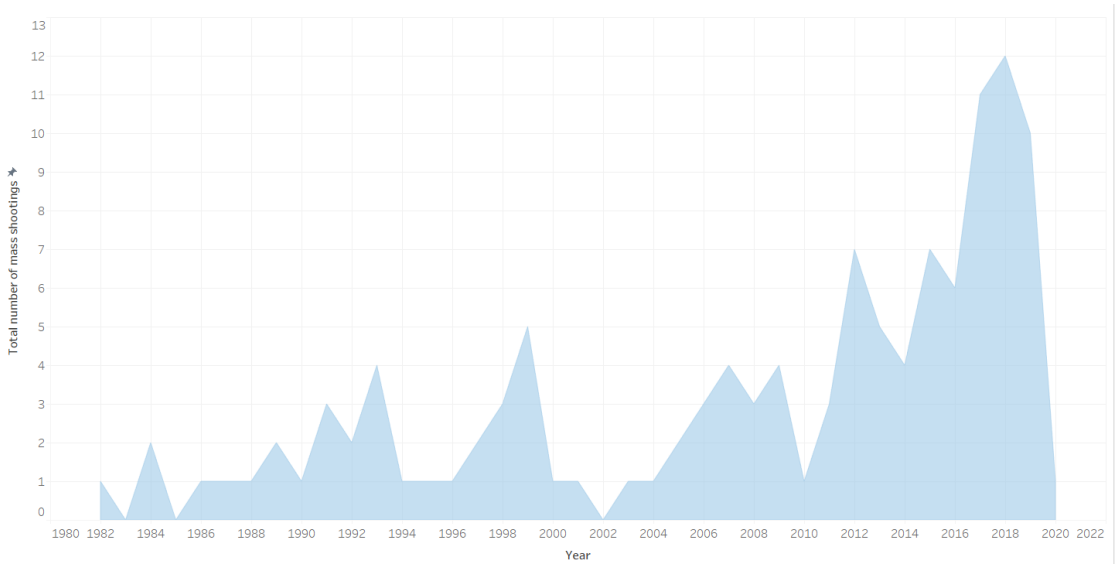


Figure 4.53 Image of Area Chart

Figure 4.54 shows that the majority of the participants, 27.7% of the total group, chose somewhat high preferences using a radar chart with 31 frequencies. Low preference is the least with 4 frequencies and 3.6% of the total participants.

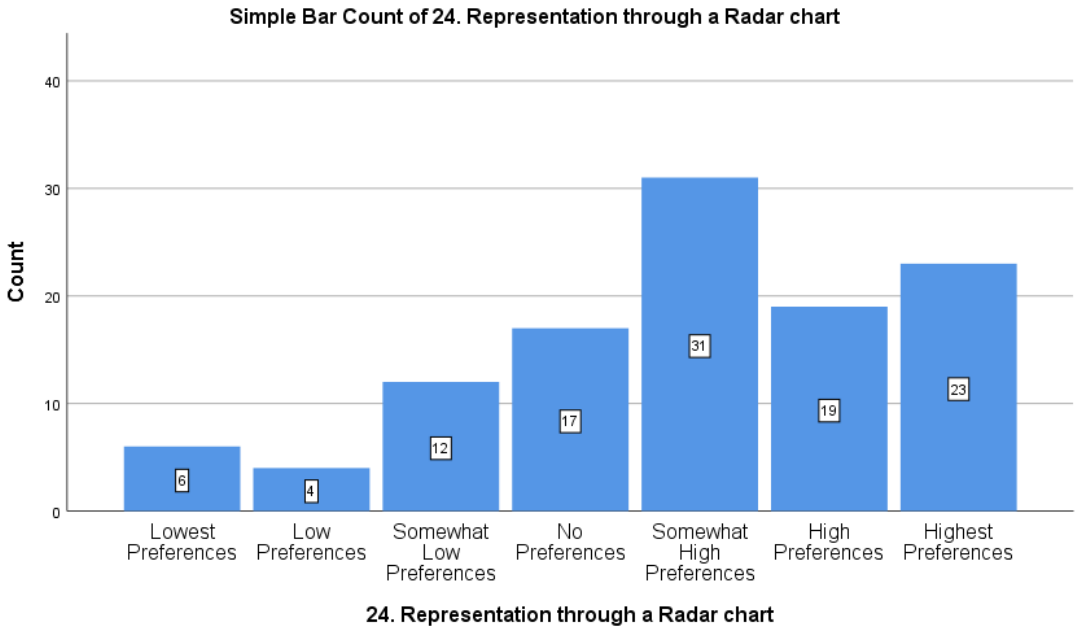


Figure 4.54 Vertical Bar of Radar Chart

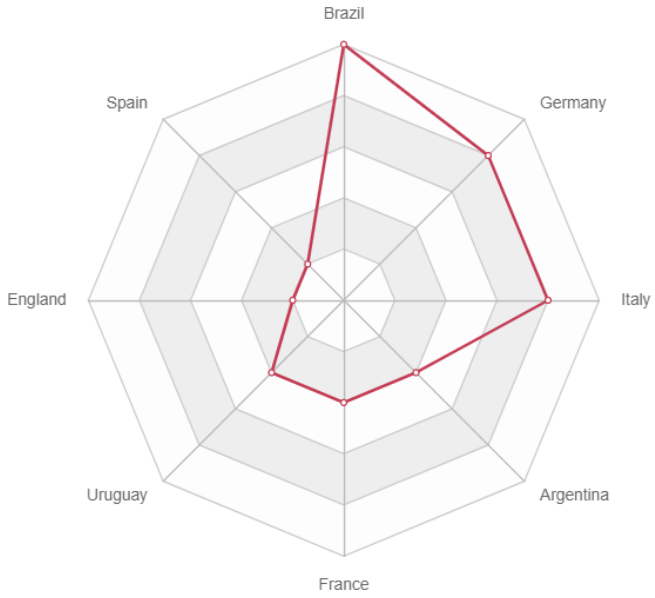


Figure 4.55 Image of Radar Chart

Figure 4.56 shows that the majority of the participants, chose the lowest preferences using a word cloud with 27 frequencies. The highest preference is the least, with 6 frequencies.

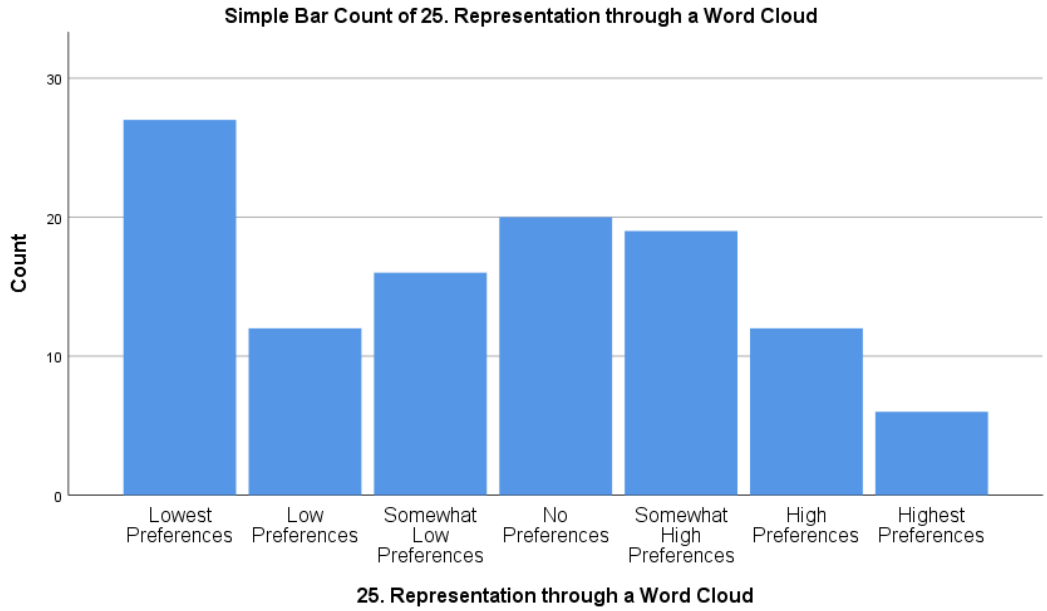


Figure 4.56 Vertical Bar of a Word Cloud

Figure 4.57 Image of Word Cloud

Figure 4.58 shows that the majority of the participants, chose the highest preferences using the horizontal bar chart with 36 frequencies. The low preference is the least, with 0 frequencies.

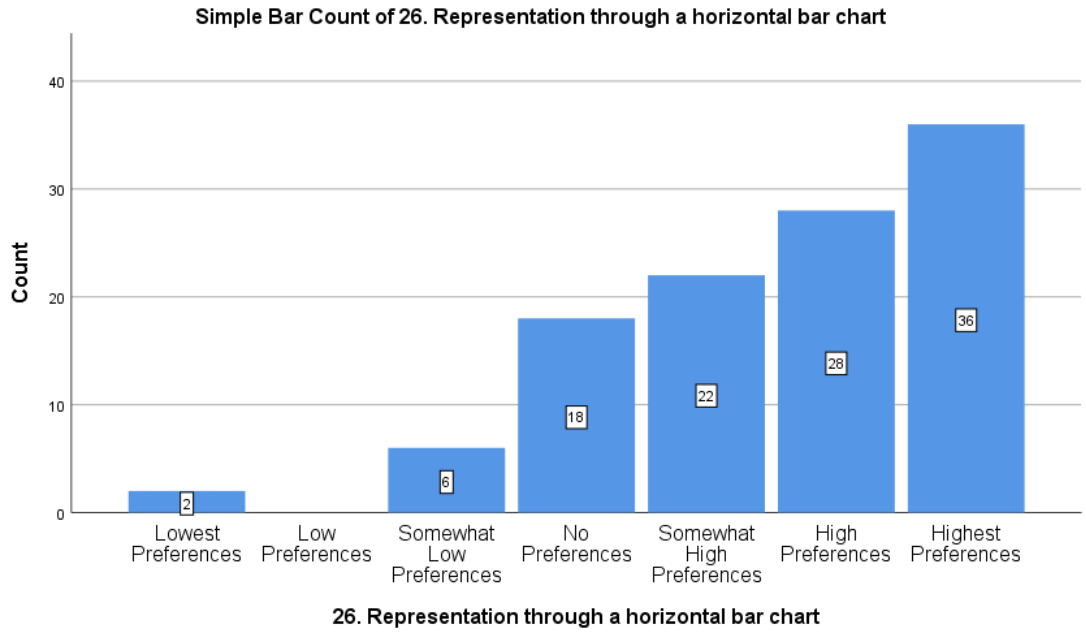


Figure 4.58 Vertical Bar of the Horizontal Bar Chart

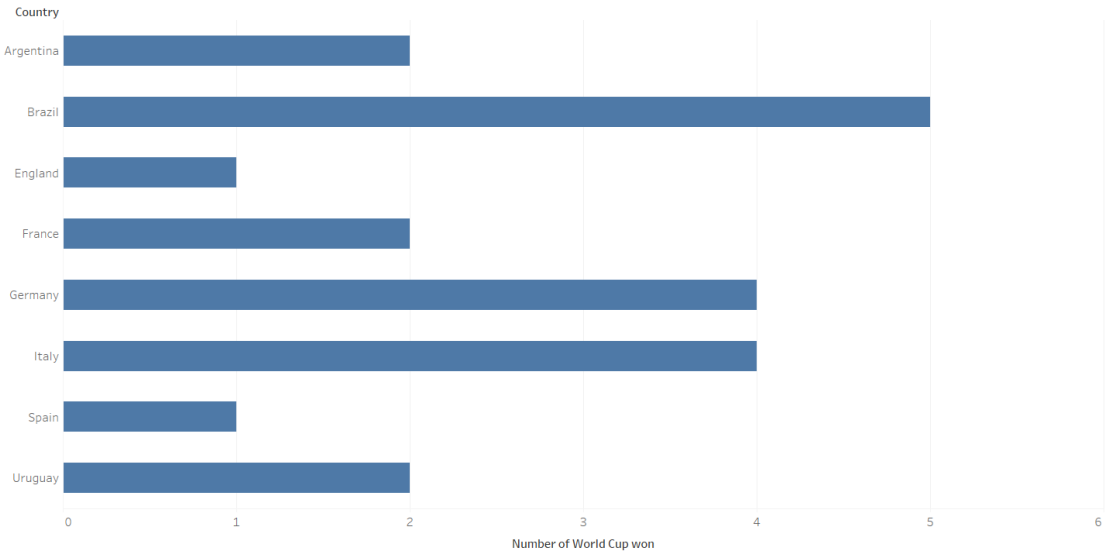


Figure 4.59 Image of Horizontal Bar Chart

Figure 4.60 reveals that the vertical bar chart with 44 frequencies was chosen by the highest preferences of participants. The low choice has the lowest frequency with 0 participant.

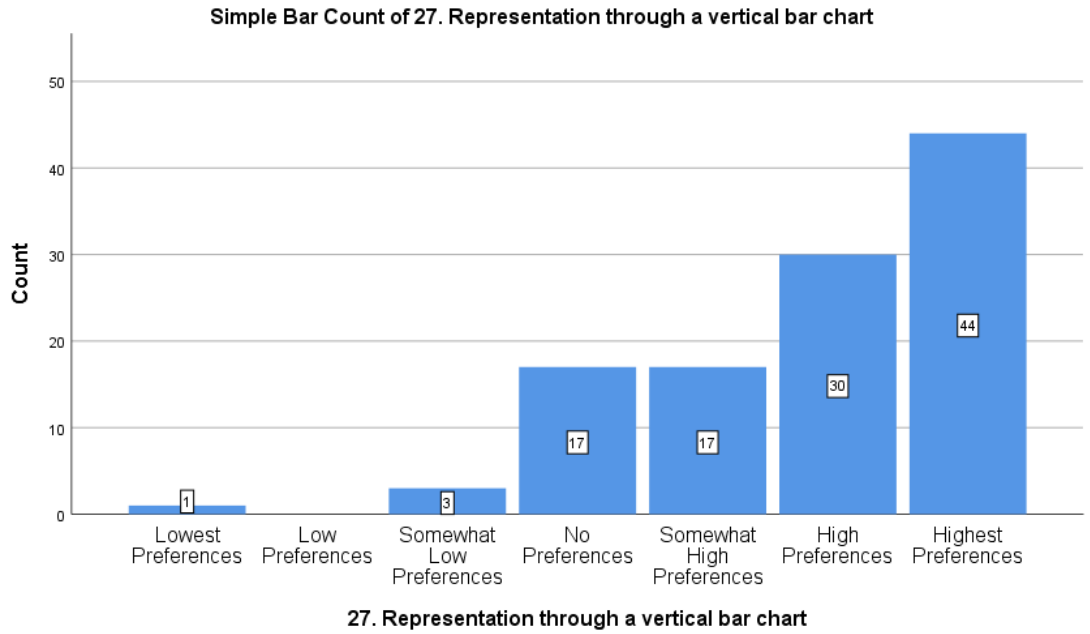


Figure 4.60 Vertical Bar of Vertical Bar Chart

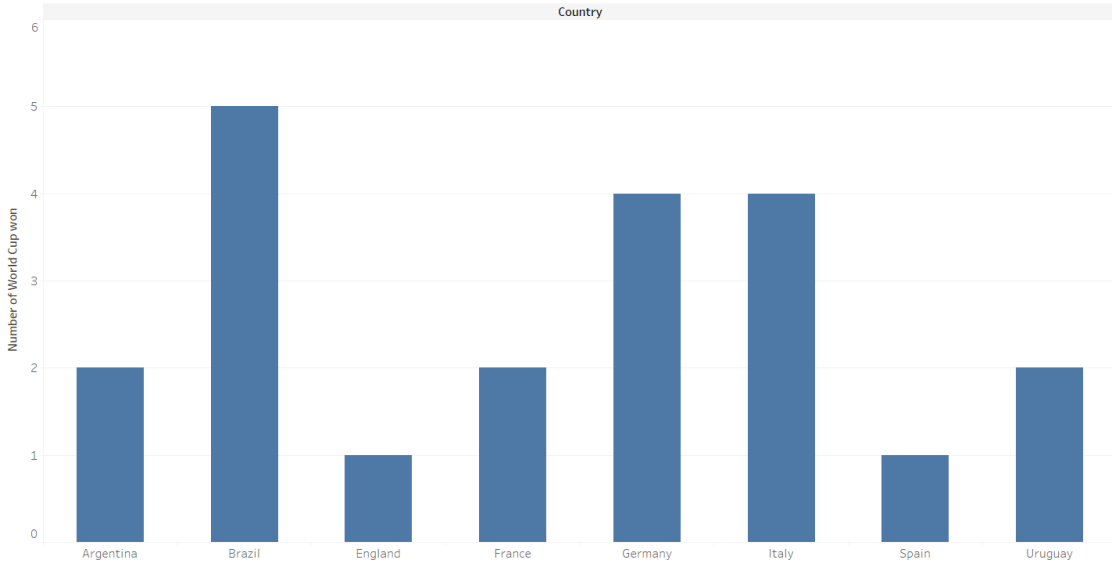


Figure 4.61 Image of Vertical Bar Chart

Figure 4.62 shows that the majority of the participants, chose the highest preferences using a pie chart with 48 frequencies. The lowest preference is the least, with 2 frequencies.

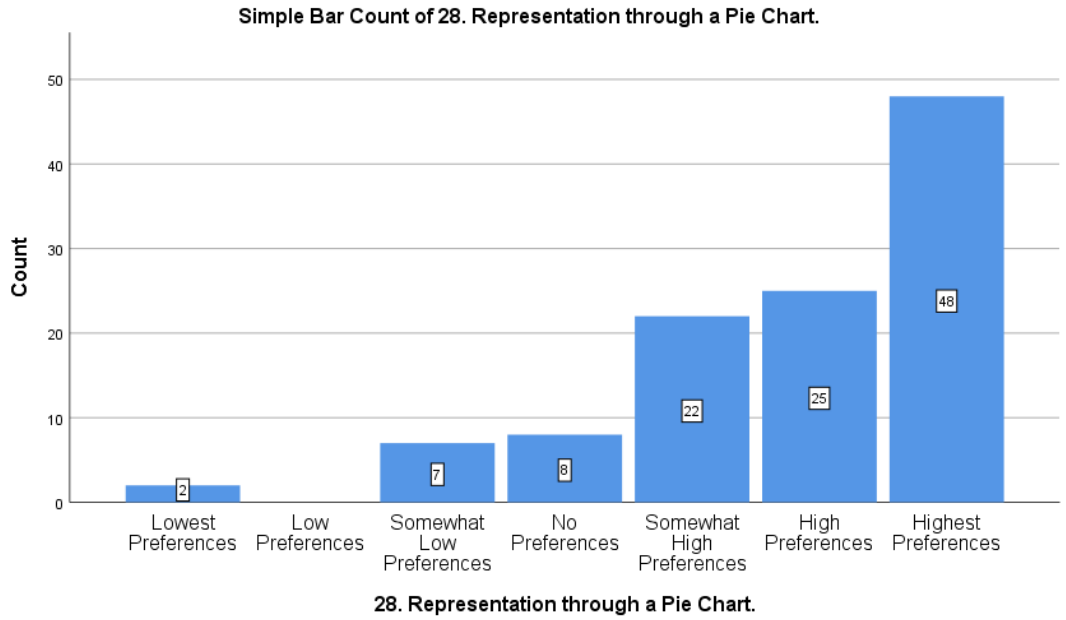


Figure 4.62 Vertical Bar of Pie Chart

Figure 4.63 Image of Pie Chart

Figure 4.64 shows that the majority of the participants, chose the highest preferences using magazine style, with 31 frequencies. The lowest and lowest preferences are the least, with 4 frequencies each.

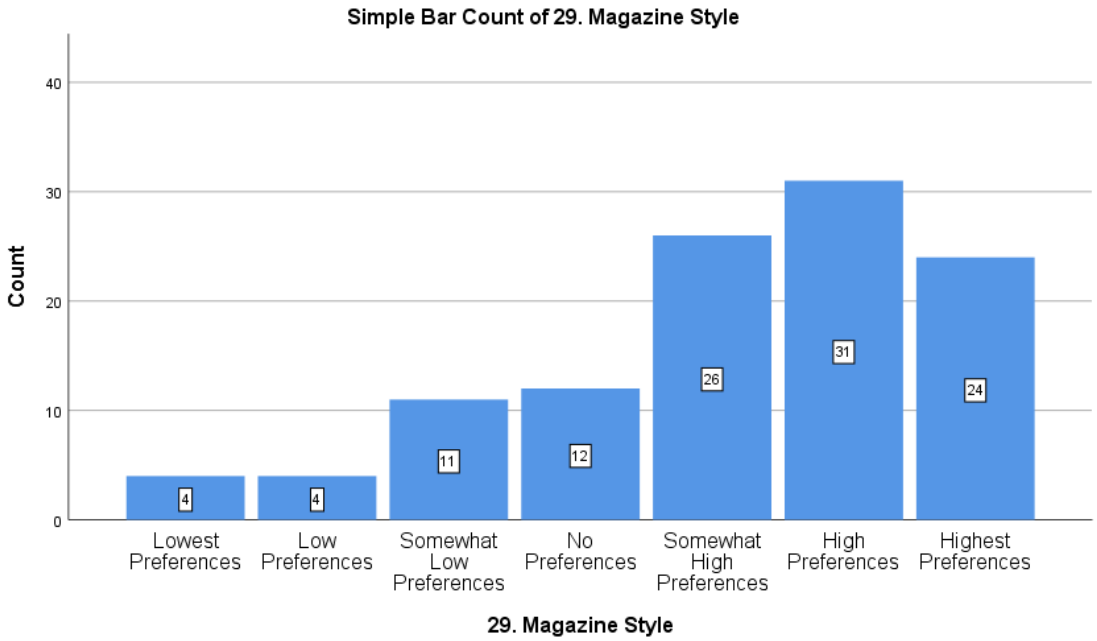


Figure 4.64 Vertical Bar of Magazine Style

Figure 4.65 Image of Magazine Style

Figure 4.67 shows that the majority of the participants, chose somewhat high preferences using the annotated chart with 27 frequencies. The lowest preference is the least, with 6 frequencies.

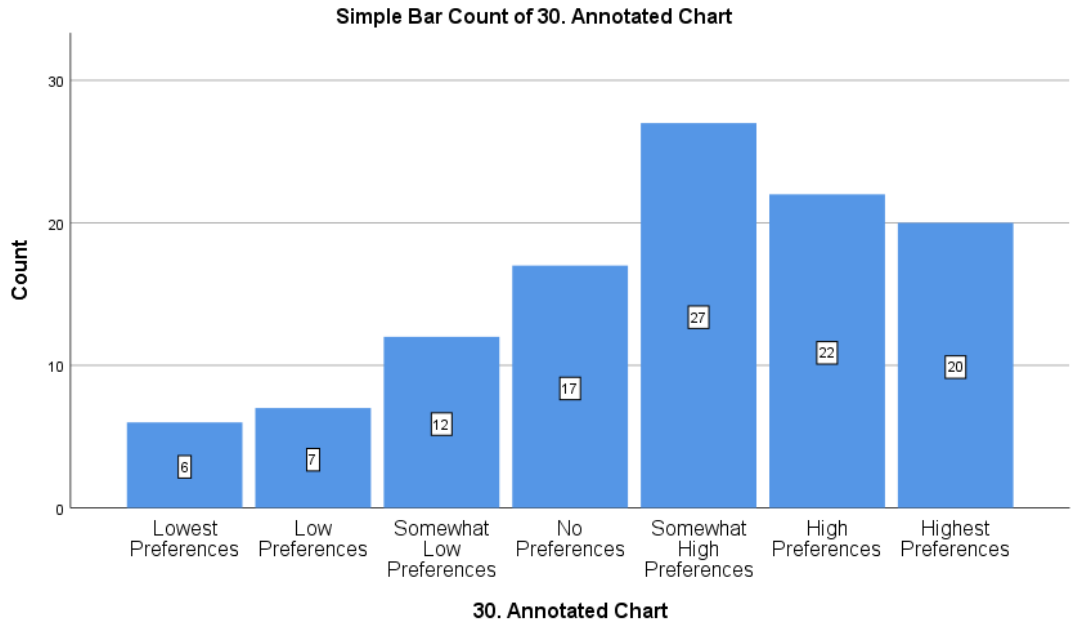


Figure 4.66 Vertical Bar of the Annotated Chart

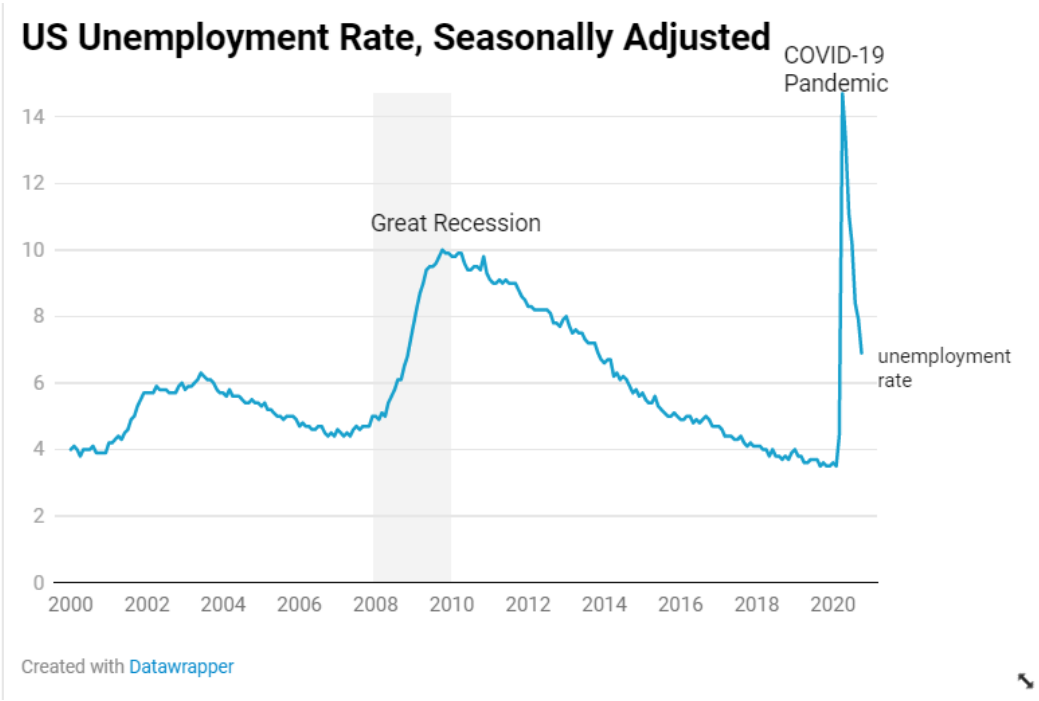


Figure 4.67 Image of Annotated Chart

Figure 4.68 shows that the majority of the participants, chose the highest preferences using the flowchart-infographic, with 40 frequencies. Low preference is the least with 3 frequencies.

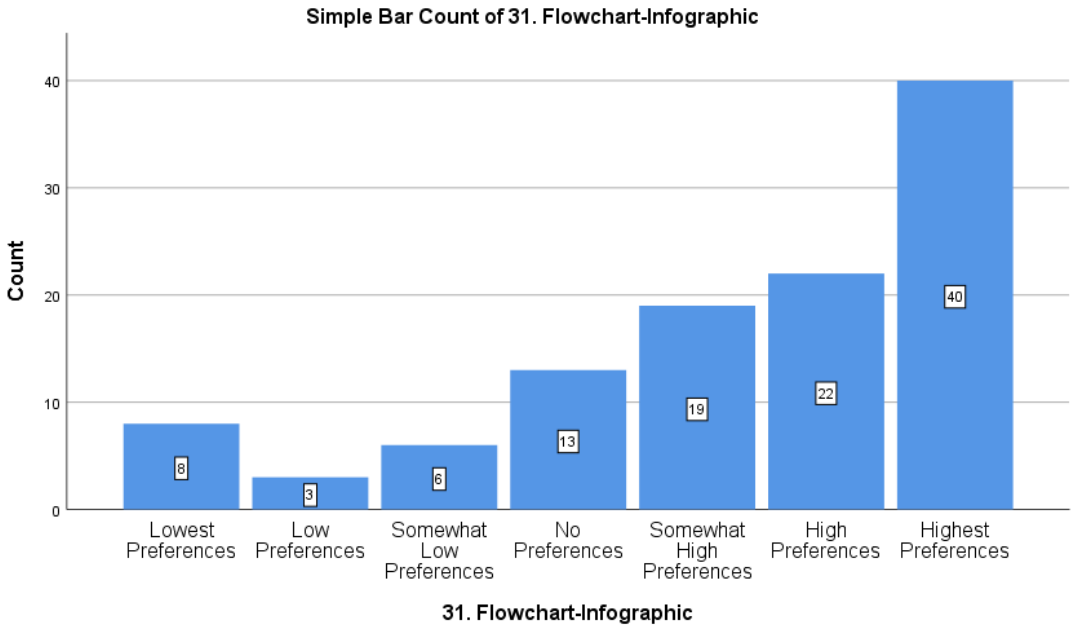


Figure 4.68 Vertical Bar of Flowchart-Infographic

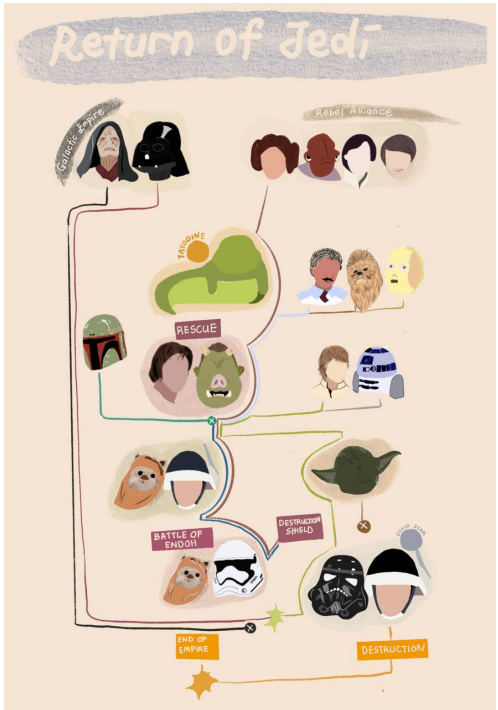


Figure 4.69 Image of Flowchart-Infographic

Figure 4.70 shows that the majority of the participants, chose somewhat high preferences using the partitioned poster with 30 frequencies. Low preference is the least with 5 frequencies.

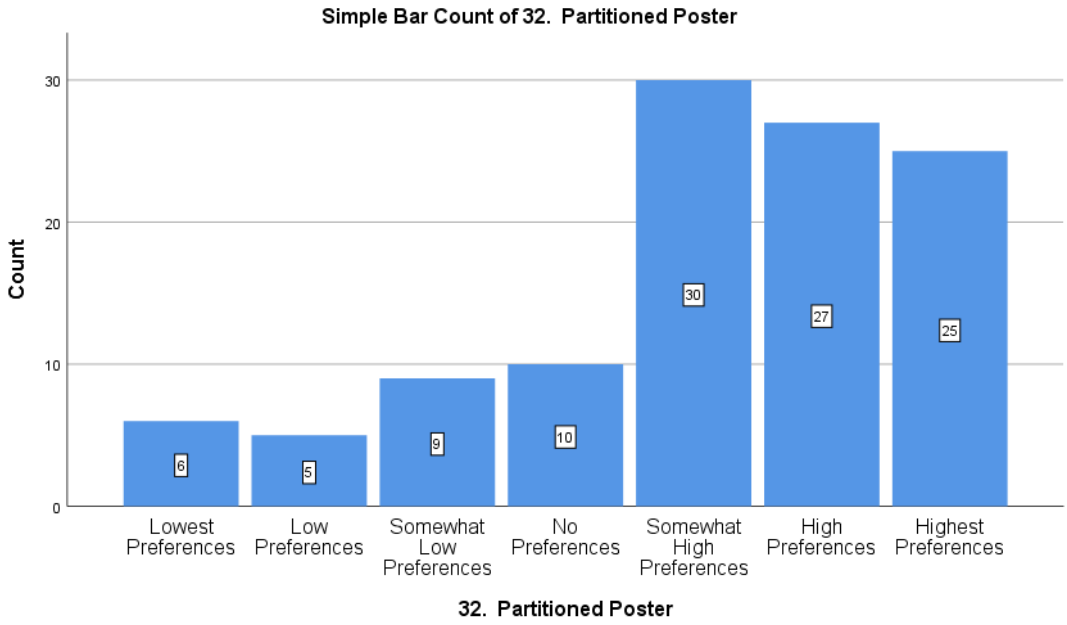


Figure 4.70 Vertical Bar of Partitioned Poster

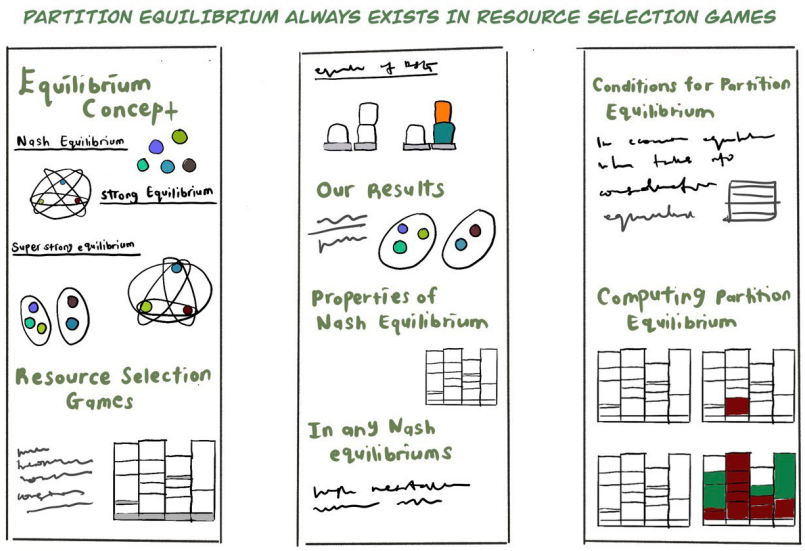


Figure 4.71 Image of Partitioned Poster

Figure 4.72 shows that the majority of the participants, chose the highest preferences using comics and animation, with 46 frequencies. The lowest and low preferences are the least with 1 frequency each.

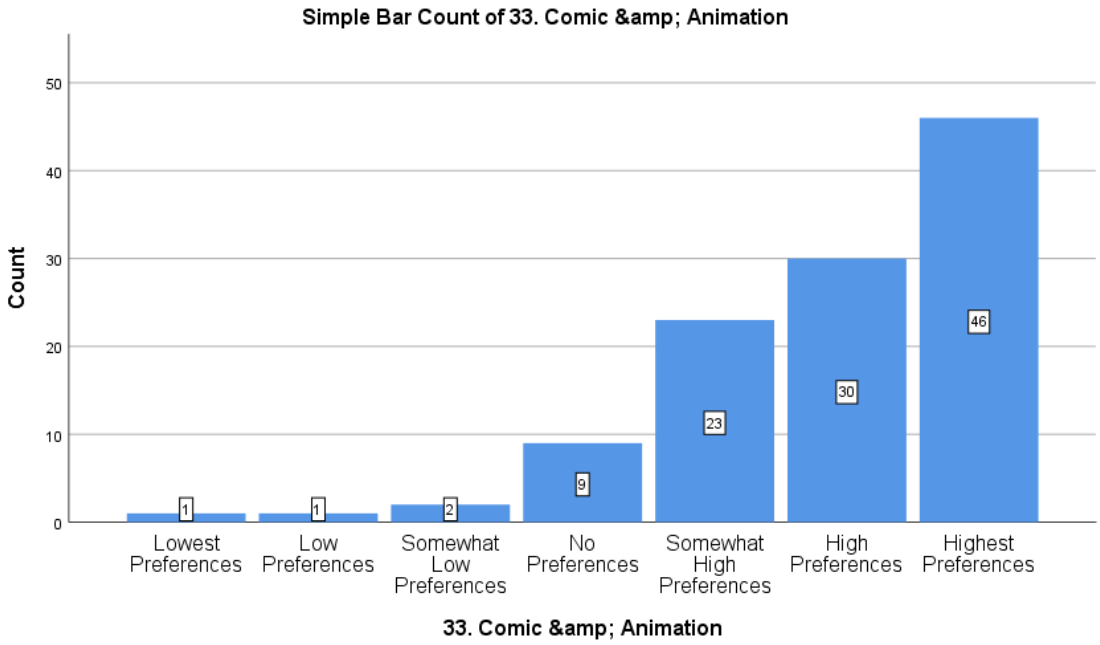


Figure 4.72 Vertical Bar of Comic and Animation

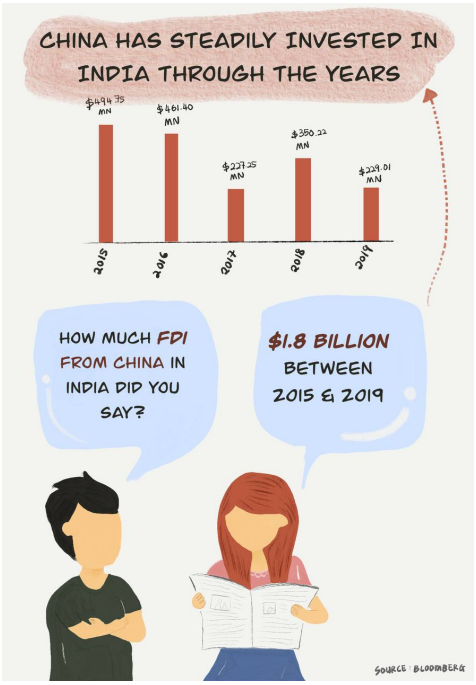


Figure 4.73 Image of Comic and Animation

Table 4.1 shows the summary of the highest number of participants' personality trait. Table 4.2 shows the summary of the lowest number of participants' personality trait. Figure 4.41 shows the heat map of the summary of the highest number of participants' visualization type preferences.

Table 4.1 Summary of the Highest Number of Participants' Personality Trait

Variables	**Values**	
	Frequencies (out of 112)	**Percentage (%)**
Low Extraversion	36	32.1
Moderate Extraversion	35	31.3
Moderate Agreeableness	35	31.3
High Agreeableness	35	31.3
High Conscientiousness	36	32.1
Moderate Neuroticism	39	34.8
Low Openness	29	25.9

Table 4.2 Summary of the Lowest Number of Participants' Personality Trait

Variables	**Values**	
	Frequencies (out of 112)	**Percentage (%)**
Very high Extraversion	4	3.6
Very high Agreeableness	9	8.0
Very high Conscientiousness	10	8.9
Very low Neuroticism	4	3.6
Very high Openness	16	14.3

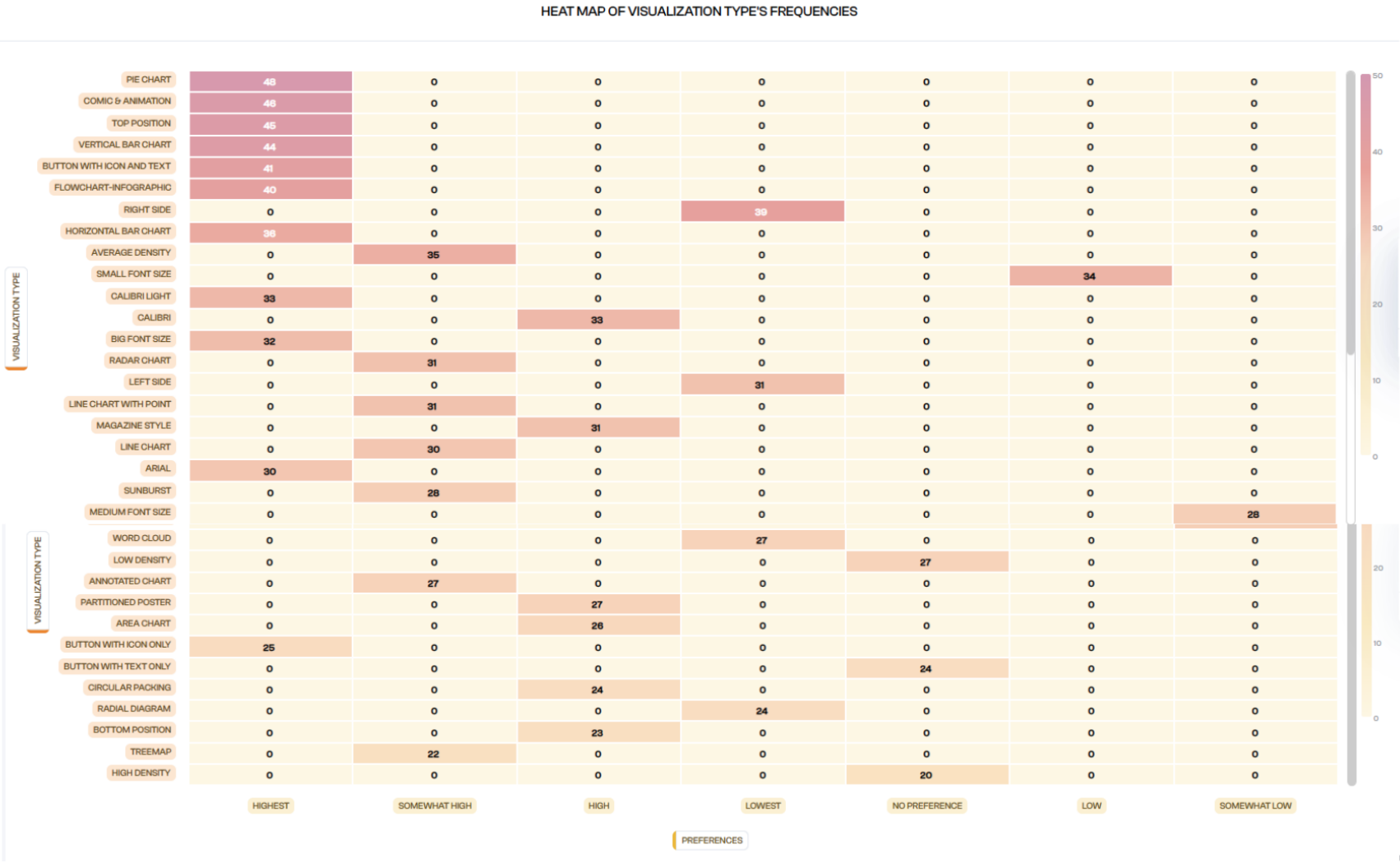


Figure 4.74 Summary of the Majority of Participant's Visualization Types Choices.

4.2.2 Descriptive Analysis

Descriptive analysis was used in this research to determine the level of personality of the respondents. The purpose of descriptive analysis is to identify broad trends in the interests of a population (Loeb et al., 2017). Tables of descriptive data for both personality and visual type are provided below.

Table 4.3 Descriptive Statistic for Personality

	N	Minimum	Maximum	Mean	Std. Deviation
Extraversion	112	1	5	2.76	1.033
Agreeableness	112	1	5	3.05	1.146
Conscientiousness	112	1	5	3.02	1.215
Neuroticism	112	1	5	3.46	1.073
Openness	112	1	5	2.79	1.359
On what device are you filling out this questionnaire?	112	1	3	2.22	.956
Do you have color blindness?	112	1	2	1.97	.162
Valid N (listwise)	112				

Table 4.4 Descriptive Statistic for Visualization Types Elements

	N	Minimum	Maximum	Mean	Std. Deviation
1. Arial	112	1	7	5.17	1.530
2. Calibri	112	1	7	5.42	1.393
3. Calibri Light	112	1	7	4.96	1.847

	N	Minimum	Maximum	Mean	Std. Deviation
4. Small font size	112	1	7	2.90	1.781
5. Medium font size	112	1	7	4.37	1.616
6. Big font size	112	1	7	5.26	1.552
7. Button with icon only.	112	1	7	4.77	1.855
8. Button with text only	112	1	7	4.95	1.615
9. Button with icon and with text	112	1	7	5.10	2.022
10. Low density	112	1	7	4.63	1.594
11. Average density	112	1	7	4.98	1.185
12. High density	112	1	7	4.30	1.888
13. Top position of the navigation bar	111	1	7	5.56	1.639
14. Bottom position of the navigation bar	112	1	7	4.24	2.059
15. Right side positioning of the navigation bar.	112	1	7	3.04	1.984
16. Left side positioning of the navigation bar.	112	1	7	3.52	2.152
17. Representation through a Treemap.	112	1	7	4.17	1.999
18. Representation through a Circular Packing diagram.	112	1	7	4.49	1.836
19. Representation through a Sunburst.	112	1	7	4.57	1.819
20. Representation through a Radial diagram	112	1	7	3.47	1.850

	N	Minimum	Maximum	Mean	Std. Deviation
21. Representation through a Linechart.	112	1	7	5.21	1.479
22. Representation through a Linechart, with points.	112	1	7	4.89	1.678
23. Representation through an Area chart.	112	1	7	5.08	1.617
24. Representation through a Radar chart	112	1	7	4.89	1.662
25. Representation through a Word Cloud	112	1	7	3.46	1.888
26. Representation through a horizontal bar chart	112	1	7	5.55	1.381
27. Representation through a vertical bar chart	112	1	7	5.81	1.263
28. Representation through a Pie Chart.	112	1	7	5.81	1.379
29. Magazine Style	112	1	7	5.15	1.589
30. Annotated Chart	111	1	7	4.78	1.708
31. Flowchart-Infographic	111	1	7	5.32	1.815
32. Partitioned Poster	112	1	7	5.09	1.680
33. Comic & Animation	112	1	7	5.91	1.212
Valid N (listwise)	109				

The table shows the number of participants (N), the minimum and maximum, which are markers for the personality and visualization type preference scores; the minimum is the lowest score, and vice versa; the mean; and the standard deviation.

According to the results, the sample as a whole has a modest degree of extraversion (M = 2.76, SD = 1.03). In addition, the sample had average to high levels of agreeableness, conscientiousness, and neuroticism (M = 3.05, SD = 1.15; M = 3.02, SD = 1.22; M = 3.46, SD = 1.07, respectively). The results revealed a low degree of openness, with a mean of 2.79 (SD = 1.34). When completing this questionnaire, the sample mostly utilizes tablets and phones (M = 2.22, SD = 0.96). The majority of subjects do not have colour blindness (M = 1.97, SD = 0.16).

The font type test findings demonstrate that all three varieties have considerable preferences. Participants prefer Arial and Calibri font types (M = 5.17, SD = 1.53; M = 5.42, SD = 1.39, respectively), whereas Calibri Light font type (M = 4.96, SD = 1.85) is neither preferred nor rejected. The font size sample demonstrates variances between all three font sizes. Participants oppose adopting a tiny font size (M = 2.90, SD = 1.85). Participants neither like nor reject medium font size (M = 4.37, SD = 1.62) and prefer large font size (M = 5.26, SD = 1.55).

Participants do not favor or reject the use of both buttons with icons and buttons with simply text (M = 4.77, SD = 1.86; M = 4.95, SD = 1.62, respectively). Participants, on the other hand, prefer buttons with both icons and text (M = 5.10, SD = 2.02). The information density type result demonstrates that the participant does not favor or reject any of the three types: low density (M = 4.63, SD = 1.59), average density (M = 4.98, SD = 1.18), and high density (M = 4.30, SD = 1.89). There are variances in the location of the navigation bar in all positions. Participants prefer to utilize the top navigation bar position (M = 5.56, SD = 1.64), rather than the right and left side navigation bar locations (M = 3.04, SD = 1.98; M = 3.52, SD = 2.15, respectively). Meanwhile, participants (M = 4.24, SD = 2.06) neither favor nor oppose utilizing the bottom location of the navigation bar.

The participant does not favor or reject utilizing the tree map, circular packing diagram, or sunburst for hierarchical visual components (M = 4.17, SD = 2.00; M = 4.49, SD = 1.84; M = 4.57, SD = 1.82, respectively). However, the radial graphic is rejected by the participants (M = 3.47, SD = 1.85). Participants prefer line charts and area charts for the change over time visual element (M = 5.21, SD = 1.485; M = 5.08, SD = 1.62, respectively), whereas the line chart with a point was neither liked nor

rejected (M = 4.89, SD = 1.68). Participants preferred horizontal bar charts and vertical bar charts for comparison visual components (M = 5.55, SD = 1.38; M = 5.81, SD = 1.26, respectively). The participant opposed utilizing a word cloud (M = 3.46, SD = 1.89) and neither liked nor opposed using a radar graphic (M = 4.89, SD = 1.66). Participants choose magazine style (M = 5.15, SD = 1.59), flowchart-infographic (M = 5.32, SD = 1.82), partitioned poster (M = 5.09, SD = 1.68), and comic animation (M = 5.91, SD = 1.21) for the narrative visual element. Using the annotated chart, participants did not favor or reject (M = 4.78, SD = 1.71).

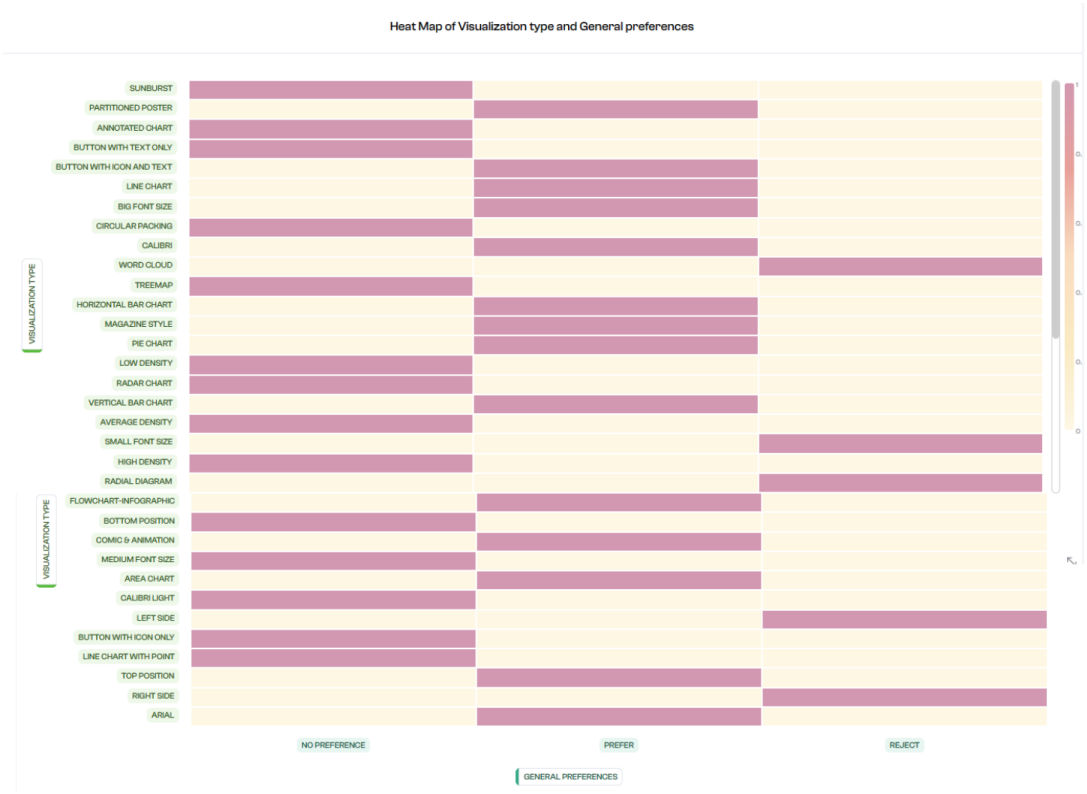


Figure 4.75 Heat Map of General Preferences on Visualization Type

4.2.3 Correlation Analysis

A Pearson correlation was calculated to analyze the relationship between the five personality qualities based on the FFM (extraversion, agreeableness, conscientiousness, neuroticism, and openness) and the visual design typeface. The findings in table 4.5 show a substantial, positive link between extraversion qualities and the Calibri light font type, with r(110) =.19 and p =.042. The openness attribute and Arial font type have a

substantial, positive connection of r(110) =.22, p = 0.19. All font styles had no link with agreeableness, conscientiousness, or neuroticism. Meanwhile, Calibri does not seem to be related to all personality characteristics.

Table 4.5 Correlation Between Personality and Font Style

	Arial	**Calibri**	**Calibri light**
Extraversion	r = .177 p = .218	r = .121 p = .204	r = .193 p = .042
Agreeableness	r = -.067 p = .483	r = -.026 p = .789	r = .069 p = .468
Conscientiousness	r = -.016 p = .866	r = .107 p = .260	r = -.012 p = .903
Neuroticism	r = -.020 p = .834	r = -.087 p = .363	r = -.026 p = .785
Openness	r = .221 p = .019	r = -.066 p = .487	r = .125 p = .188

The following results in table 4.6 reveal a substantial, positive relationship between the openness characteristic and tiny font size, r(110) =.19, p =.042. Small font sizes show no link with extraversion, agreeableness, conscientiousness, or neuroticism. There is no relationship between medium font size and all personality qualities.

Table 4.6 Correlation Between Personality and Font Size

	Small font size	**Medium font size**	**Big font size**
Extraversion	r = .105 p = .273	r = .053 p = .577	r = .118 p = .216
Agreeableness	r = -.020 p = .832	r = -.016 p = .871	r = .012 p = .897

	Small font size	Medium font size	Big font size
Conscientiousness	r = -.030 p = .754	r = .084 p = .380	r = -.007 p = .940
Neuroticism	r = -.104 p = .277	r = .048 p = .612	r = .085 p = .370
Openness	r = .192 p = .042	r = .126 p = .184	r = .074 p = .441

The findings in table 4.7 indicate a statistically significant and positive relationship between extraversion and buttons designed with a text-only style (r(110) =.31, p =.001). There exists a notable and positive link between conscientiousness and button text style, as shown by the statistical analysis (r(110) =.24, p =.010). The findings of the study indicate a statistically significant and positive association between the openness attribute and the button with text style (r(110) = .28, p = .003). The qualities of agreeableness and neuroticism exhibit no association with the button with text style. Conversely, both the button with icon and button with icon and text styles show no correlation with any of the personality traits.

Table 4.7 Correlation Between Personality and Button Style

	Button with icon only	Button with text only	Button with icon and text
Extraversion	r = .182 p = .055	r = .311 p = .001	r = .102 p = .285
Agreeableness	r = -.041 p = .670	r = -.062 p = .518	r = .169 p = .075
Conscientiousness	r = -.050 p = .600	r = .244 p = .010	r = -.041 p = .667
Neuroticism	r = -.014 p = .881	r = .090 p = .347	r = .000 p = 1.00
Openness	r = .037 p = .696	r = .278 p = .003	r = .050 p = .598

The result in table 4.8 shows a significant, positive correlation between the extraversion trait and high density, r(110) =.21, p =.024. The other four personality traits have zero correlation with high information density. There is no correlation between low information density and average information density for all personality traits.

Table 4.8 Correlation Between Personality and Information Density

	Low density	**Average density**	**High density**
Extraversion	r = .088 p = .355	r = .144 p = .131	r = .204 p = .031
Agreeableness	r = .006 p = .951	r = .001 p = .994	r = .026 p = .788
Conscientiousness	r = -.145 p = .126	r = .082 p = .393	r = .2037 p = .699
Neuroticism	r = .130 p = .172	r = -.071 p = .454	r = -.171 p = .071
Openness	r = .092 p = .332	r = -.058 p = .541	r = .141 p = .137

In table 4.9, the association between openness and the right location of the navigation bar is substantial and positive (r(110) =.23, p =.016), but the correlation between extraversion, agreeableness, conscientiousness, and neuroticism is zero. There is no discernible association between the top and left placements of the navigation bar and any specific personality characteristics. A statistically significant and positive connection was observed between extraversion and the use of the bottom navigation bar (r(110) =.19, p =.042).

Table 4.9 Correlation Between Personality and Position of The Navigation Bar

	Top navigation bar	**Right navigation bar**	**Bottom navigation bar**	**Left navigation bar**
Extraversion	r =- .067 p = .488	r = .023 p = .811	r = .193 p = .042	r = .049 p = .611
Agreeableness	r = .074 p = .443	r = -.116 p = .223	r = -.097 p = .308	r = -.059 p = .538
Conscientiousness	r = -.051 p = .599	r = -.146 p = .124	r = .059 p = .533	r = -.093 p = .329
Neuroticism	r = .013 p = .893	r = .181 p = .056	r = -.079 p = .410	r = .174 p = .067
Openness	r = -.121 p = .205	r = .228 p = .016	r = .180 p = .058	r = .165 p = .083

In hierarchy visual style, tree map and circular packing styles have zero correlation with all five personality traits in table 4.10. The findings demonstrates a substantial, positive link between extraversion and sunburst visual style, r(110) =.20, p =.032. The openness characteristic and the radial diagram likewise have a substantial, positive connection, r(110) =.21, p =.030. In the sunburst and radial diagrams, there is no link between agreeableness, conscientiousness, and neuroticism.

Table 4.10 Correlation Between Personality and Hierarchy Visual Elements

	Tree map	**Circular Packing**	**Sunburst**	**Radial diagram**
Extraversion	r = .046 p = .629	r = -.056 p = .559	r = .203 p = .032	r = .178 p = .060
Agreeableness	r = -.094 p = .322	r = -.034 p = .722	r = -.101 p = .288	r = -.004 p = .970
Conscientiousness	r = -.024 p = .806	r = .000 p = .999	r = -.037 p = .697	r = -.036 p = .708

	Tree map	Circular Packing	Sunburst	Radial diagram
Neuroticism	r = -.049 p = .608	r = .018 p = .850	r = -.098 p = .306	r = .090 p = .344
Openness	r = -.119 p = .211	r = .068 p = .477	r = .072 p = .452	r = .206 p = .030

In terms of visual style change over time, area charts and line charts with points have zero correlation with all five personality traits in table 4.11. Results show a significant, positive correlation for both extraversion and openness with a line chart: r(110) =.31, p =.001, and r(110) =.23, p =.013 respectively. There is zero correlation between agreeableness, conscientiousness, and neuroticism on a line chart.

Table 4.11 Correlation Between Personality and Change Over Time Visual Elements

	Line chart	Line chart with point	Area chart
Extraversion	r = .305 p = .001	r = .073 p = .443	r = .001 p = .992
Agreeableness	r = -.134 p = .158	r = .069 p = .472	r = .046 p = .628
Conscientiousness	r = .108 p = .257	r = -.132 p = .167	r = -.134 p = .160
Neuroticism	r = -.130 p = .171	r = .022 p = .815	r = -.037 p = .700
Openness	r = .234 p = .013	r = .183 p = .053	r = .106 p = .265

All five personality qualities show no link with horizontal bar charts, vertical bar charts, or pie charts when compared to visual style in table 4.12. Extraversion and radar have a substantial positive association, r(110) =.19, p =.047, according to the findings. There is no link between agreeableness, conscientiousness, neuroticism, and

openness on a horizontal bar chart. The association between agreeableness and word cloud is substantial and favorable, r(110) =.20, p =.040. In a word cloud, there is no association between extraversion, conscientiousness, neuroticism, and openness.

Table 4.12 Correlation between Personality and Comparison Visual Elements

	Radar Chart	**Word Cloud**	**Vertical bar chart**	**Horizontal bar chart**	**Pie chart**
Extraversion	r = .188 p = .047	r = .146 p = .126	r = .170 p = .073	r = .076 p = .429	r = .132 p = .164
Agreeableness	r = -.115 p = .226	r = -.195 p = .040	r = .027 p = .780	r = .044 p = .642	r = .035 p = .715
Conscientiousness	r = -.119 p = .210	r = -.070 p = .461	r = .005 p = .960	r = .026 p = .788	r = .072 p = .451
Neuroticism	r = -.003 p = .977	r = -.065 p = .494	r = .072 p = .453	r = .004 p = .969	r = -.155 p = .103
Openness	r = -.034 p = .720	r = .159 p = .095	r = .121 p = .202	r = .123 p = .195	r = .113 p = .235

In the context of data narrative visual style, it can be seen that there is no significant link between the five personality types and the use of annotated charts, flowchart-infographics, comics, and animation in table 4.13. The findings indicate a statistically significant inverse relationship between agreeableness and partitioned posters (r(110) =.20, p =.035). There is no discernible association seen between the personality traits of extraversion, conscientiousness, neuroticism, and openness as shown on partitioned boards. The findings of the study show demonstrate a statistically significant inverse relationship between conscientiousness and magazine style (r(110) = -.24, p =.010). There is no discernible association seen between extraversion, agreeableness, neuroticism, and openness as shown in magazine-style content

Table 4.13 Correlation between Personality and Storytelling Visual Elements

	Magazine style	**Annotated Chart**	**Flowchart-Infographic**	**Partitioned Poster**	**Comic & Animation**
Extraversion	r = -.098 p = .303	r = .100 p = .298	r = -.151 p = .114	r = -.065 p = .494	r = -.017 p = .856
Agreeableness	r = .000 p = .996	r = -.049 p = .612	r = -.060 p = .531	r = -.199 p = .035	r = .049 p = .609
Conscientiousness	r = -.244 p = .010	r = -.080 p = .403	r = -.100 p = .296	r = -.054 p = .574	r = -.017 p = .857
Neuroticism	r = .112 p = .238	r = -.064 p = .508	r = .057 p = .553	r = -.003 p = .977	r = -.059 = .540
Openness	r = .028 p = .772	r = .176 p = .065	r = -.125 p = .190	r = .-181 p = .056	r = -.505 p = .600

Table 4.14 Summary Correlation Between Personality and Storytelling Visual Elements

Visualization types with personality	**Correlation value**
Calibri Light with Extraversion	r(110) =.29, p =.042
Arial with Openness	*r(110) =.22, p =.019*
Small font size with openness	r(110) =.19, p =.042
Button with text, with extraversion	r(110) = .31, p = .001
Button with text, with conscientiousness	r(110) = .24, p = .010
Button with text, with openness	r(110) = .28, p = .003
High density with extraversion	r(110) = .21, p = .024
Bottom navigation bar with extraversion	r(110) = .19, p = .042
Right navigation bar with openness	r(110) = .23, p = .016
Sunburst with extraversion	, r(110) = .20, p = .032
Radial diagram with openness	r(110) = .21, p = .030

Visualization types with personality	Correlation value
Line chart with extraversion	, r(110) = .31, p = .001
Line chart with openness	r(110) = .23, p = .013
Radar chart with extraversion	r(110) = .19, p = .047
Word Cloud with agreeableness	r(110) = .20, p = .040
Partitioned poster with agreeableness	r(110) = .20, p = .035
Magazine style with conscientiousness	r(110) = -.24, p = .010

4.2.4 Chi-Square Analysis

The Chi-square test was used to uncover personality differences in user preferences for visualization styles. There are some notable links between personality factors and user preferences for visualization kinds of components, according to the correlation study. The chi-square test may be used to investigate the particulars of each connection and to find the differences in personality characteristics for each visual design element. Because the variables in this study are ordinal, the linear-by-linear association statistic is used.

The questionnaire employs a 7-likert scale, with the number on the scale representing participants' degree of favorability for the chosen visual style. Lowest preferences (1), low preferences (2), relatively low preferences (3), no preferences (4), somewhat high preferences (5), high preferences (6), and highest preferences (7) are among the options. A number scale was used to categorise the personality attribute into five levels. There are five options: 1 (very low), 2 (low), 3 (average), 4 (high), and 5 (very high). For example, a person with level 5 extraversion has a very high degree of extraversion.

To investigate the association between the openness personality characteristic and Arial typeface, a chi-square test was used in figure 4.43 and table 4.15. These factors had a significant relationship: X^2 (1, N = 112) = 5.4, p =.020. The image above depicts the association between the Arial font style and openness personality qualities.

The majority of participants (30) picked Arial as their preferred font type; both the lowest and lowest alternatives have the same lowest number of participants, which is 3, respectively. The table also shows that the highest, high, and somewhat high preferences options have more participants (30, 17, and 29 participants, respectively) than the somewhat low, low, and lowest preferences options, indicating that the majority of participants prefer the idea of using Arial as a font style. The chart above reveals that the majority of participants in the highest preference choice have very high openness characteristics, with 8 individuals, while players with very low and low openness levels are in the minority, with 4 participants for each option. Participants with low openness levels, on the other hand, had the largest preference for utilizing the Arial typeface, with either no or moderately high preferences.

Crosstab

Count

		1. Arial							
		Lowest Preferences	Low Preferences	Somewhat Low Preferences	No Preferences	Somewhat High Preferences	High Preferences	Highest Preferences	Total
Openness	Very Low	1	1	1	6	8	3	4	24
	Low	0	0	1	11	11	2	4	29
	Moderate	1	1	2	1	5	5	7	22
	High	1	1	1	5	4	2	7	21
	Very High	0	0	2	0	1	5	8	16
Total		3	3	7	23	29	17	30	112

Figure 4.76 Crosstab Table Between Openness and Arial Font Style

Table 4.15 Chi-Square Tests of Arial Font with Openness Personality Trait

	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	33.499[a]	24	.094
Likelihood Ratio	39.499	24	.024
Linear-by-Linear Association	5.440	1	.020
N of Valid Cases	112		

To investigate the association between extraversion personality qualities and the Calibri Light typeface, a chi-square test was used in figure 4.44 and table 4.16. These factors had a significant relationship: X^2 (1, N = 112) = 4.1, p =.042. According to the table above, the majority of participants picked Calibri Light as a font style with 33 participants, while the lowest preferred choice had the fewest participants with 5 participants. The table also shows that the highest, high, and somewhat high options have more participants, with 33, 19, and 17 participants, respectively, than the somewhat low, low, and lowest options, indicating that the majority of participants prefer the idea of using Calibri Light as a font style. According to the graph above, individuals with an average extraversion level (3) make up the majority, with 13 people choosing the highest preferred choice.

		Lowest Preferences	Low Preferences	Somewhat Low Preferences	No Preferences	Somewhat High Preferences	High Preferences	Highest Preferences	Total
Extraversion	Very Low	0	2	3	2	2	3	0	12
	Low	3	2	8	4	5	4	10	36
	Moderate	0	2	3	4	7	6	13	35
	High	2	0	4	3	3	5	8	25
	Very High	0	1	0	0	0	1	2	4
Total		5	7	18	13	17	19	33	112

Figure 4.77 Crosstab Table Between Extraversion and Calibri Light Font Style

Table 4.16 Chi-Square Tests of Calibri Light Extraversion Personality Trait

	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	21.912[a]	24	.585
Likelihood Ratio	28.852	24	.226
Linear-by-Linear Association	4.116	1	.042
N of Valid Cases	112		

To investigate the association between openness personality qualities and tiny text size, a chi-square test was used in figure 4.45 and table 4.17. These factors had a

significant relationship: $X^2(1, N = 112) = 4.1$, $p = .043$. The table above indicates that the majority of participants (34 in total) picked the low preference option to utilize a tiny font size, while both the highest and high preference selections had the fewest participants (6 in total). The table also shows that the lowest, low, and somewhat low preference options have more participants (27, 34, and 17 respectively) than the somewhat high, high, and highest preference options, indicating that the majority of participants oppose the use of a small font size. The chart above reveals that people with the low openness trait (2) outnumber those with the low preferences option by a factor of ten.

		Lowest Preferences	Low Preferences	Somewhat Low Preferences	No Preferences	Somewhat High Preferences	High Preferences	Highest Preferences	Total
Openness	Very Low	7	9	5	1	1	0	1	24
	Low	7	10	6	2	3	0	1	29
	Moderate	6	4	3	1	2	6	0	22
	High	4	5	3	3	2	0	4	21
	Very High	3	6	0	2	5	0	0	16
Total		27	34	17	9	13	6	6	112

Figure 4.78 Crosstab Table Between Openness and Small Font Size

Table 4.17 Chi-Square Tests of Small Font Size with Openness Personality Trait

	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	49.661[a]	24	.002
Likelihood Ratio	44.852	24	.006
Linear-by-Linear Association	4.106	1	.043
N of Valid Cases	112		

A chi-square test was used to investigate the link between extraversion personality characteristics and text-only buttons in figure 4.46 and table 4.18. These factors had a significant relationship: X^2 $(1, N = 112) = 10.7$, $p = .001$. The table above reveals that the majority of participants (24 participants) picked the no preference option

to utilize the button with text alone, while the low preference option had the fewest participants (3 people). The table also reveals that the highest, high, and somewhat preferred alternatives, each with 23 participants, have more participants than the somewhat low, low, and lowest desired options, showing that the majority of participants favor the notion of utilizing the button with text alone. The chart above demonstrates that people with the low extraversion characteristic (2) outnumber those with no preferences by a factor of ten.

		Lowest Preferences	Low Preferences	Somewhat Low Preferences	No Preferences	Somewhat High Preferences	High Preferences	Highest Preferences	Total
Extraversion	Very Low	1	1	3	3	3	1	0	12
	Low	1	1	3	10	6	7	8	36
	Moderate	3	1	5	6	8	6	6	35
	High	0	0	0	5	6	8	6	25
	Very High	0	0	0	0	0	1	3	4
Total		5	3	11	24	23	23	23	112

Figure 4.79 Crosstab Table Between Extraversion and Button with Text Only

Table 4.18 Chi-Square Tests of Button with Text Only with Extraversion Personality Style

	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	26.647[a]	24	.321
Likelihood Ratio	31.553	24	.138
Linear-by-Linear Association	10.712	1	.001
N of Valid Cases	112		

A chi-square test was used to investigate the link between the conscientiousness personality characteristic and the text-only button in figure 4.47 and table 4.19. These factors had a significant relationship: X^2 (1, N = 112) = 6.6, p =.010. The table above reveals that the majority of participants (24 participants) picked the no preference option to utilize the button with text alone, while the low preference option had the fewest

participants (3 people). The table also reveals that the highest, high, and somewhat preferred alternatives, each with 23 participants, have more participants than the somewhat low, low, and lowest desired options, showing that the majority of participants favor the notion of utilizing the button with text alone. The chart above demonstrates that people with moderate conscientiousness trait (2) outnumber those with no preferences by a factor of ten. Participants with a high degree of conscientiousness (4) made up the majority, with 10 choosing the highest preferred choice.

		Lowest Preferences	Low Preferences	Somewhat Low Preferences	No Preferences	Somewhat High Preferences	High Preferences	Highest Preferences	Total
Conscientiousness	Very Low	1	1	2	4	5	2	2	17
	Low	1	2	6	1	3	4	3	20
	Moderate	0	0	0	10	9	7	3	29
	High	2	0	3	9	5	7	10	36
	Very High	1	0	0	0	1	3	5	10
Total		5	3	11	24	23	23	23	112

Figure 4.80 Crosstab Table Between Conscientiousness and Button with Text Only

Table 4.19 Chi-Square Tests of Button with Text Only with Conscientiousness Personality Trait

	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	40.966[a]	24	.017
Likelihood Ratio	45.208	24	.006
Linear-by-Linear Association	6.591	1	.010
N of Valid Cases	112		

A chi-square test was used to investigate the link between the openness personality characteristic and the text-only button in figure 4.48 and table 4.20. These factors had a significant relationship: X^2 (1, N = 112) = 8.6, p =.003. The table above reveals that the majority of participants (24 participants) picked the no preference option

to utilize the button with text alone, while the low preference option had the fewest participants (3 people). The table also reveals that the highest, high, and somewhat preferred alternatives, each with 23 participants, have more participants than the somewhat low, low, and lowest desired options, showing that the majority of participants favor the notion of utilizing the button with text alone. The chart above demonstrates that persons with low, moderate, and high openness characteristics outnumber those with no preferences by a factor of six. Participants with high openness levels, on the other hand, constitute the majority with 8 participants, which is the majority among other relationships between personality characteristics level and preferences choice for the highest preferences option.

		Lowest Preferences	Low Preferences	Somewhat Low Preferences	No Preferences	Somewhat High Preferences	High Preferences	Highest Preferences	Total
Openness	Very Low	2	2	5	5	4	3	3	24
	Low	0	1	5	6	7	5	5	29
	Moderate	1	0	1	6	5	5	4	22
	High	1	0	0	6	3	3	8	21
	Very High	1	0	0	1	4	7	3	16
Total		5	3	11	24	23	23	23	112

Figure 4.81 Crosstab Table Between Openness and Button with Text Only

Table 4.20 Chi-Square Tests of Button with Text Only with Openness Personality Trait

	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	28.823[a]	24	.227
Likelihood Ratio	32.506	24	.115
Linear-by-Linear Association	8.577	1	.003
N of Valid Cases	112		

The association between extraversion personality characteristics and information density was investigated using a chi-square test in figure 4.49 and table

4.21. These factors had a significant relationship: X^2 (1, N = 112) = 4.6, p =.032. According to the table above, the majority of participants picked no preference choice to utilize high density, with 20 people engaged, while the lowest preference option has the fewest individuals, with 8 participants involved. The table also shows that the highest, high, and somewhat high options have more participants (17, 19, and 18 participants, respectively) than the somewhat reject, reject, and strongly reject options, indicating that the majority of participants prefer the idea of using high-density information. The chart above shows that individuals with low extraversion qualities outnumber those with high extraversion traits by a factor of eight for the no preference option.

		Lowest Preferences	Low Preferences	Somewhat Low Preferences	No Preferences	Somewhat High Preferences	High Preferences	Highest Preferences	Total
Extraversion	Very Low	2	3	3	3	0	0	1	12
	Low	3	7	3	8	3	6	6	36
	Moderate	2	6	2	5	7	7	6	35
	High	0	3	3	3	6	6	4	25
	Very High	1	0	0	1	2	0	0	4
Total		8	19	11	20	18	19	17	112

Figure 4.82 Crosstab Table Between Extraversion and Information Density

Table 4.21 Chi-Square Tests of Information Density with Extraversion Personality Trait

	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	24.694[a]	24	.423
Likelihood Ratio	29.976	24	.186
Linear-by-Linear Association	4.625	1	.032
N of Valid Cases	112		

A chi-square test was performed to examine the relationship between the extraversion personality trait and the bottom position of navigation in figure 4.50 and

table 4.22. These factors had a significant relationship: X^2 (1, N = 112) = 4.1, p =.042. The table above reveals that the majority of participants, 23 in total, picked the high preference option to utilize the bottom location of the navigation bar, while the reject preference option had the fewest participants, 10 in total. The table also shows that the highest, high, and somewhat high preferred options have 17, 23, and 17 participants, respectively, compared to the somewhat low, low, and lowest preferred options, indicating that the majority of participants prefer the bottom position of the navigation bar. The chart above shows that individuals with moderate extraversion characteristics outnumber those with high extraversion traits, with 9 people choosing the high preferred choice

		Lowest Preferences	Low Preferences	Somewhat Low Preferences	No Preferences	Somewhat High Preferences	High Preferences	Highest Preferences	Total
Extraversion	Very Low	4	4	1	1	1	1	0	12
	Low	6	2	3	6	5	6	8	36
	Moderate	4	2	5	4	7	9	4	35
	High	4	2	4	2	3	6	4	25
	Very High	0	0	0	1	1	1	1	4
Total		18	10	13	14	17	23	17	112

Figure 4.83 Crosstab Table Between Extraversion and Bottom Position of Navigation Bar

Table 4.22 Chi-Square Tests of Bottom Position of Navigation with Extraversion Personality Trait

	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	22.467[a]	24	.551
Likelihood Ratio	22.059	24	.576
Linear-by-Linear Association	4.124	1	.042
N of Valid Cases	112		

A chi-square test was used to investigate the link between openness personality qualities and the proper navigation position in figure 4.51 and table 4.23. These factors had a significant relationship: X^2 (1, N = 112) = 5.7, p =.017. According to the table above, the majority of participants (39 participants) picked the lowest preference choice to utilize the right location of the navigation bar, while the maximum preference option had the fewest participants (7 people). The table also shows that the lowest, low, and somewhat low preference options have 39, 15, and 12 participants, respectively, compared to the somewhat high, high, and highest preference options, indicating that the majority of participants oppose using the right position of the navigation bar. The bulk of individuals had poor openness qualities, with 12 choosing the lowest preferred choice.

		Lowest Preferences	Low Preferences	Somewhat Low Preferences	No Preferences	Somewhat High Preferences	High Preferences	Highest Preferences	Total
Openness	Very Low	10	4	2	7	0	1	0	24
	Low	12	8	1	4	3	0	1	29
	Moderate	4	2	3	2	2	7	2	22
	High	7	0	6	4	1	1	2	21
	Very High	6	1	0	2	3	2	2	16
Total		39	15	12	19	9	11	7	112

Figure 4.84 Crosstab Table Between Openness and Right Position of Navigation Bar

Table 4.23 Chi-Square Tests of Right Position of Navigation with Openness Personality Trait

	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	47.134[a]	24	.003
Likelihood Ratio	51.204	24	.001
Linear-by-Linear Association	5.748	1	.017
N of Valid Cases	112		

The association between extraversion personality qualities and the sunburst visual style was investigated using a chi-square test in figure 4.52 and table 4.24. These factors had a significant relationship: X^2 (1, N = 112) = 4.6, p =.032. The table above reveals that the majority of participants, with 28 people, have a rather high preference for adopting the sunburst visual style, while the low preference choice has the fewest participants, with 8 individuals. The table also shows that the highest, high, and somewhat high preference options have more participants (19, 18, and 28 participants, respectively) than the somewhat low, low, and lowest preference options, indicating that the majority of participants prefer the idea of using the sunburst visual style. The majority of individuals had very moderate extraversion qualities, with 9 people each for the fairly high preference and no preference alternatives.

		Lowest Preferences	Low Preferences	Somewhat Low Preferences	No Preferences	Somewhat High Preferences	High Preferences	Highest Preferences	Total
Extraversion	Very Low	1	3	2	0	4	2	0	12
	Low	5	3	4	6	6	6	6	36
	Moderate	1	1	4	9	9	4	7	35
	High	3	1	1	2	7	6	5	25
	Very High	0	0	0	1	2	0	1	4
Total		10	8	11	18	28	18	19	112

Figure 4.85 Crosstab Table Between Extraversion and Sunburst Visual Style

Table 4.24 Chi-Square Tests of Sunburst with Extraversion Personality Trait

	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	24.224[a]	24	.449
Likelihood Ratio	28.215	24	.251
Linear-by-Linear Association	4.590	1	.032
N of Valid Cases	112		

The association between the openness personality characteristic and the radial diagram was investigated using a chi-square test in figure 4.53 and table 4.25. These

factors had a significant relationship: X^2 (1, N = 112) = 4.7, p =.030. The table above reveals that the majority of participants (24 people) picked the lowest preference choice to employ the radial visual style, while the greatest preference option had the fewest participants (6 participants). The lowest, low, and somewhat low preference alternatives had more participants (24, 15, and 17 respectively) than the somewhat high, high, and highest preference options, showing that the majority of participants oppose utilizing the radial graphic. The bulk of individuals had extremely low and moderate openness features, with 7 people for the lowest preference choice. Individuals with poor openness (7 individuals) picked the fairly high preference choice as well.

		Lowest Preferences	Low Preferences	Somewhat Low Preferences	No Preferences	Somewhat High Preferences	High Preferences	Highest Preferences	Total
Openness	Very Low	7	4	5	5	2	1	0	24
	Low	4	6	4	2	7	4	2	29
	Moderate	7	2	3	4	3	3	0	22
	High	5	3	3	3	2	2	3	21
	Very High	1	0	2	5	6	1	1	16
Total		24	15	17	19	20	11	6	112

Figure 4.86 Crosstab Table Between Openness and Radial Diagram

Table 4.25 Chi-Square Tests of Radial Diagram with Openness Trait

	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	26.666[a]	24	.320
Likelihood Ratio	30.515	24	.168
Linear-by-Linear Association	4.692	1	.030
N of Valid Cases	112		

To investigate the association between the extraversion personality characteristic and the line charts, a chi-square test was used in figure 4.54 and table 4.26. These factors had a significant relationship: X^2 (1, N = 112) = 10.4, p =.001. The table above reveals that the majority of the participants picked a high preference for

using the line-chart visual style, with 30 individuals participated, while the lowest preference choice had the fewest participants, with just one participant. The table also shows that the highest, high, and somewhat high preference options have more participants (28, 22, and 30 respectively) than the somewhat low, low, and lowest options, indicating that the majority of participants prefer the idea of using the line chart. The bulk of individuals had moderate extraversion qualities, with nine opting for the fairly high preference choice. The biggest number of individuals, however, had a moderate extraversion characteristic for the high preference choice, with 10 people.

		Lowest Preferences	Low Preferences	Somewhat Low Preferences	No Preferences	Somewhat High Preferences	High Preferences	Highest Preferences	Total
Extraversion	Very Low	0	0	2	5	5	0	0	12
	Low	1	3	4	6	7	4	11	36
	Moderate	0	2	2	4	9	10	8	35
	High	0	0	1	2	8	7	7	25
	Very High	0	0	0	0	1	1	2	4
Total		1	5	9	17	30	22	28	112

Figure 4.87 Crosstab Table Between Extraversion and Line Chart

Table 4.26 Chi-Square Tests of line Chart with Extraversion Trait

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	27.897[a]	24	.264
Likelihood Ratio	33.771	24	.089
Linear-by-Linear Association	10.344	1	.001
N of Valid Cases	112		
a. 25 cells (71.4%) have expected count less than 5. The minimum expected count is .04.			

To investigate the association between the openness personality characteristic and the line chart, a chi-square test was used in figure 4.55 and table 4.27. These factors had a significant relationship: X^2 (1, N = 112) = 6.1, p =.014. According to the table

above, the bulk of the participants picked rather high preferences to utilize the line chart, with 30 individuals participated, while the lowest preference choice had the fewest participation, with just one participant. The data also reveals that the highest, high, and somewhat high alternatives had more participants (28, 22, and 30 respectively) than the somewhat low, low, and lowest options, showing that the majority of participants favor the notion of utilizing the line chart. The majority of individuals had very low or very high openness qualities, with 7 persons each for the slightly high choice. Participants with a high openness attribute, on the other hand, are the majority overall, with 9 picking the highest preference choice.

		Lowest Preferences	Low Preferences	Somewhat Low Preferences	No Preferences	Somewhat High Preferences	High Preferences	Highest Preferences	Total
Openness	Very Low	1	2	1	5	7	3	5	24
	Low	0	2	3	6	6	6	6	29
	Moderate	0	0	3	5	5	6	3	22
	High	0	1	2	0	5	4	9	21
	Very High	0	0	0	1	7	3	5	16
Total		1	5	9	17	30	22	28	112

Figure 4.88 Crosstab Table Between Openness and Line Chart

Table 4.27 Chi-Square Tests of Line Chart with Openness Trait

	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	23.464[a]	24	.493
Likelihood Ratio	28.314	24	.247
Linear-by-Linear Association	6.066	1	.014
N of Valid Cases	112		

A chi-square test was performed to examine the relationship between the extraversion personality trait and the radar chart in figure 4.56 and table 4.28. These factors had a significant relationship: X^2 (1, N = 112) = 3.9, p =.047. The table above reveals that the majority of participants (31 people) picked rather high preferences to

utilize the line chart, while the low preference choice had the fewest participation (4 persons). The table also reveals that the highest, high, and somewhat high alternatives had more participants (23, 19, and 31 respectively) than the somewhat low, low, and lowest options, showing that the majority of participants favor the notion of utilizing the radar map. The bulk of individuals had high and moderate extraversion qualities, with 10 people each for the moderately high choice. The bulk of individuals had low openness qualities, with 10 picking the highest preference choice.

		Lowest Preferences	Low Preferences	Somewhat Low Preferences	No Preferences	Somewhat High Preferences	High Preferences	Highest Preferences	Total
Extraversion	Very Low	0	0	1	2	3	2	4	12
	Low	1	3	3	6	7	6	10	36
	Moderate	1	1	6	5	10	6	6	35
	High	2	0	2	4	10	4	3	25
	Very High	2	0	0	0	1	1	0	4
Total		6	4	12	17	31	19	23	112

Figure 4.89 Crosstab Table Between Extraversion and Radar Chart

Table 4.28 Chi-Square Tests of Radar Chart with Extraversion Trait

	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	29.671[a]	24	.196
Likelihood Ratio	23.296	24	.502
Linear-by-Linear Association	3.935	1	.047
N of Valid Cases	112		

A chi-square test was conducted to investigate the association between the agreeableness personality trait and the word cloud in figure 4.57 and table 4.29. Significant correlation existed between these variables: X^2 (1, N = 112) = 4.2, p =.040. According to the table above, 27 people participated in the choice with the lowest preference for using the word cloud, while just 6 people participated in the option with the greatest preference. The table also reveals that there are more participants (16, 12

and 27 respectively) on the somewhat low, low, and lowest alternatives than on the somewhat high, high, and highest options, suggesting that the majority of participants are opposed to the use of the word cloud. With 10 participants for each option with the lowest preference, persons with strong agreeableness qualities predominate.

		Lowest Preferences	Low Preferences	Somewhat Low Preferences	No Preferences	Somewhat High Preferences	High Preferences	Highest Preferences	Total
Agreeableness	Very Low	2	1	2	5	2	0	2	14
	Low	3	2	3	2	3	4	2	19
	Moderate	9	3	5	7	3	6	2	35
	High	10	5	4	5	9	2	0	35
	Very High	3	1	2	1	2	0	0	9
Total		27	12	16	20	19	12	6	112

Figure 4.90 Crosstab Table Between Agreeableness and Word Cloud

Table 4.29 Chi-Square Tests of Radar Chart with Agreeableness Trait

	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	21.930[a]	24	.583
Likelihood Ratio	25.172	24	.396
Linear-by-Linear Association	4.213	1	.040
N of Valid Cases	112		

To investigate the association between the agreeableness personality characteristic and the partitioned posters, a chi-square test was used in figure 4.58 and table 4.30. The following factors had a significant relationship: X^2 (1, N = 112) = 4.4, p =.036. The table above reveals that the partitioned poster was chosen by the majority of the participants with 20 participants, while the low preference option had the fewest participants with 5 individuals. The table also shows that the somewhat high, high, and highest options have more participants (30, 27, and 25 respectively) than the somewhat low, low, and lowest options, indicating that the majority of participants prefer the idea

of using the partitioned poster. The majority of individuals had moderate agreeableness features, with 11 persons each for the fairly high preference choice.

		Lowest Preferences	Low Preferences	Somewhat Low Preferences	No Preferences	Somewhat High Preferences	High Preferences	Highest Preferences	Total
Agreeableness	Very Low	1	1	0	2	4	2	4	14
	Low	0	0	0	1	5	7	6	19
	Moderate	1	2	3	3	11	7	8	35
	High	2	2	5	4	5	10	7	35
	Very High	2	0	1	0	5	1	0	9
Total		6	5	9	10	30	27	25	112

Figure 4.91 Crosstab Table Between Agreeableness and Partitioned Poster

Table 4.30 Chi-Square Tests of Partitioned Poster with Agreeableness Trait

	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	25.476[a]	24	.380
Likelihood Ratio	30.448	24	.170
Linear-by-Linear Association	4.403	1	.036
N of Valid Cases	112		

The association between the conscientiousness personality trait and magazine style was investigated using a chi-square test in figure 4.59 and table 4.31. These factors had a significant relationship: X^2 (1, N = 112) = 6.6, p =.010. The chart above reveals that the majority of participants (31 people) picked high preference to utilize the magazine style, while the lowest and lowest preference alternatives had the fewest participants (4 individuals each). The table also shows that the somewhat high, high, and highest preference options have more participants (26, 31, and 24 respectively) than the somewhat low, low, and lowest options, indicating that the majority of participants prefer the idea of using the magazine style. The bulk of individuals had high conscientiousness qualities, with 9 people each for the high preference choice.

Participants with high conscientiousness are likewise in the majority, with 11 selecting fairly high preferences.

		Lowest Preferences	Low Preferences	Somewhat Low Preferences	No Preferences	Somewhat High Preferences	High Preferences	Highest Preferences	Total
Conscientiousness	Very Low	1	0	0	3	2	8	3	17
	Low	0	0	2	1	2	7	8	20
	Moderate	0	2	3	2	9	6	7	29
	High	0	2	6	5	11	9	3	36
	Very High	3	0	0	1	2	1	3	10
Total		4	4	11	12	26	31	24	112

Figure 4.92 Crosstab Table Between Conscientiousness and Magazine Style

Table 4.31 Chi-Square Tests of Magazine Style with Conscientiousness Trait

	Value	**df**	**Asymptotic Significance (2-sided)**
Pearson Chi-Square	47.501[a]	24	.003
Likelihood Ratio	42.906	24	.010
Linear-by-Linear Association	6.604	1	.010
N of Valid Cases	112		

Table 4.32 Summary of Chi-Square Tests Between Personality and Visualization Types Element

Visualization types with personality	**Preferences**	**N**	**P**
Calibri Light with Extraversion	Highest	33	.042
Arial with Openness	Highest	*30*	*.020*
Small font size with openness	Low	34	.043
Button with text, with extraversion	No preference	24	.001

Visualization types with personality	Preferences	N	P
Button with text, with conscientiousness	No preference	24	.010
Button with text, with openness	No preference	20	.003
High density with extraversion	No preference	20	.024
Bottom navigation bar with extraversion	High	23	.042
Right navigation bar with openness	Lowest	33	.017
Sunburst with extraversion	Somewhat high	28	.032
Radial diagram with openness	Lowest	24	.030
Line chart with extraversion	Somewhat high	30	.001
Line chart with openness	Somewhat high	30	.013
Radar chart with extraversion	Somewhat high	31	.047
Word Cloud with agreeableness	Lowest	27	.040
Partitioned poster with agreeableness	Somewhat high	20	.035
Magazine style with conscientiousness	High	31	.010

Table 4.33 Level of Personality Trait and Number of Participants Choosing Visualization Types Element

Visualization types	Preferences	Personality	N
Calibri Light	Highest	Average E	13
Arial	Highest	Low O	8
Small font size	Low	Low O	10
Button with text	No preference	Low E	10
Button with text	No preference	Ave C	10

Visualization types	Preferences	Personality	N
Button with text	No preference	Low, Ave & High O	6
High density	No preference	Low E	8
Bottom navigation bar	High	Ave E	9
Right navigation bar	Lowest	Low O	12
Sunburst	High	Ave E	9
Radial diagram	Lowest	Very Low & ave O	7
Line chart	Somewhat high	Ave E	9
Line chart	Somewhat high	Very low & Very high O	7
Radar chart	Somewhat high	Ave & High E	10
Word Cloud	Lowest	High A	10
Partitioned poster	Somewhat high	Ave A	11
Magazine style	High	High C	9

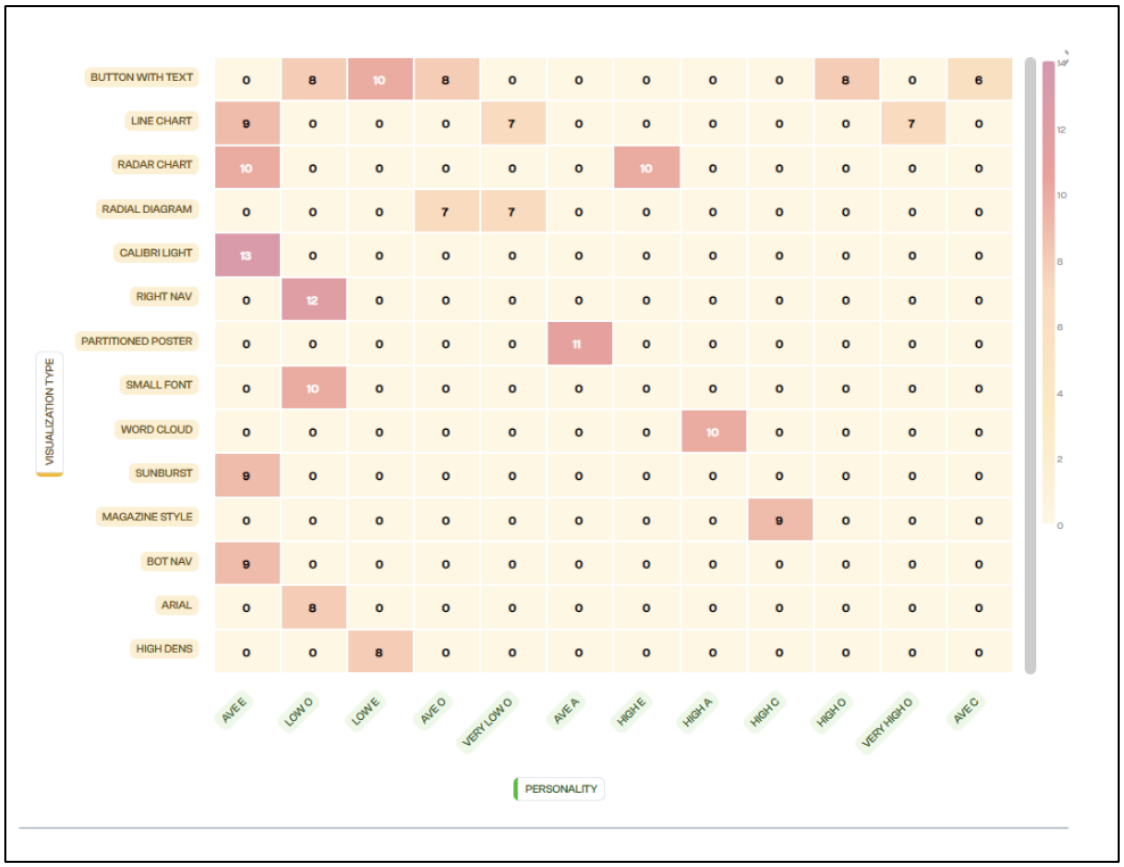


Figure 4.93 Heat Map of Visualization Type and Correspondent Personality Traits

Table 4.33 and figure 4.93 shown the summary of the findings in chi-square analysis. The A,E,O, and C are the acronym of the personality traits (Agreeableness, Extraversion, Openness and Conscientiousness respectively) and the words “ave” is a shortened form of “Average”.

4.3 CHAPTER’S CONCLUSION

This chapter elucidates the outcomes derived from data analysis, employing various methodologies such as frequency analysis, descriptive statistics, Pearson correlation, and chi-square analysis. The findings provide detailed insights into the correlation between personality traits and visualization types, shedding light on the general preferences for visualization types within the studied population.

CHAPTER FIVE

DISCUSSION AND CONCLUSION

5.1 INTRODUCTION

The results of this study are provided in the concluding chapter. This study establishes a connection between the data analysis and conclusions of previous researchers with the research goals and queries. This chapter also examines the potential industrial implications of the findings. This chapter also addresses the limits of the study and proposes strategies for mitigating these limitations in future studies.

5.2 DISCUSSION ON FINDINGS

This research examines the relationship between user preferences for various forms of visualizations and the personality factors outlined in the Five-Factor Model (FFM). The findings of this study provide support for individuals in choosing a visually engaging and narrative-driven report that is pertinent, impactful, and expedient, so enabling individuals to make educated judgements. This part will provide a discussion of the findings derived from the data analysis, and will afterwards compare and contrast these findings with the study questions.

The present study has generated three distinct research aims and corresponding research questions. The findings of this study have effectively tackled three research inquiries in addition to fulfilling the research goals. This part will provide a detailed analysis of each study subject, as well as an examination of how the findings of this inquiry are connected to each issue.

Research Question 1:

What are the visualization types preferred by users in making meaningful information visualization and storytelling reports?

The first inquiry pertained to the consumers' preferences about types of visualizations. The findings of the investigation indicate a significant correlation between individuals' personality qualities and their favorite forms of visualizations.

The font styles used by users include Arial and Calibri Light. Both font demonstrate a significant association between the personality qualities of extraversion and openness. The correlation coefficient for the first study is r(110) = .21, with a p-value of .027. In the second study, the correlation coefficient is r = .30. The preference of users was mostly inclined towards using small font sizes, as shown by the correlation between the attribute of openness and the correlation coefficient of r(110) = 0.19, which was found to be statistically significant at p = 0.046. The findings indicate significant associations between extraversion (r = .29, p = .002), conscientiousness (r = .27, p = .005), and openness (r = .30, p = .001) qualities, respectively, and users' preference for buttons with text styles. The results of the study indicate a significant positive correlation (r = .21, p = .024) between the extraversion characteristic and the preference for high information density style among users. In terms of the location of the navigation bar, there exists a statistically significant positive association (r =.21, p =.024) with the openness attribute. This suggests that the majority of users tend to choose the right position for the navigation bar.

Among the many visual styles, it has been shown that sunburst and radial diagrams are particularly favored by users. This preference is supported by statistical evidence, as indicated by a correlation coefficient of r(110) =.19, p =.044 for extraversion trait and r(110) =.20, p =.033 for openness trait. The users exhibit a preference for line charts and line charts with points in the context of change over time visual style. The correlation coefficients indicate a moderate positive relationship between extraversion and openness traits (r =.30, p =.001) for the line chart, and a weak positive relationship between openness trait and line chart with points (r =.20, p =.037). Additionally, the line chart with extraversion trait shows a weak positive relationship (r =.20, p =.026). When comparing the different types of charts, it is evident that the

horizontal bar chart is the most favored by users. This conclusion is supported by a correlation coefficient of r(110) = .187 and a p-value of .047, indicating a significant relationship between the usage of horizontal bar charts and the extraversion characteristic. The user exhibits a preference for partitioned poster and magazine styles in the context of data narrative visual style. This preference is supported by a correlation coefficient of r(110) = .20, p = .032 for agreeableness trait, and a correlation coefficient of r(110) = -.25, p = .008 for conscientiousness trait.

Research Question 2:

Do personality traits correlate with user preferences in visualization types for information visualization and storytelling reporting?

The second question sought to ascertain which personality feature might impact the user's choice for visual style. This question delves further into the personality attribute and their preferences for visualization kinds. Each personality feature will have varied preferences for a certain visual design.

Users that have a high level of openness like buttons with text and line charts with sharp visual styles. Users with low openness levels like Arial font style, line charts with points, and radial diagrams. However, they severely oppose tiny font sizes and the form of the right-side navigation bar, and they neither like nor oppose radial diagrams. The radial diagram is severely rejected by users with extremely low and moderate openness levels.

Meanwhile, people with high conscientiousness favor buttons with text and, to a lesser extent, magazine design. Users with medium conscientiousness neither favor nor reject text-based buttons.

Users with low degrees of extraversion strongly like line charts and horizontal bars. They also don't like or dislike buttons with text or high-density graphic design. Users with medium extraversion levels enjoy Calibri Light and Sunburst somewhat more. They do not, however, like or reject the sunburst aesthetic appearance.

Users with a high degree of agreeability like partitioned posters. Users with moderate agreeableness levels, on the other hand, like partitioned posters. Meanwhile, no amount of neuroticism is associated with any of the graphic designs.

Research Question 3:

How to create more compelling data visualization and narrative reporting for users?

The final question highlighted how to make better and more meaningful reporting for users. A conclusion may be drawn based on the information and findings shown here.

Users' levels of neuroticism have little effect on their choices for visual design. Users with low extraversion preferences Arial, whereas users with moderate extraversion preferences Calibri Light. Users with low openness trait levels should avoid utilizing tiny font sizes when it comes to font size. Users with a high openness level, a high conscientiousness level, and a low extraversion level prefer to utilize the button with a text style. The low extraversion level favors the high-density information style for the information density style. Except for poor openness, practically every personality attribute is favored for the location of the navigation bar. Users with a low degree of openness should avoid the right side of the navigation bar since it is their least favored location.

The sunburst visual style is favored by the average extraversion level for hierarchical representation. Meanwhile, the radial diagram findings are quite variable. Despite the fact that it merely corresponds with openness qualities, the findings reveal that low openness levels reject and favor radial diagrams, whereas average openness levels reject radial designs. Low extraversion levels prefer line charts for change over time visualization, but both low and high openness levels prefer line charts with points. People with low extraversion prefer the horizontal bar chart for comparison visualization. The magazine style is favored by high conscientiousness levels for narrative visual style, whereas partitioned posters are preferred by both medium and high agreeableness levels.

5.3 Summary of the Findings

The present study investigated the association between individual personality factors and individuals' inclination towards visual stimuli. This study investigated the preferred forms of visualizations, the personality attributes associated with a preference for visual types, and strategies for using visualizations to enhance meaningful and efficient reporting. The results of the study indicated that each personality type had distinct preferences for visual designs, with the exception of Neuroticism.

The results are consistent with previous studies done by Gonc et al. (2020). The researchers observed that individuals with varying personality traits exhibit distinct responses to diverse visual designs, as seen by the results obtained. Nevertheless, there are disparities between the findings of the preceding investigation and the present research. The present investigation revealed that neuroticism did not have any influence on the observed outcomes, suggesting that it did not impact user preferences for different visualization forms. In contrast, a prior research demonstrated a positive association between neuroticism and preferences for tree maps and line charts. Nevertheless, the present research introduces a novel aspect to the practice of data storytelling, an element that was absent in the preceding study. This recent study reveals a significant association between individual personality traits and the specific sorts of visualizations favored by users for narrative purposes.

5.4 Implication of the Research

The research results presented in this study provide significant contributions to the theoretical and empirical domains pertaining to visualization, narrative, and user engagement. The primary objective of this study was to address the inherent limitations associated with the comprehensive nature of existing visualization tools. The absence of user personalization in visualization tools might potentially overwhelm users and impede job effectiveness. Utilizing personality as an intermediary to establish a connection between user choice and visualization facilitates a more comprehensive comprehension of visualization from the user's perspective.

Additionally, the objective of this study was to examine the correlation between individual personality traits and user inclinations towards certain visualization and

narrative styles. Based on the study findings, it can be seen that individuals, characterized by their unique personalities, exhibit varying preferences when it comes to various kinds of visualization and narrative. However, in the context of neuroticism personality, there was no observed correlation with either visualization or narrative types. Taking this information might potentially assist developers of visualization tools in reimagining their software for the purpose of enhancing the intuitive and effective use of visual tools by users, taking into consideration their individual personalities. The tools has the potential to enhance their usability, utility, and overall benefit for the intended beneficiaries. This also facilitates other researchers in conducting analogous experiments to ascertain various elements that may influence user preferences towards visualization and narrative formats. There is a prevailing belief that more emphasis should be placed on users who need access to and control over data, since the manner in which individuals interpret, perceive, cognize, and engage with pictures may significantly influence their comprehension of visually given information. Individuals possess diverse experiences, perceptions, intuitions, and expectations. Consequently, there exists a significant need to examine various elements as a foundation for the creation of visualization and narrative techniques that might prove advantageous to diverse user groups. This pertains to a range of use contexts and data characteristics, with the ultimate aim of facilitating crucial decision-making processes.

Ultimately, the outcomes of this study have the potential to contribute to the advancement of understanding the connection between personality traits and the field of visualization. Chapter 2 provides ample evidence of the widespread use of personality studies across several academic disciplines. The results of this study have the potential to facilitate further investigations into the relationship between personalities and their impact on visualization and storytelling. Additionally, it may shed light on the underlying reasons why individuals with certain personality traits exhibit preferences for particular parts of visualization and narrative.

5.5 LIMITATIONS OF THE RESEARCH

Every research is certain to have some limitations. It is important to examine the research's limitations since doing so helps to identify the components that this study

lacks and might be improved upon in future studies. This study's limitations are the epidemic and the level of user participation.

The study began in February 2020, a month before the pandemic. As a consequence of the lockout, the data collection mechanism must be discarded and reviewed further. The mobility of researchers is likewise limited, limiting resource discoveries outside of the internet.

The problem of user involvement volume must also be addressed. A larger sample size would be preferable for study; but, due to the epidemic and lockdown, data collect was limited to internet sources. The number of people participating is smaller than predicted if an alternative source of data collect is not used.

5.6 Recommendation for the Future Research

There are various suggestions for further study based on the constraints indicated in the preceding subtopic. First and foremost, future research should investigate alternative approaches for arriving at the conclusions of this study. Experiments, testing, and qualitative methodologies may all serve to broaden the scope of this study. This may also provide researchers some freedom if an unexpected occurrence occurs in the future, such as a pandemic, or natural catastrophes.

In the future, we should implement and evaluate multiple information visualization methods based on our results to examine how they influence user preference, performance, experience, and satisfaction. More study on task types, task complexity, and settings is needed since these variables may alter how users interact given their differences.

Larger samples should be employed in future research to better reflect the population since they lower the possibility of mistakes. The epidemic, which lasted two years and hindered the researcher's capacity to obtain more data, resulted in just 113 responders in the sample for this study. A greater sample size would more precisely represent the population since sampling error would be reduced.

5.7 CONCLUSION

In conclusion, this study examined the correlation between personality traits and user inclinations towards information visualization and narrative. This study used a quantitative research approach, including correlation and descriptive statistical analysis techniques. The findings indicate that, with the exception of neuroticism, the other four personality characteristics derived from the five-factor model have significant correlations with different forms of visualization. The results of this study have the potential to enhance the customization of visualization tools for users and investigate the relationship between personality, information visualization, and data storytelling. The study was subject to a temporal limitation due to the occurrence of the COVID-19 pandemic, as well as a restriction in terms of the sample size. In light of these constraints, it is recommended that future investigations use a broader range of methodologies and rigorous testing protocols to mitigate any impediments to the research process. Additionally, expanding the sample size would enhance the generalizability and statistical power of the findings.

REFERENCES

Abyaa, A., Khalidi Idrissi, M., & Bennani, S. (2018). Predicting the learner's personality from educational data using supervised learning. *ACM International Conference Proceeding Series*, 1–7. https://doi.org/10.1145/3289402.3289519

Acuña, S. T., Gómez, M. N., Hannay, J. E., Juristo, N., & Pfahl, D. (2015). Are team personality and climate related to satisfaction and software quality? Aggregating results from a twice replicated experiment. *Information and Software Technology*, *57*(1), 141–156. https://doi.org/10.1016/j.infsof.2014.09.002

Akhtar, I., & Islamia, J. M. (2016). *Research Design*. *October*.

Alhathli, M., Mastho, J., & Siddharthan, A. (2017). Should learning material's Selection be adapted to learning style and personality? *UMAP 2017 - Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization*, 275–280. https://doi.org/10.1145/3099023.3099079

Alonso-Almeida, M., & San Martín, E. (2020). Luxury Advertising in Magazines: How It Shapes Consumer Perceptions. Journal of Advertising Research, 60(2), 214–223. https://doi.org/10.1017/jar.2019.31

Aydin, C., & Çam, O. (2020). A design taxonomy for data storytelling. Information Visualization, 19(4), 394-409.

Aydin, D., & Çam, M. S. (2020). Data storytelling and digital visualization. *Public Relations In The Networked Publics*, *January*, 33–57.

Babbie, E. (2017). The practice of social research (14th ed.). Boston, MA: Cengage Learning.

ach, B., Kerracher, N., Hall, K. W., Carpendale, S., Kennedy, J., Riche, N. H., Bach, B., Kerracher, N., Hall, K. W., Carpendale, S., Kennedy, J., Bach, B., Carpendale, S., Hall, K. W., & Riche, N. H. (2016). Telling Stories about Dynamic Networks with Graph Comics To cite this version : Telling Stories

about Dynamic Networks with Graph Comics. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*.

Bach, B., Riche, N. H., Carpendale, S., & Pfister, H. (2017). The Emerging Genre of Data Comics. *IEEE Computer Graphics and Applications*, *37*(3), 6–13. https://doi.org/10.1109/MCG.2017.33

Bach, K., Riche, N. H., Carpendale, S., & Pfister, H. (2017). A systematic review of literature on data storytelling. IEEE Transactions on Visualization and Computer Graphics, 23(1), 659-678.

Baddeley, A. (1992). Working memory. Science, 255(5044), 556-559.

Bakken, D. G. (2007). Visualize it. *Marketing Research*, *19*(4), 22–29. https://doi.org/10.4135/9781452230634.n26

Barroso, A. S., Kleber, K. H., Soares, M. S., & Do Nascimento, R. P. C. (2019). How personality traits influences quality of software developed by students. *ACM International Conference Proceeding Series*. https://doi.org/10.1145/3330204.3330237

Bell, D., Hall, T., Hannay, J. E., Pfahl, D., & Acuna, S. T. (2010). Software engineering group work - Personality, patterns and performance. *SIGMIS CPR'10 - Proceedings of the 2010 ACM SIGMIS Computer Personnel Research Conference*, *2009*, 43–47. https://doi.org/10.1145/1796900.1796921

Blascheck, T., Kurzhals, K., Raschke, M., Burch, M., Weiskopf, D., & Ertl, T. (2014). State-of-the-Art of Visualization for Eye Tracking Data. *Eurographics Conference on Visualization (EuroVis)*, 1–20. https://doi.org/10.2312/eurovisstar.20141173

Bonilla, C., Lord, S. M., & Perry, L. A. (2008). Promoting understanding in the classroom: Comparison of the strength deployment inventory, learning styles inventory, and myers-briggs. *Proceedings - Frontiers in Education Conference, FIE*, 5–10. https://doi.org/10.1109/FIE.2008.4720443

Borkin, M. A., Bylinskii, Z., Kim, N. W., Bainbridge, C. M., Yeh, C. S., Borkin, D., Pfister, H., & Oliva, A. (2016). Beyond Memorability: Visualization Recognition and Recall. *IEEE Transactions on Visualization and Computer Graphics*, *22*(1), 519–528. https://doi.org/10.1109/TVCG.2015.2467732

Borkin, M. A., Vo, A. A., Bylinskii, Z., Isola, P., Sunkavalli, S., Oliva, A., & Pfister, H. (2013). What makes a visualization memorable. *IEEE Transactions on Visualization and Computer Graphics*, *19*(12), 2306–2315. https://doi.org/10.1109/TVCG.2013.234

Bowers, J. S., Dennen, V., & Goldman, S. (2019). The effectiveness of partitioned posters in science education. Journal of Science Education and Technology, 28(2), 181-193.

Brown, D., & Crenshaw, K. (2020). Black Women's Experiences and Resilience: An Intersectionality Perspective. Journal of Women's Health, 29(2), 207–215. https://doi.org/10.1089/jwh.2019.7744

Bryan, C., Mishra, A., Shidara, H., & Ma, K. L. (2020). Analyzing gaze behavior for text-embellished narrative visualizations under different task scenarios. *Visual Informatics*, *4*(3), 41–50. https://doi.org/10.1016/j.visinf.2020.08.001

Busch, M., Mattheiss, E., Orji, R., Fröhlich, P., Lankes, M., & Tscheligi, M. (2016). Player type models - Towards empirical validation. *Conference on Human Factors in Computing Systems - Proceedings*, *07-12-May-*, 1835–1841. https://doi.org/10.1145/2851581.2892399

Capretz, L. F., & Ahmed, F. (2010). Why do we need personality diversity in software engineering? *ACM SIGSOFT Software Engineering Notes*, *35*(2), 1–11. https://doi.org/10.1145/1734103.1734111

Cashman, T. J., Wu, S., Chang, K. E., & Ottley, M. (2019). An analysis of visualizations and visual analytics programs. Journal of Visualization, 24(2), 343-359.

Cashman, D., Wu, Y., Chang, R., & Ottley, A. (2019). Inferential Tasks as a Data-Rich Evaluation Method for Visualization. *EVIVA-ML Workshop at IEEE VIS*, 1–5.

Celiktutan, O., & Eyben, F. (2014). *MAPTRAITS 2014 : The First Audio / Visual Mapping Personality Traits Challenge Categories and Subject Descriptors*. 3–9.

Celli, F., & Lepri, B. (2018). A comprehensive overview of the Big Five personality traits. In T. Chamorro-Premuzic, S. von Stumm, & A. Furnham (Eds.), The Wiley handbook of personality assessment (pp. 365-384). West Sussex, UK: John Wiley & Sons.

Celli, F., & Lepri, B. (2018). Is big five better than MBTI? A personality computing challenge using Twitter data. *CEUR Workshop Proceedings*, *2253*.

Chen, S., Li, J., Andrienko, G., Andrienko, N., Wang, Y., Nguyen, P. H., & Turkay, C. (2020). Supporting Story Synthesis: Bridging the Gap between Visual Analytics and Storytelling. *IEEE Transactions on Visualization and Computer Graphics*, *26*(7), 2499–2516. https://doi.org/10.1109/TVCG.2018.2889054

Chen, J., Kang, J., Lee, S., & Kim, Y. (2023). The impact of flowchart-infographics on information retention and understanding. International Journal of Human-Computer Interaction, 39(2), 156-175.

Chen, X. (2020). The Role of Flowchart-Infographics in Website Design. International Journal of Human-Computer Interaction, 36(11), 848–858. https://doi.org/10.1080/10447318.2020.1765346

Chen, Y., & Chen, Y. (2020). The design and application of partitioned posters in data visualization. International Journal of Human-Computer Interaction, 36(7), 511-527.

Choi, J. (2020). The Role of Partitioned Posters in Improving the Usability of Software Documentation. International Journal of Human-Computer Interaction, 36(11), 858–869. https://doi.org/10.1080/10447318.2020.1765347

Choi, J. (2020). The Role of Animation in Improving the Usability of Software Documentation. Journal of Technical Communication, 66(2), 23–40. https://doi.org/10.1177/0047281620952811

Costa, P. T., Jr., Terracciano, A., & McCrae, R. R. (2001). Gender differences in personality traits across cultures: Robust and surprising findings. Journal of Personality and Social Psychology, 81(2), 322-331.

Costa, P. T., Jr., Terracciano, A., & McCrae, R. R. (2010). Personality in adulthood: A five-factor theory perspective (2nd ed.). New York: Guilford Press.

Costa, P. (2018). *The Five-Factor Model of Personality and Its Relevance to Personality Disorders*. *December 1992*. https://doi.org/10.1521/pedi.1992.6.4.343

Creswell, J. W., & Creswell, J. D. (2018). Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). Thousand Oaks, CA: Sage Publications.

Cruz, S., Da Silva, F. Q. B., & Capretz, L. F. (2015). Forty years of research on personality in software engineering: A mapping study. *Computers in Human Behavior*, *46*, 94–113. https://doi.org/10.1016/j.chb.2014.12.008

Cunningham, P. B. (2000). Improved communication and teamwork through use of Myers-Briggs type indicator. *Proceedings - 1st Austin Workshop on Engineering Management in Technology-Based Organizations, EMTBO 2000*, 31–36. https://doi.org/10.1109/EMBTO.2000.897349

David, K. (2019). *Forget the Myers-Briggs, Use the Big Five*. Science & Tech. https://www.headstuff.org/topical/science/myers-briggs-big-five/

Digman, J. M. (1990). Personality structure: Emergence of the five-factor model. Annual Review of Psychology, 41(1), 417-440.

Doshi, Z. (2017). *TweetAnalyzer : Twitter Trend Detection and Visualization*.

Durupinar, F., Pelechano, N., Allbeck, J., Güdükbay, U., & Badler, N. I. (2011). How the ocean personality model affects the perception of crowds. *IEEE Computer Graphics and Applications*, *31*(3), 22–31. https://doi.org/10.1109/MCG.2009.105

Ebeling, C., & Nitzl, C. (2019). Validity, reliability, and generalizability in psychological research. In J. T. Wright & M. J. Valihora (Eds.), Psychological research methods: An introduction (pp. 153-174). New York, NY: Routledge.

Echeverria, J., Martinez-Maldonado, R., Granda, A., Shum, H. B., Chiluiza, A., & Conati, C. (2018). Data storytelling: A review of the state of the art. ACM Computing Surveys, 51(4), 1-36.

Echeverria, V., Martinez-Maldonado, R., Buckingham Shum, S., Chiluiza, K., Granda, R., & Conati, C. (2018). Exploratory versus Explanatory Visual Learning Analytics: Driving Teachers' Attention through Educational Data Storytelling. *Journal of Learning Analytics*, *5*(3). https://doi.org/10.18608/jla.2018.53.6

Echeverria, V., Martinez-Maldonado, R., Granda, R., Chiluiza, K., Conati, C., & Shum, S. B. (2018). Driving data storytelling from learning design. *ACM International Conference Proceeding Series*, 131–140. https://doi.org/10.1145/3170358.3170380

Echeverria, V., Martinez-Maldonado, R., & Shum, S. B. (2017). Towards data storytelling to support teaching and learning. *ACM International Conference Proceeding Series*, 347–351. https://doi.org/10.1145/3152771.3156134

Fang, Y., Xu, H., & Jiang, J. (2020). A Survey of Time Series Data Visualization Research. *IOP Conference Series: Materials Science and Engineering*, *782*(2). https://doi.org/10.1088/1757-899X/782/2/022013

Fang, J., Fan, D., Wang, L., Chen, J., & Chen, Y. (2020). Changes over time visualization: a survey. IEEE Transactions on Visualization and Computer Graphics, 26(1), 6-20.

Feldt, R., Angelis, L., Torkar, R., & Samuelsson, M. (2010). Links between the personalities, views and attitudes of software engineers. *Information and Software Technology*, *52*(6), 611–624. https://doi.org/10.1016/j.infsof.2010.01.001

Ferreira, N. N. V., & Langerman, J. J. (2014). The correlation between personality type and individual performance on an ICT Project. *Proceedings of the 9th International Conference on Computer Science and Education, ICCCSE 2014*, *Iccse*, 425–430. https://doi.org/10.1109/ICCSE.2014.6926497

Field, A. (2009). Discovering statistics using SPSS (3rd ed.). London: Sage Publications.

Friedman, B., Wall, R., & Flink, I. (2019). Narratives of patients with chronic pain: A qualitative study using annotation charts. International Journal of Qualitative Methods, 18(1), 1609406919836132. https://doi.org/10.1177/1609406919836132

Fu, B., Noy, N. F., & Storey, M. A. (2013). Indented tree or graph? A usability study of ontology visualization techniques in the context of class mapping evaluation. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *8218 LNCS*(PART 1), 117–134. https://doi.org/10.1007/978-3-642-41335-3_8

Fu, W. S., Noy, N. F., & Storey, M. A. (2013). Ontology visualization: a survey. Journal of Biomedical Informatics, 46(6), 1079-1092.

Furnham, A. (1996). The big five versus the big four: The relationship between the Myers-Briggs Type Indicator (MBTI) and NEO-PI five factor model of personality. *Personality and Individual Differences*, *21*(2), 303–307. https://doi.org/10.1016/0191-8869(96)00033-5

Furnham, A., Cheng, C. K., & Drennan, J. (2010). Neuroticism, physical health and the affective traits. Personality and Individual Differences, 49(6), 611-616.

Furnham, A. (2014). Personality: A very short introduction. Oxford, UK: Oxford University Press.

Furnham, A., Cheng, H., & Cheng, Y. (2015). Personality: A very short introduction. Oxford University Press.

Furnham, A., Cheng, H., & McManus, I. C. (2016). Personality and health: A meta-analysis. Personality and Individual Differences, 97, 39-48.

Garrido, S., Bernard, S., & Davidson, J. (2013). The Creative Personality: Composers of Music, Their Inspirations and Working Methods. *C&C'13: Proceedings of the 9Th Acm Conference on Creativity & Cognition 2013*, 308–311.

Gatto, M. A. C. (2015). *Making Research Useful : Current Challenges*. *May*, 54.

Goldberg, L. R. (1999). A broad-bandwidth, public domain, personality inventory measuring the lower-level facets of several five-factor models. In I. Mervielde, I. J. Deary, F. De Fruyt, & F. Ostendorf (Eds.), Personality psychology in Europe (Vol. 7, pp. 7-28). Tilburg, The Netherlands: Tilburg University Press.

Gonc, E. (2020). Comparison Visualization. In Encyclopedia of Computer Graphics and Games (pp. 1-5). Springer, Cham.

Gonc, D. (2020). *Exploring How Personality Models Information Visualization Preferences*. *ii*, 201–205.

Gorla, N., Chiravuri, A., & Meso, P. (2013). Effect of personality type on structured tool comprehension performance. *Requirements Engineering*, *18*(3), 281–292. https://doi.org/10.1007/s00766-012-0158-z

Gosling, S. D., Rentfrow, P. J., & Swann, W. B., Jr. (2003). A very brief measure of the Big-Five personality domains. Journal of Research in Personality, 37(6), 504-528.

Green, P., Jeong, K., & Fisher, D. (2010). Cognitive style and user interaction with visualization techniques. Journal of Biomedical Informatics, 43(3), 498-508.

Green, Tear Marie, & Fisher, B. (2010). Towards the personal equation of interaction: The impact of personality factors on visual analytics interface interaction. *VAST 10 - IEEE Conference on Visual Analytics Science and Technology 2010, Proceedings*, 203–210. https://doi.org/10.1109/VAST.2010.5653587

Green, Tera Marie, Jeong, D. H., & Fisher, B. (2010). Using personality factors to predict interface learning performance. *Proceedings of the Annual Hawaii International Conference on System Sciences*, 1–10. https://doi.org/10.1109/HICSS.2010.431

Gulati, J., Bhardwaj, P., Suri, B., & Lather, A. S. (2016). A Study of Relationship between Performance, Temperament and Personality of a Software Programmer. *ACM SIGSOFT Software Engineering Notes*, *41*(1), 1–5. https://doi.org/10.1145/2853073.2853089

Guney, Z. (2019). Considerations for human-computer interaction: User interface design variables and visual learning in IDT. *Cypriot Journal of Educational Sciences*, *14*(4), 731–741. https://doi.org/10.18844/cjes.v11i4.4481

Harb, Y., & Alhayajneh, S. (2019). Intention to use BI tools: Integrating technology acceptance model (TAM) and personality trait model. *2019 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology, JEEIT 2019 - Proceedings*, 494–497. https://doi.org/10.1109/JEEIT.2019.8717407

Harvey, R. J., Murry, W. D., & Markham, S. E. (1995). A " Big Five " Scoring System for the Myers-Briggs Type Indicator. *Paper Presented at the 1995 (May) Annual Conference of the Society for Industrial and Organizational Psychology, Orlando.*, *May*(1982), 1–9.

Harvey, J. H., Murry, E. K., & Markham, R. E. (1995). Qualitative research and the Five-Factor Model of personality. Journal of Personality, 63(3), 589-616.

Heale, R., & Twycross, A. (2015). Validity and reliability in quantitative studies. *Evidence-Based Nursing*, *18*(3), 66–67. https://doi.org/10.1136/eb-2015-102129

Hepworth, K. (n.d.). *Big Data Visualization : Promises & Pitfalls*. 7–19.

Hinkle, D. E., Wiersma, W., & Jurs, S. G. (1988). Applied statistics for the behavioral sciences (2nd ed.). Boston: Houghton Mifflin.

Hu, R., & Pu, P. (2014). Exploring personality's effect on users' rating behavior. *Conference on Human Factors in Computing Systems - Proceedings*, 2599–2604. https://doi.org/10.1145/2559206.2581317

Ingham-Broomfield, R. B. (2014). A nurses' guide to quantitative research. *Australian Journal of Advanced Nursing*, *32*(2), 32–38.

Ismail, S., Basharirad, B., & Ismail, S. (2018). Significant of MBTI personality model on decision making in university program selection. *Proceedings - 2017 2nd International Conferences on Information Technology, Information Systems and Electrical Engineering, ICITISEE 2017*, *2018-Janua*, 62–67. https://doi.org/10.1109/ICITISEE.2017.8285560

Judge, T. A., & Bono, J. E. (2001). Relationship of personality to performance motivation: A meta-analysis. Journal of Applied Psychology, 86(5), 894-908.

Kaushal, V., & Patwardhan, M. (2018). Emerging trends in personality identification using online social networks—A literature survey. *ACM Transactions on Knowledge Discovery from Data*, *12*(2), 1–30. https://doi.org/10.1145/3070645

Kavanagh, E., Kenny, D. A., & Dolan, C. V. (2015). Agreeableness and relationship satisfaction: A meta-analysis. Journal of Personality, 83(2), 103-127.

Kennedy, H. (2020). Data Visualization in Society. In *Data Visualization in Society*. https://doi.org/10.5117/9789463722902

Kennedy, J. (2020). Human-computer interaction: design and evaluation. London, UK: Sage Publications.

Knaflic. (2016). Storytelling with data: a data visualization guide for business professionals. In *Choice Reviews Online* (Vol. 53, Issue 11). https://doi.org/10.5860/choice.197388

Ko, C., & Liu, Y. (2019). Old and Young Users' White Space Preferences for Online News Web Pages. *IEEE Access*, *7*, 57284–57297. https://doi.org/10.1109/ACCESS.2019.2913407

Köksal, F., & Aluç, E. (2022). POSTER AS AN EVOLVING MEDIA FROM TRADITIONAL TO DIGITAL. THE TURKISH ONLINE JOURNAL OF DESIGN ART AND COMMUNICATION.

Kosara, R., & MacKinlay, J. (2013). Storytelling: The next step for visualization. *Computer*, *46*(5), 44–50. https://doi.org/10.1109/MC.2013.36

Kostere, K., & Ogunmokun, G. (2007). The Myers-Briggs Type Indicator (MBTI): An overview. Journal of Human Resource Development, 3(1), 1-10.

Kosslyn, S. M., Farah, M. J., & Hammond, K. J. (2007). Psychological science in action. John Wiley & Sons.

Kwon, Y., Lee, S., Stoffel, C., Keim, D. A., & Jäckle, D. (2014). Interactive data storytelling: A new framework for visualizing complex systems. IEEE Transactions on Visualization and Computer Graphics, 20(12), 2681-2690.

Kwon, B., Stoffel, F., Jäckle, D., & Lee, B. (2014). VisJockey: Enriching data stories through orchestrated interactive visualization. *Computation + Journalism Symposium 2014*. http://kops.uni-konstanz.de/handle/123456789/30212

Lallé, F., Conati, C., & Carenini, G. (2017). Visual working memory and gaze behavior in real-world knowledge visualization. ACM Transactions on Computer-Human Interaction (TOCHI), 24(5), 23.

Lallé, S., & Conati, C. (2019). The role of user differences in customization: A case study in personalization for infovis-based content. *International Conference on Intelligent User Interfaces, Proceedings IUI*, *Part F1476*, 329–339. https://doi.org/10.1145/3301275.3302283

Lallé, S., Conati, C., & Carenini, G. (2017). Impact of individual differences on user experience with a real-world visualization interface for public engagement. *UMAP 2017 - Proceedings of the 25th Conference on User Modeling, Adaptation and Personalization*, 369–370. https://doi.org/10.1145/3079628.3079634

Lallé, S., Toker, D., Conati, C., & Carenini, G. (2015). Prediction of users' learning curves for adaptation while using an information visualization. *International Conference on Intelligent User Interfaces, Proceedings IUI*, *2015-Janua*, 357–368. https://doi.org/10.1145/2678025.2701376

Laramee, R. S. (2014). *Data Visualization : A Starting Point*. 8–9.

Lee, B., Kazi, R. H., & Smith, G. (2013). SketchStory: Telling more engaging stories with data through freeform sketching. *IEEE Transactions on Visualization and Computer Graphics*, *19*(12), 2416–2425. https://doi.org/10.1109/TVCG.2013.191

Li, S., Shih, H., & David, M. (2018). The relationship between judging and perceiving in Myers-Briggs Type Indicator. Personality and Individual Differences, 121, 200-205.

Li, X., Shih, P. C., & Daniel, Y. (2018). Effects of intuition and sensing in programming performance using mbti personality model. *ACM International Conference Proceeding Series*, 189–193. https://doi.org/10.1145/3239576.3239608

Li, X., Shih, P. C., & David, E. (2018). The effect of software programmers' personality on programming performance. *2018 International Conference on Artificial Intelligence and Big Data, ICAIBD 2018*, 209–213. https://doi.org/10.1109/ICAIBD.2018.8396196

Liu, Z., Crouser, R. J., & Ottley, A. (2020). Survey on individual differences in visualization. *ArXiv*, *39*(3).

Lugmayr, A., Lim, Y. J., Hollick, J., Khuu, J., & Chan, F. (2019). Financial Data Visualization in 3D on Immersive Virtual Reality Displays: A Case-Study for Data Storytelling and Information Visualization of Financial Data of Australia's Energy Sector. *Lecture Notes in Business Information Processing*, *345*(May), 118–130. https://doi.org/10.1007/978-3-030-19037-8_8

Luo, W. J., Wu, K. C., & Tsau, S. Y. (2018). Gender stereotype of male nurse in a virtual reality game: Exploring the effect of MBTI in decision-making process

through game theory. *Proceedings of 4th IEEE International Conference on Applied System Innovation 2018, ICASI 2018*, 418–421. https://doi.org/10.1109/ICASI.2018.8394273

Lussier, R. N., & Achua, C. F. (2010). Leadership: Theory, application, & skill development (4th ed.). Boston, MA: Cengage Learning.

Lynam, D., Miller, J., Vize, C., & Crowe, M. (2020). *Agreeableness in the HEXACO*. *July*. https://doi.org/10.31234/osf.io/nvxpb

Magness, J. B., & Roslewicz, E. A. (2009). An innovative Myers-Briggs type indicator educational experience used in an information technology capstone course. *SIGITE'09 - Proceedings of the 2009 ACM Special Interest Group for Information Technology Education*, 144–149. https://doi.org/10.1145/1631728.1631767

McCrae, R. R., & Allik, J. (2002). The Five-Factor Model of personality across cultures. In R. R. McCrae & J. Allik (Eds.), The Five-Factor Model of personality across cultures (pp. 3-17). New York, NY: Kluwer Academic/Plenum.

McCrae, R. R., & Costa, P. T., Jr. (2008). The five-factor theory of personality. In O. P. John, R. W. Robins, & L. A. Pervin (Eds.), Handbook of personality: Theory and research (3rd ed., pp. 159-181). New York: Guilford Press.

McDonald, R. P. (2015). Test theory: A unified treatment. Routledge.

Messick, S. (1989). Validity. In R. L. Linn (Ed.), Educational measurement (3rd ed., pp. 13-103). New York, NY: American Council on Education and Macmillan.

Minelli, R., Baracchi, L., Mocci, A., & Lanza, M. (2014). Visual storytelling of development sessions. *Proceedings - 30th International Conference on Software Maintenance and Evolution, ICSME 2014*, 416–420. https://doi.org/10.1109/ICSME.2014.65

Mirza, I. A., Mulla, S., Parekh, R., Sawant, S., & Singh, K. M. (2015). Generating personalized job role recommendations for the IT sector through predictive analytics and personality traits. *Proceedings - International Conference on*

Technologies for Sustainable Development, ICTSD 2015, 1–4. https://doi.org/10.1109/ICTSD.2015.7095894

Mohamad Marzuki, M. F., Yaacob, N. A., & Yaacob, N. M. (2018). Translation, cross-cultural adaptation, and validation of the Malay version of the system usability scale questionnaire for the assessment of mobile apps. *JMIR Human Factors*, *5*(2). https://doi.org/10.2196/10308

Moretti, M., De Chiara, F., & Napolitano, M. (2018). Beyond transparency: Making the Italian public administration more accessible through data storytelling. *Information Visualization - Biomedical Visualization, Visualization on Built and Rural Environments and Geometric Modelling and Imaging, IV 2018*, *July*, 247–250. https://doi.org/10.1109/iV.2018.00050

Moustakas, C. (2011). Research Design and Methodology. *Heuristic Research : Design, Methodology, and Applications*, 38–58. https://doi.org/10.4135/9781412995641.d21

Muzumdar, J. (2016). An Overview of Comic Books as an Educational Tool and Implications for Pharmacy. Innovations in pharmacy.

Myers, I. B., & McCaulley, M. H. (1985). Manual: A guide to the development and use of the Myers-Briggs Type Indicator. Palo Alto, CA: Consulting Psychologists Press.

Newsom, L., Miller, S., & Chesson, M. (2021). Use of Digital vs Printed Posters for Teaching and Learning in Pharmacy Education. American Journal of Pharmaceutical Education.

Nguyen, H., & Le, H. (2012). The use of the Myers-Briggs Type Indicator in higher education: A critical review. Educational Research Review, 7(1), 53-67.

Nov, O., Arazy, O., López, C., & Brusilovsky, P. (2013). Exploring personality-targeted UI design in online social participation systems. *Conference on Human Factors in Computing Systems - Proceedings*, 361–370. https://doi.org/10.1145/2470654.2470707

Oliver, J. (2019). 済無No Title No Title. In *Hilos Tensados* (Vol. 1, Issue). https://doi.org/10.1017/CBO9781107415324.004

Ottley, M. R., Yang, Y. H., & Chang, C. C. (2015). Investigating the effect of locus of control on user preferences and performance for hierarchical visual designs. International Journal of Human-Computer Studies, 78, 37-49.

Ottley, A., Yang, H., & Chang, R. (2015). Personality as a predictor of user strategy: How locus of control affects search strategies on tree visualizations. *Conference on Human Factors in Computing Systems - Proceedings*, *2015-April*(April), 3251–3254. https://doi.org/10.1145/2702123.2702590

Peever, N., Johnson, D., & Gardner, J. (2012). Personality & video game genre preferences. *ACM International Conference Proceeding Series*, 3–5. https://doi.org/10.1145/2336727.2336747

Petrovich, C. (2020). *Data visualization tools for web applications - a survey*. *July*. https://doi.org/10.13140/RG.2.2.27342.89920

Pieterse, V., Leeu, M., & Van Eekelen, M. (2018). How personality diversity influences team performance in student software engineering teams. *2018 Conference on Information Communications Technology and Society, ICTAS 2018 - Proceedings*, 1–6. https://doi.org/10.1109/ICTAS.2018.8368749

Pittenger, D. J. (2005). The validity and reliability of the Myers-Briggs Type Indicator. Consulting Psychology Journal: Practice and Research, 57(4), 210-221.

Purdioux, L. (2016). Predicting deception detection ability based on the concept of self-compassionate personality trait, openness personality structure, and agreeableness personality structure. *Dissertation Abstracts International: Section B: The Sciences and Engineering*, *77*(6-B(E)), No-Specified. http://ovidsp.ovid.com/ovidweb.cgi?T=JS&PAGE=reference&D=psyc13a&NEWS=N&AN=2016-42148-130

Ren, D., & Tobias, H. (n.d.). *ChartAccent : Annotation for Data-Driven Storytelling*.

Ren, T., & Tobias, D. (2017). A design space for chart annotations. IEEE Transactions on Visualization and Computer Graphics, 23(1), 679-688.

Rocha, F., Bremgartner, V., Valim, M., Bonifacio, B., & Fernandes, P. (2018). The influence of the student's personality type on the preference of the computer science learning process. *Proceedings - 2018 44th Latin American Computing Conference, CLEI 2018*, 811–819. https://doi.org/10.1109/CLEI.2018.00102

Russo, D., & Stol, K. (2020). *Gender Differences in Personality Traits of Software Engineers*. *5589*(April). https://doi.org/10.1109/TSE.2020.3003413

Russo, A., & Stol, K. (2020). Personality traits and psychological well-being: A review of the Big Five and the Dark Triad. Personality and Individual Differences, 160, 109844.

Salleh, N., Mendes, E., & Grundy, J. (2011). The effects of openness to experience on pair programming in a higher education context. *2011 24th IEEE-CS Conference on Software Engineering Education and Training, CSEE and T 2011 - Proceedings*, 149–158. https://doi.org/10.1109/CSEET.2011.5876082

Salleh, N., Mendes, E., Grundy, J., & Burch, G. S. J. (2010). An empirical study of the effects of conscientiousness in pair programming using the five-factor personality model. *Proceedings - International Conference on Software Engineering*, *1*, 577–586. https://doi.org/10.1145/1806799.1806883

Schmidt, T., Wittmann, V., & Wolff, C. (2019). The influence of participants' personality on quantitative and qualitative metrics in usability testing. *ACM International Conference Proceeding Series*, 115–126. https://doi.org/10.1145/3340764.3340787

Schreder, G., Windhager, F., Smuc, M., & Mayr, E. (2016). A Mental Models Perspective on Designing Information Visualizations for Political Communication. *JeDEM - EJournal of EDemocracy and Open Government*, *8*(3), 80–99. https://doi.org/10.29379/jedem.v8i3.443

Scott, C. (2007). Written in red, white, and blue: A comparison of comic book propaganda from world war II and September 11. *Journal of Popular Culture*, *40*(2), 325–343. https://doi.org/10.1111/j.1540-5931.2007.00381.x

Segel, E., & Heer, J. (2010). Narrative visualization: Telling stories with data. *IEEE Transactions on Visualization and Computer Graphics*, *16*(6), 1139–1148. https://doi.org/10.1109/TVCG.2010.179

Shameem, M., Kumar, C., & Chandra, B. (2017). A proposed framework for effective software team performance: A mapping study between the team members' personality and team climate. *Proceeding - IEEE International Conference on Computing, Communication and Automation, ICCCA 2017*, *2017-Janua*, 912–917. https://doi.org/10.1109/CCAA.2017.8229936

Sheidin, J., Lanir, J., Conati, C., Toker, D., & Kuflik, T. (2020). The effect of user characteristics in time series visualizations. *International Conference on Intelligent User Interfaces, Proceedings IUI*, *December*, 380–389. https://doi.org/10.1145/3377325.3377502

Si, C., Pisan, Y., & Tan, C. T. (2016). Understanding players' map exploration styles. *ACM International Conference Proceeding Series*, *01-05-Febr*. https://doi.org/10.1145/2843043.2843480

Sperling_VM_Model_1963.pdf. (n.d.).

Sperling, G. (1963). A model for visual memory tasks. Human Factors, 5(3), 19-31.

Taherdoost, H. (2018). Validity and Reliability of the Research Instrument; How to Test the Validation of a Questionnaire/Survey in a Research. *SSRN Electronic Journal*, *September*. https://doi.org/10.2139/ssrn.3205040

Tlili, A., Denden, M., Essalmi, F., Jemni, M., Huang, R., & Chang, T. W. (2019). Personality effects on students' intrinsic motivation in a gamified learning environment. *Proceedings - IEEE 19th International Conference on Advanced Learning Technologies, ICALT 2019*, *2161-377X*(Imi), 100–102. https://doi.org/10.1109/ICALT.2019.00036

Toker, D., Conati, C., Steichen, B., & Carenini, G. (2013). *Individual user characteristics and information visualization*. 295. https://doi.org/10.1145/2470654.2470696

Tong, C., Roberts, R., Borgo, R., Walton, S., Laramee, R. S., Wegba, K., Lu, A., Wang, Y., Qu, H., Luo, Q., & Ma, X. (2018). Storytelling and visualization: An extended survey. *Information (Switzerland)*, *9*(3), 1–42. https://doi.org/10.3390/info9030065

Tripp, J. F. (2019). Data Visualization. *International Series in Operations Research and Management Science*, *264*(November), 111–135. https://doi.org/10.1007/978-3-319-68837-4_5

Trochim, W. M. K. (2006). The research methods knowledge base (3rd ed.). Mason, OH: Cengage Learning.

Usman, M., & Minhas, N. M. (2019). Use of personality tests in empirical software engineering studies: A review of ethical issues. *ACM International Conference Proceeding Series*, 237–242. https://doi.org/10.1145/3319008.3319032

Vaida, M. F. (2019). Collaborative education teams development using alternative methodologies. *ACM International Conference Proceeding Series*, 223–227. https://doi.org/10.1145/3369255.3369280

Van Lange, P. A. M., Joireman, J., Parks, C. D., & Van Dijk, E. (2013). Agreeableness: A social psychological perspective. In M. R. Leary & J. P. Tangney (Eds.), Handbook of individual differences in social behavior (pp. 85-98). New

Venkitachalam, D. R. (2003). *Validity and Reliability of Questionniares*.

Wang, Z., Sapienza, A., Culotta, A., & Ferrara, E. (2019). Personality and behavior in role-based online games. *IEEE Conference on Computatonal Intelligence and Games, CIG*, *2019-Augus*, 1–8. https://doi.org/10.1109/CIG.2019.8848027

Weilemann, E. (2019). A winning team-what personality has to do with software engineering. *Proceedings - 2019 IEEE/ACM 41st International Conference on*

Software Engineering: Companion, ICSE-Companion 2019, 252–253. https://doi.org/10.1109/ICSE-Companion.2019.00100

Wiesche, M., & Krcmar, H. (2014). The relationship of personality models and development tasks in software engineering. *SIGMIS-CPR 2014 - Proceedings of the 2014 Conference on Computers and People Research*, 149–161. https://doi.org/10.1145/2599990.2600012

Wu, L., Zhou, Z., & Chen, B. (2011). The application of MBTI personality type theory in the Bank management. *Proceedings - 2011 6th IEEE Joint International Information Technology and Artificial Intelligence Conference, ITAIC 2011*, *1*, 455–458. https://doi.org/10.1109/ITAIC.2011.6030246

Yan, S. (2010). Successful implementation of e-learning from the situated cognition and MBTI perspective. *2010 International Conference on Computer Design and Applications, ICCDA 2010*, *2*(Iccda), V2-123-V2-125. https://doi.org/10.1109/ICCDA.2010.5541142

Yang, H., Li, Y., & Zhou, M. X. (2014). Understand users' comprehension and preferences for composing information visualizations. *ACM Transactions on Computer-Human Interaction*, *21*(1). https://doi.org/10.1145/2541288

Yilmaz, M., & O'Connor, R. V. (2012). Towards the understanding and classification of the personality traits of software development practitioners: Situational context cards approach. *Proceedings - 38th EUROMICRO Conference on Software Engineering and Advanced Applications, SEAA 2012*, 400–405. https://doi.org/10.1109/SEAA.2012.62

Yin, R. K. (2014). Case study research: Design and methods (5th ed.). Thousand Oaks, CA: Sage Publications.

Yusoff, M. S. B. (2019). ABC of Content Validation and Content Validity Index Calculation. *Education in Medicine Journal*, *11*(2), 49–54. https://doi.org/10.21315/eimj2019.11.2.6

Zahl, H. A., & Reilley, E. M. (1958). Exploratory research. *Physics Today*, *11*(8), 20–22. https://doi.org/10.1063/1.3062684

Zanan, M. F. B. b. M., & Aziz, M. S. A. (2022). A Review On The Visual Design Styles In Data Storytelling Based On User Preferences And Personality Differences. *2022 IEEE 7th International Conference on Information Technology and Digital Applications (ICITDA)*, 1–7. https://doi.org/10.1109/ICITDA55840.2022.9971409

Zanan, M. F. B. b. M., & Aziz, M. S. A. (2023). Visual Design Elements for Data Storytelling Based on Personality Traits: A Case of Undergraduate Students. In *Journal of Applied Technology and Innovation, 7(1)*.

Zeng, L., Chen, D., Xiong, K., Pang, A., Huang, J., & Zeng, L. (2016). Medical university students' personality and learning performance: Learning burnout as a mediator. *Proceedings - 2015 7th International Conference on Information Technology in Medicine and Education, ITME 2015*, 492–495. https://doi.org/10.1109/ITME.2015.143

Zhang Y., & Ying Z. (2011). The effect of outliers on the Pearson correlation coefficient. Journal of Modern Applied Statistical Methods, 10(1), 358-366.

Zhao, X., Chen, L., Wang, Y., G. Andrienko, N., & Andrienko, G. (2015). Sketch-based data storytelling: An exploratory study. IEEE Transactions on Visualization and Computer Graphics, 21(3), 414-423.

Zhao, Z., Marr, R., & Elmqvist, N. (2015). Data Comics: Sequential Art for Data-Driven Storytelling. *HCIL Technical Report*, *15*(Figure 1), 12. https://www.semanticscholar.org/paper/Data-Comics-%3A-Sequential-Art-for-Data-Driven-Zhao-Marr/43f6a7a70a9cc3dfdaec99f0c240a04830191827?p2df

Ziemkiewicz, C., Ottley, A., Crouser, R. J., Chauncey, K., Su, S. L., & Chang, R. (2012). Understanding visualization by understanding individual users. *IEEE Computer Graphics and Applications*, *32*(6), 88–94. https://doi.org/10.1109/MCG.2012.120

Ziemkiewicz, C., Ottley, A., Crouser, R. J., Yauilla, A. R., Su, S. L., Ribarsky, W., & Chang, R. (2013). How visualization layout relates to locus of control and other personality factors. *IEEE Transactions on Visualization and Computer Graphics*, *19*(7), 1109–1121. https://doi.org/10.1109/TVCG.2012.180

Ziemkiewicz, C., Ottley, M., Crouser, R., Yauilla, J., Su, A., Ribarsky, W., & Chang, C. C. (2013). Investigating the effect of locus of control on user performance in visual analytics tasks. In Proceedings of the 2013 conference on Visual analytics science and technology (VAST), 1-10.

APPENDIX I USER PREFERENCES VISUALIZATION TYPES QUESTIONNAIRE

Preferences Questionnaire

Welcome!

You were invited to participate in the following research study: A study on personality differences and user preference in visual design for information visualization and storytelling reporting.

In this study, we are trying to relate Conscientiousness, a personality variable of the Five-Factor Model, with preferences for styles of different elements in information visualization and storytelling. Thus, the present questionnaire serves to collect your preferences for graphic elements presenting several illustrative styles.

First, we collect your personality identifier and the context in which you are completing this questionnaire. Then, you will be presented with various aspects of graphic design. We ask that you review all the different styles presented and respond to all scales with your preferences.

This questionnaire takes about 10 minutes. There are no right or wrong answers.

All data will be treated anonymously, and you are free to withdraw at any time. Findings from this study will be used for research purposes and for publication only

If you believe there is something wrong with the content of this questionnaire, please contact the investigator (s) at mfarisbasheer@gmail.com

We thank you in advance for your cooperation.

Compensation: You will be rewarded a KFC voucher for participating in this study.

A. **User Context**: In this section, you will answer questions that help us understand your context. Again, there are no right or wrong questions, so your answers will help us to understand if your context affects your answers in the following sections.

Go to http://www.personal.psu.edu/faculty/j/5/j5j/IPIP/ipipneo120.htm for the personality test and rate each statement accurately that describes you. It is advisable to use computer to complete the personality tests. If you are using tablet or phone, it is advisable to screenshot your answer.

After that, choose in which groups your score belongs to for each of the main 5 traits (Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness to experience).

Extraversion

○ ○ ○ ○ ○

0-19 20-39 40-59 60-79 80-99

Agreeableness

○ ○ ○ ○ ○

0-19 20-39 40-59 60-79 80-99

Conscientiousness

○ ○ ○ ○ ○

0-19 20-39 40-59 60-79 80-99

Neuroticism

○ ○ ○ ○ ○

0-19 20-39 40-59 60-79 80-99

Openness

○ ○ ○ ○ ○

0-19 20-39 40-59 60-79 80-99

On what device are you filling out this questionnaire?

○ ○ ○ ○

PC Tablet Mobile Phone Other:_____

Do you have colour blindness?

Yes No

Email:

B. Design Preferences: Then, you will be presented with various graphic elements with different design styles. We ask that you review all the different styles presented and respond to all scales with your preferences. Note that the options are not mutually exclusive, that is, you can like several styles equally, without having to establish an order between them.

Font: Rate each of the following fonts according to your preference.

1. Arial

This is Arial

Mark only one oval

	1	2	3	4	5	6	7	
Low preferences								High preferences

2. Calibri

This is Calibri

Mark only one oval

1 2 3 4 5 6 7

Low preferences ◯ ◯ ◯ ◯ ◯ ◯ ◯ High preferences

3. Calibri Light

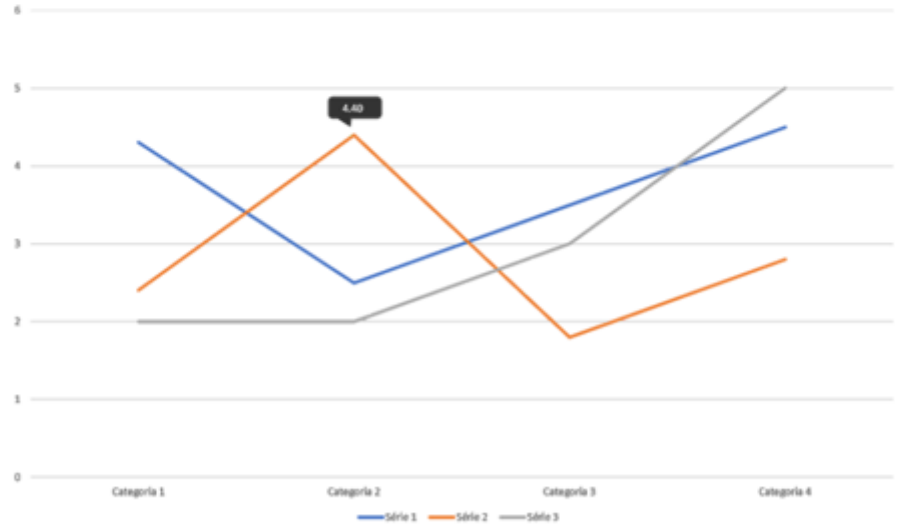
This is Calibri Light

Mark only one oval

1 2 3 4 5 6 7

Low preferences ◯ ◯ ◯ ◯ ◯ ◯ ◯ High preferences

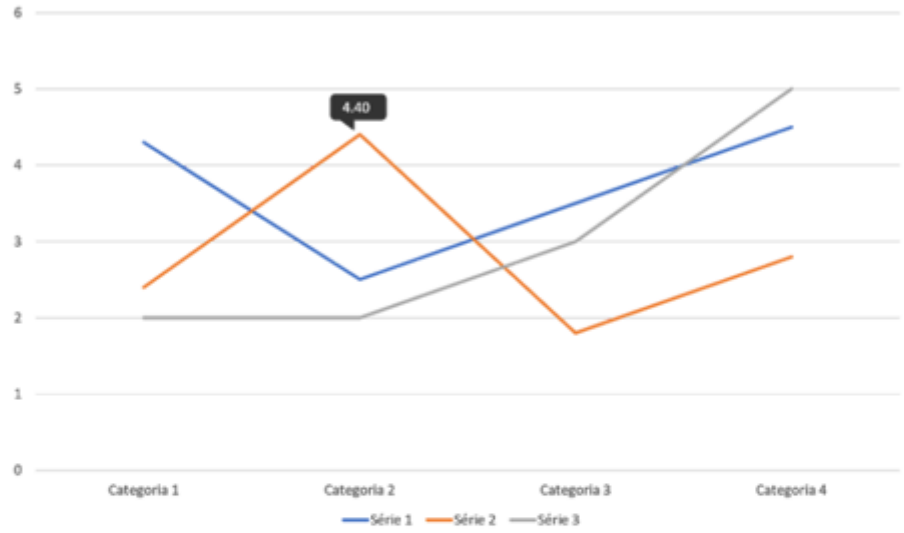
4. Small font size



Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

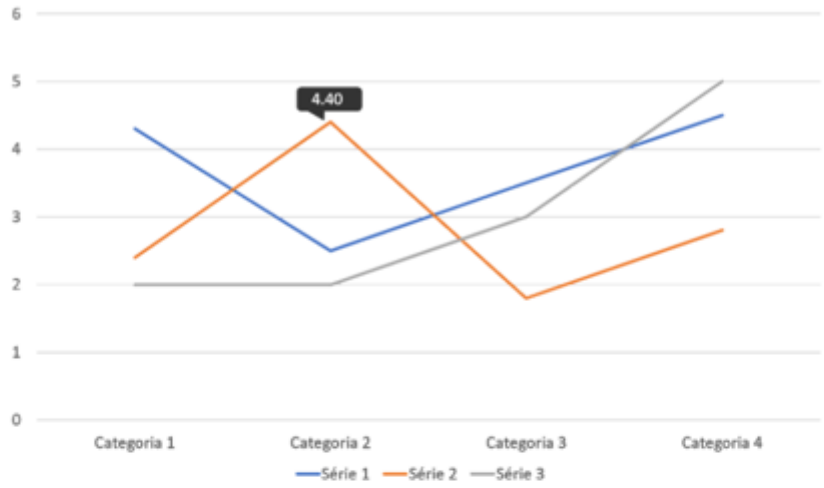
5. Medium font size



Mark only one oval.

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

6. Big font size



Mark only one oval.

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

Buttons and icons: Evaluate your preference on the following information buttons

7. Button with icon only.

Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

8. Button with text only

Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

9. Button with icon and with text

Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

Information Density: preference according to the density of information in relation to the screen size of each of the following interfaces.

10. Low density

Mark only one oval

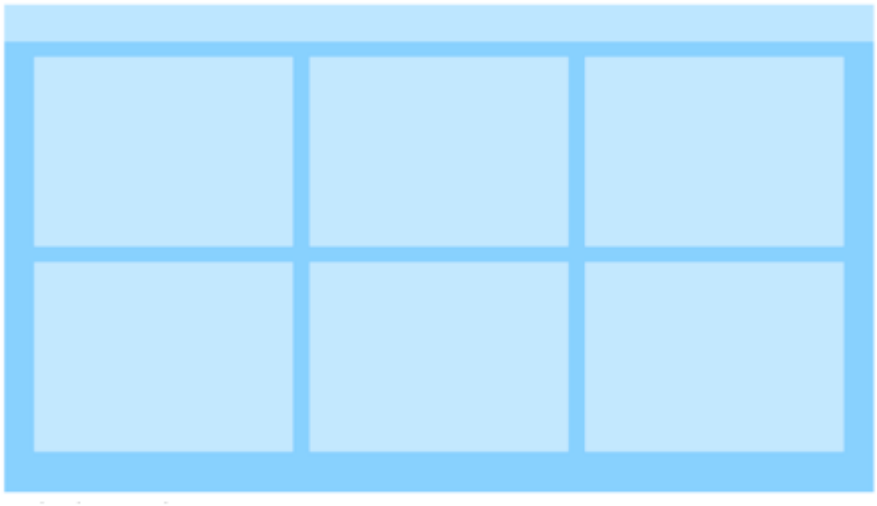
	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

11. Average density

Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	⬭	⬭	⬭	⬭	⬭	⬭	⬭	High preferences

12. High density

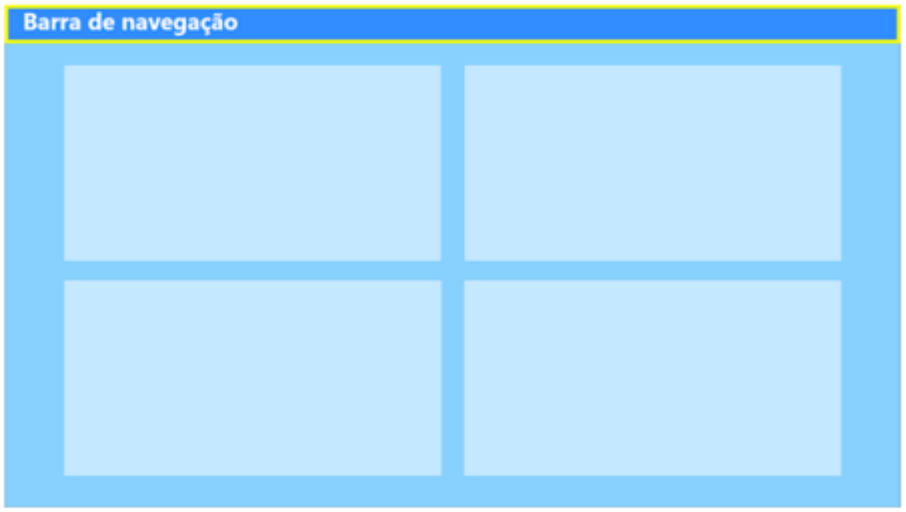


Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	⬭	⬭	⬭	⬭	⬭	⬭	⬭	High preferences

Navigation bar position: Evaluate each panel according to your preference in relation to the positioning of the navigation bar on the screen.

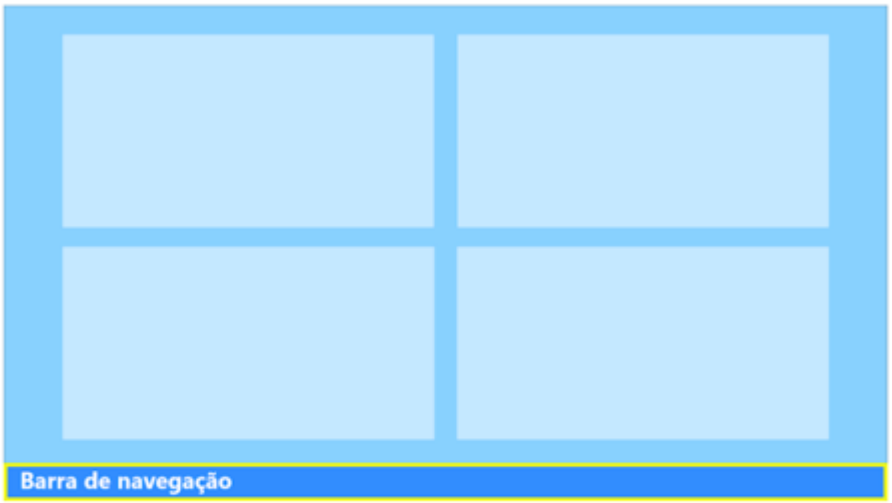
13. Top position of the navigation bar



Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

14. Bottom position of the navigation bar



Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

15. Right side positioning of the navigation bar.

Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

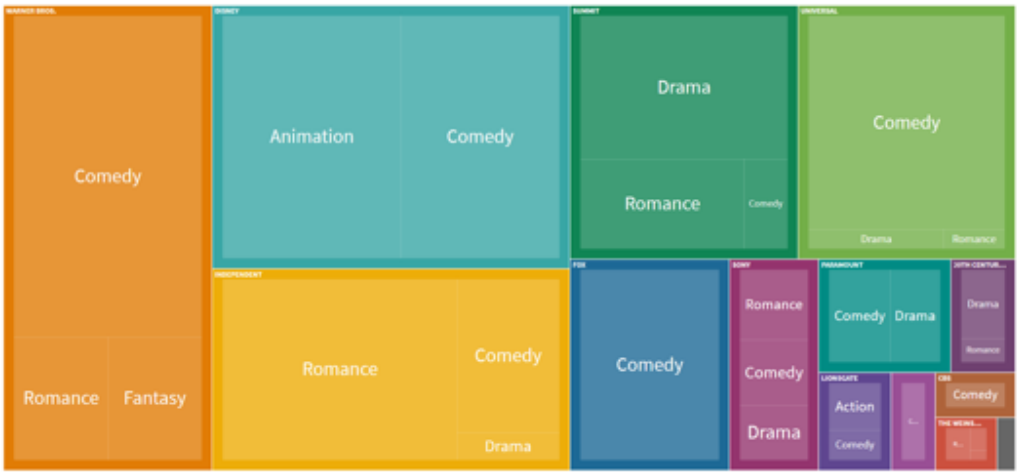
16. Left side positioning of the navigation bar.

Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

Hierarchy Visualization: The following contexts represent company and their number of movies based on genres.

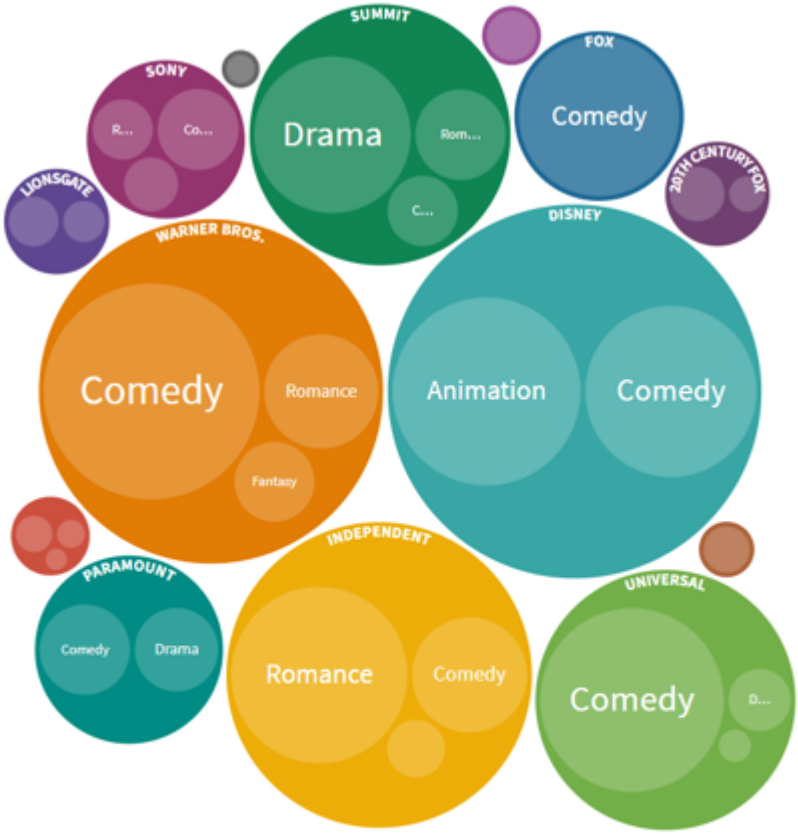
17. Representation through a Treemap.



Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

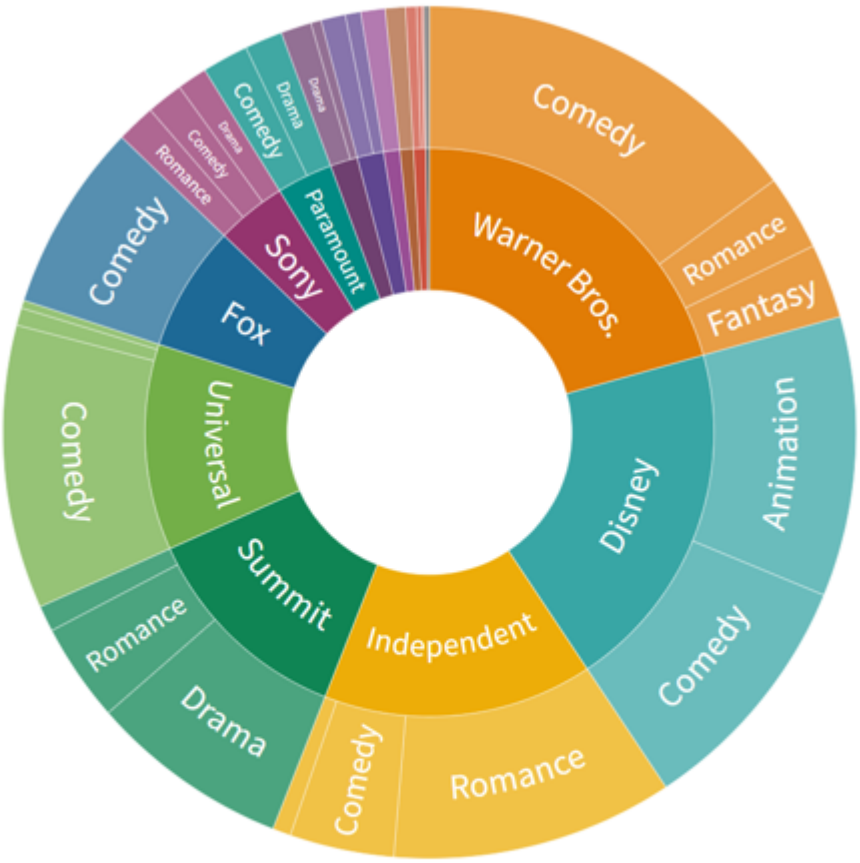
18. Representation through a Circular Packing diagram.



Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

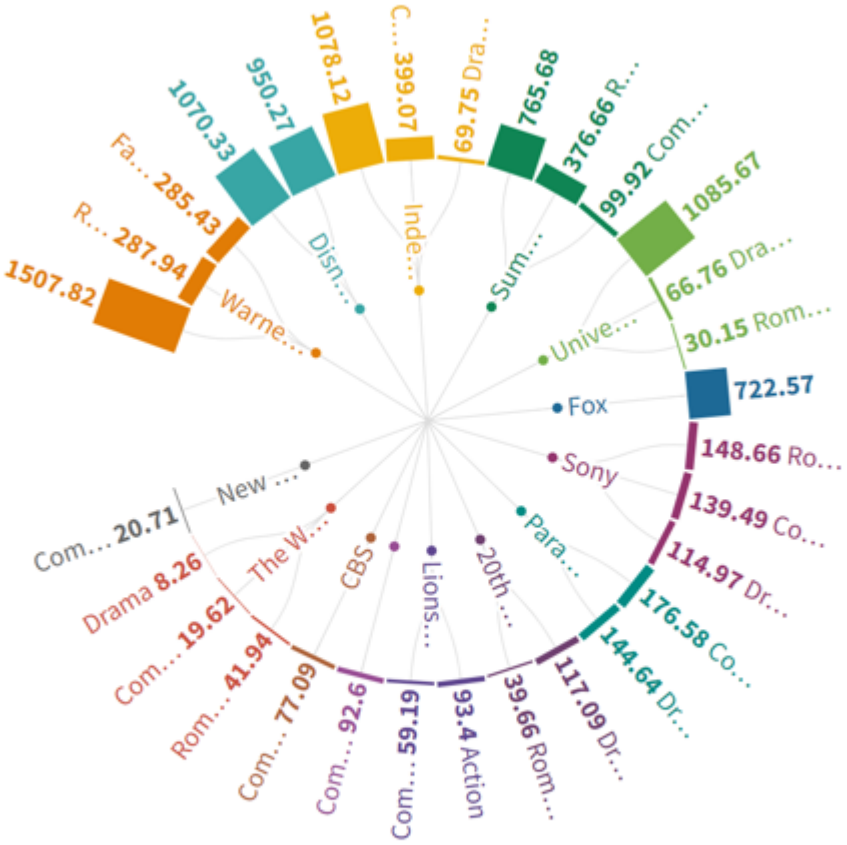
19 Representation through a Sunburst.



Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

20. Representation through a Radial diagram

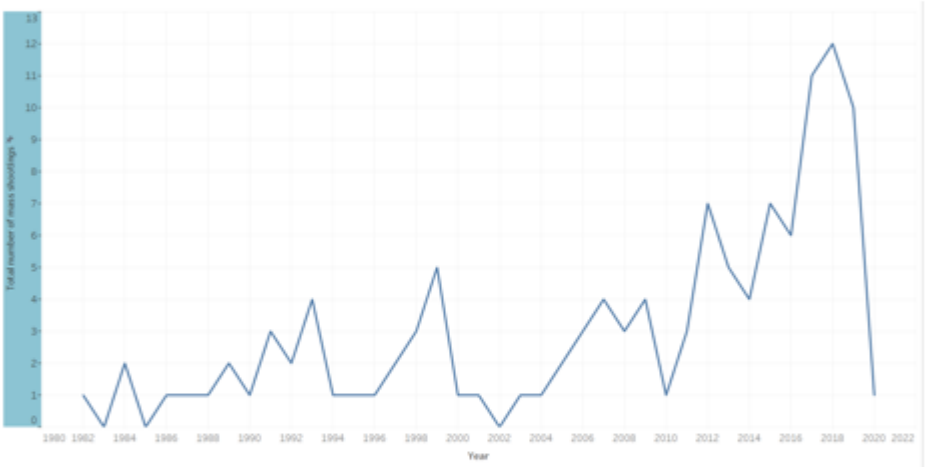


Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

Change over time visualization: The following contexts refer to the number of mass shooting in USA. Assess your preference in representing the data using the various visuals

21. Representation through a Linechart.



Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	⬭	⬭	⬭	⬭	⬭	⬭	⬭	High preferences

22. Representation through a Linechart, with points.

Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	⬭	⬭	⬭	⬭	⬭	⬭	⬭	High preferences

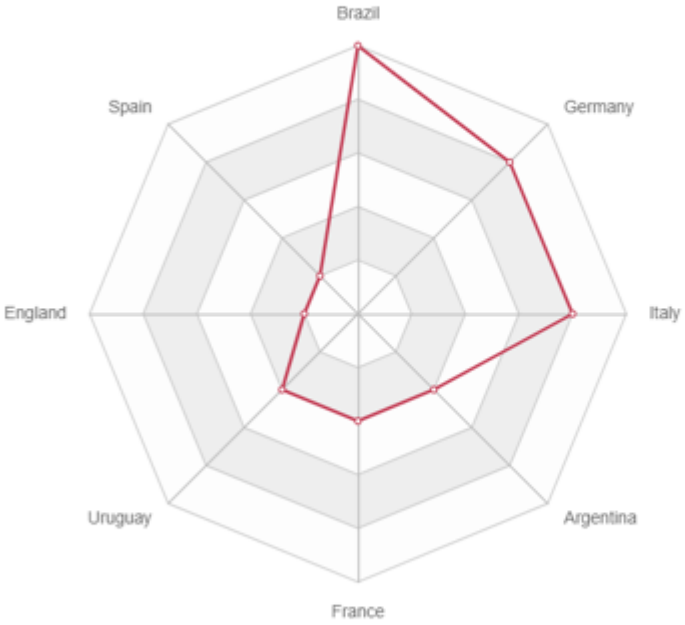
23. Representation through an Area chart

Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

Comparison visualization: The following contexts represent the number of world cup won between eight different countries (England, Italy, France, Brazil, Argentina, Germany, Spain, and Uruguay). Assess your preference in each of them, according to the representation of the data

24. Representation through a Radar chart



Mark only one oval

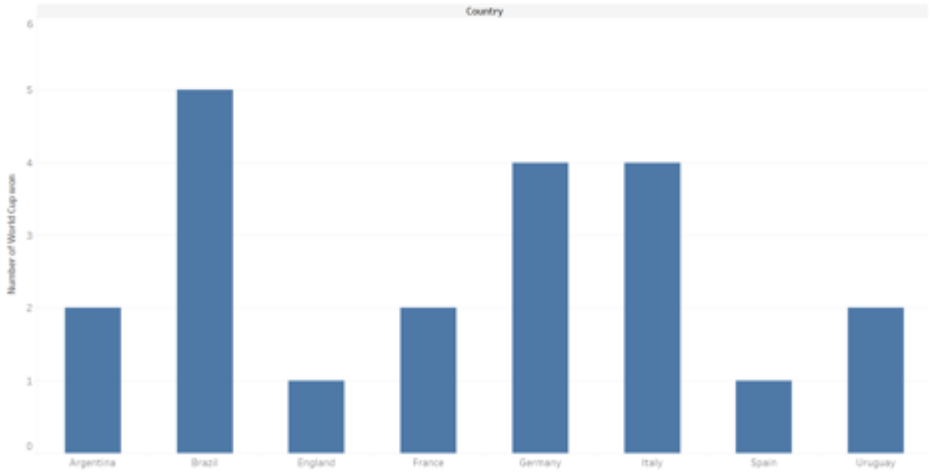
	1	2	3	4	5	6	7	
Low preferences	⬭	⬭	⬭	⬭	⬭	⬭	⬭	High preferences

25. Representation through a Word Cloud

Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

26. Representation through a vertical bar chart

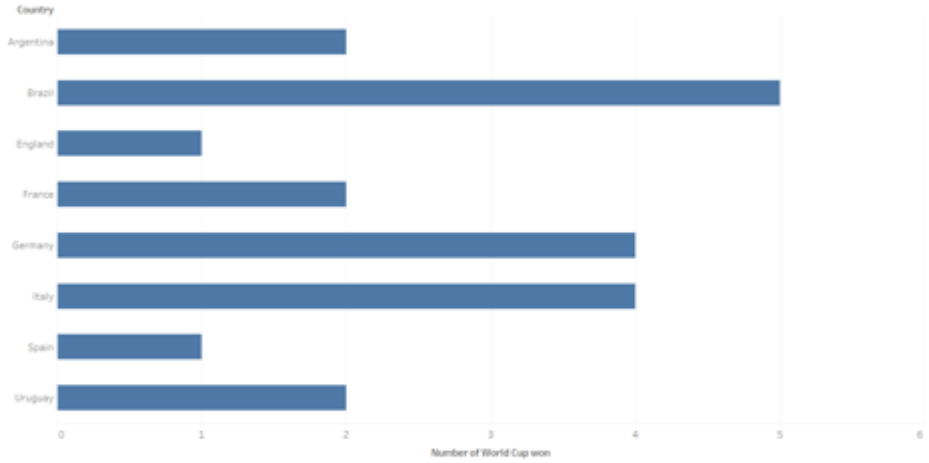


Mark only one oval

1 2 3 4 5 6 7

Low preferences ◯ ◯ ◯ ◯ ◯ ◯ ◯ High preferences

27. Representation through a horizontal Bar chart



Mark only one oval

1 2 3 4 5 6 7

Low preferences ◯ ◯ ◯ ◯ ◯ ◯ ◯ High preferences

28. Representation through a Pie Chart.

Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

Storytelling Styles preferences: Assess your preferences on which of the storytelling styles you prefer to use

29. Magazine Style

TECHNOLOGY NOW

THE WORLD DURING COVID-19 CRISIS

SCI BUZZ >

COVID-19 TRANSMITTED

We know that the disease is caused by the SARS-CoV-2 virus, which spreads between people in several different ways.
The virus can spread from an infected person's mouth or nose in small liquid particles when they cough, sneeze, speak, sing or breathe. These particles range from larger respiratory droplets to smaller aerosols.

- Current evidence suggests that the virus spreads mainly between people who are in close contact with each other, typically within 1 metre (short-range). A person can be infected when aerosols or droplets containing the virus are inhaled or come directly into contact with the eyes, nose, or mouth.
- The virus can also spread in poorly ventilated and/or crowded indoor settings, where people tend to spend longer periods of time. This is because aerosols remain suspended in the air or travel farther than 1 metre (long-range).

People may also become infected by touching surfaces that have been contaminated by the virus when touching their eyes, nose or mouth without cleaning their hands

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INDUSTRY >

VACCINE BREAKTHROUGHS

The first COVID-19 vaccines has been authorized in the United Kingdom, the United States and the the European Union. The Pfizer-BioNTech COvid-19 vaccine and the Moderna COVID-19 vaccine was authorized on January 2021.

DETAIL >

SKEPTICAL BEHIND THE VACCINES

A debunked claim from the early days of the pandemic -- that the COVID-19 vaccines contain microchips -- is spreading anew online, courtesy of a TikTok video circulating across platforms.
"AstraZeneca Bluetooth side effect," says the text on the two-part TikTok video, which shows a man who claims that his body has been connecting to Bluetooth-enabled devices ever since he got the AstraZeneca shot. One hashtag on the video: "#chipped."

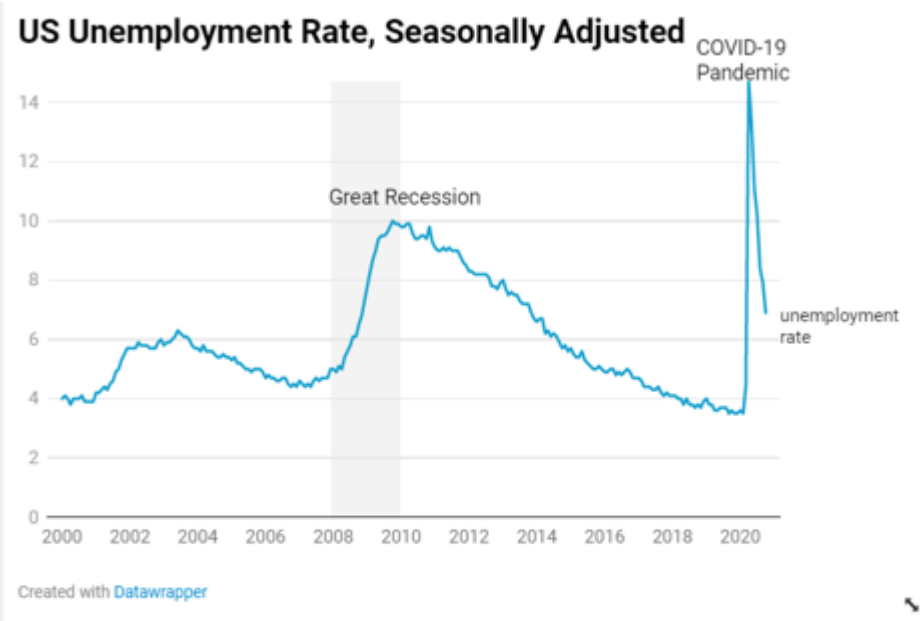
The ingredients for the AstraZeneca COVID-19 vaccine are publicly available online, including on government websites where the vaccine is approved for use, such as Australia, Canada and the United Kingdom. (The vaccine has not been authorized for emergency use in the U.S.)

It does not contain anything related to Bluetooth technology or microchips. PolitiFact has fact-checked several claims alleging that the vaccines contain microchips, all inaccurate.

Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

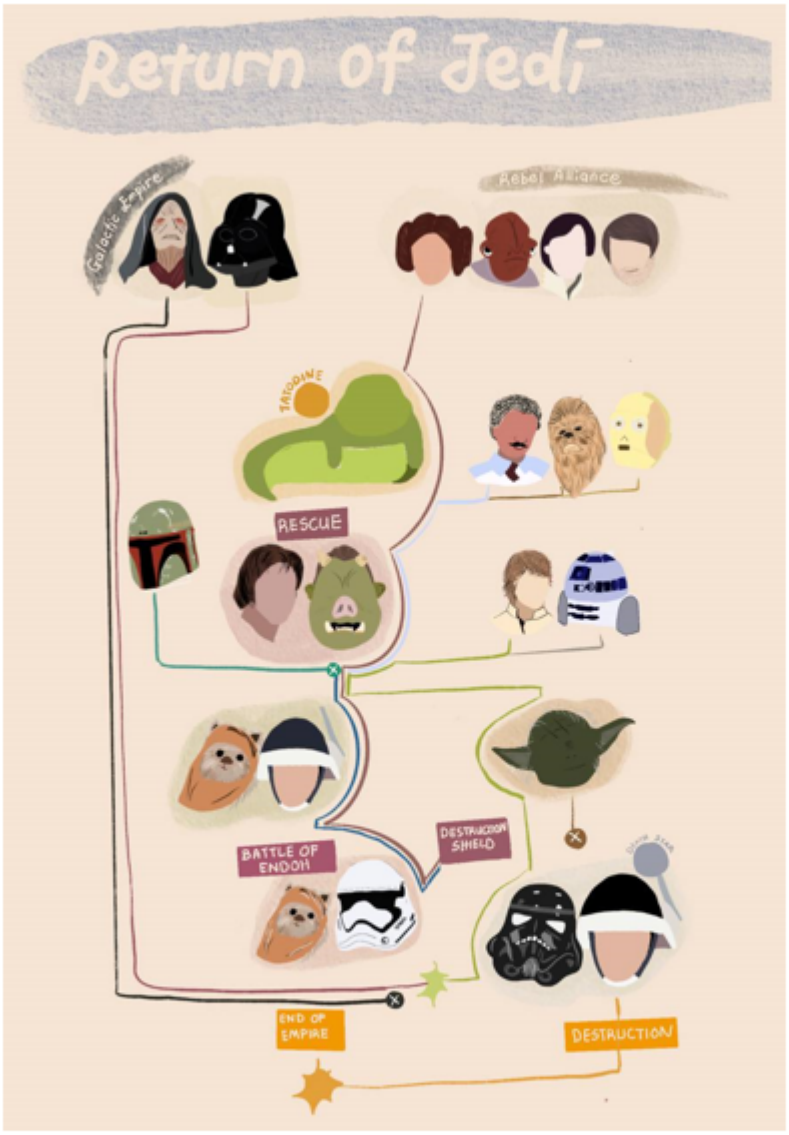
37. Annotated Chart



Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	⬭	⬭	⬭	⬭	⬭	⬭	⬭	High preferences

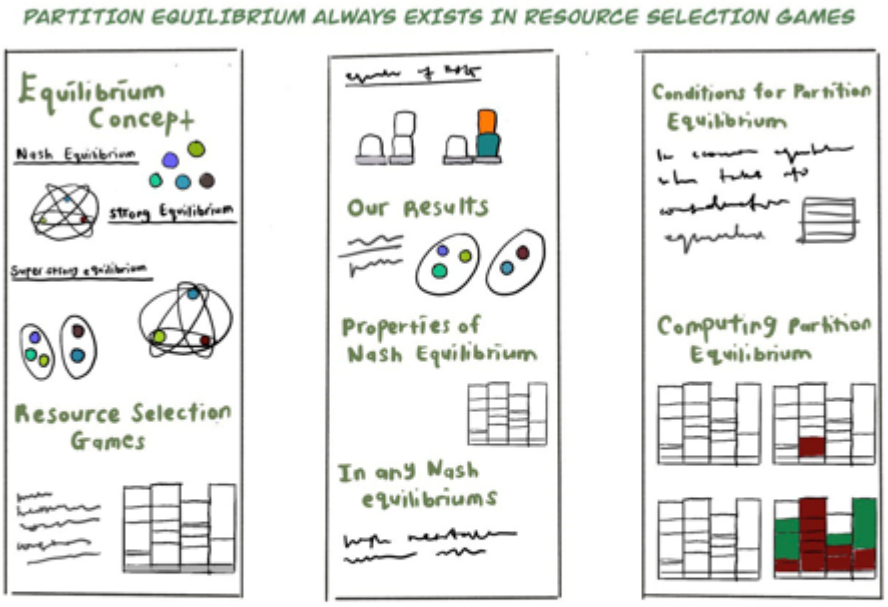
38. Flowchart-Infographic



Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

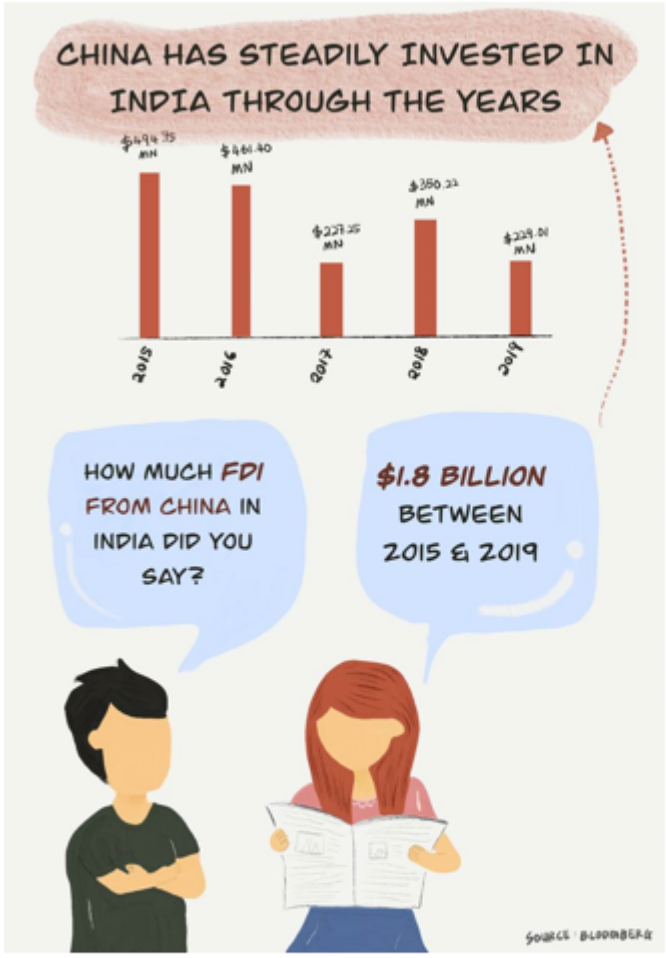
39. Partitioned Poster



Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

40. Comic & Animation



Mark only one oval

	1	2	3	4	5	6	7	
Low preferences	◯	◯	◯	◯	◯	◯	◯	High preferences

APPENDIX II INTERNATIONAL PERSONALITY ITEM POOL SURVEY

Age: [ ] Please enter your age (in years) before continuing.

When selecting your country, please indicate the country to which you feel you belong the most, whether by virtue of citizenship, length of residence, or acculturation.

Country: [Select Your Country] Please select your country before continuing.

1.	Worry about things.	Very Inaccurate ○	Moderately Inaccurate ○	Neither Accurate Nor Inaccurate ○	Moderately Accurate ○	Very Accurate ○
2.	Make friends easily.	Very Inaccurate ○	Moderately Inaccurate ○	Neither Accurate Nor Inaccurate ○	Moderately Accurate ○	Very Accurate ○
3.	Have a vivid imagination.	Very Inaccurate ○	Moderately Inaccurate ○	Neither Accurate Nor Inaccurate ○	Moderately Accurate ○	Very Accurate ○
4.	Trust others.	Very Inaccurate ○	Moderately Inaccurate ○	Neither Accurate Nor Inaccurate ○	Moderately Accurate ○	Very Accurate ○
5.	Complete tasks successfully.	Very Inaccurate ○	Moderately Inaccurate ○	Neither Accurate Nor Inaccurate ○	Moderately Accurate ○	Very Accurate ○
6.	Get angry easily.	Very Inaccurate ○	Moderately Inaccurate ○	Neither Accurate Nor Inaccurate ○	Moderately Accurate ○	Very Accurate ○
7.	Love large parties.	Very Inaccurate ○	Moderately Inaccurate ○	Neither Accurate Nor Inaccurate ○	Moderately Accurate ○	Very Accurate ○
8.	Believe in the importance of art.	Very Inaccurate ○	Moderately Inaccurate ○	Neither Accurate Nor Inaccurate ○	Moderately Accurate ○	Very Accurate ○
9.	Use others for my own ends.	Very Inaccurate ○	Moderately Inaccurate ○	Neither Accurate Nor Inaccurate ○	Moderately Accurate ○	Very Accurate ○
10.	Like to tidy up.	Very Inaccurate ○	Moderately Inaccurate ○	Neither Accurate Nor Inaccurate ○	Moderately Accurate ○	Very Accurate ○
11.	Often feel blue.	Very Inaccurate ○	Moderately Inaccurate ○	Neither Accurate Nor Inaccurate ○	Moderately Accurate ○	Very Accurate ○
12.	Take charge.	Very Inaccurate ○	Moderately Inaccurate ○	Neither Accurate Nor Inaccurate ○	Moderately Accurate ○	Very Accurate ○

APPENDIX III VALIDATION FORM OF QUESTIONNAIRE