A REVIEW ON THE VISUAL DESIGN STYLES IN DATA STORYTELLING BASED ON USER PREFERENCES AND PERSONALITY DIFFERENCES

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***Abstract*— The proliferation of data analytics has led to a vast application of data visualization and storytelling in a variety of disciplines extending across banking, sports to healthcare. Data, information, and knowledge are transformed into interactive visual representations that convey a meaningful story. In big data analytics, relevant and high-quality graphical insights ought to be factually accurate and relevant to make a key decision. Data storytelling has become an effective way to apply information visualization as it can enhance communication effectiveness. Using visualization as a tool to enhance narrative for the viewers in enforcing data storytelling as a way to understand data and information. Findings suggest that an individual's personality variations correspond strongly with a user's preference toward visual design styles for visualization and storytelling. This paper investigates previous studies regarding personality, information visualization, narrative, and storytelling, as well as their interrelationships through online databases. The future direction of the present study.**

Keywords*— Information visualization, Visualization tool, Storytelling, Personality Traits, Five-Factor Model, User Preferences, Visualization Design Styles.

I. INTRODUCTION

The usage of data in today's world is priceless, and visualizations have become a key feature in most industries throughout the world, including commerce, entertainment, architecture, and science [1]. It has become critical for academic establishments to incorporate this discipline to adjust to the changing epoch of modern communication technology, wherein expertise and how data is communicated and conveyed will become critical factors in stimulating economic growth across all industries [2]. The ever-growing amount of digital information has led the user to explore information visualization to convey information effectively[3]. Data, information, and knowledge are transformed into dynamic or interactive pictorial representations that create a compelling story. Effective and high-quality visualization reports for data analytics should be technically correct and relevant to make key choices. The ever-growing amount of data will inevitably overwhelm users in the ever-expanding digital world; in fact, by 2020, there will be 40 zettabytes of data, most of which will never be used without the proper analysis[4], which may be fixed by employing visualization. The view that information visualization is a successful tactic for boosting research uptake is shared by research institutions and knowledge intermediaries who follow the trend. A search of the Overseas Development Institute's webpage reveals a six-fold increase in information visualization from 2014 to 2015. SciDev.Net, for instance, produced more data visualisation elements in stories by 60% between 2015 and 2016 [5].

Notwithstanding a lengthy history of work examining the relationship between personality traits and information visualization, there are few positive outcomes. In the research sector, most research on personality characteristics is undertaken by professionals in other fields, such as engineering. Numerous researchers have worked hard to provide a solid framework for understanding the nature and influence of personality. The conceptual explanation's primary focus was frequently on domains other than data analytics, information visualization, and storytelling. Nevertheless, the principles and achievements of those professions remain appropriate for application in the field of information visualization and storytelling fields. Previous researchers studied gender variations in personality attributes of computer programmers in their research on psychology and engineering. The authors conducted a survey investigation to gather personal traits from 483 software engineers using the HEXACO model. The HEXACO model is a more advanced variant of the Five-Factor Model (FFM) framework. Five-Factor Model (FFM) is a personality indicator with five elements. The primary distinction between HEXACO and FFM is the inclusion of a sixth feature, Honesty-Humility [6]. According to the study, women rank better in Honesty-Humility, a feature strongly associated with job productivity and organizational success; female software developers rank better across both Emotionality and Openness to Experience. Such findings assist technology firms in predicting the teamwork performance of new personnel based on sex, as well as understanding which staff may be more prepared to advocate new enterprises from a psychological standpoint [7].

Although various data visualizing tools currently exist that help with visualizing tasks, the technologies inherently struggle with the limitations of the "one-size-fits-all" approach, which disregards growing preference variances [8]. This constraint provides consumers with limited personalization, they may acquire services that they may not require, and consumers may miss out on profitable chances from distinguishing features. Designers' uniform approach also overlooks the significance of individuality in data storytelling, which may add to the gap between consumers and designers [8]. Customized visualization may solve some previously recognized negative consequences of dashboards and visual analytics [9]. Earlier studies discussed the problem by examining user memorability toward the visualization [10] and by identifying user characteristics, task complexity, and visualization kind using an eye gazing tracking instrument [9]. Yet, little research has been conducted on how personality traits affect information visualization and storytelling choices from a design standpoint. The visualization can create and improve visualization tools depending on the user preferences [11].

The purpose of this paper is to investigate the relationship between personality traits and user preferences of visual design styles toward meaningful and efficient data storytelling for people to make an informed decision. Data storytelling is a technique of combining several visual design styles with being incorporated into a narrative. This paper attempted to fill the gap between how individuals' personalities influence their decisions regarding storytelling with data. Discovering the effect of personality and user preference on data storytelling can be valuable and helpful when making important decisions.

II. METHOD

In searching and reviewing the articles, the authors started by searching the articles from a list of journals and proceedings in main online databases such as IEEE Xplore Digital Library, ACM Digital Library, and Google Scholar dated from February 2020 until June 2021. The researcher uses different keywords and combinations to find the best result (Personality; Myers-Briggs Type Indicator; Extraversion; Introversion; Sensing; Intuition; Thought; Feeling; Judgment; Perception; Five-Factor Model; Openness to Experience; Conscientiousness; Agreeableness; Neuroticism; Locus of Control; User Preferences; User Interfaces; IPIP-NEO; Information Visualization; Data Visualization; Data Storytelling; Individual Differences; Students; Visualization tool; Visual Design; Usability). The Boolean operators "and" and "or" were used to search the database. There were no restrictions on publication dates; however, the emphasis was on the latest trend. The authors identified 235 relevant papers. Figure 1 shows the flow chart of the process of filtering and reviewing research papers, journal articles, and proceedings.

III. PERSONALITY

Personality is a school of thought, feeling, and patterns of behaviour based on established characteristics that forecast a person's behaviour and attitudes [7]. Personality is also described as human variances that form a pattern in thoughts, feelings, and behaviour [12]. Throughout history, academics have proposed several indicators to aid in understanding personality by blending information from Pythagorean, Platonic, Jewish, Christian, Hindu, Buddhist, and Sufi traditions (Vaida, 2019). Several personality indicators have been introduced, such as Myer-Briggs Type Indicator (MBTI), Five-Factor Model (FFM), Enneagram, and others [8].

A. Myers-Briggs type Indicator (MBTI)

The Myers-Briggs type indicator (MBTI) is one of the personality assessments founded on a philosophical idea presented by renowned Swiss psychologist Carl. G. Jung was then developed in the United States by Katherine C. Briggs, Isabel Briggs Myers, and her daughter [13]. Carl G Jung identified four elements of personality (Extroversion, and Introversion (E-1), Sensing and Intuitive (S-N), Feeling and Thinking (F-T), and Perceptive and Judging (P-J)) each with cross-polarization properties. Based on the combination of four qualities, these measures may be used to produce 16 unique personality forms [14]. Examples of the personality types that exist according to the MBTI test are ENFJ (the combination of Extroversion, Intuitive, Feeling, and Judgement) and ISTP (the combination of Introversion, Sensing, Thinking, and Perceptive).

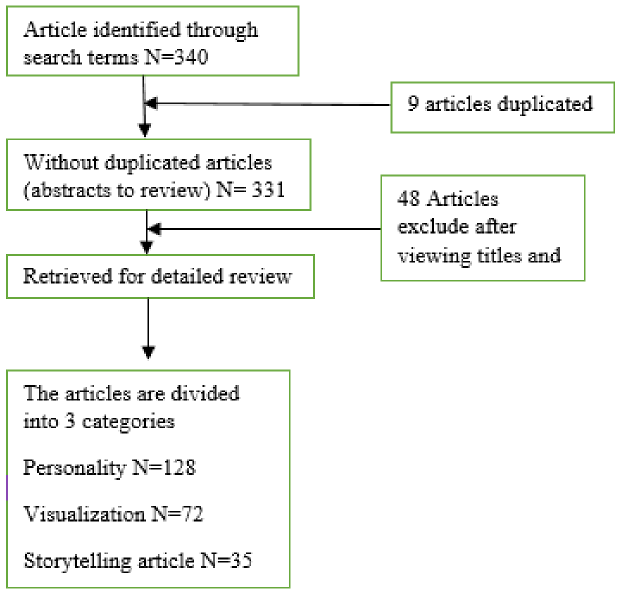

Fig. 1. Flow chart of filtered and reviewed papers, journal articles, and proceedings.

Each personality type varied from the other as each dimension exhibited different habits, attitudes, and the way they viewed the world. Extroversion and Introversion (E-1) describe the preference for existence, Sensing and Intuitive (S-N), describe how a person prefers to gather knowledge, Feeling and Thinking (F-T), represents the person's preferred method of conclusion, and Perceptive and Judging (P-J), describes how a person prefers to make decisions [15]. It is no surprise that the MBTI is so well-known. The conclusions of studies on the MBTI's reliability and validity were satisfactory [16].

B. Five-Factor Model (FFM)

The Five-Factor Model (FFM) is a widely used personality indicator. Robert McCrae and Paul Costa created this model, which defines personality in terms of five main elements [17]. According to psychologist Lewis Goldberg, FFM is also known as the "Big Five" Personality Factors, and he developed the International Personality Item Pool (IPIP), which is a database of descriptive statements linked to each feature [18]. The indicator is often referred to as OCEAN, which is an acronym for the five broad factors (openness, conscientiousness, extraversion, agreeableness, neuroticism) and three basic needs, the need for influence, the need for security, and tranquillity [19].

The first FFM element is openness to new experiences. This personality attribute refers to a desire or ability to adapt to changing experiences and adjustments [20]. The second FFM factor is conscientiousness, which refers to a person's ability to concentrate on their objectives or task [21]. The third factor of FFM is extraversion, which is typified by a trusting and optimistic attitude toward others and is linked with someone being gregarious, aggressive, and chatty [22]. The fourth factor is agreeableness, which is frequently associated with a proclivity to be conscientious and collaborative [22]. Finally, neuroticism is a measure of an individual's psychological development [20]. FFM was selected as a superior alternative to other indicators for use as a personality indicator since FFM scores had a complete influence on class distribution and simpler prediction tasks [23].

The FFM is statistically accurate, with each component having a high level of 'constructive validity,' which guarantees that any one of the traits fits Adam Grant's four category requirements. Unlike the MBTI, the FFM has a higher prediction accuracy [24]. FFM is favoured, particularly in academic settings. The MBTI test result is quite inaccurate. If a person retakes the test after 5 weeks, there seems to be a 50% possibility that he or she will be allocated to a certain type of test. In other words, reliability is equivalent to a coin toss [24]. Table 1 shows each personality trait according to FFM and their description based on their scores.

TABLE I. THE SUMMARY OF THE FFM

Personality Trait	**Score**	
	Low score	***High score***
Openness	Favors conservative values, judges in conventional terms.	Values intellectual matters, rebelling, non-conforming
Conscientiousness	Self-indulgent, engages in daydreams	Behaves ethically, dependable, responsible
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

IV. INFORMATION VISUALIZATION

The increasing relevance of data analytics in today's world has given rise to information visualization. Data analysis enables individuals to extract data, think critically, and aid decision-making [25]. Data is any fact, quantity, or piece of information gathered for the purpose of the study. For example, to construct a research study, sufficient data must be gathered to confirm the theory presented in the research paper; therefore, the analytical process is happening [26]. This method has significantly contributed to modern cultures, such as describing a country's economic prosperity, a graphical PowerPoint presentation about a topic in an institution, or as basic as retelling a tale to a toddler [27]. Humans prefer to comprehend things they perceive, understand, or sense, regardless of the evidence present; witnessing is strongly associated with reality [28]. Because of its broad array of applications throughout many fields, the fascinating and lively topic of information visualization has become an extremely important area of research. With the use of the human visual system, information visualization is critical to the interpretation of large, complicated data sets.

The information spreading has been unprecedented since the digital age. The goal of visual design in information visualization is to maximize the visual appeal and utility of a design/product by the use of proper imagery, font, whitespace, design, and coloring [29]. The visual design contributes to a more in-depth comprehension of both the function of software as well as its consumers; hence, examining the link between visual designs and personality may assist designers in focusing on the development of the UI (User-Interface and its adaptability suiting the users [26]. Organizations have followed a data-driven approach and used visualization techniques to disseminate information visualization, but this may also prove to be more detrimental to the goals if the audience does not understand the visualization [30]. One example is the use of visualizations during a development session while interacting with the source code utilizing Integrated Development Environments (IDEs) such as browsers, debuggers, and inspectors [31]. Minelli, Baracchi, Mocci, and Lanza's (2014) study encapsulates the interaction between developers and the IDE by employing a recording tool, DFlow. The DFlow visualization aids in providing a deeper understanding of the developer's actions within the IDE. For instance, the developer frequently opens all the windows on the upper left side of the screen, obscuring the upper half of the large window. The information gathered was leveraged to gain a better understanding of developer habits when working with the IDE.

Recognizing the viewers makes visual analytics more pleasant to interpret, as well as the narrative process is much easier to build. The power to make narratives from information has become incredibly useful in the era of information and the demand for data-based policymaking. Whenever it comes to sharing scientific studies, soliciting funding for a non-profit, delivering to a corporate board, or just proving a statement over to the crowd, effective information visualizations may be the key differentiator [30]. Findings suggest that individual personality distinctions correspond strongly with users' preference for InfoVis. The goal of information visualizations is to assist people in exploring, navigating, and comprehending vast amounts of data to convert it into skills and data [32].

V. DATA STORYTELLING

Data storytelling is a process of employing information to create a narrative. Data storytelling is becoming an excellent process of leveraging visualization tools since it has the potential to boost communication effectiveness [9]. Data storytelling can take numerous forms, such as a billboard including information to convey a message, PowerPoint slides by students to a professor and peers, and a financial review in the finance industry. Communication with audiences lacking high analytical abilities is challenging, especially when dealing with visualizations of complicated theories, concepts, or issues that utilize extensive computational, visual, and interactive approaches [33]. The researchers indicated that the way the content was displayed might be too sophisticated for the intended audience [33]. Figure 2 below shows the various uses of data storytelling.

Visualization enables users to swiftly absorb massive volumes of data in a visual system by communicating everything through graphical representation, including bar charts. [34]. On the other hand, some visualizations place excessive pressure on viewers because they are frequently presented without adequate direction. If the viewer has never seen an image before, he or she must learn how to understand it through his or her effort [35]. Data storytelling, according to Dolan, is more than just data visualization or technological expertise. It blends storyline and verbal and textual presentation skills to ensure the smooth operation of knowledge to the viewer [36].

Fig. 2. Various us data storytelling.

To make successful storytelling, one must consider the human factor such as the effectiveness of the views, visual style, attractiveness, visualization literacy, the type of audience, profession, educational background, perceptiveness toward the presenter and data visualization, and the information that the audience desired, are the factors that need to be known that can help in making successful storytelling from knowing the importance of a good understanding of the context [37]. Bach (2017) uses data comics to communicate facts and data. Data comics are influenced by various graphical genres that portray motion and order [38]. Storytelling has recently received a lot of interest in the visualization domain, especially when interacting with audiences. Figure 2 show various use of data storytelling in daily life. A previous study found that communicating with viewers who lack advanced analytic skills is difficult, particularly when working with visualization of complex information that employs complicated algorithmic, graphic, and interactive techniques. The researchers also stated the way to present that information could be too nuanced for target audiences [33].

Nonetheless, data storytelling might be considered a new language for information visualization. Especially compared to past studies, data storytelling requires a tremendous amount of visual design aesthetic. This necessitated presenting analytical data in simpler forms are often used in graphical storytelling systems. To create a great storyline, data storytelling highlights the importance of choosing the appropriate material to communicate with intended audiences [33].

VI. Incorporating Personality in the User-Interface of the Visualization Tools

Several studies show a relationship between personality and hierarchical visual designs. According to a recent study, personality influences how people communicate with visuals [8]. In a study exploring the motivations to use business intelligence (BI) tools by incorporating the technology acceptance model (TAM) and the five-factor model, the researchers determined that individuals with greater conscientiousness seem to be keener to discover ways of using new tech that will facilitate them to achieve positive results by the hypothesized model used by a structural equation modeling (SEM) [22]. In another study, the authors performed a user assessment in which respondents were requested to respond, search, and causal inference queries about data in four basic hierarchy visual representations in an attempt to discover an affiliation between the visualization framework and a locus of control and other personality variables [39]. Locus of control (LOC) measures the degree to which individuals view themselves as in control of events (internal) rather than being governed by outside events (external) [39]. The study found that people with a stronger internal LOC perform substantially slower on inferential tasks but do as well on search tasks. Inferential tasks demand a user to reach an unprompted decision depending on their problem-solving and reasoning abilities [40]. A common inferential task used in evaluating visualization, for example, is as follows: "In the visualization, note that there is a link between data elements A and B." "Does the same connection appear elsewhere in the data?" [40]. An example of s search task question is, “Within the classification ’Batrachuperus,’ which species were most recently updated?” [39]. Prior study indicates that visualizations assist the author in distinguishing between internal and external locus of control, as well as the difficulties encountered when utilizing each visualization’s interfaces.

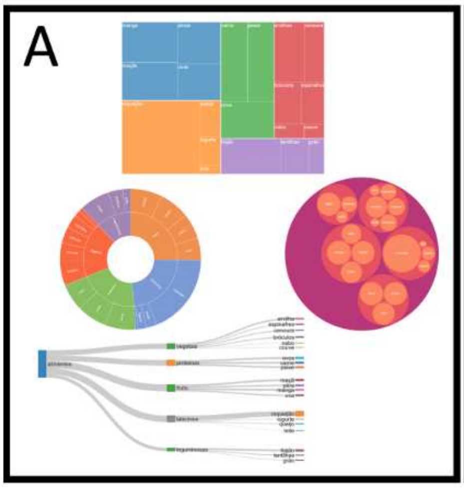

Fig. 3. Hierarchical visualization – Treemap, Circular Packing, Sunburst, and Sankey diagram. Photo from a research paper title Incorporating personality in user interface design: A review by Alves, Natálio, Henriques-Calado and Gama, 2020 [8].

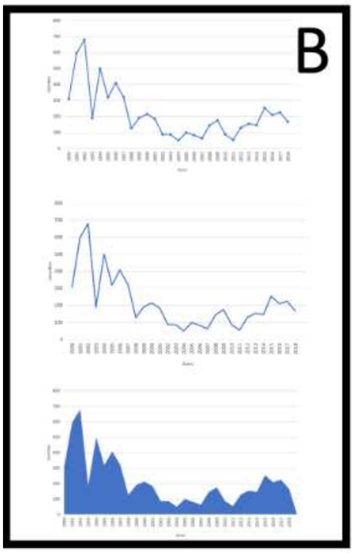

Fig. 4. Evolution over time visualization – Line charts with and without points and an area chart. Photo from a research paper titled Incorporating personality in user interface design: A review by Alves, Natálio, Henriques-Calado and Gama, 2020 [8].

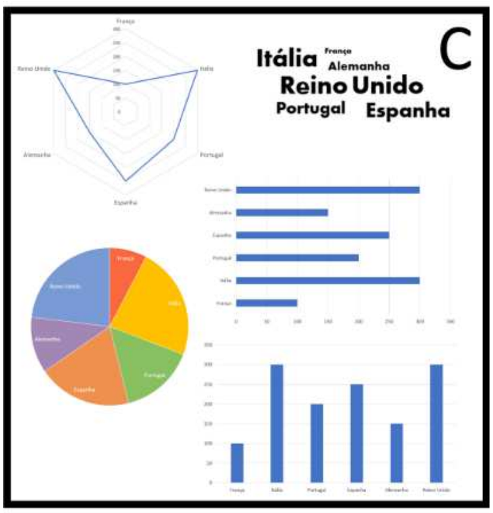

Fig. 5. Comparison visualization – Radar chart, Word Cloud, Pie Chart, and Horizontal and Vertical bar. Photo from a research paper titled Incorporating personality in user interface design: A review by Alves, Natálio, Henriques-Calado and Gama, 2020 [8].

A previous study explored whether personality affects user perceptions of visual design style. They employed hierarchical evolution over time and comparison visual designs [8]. Figures 3,4, and 5 show the example of a hierarchy, evolution over time, and comparison visualization. The researcher utilized three distinct types of surveys with 64 participants. The researchers noted a link between each participant's user choices and personality type. The finding of the research show individuals with neuroticism are opposed to line charts with points, but individuals with high and medium extraversion prefer the sunburst visual style in the hierarchy category. Individual with high conscientiousness prefers line charts with points, whereas those with low conscientiousness prefer sunburst charts. These analysis results encourage incorporating in-depth personality synergies with InfoVis into the visualization framework design process [8]. Distinct visual styles or layouts, according to Ko and Liu, 2019, can impact the user preferences of users from various populations [11]. They polled 249 people in their study to explore user white-space ratio expectations for journalism web pages. They selected examples from the top ten news sites worldwide as well as the top ten websites in Taiwan. Individuals aged 31 to 45, even those over 61 and above, prefer websites with less white space, according to the data. The majority of users disliked messiness, complexity, wordy sites, ambiguous layout, and blogs that appeared like flyers, according to the findings of this survey.

Ottley, Yang, and Chang (2015) conducted a study using two hierarchical visual designs, an indented tree and a dendrogram, to assess how LOC influences user preferences and effectiveness for each visual design. Figure 6 shows the visual design of both the Indented Tree and Dendrogram. Researchers found a strong correlation between LOC and visual designs. They discovered that external LOC dealing with the indented tree was nearly twice as quick as dealing with the dendrogram, and vice versa, compared to Internal LOC [41]. The researcher utilized Amazon's Mechanical Turk, a website where requesters may offer labor as Human Intelligence Tasks (HITs), to enroll 54 individuals to study how the personality attribute locus of control (LOC) influences user search tactics. They also discovered that externals LOC fit brilliantly with the indented tree, whereas internals performed better with the dendrogram. This study contributed to a deeper understanding of how variations affect visualization utilization and how researchers may work to expand visualizations that best suit customers' cognitive demands.

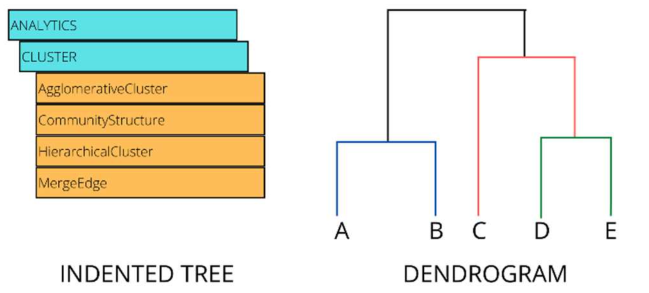

Fig. 6. Visual designs of Indented Tree and Dendogram

The combination of several visual design styles to make data storytelling makes it unique for future research. For example, one of the visual designs of data storytelling, magazine style, consists of font styles, font size, the density of information in the visual, and the position of images. This research provides some recommendations including focusing on user preferences based on personality traits and data storytelling.

CONCLUSION

This work contributes to a deeper understanding of personality, data visualization, and storytelling. Business analytics programs such as Microsoft Power BI or Tableau may be able to implement their services according to the user's personality by attempting to make their services more adaptable and cater to various types of individuals. Exploring the effect of personality and user preferences on information visualization and storytelling is necessary and beneficial in this data-driven world. This paper may help in improving the effectiveness of the design-related teaching and learning process. It is especially hard to construct such mixed-initiative data storytelling tools since visualizations are widely supported to aid complicated reasoning and decision-making. Yet, efficient adaptable solutions can significantly improve a user's capacity to execute a wide range of jobs.

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