Accessible Data Visualization for ASRS-Positive University Students: A Multi-Criteria Analysis of Performance Efficiency and User Engagement

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Declaration

It is hereby declared that

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Abstract

Attention-Deficit Hyperactivity Disorder (ADHD) creates substantial educational and economic challenges, but digital information architecture often overlooks neurodiverse cognitive profiles, which results in overcrowded designs that cause cognitive overload. The study focuses on the effectiveness of the various data visualization formats on the processing efficiency and physiological stress among University students classified by the Adult ADHD Self-Report Scale (ASRS v1.1). The methodology employed a multi-criteria experimental study with 70 participants (40 ASRS-negative, 30 ASRS-positive) evaluating eight different visualization formats: Plain Text, Highlighted Text, Bar Charts, Bar Charts with Images, Pictographs, Simplified Infographics, Detailed Infographics, and Text modified by Artificial Intelligence. Inverse Efficiency Score (IES) was used to measure performance, and medical-grade pulse oximeters recorded real-time physiological stress measurements. Statistical rigour was ensured using Two-Way Mixed ANOVA, Linear Mixed-Effects Models (LMM), MANOVA, Bonferroni correction and Bayes Factors. Results revealed a very strong level of interaction ($p < 0.001$) that visualization formats have different effects on individuals with ADHD or ADHD likelihood. Plain Text, Bar Charts, and Bar Charts with Images maintained almost similar cognitive equity between both groups. Contrarily, Detailed Infographics and AI-Modified Text caused severe performance impairment (Hedges' g = -1.775 and -1.162, respectively). Paradoxically, traditional attentional aids like text highlighting acted as visual noise, impairing ASRS-positive performance. Moreover, a critical finding revealed preference-performance dissociation: ADHD and ADHD-likelihood (ASRS-positive) individuals favoured visually complex designs that objectively hindered their accuracy and processing speed, underscoring the necessity for empirical metrics over subjective feedback. The practical design suggestions presented in the findings are based on concrete, empirically grounded results to establish digital learning environment settings that accommodate ADHD and ADHD-likelihood population.

Keywords: ADHD, Neurodiversity, ASRS (Adult ADHD Self-Report Scale), Accessible Data Visualization, User-Centred Design (UCD), Inverse Efficiency Score (IES), Biofeedback, Human-Computer Interaction (HCI), ANOVA, Linear Mixed-Effects Models (LMM), MANOVA, Preference-Performance Dissociation

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Our gratitude goes to the Institutional Review Board (IRB) of Brac University that reviewed the ethics and ensured the utmost privacy and professional responsibility.

We would like to wholeheartedly thank all the students at the university communities that participated in the study as volunteers. Their input gave the empirical basis in determining the safe and accessible data visualization format that the university students can use to make their work and life more efficient and easier.

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Chapter 1

Introduction

1.1 Background

ADHD is a neurodevelopmental condition where there are persistent patterns of inattention, hyperactivity, and impulsivity that interfere with daily functioning [1]. Global prevalence estimates suggest that around 5 - 7% of children and 2.5% of adults have symptoms of ADHD [2], [3], with university populations having high rates of 2 - 8% [4]. In wider South Asian settings, prevalence estimates vary between 6 - 12% from school-aged populations [5]. Still, research addressing the specific needs of university students suffering from the likelihood of having ADHD is critically limited.

The economic and societal cost of having an individual with an ADHD diagnosis is high. Research suggests that untreated ADHD leads to about 12% loss to income [6], with direct financial costs of more than $7.45 billion and well-being costs of $5.31 billion in a year [7]. Students with ADHD exhibit significantly poorer academic achievement, where 79% score below their neurotypical peers [8]. These individuals are at higher risk for dropping out, getting retained, and lower GPAs [9], with cascading effects throughout their professional lives.

Data visualization has now become ubiquitous throughout academia, the workplace, and in personal life, and is a central medium for information comprehension and decision-making [10]. Modern educational environments are increasingly dependent on the presentation of data in visual form, ranging from lecture slides containing charts to online learning dashboards, requiring students to make rapid sense of a variety of data visualization formats. However, conventional visualization design guidelines are created primarily for neurotypical populations, which can lead to systematic accessibility barriers for individuals with ADHD symptoms [11].

Despite increasing awareness of the importance of accessible visualization design [12], empirical research related to the specific cognitive processing issues associated with an individual with ADHD is rare. The field has made incredible progress in accommodating visual impairments, including color vision deficiencies [13], [14] and blindness [15], [16], but neurodiversity informed design principles are largely absent from mainstream accessibility frameworks.

A standardized screening tool for the likelihood of having symptoms of ADHD in adult populations is the ADHD Self-Report Scale (ASRS v1.1), which was developed by the World Health Organization (WHO) [17], [18]. With a specificity of about 99%, this tool allows researchers to systematically examine the cognitive differences between ASRS-positive (high likelihood of having the symptoms) and ASRS-negative cohorts, providing a means to conduct rigorous research on accessibility within the university setting.

1.2 Rational of the Study

The academic difficulties encountered by university students with ADHD have been well-documented. These individuals face severe problems in their ability to pay attention for a sustained period, their working memory, and executive functioning [19], [20], which directly affects their ability to process information-dense visual materials. When faced with cluttered or badly organized visualizations, students with symptoms of ADHD often suffer from cognitive overload, resulting in a less efficient capacity to comprehend [21].

Recent groundbreaking work by Tran et al. [22] has demonstrated that individuals suffering from ADHD exhibit unique patterns of response to visualizations, such as color schemes, text density, and visual embellishments. Their crowdsourced study (n = 147; 70 ADHD and 77 Non-ADHD) found that while color hue had no differential effects, text annotation density and task-relevant pictographic embellishments had significant task-dependent effects on performance. Critically, they found a preference-performance dissociation: the participants with ADHD preferred formats that were high in visuals, which did not correlate with good response times or accuracy [22]. However, this study considered isolated elements of a chart (color, text, embellishments), instead of full format comparisons, leaving a critical gap that is addressed in this research.

Furthermore, the geographic concentration of research on the topic of ADHD in the Western world context [23] restricts the generalizability of the existing research findings to Global South populations. University students in the broader South Asian areas lie in a critically underserved population in accessibility research and require culturally situated empirical research.

A critical methodological gap exists in the reliance on subjective self-report measures without physiological validation. While participants can indicate perceived difficulty or preference, these subjective ratings may not be an accurate representation of actual cognitive strain. ADHD sufferers can habituate their high mental effort levels or blame physiological stress, so biometric objective validation is useful to obtain conclusive results.

1.3 Problem Statement

Individuals with ADHD have a high likelihood of having systematic difficulties in processing visualizations of data due to executive function deficits, attentional control difficulties, and susceptibility to visual distraction [24], [25]. Current visualization design frameworks fail to adequately take these neurocognitive differences into account, leading to three critical problems: first, current accessibility standards, such as WCAG [26] and Chartability [12], are primarily focused on individuals with visual impairments, with very little information as to what full visualization form is most effective in working with individuals with ADHD. Designers do not have empirical data about the complete visualization formats that maximize comprehension while minimizing cognitive overload for users who are very likely to have ADHD. Second, preliminary evidence does suggest that ASRS-positive individuals may be biased toward visually complex formats such as Detailed infographics that actually reduce their processing efficiency [22], [27]. This preference-performance gap, which is based on the aesthetic-usability effect [28], [29], makes it hard to rely on user feedback alone. Without some objective evaluation of performance, designers can produce visually appealing interfaces that are paradoxically counterproductive to the accuracy and speed of the user with ADHD. Third, earlier reports on the feasibility of visualization for difficulties associated with the average student with ADHD have been based mainly on self-reports of difficulty without physiological validation of cognitive load [22]. Subjective measures do not allow one to differentiate with certainty between actual neurophysiological stress and motivational factors or habituation to the experienced high level of mental effort. These gaps collectively make it difficult to create inclusive digital learning environments that support cognitive equity, the notion that neurodiverse students should be able to mine information from visualizations with the same efficiency as their neurotypical peers.

1.4 Objective

This study is aimed at establishing an evidence-based framework for accessible data visualization design targeted at ASRS-positive university students through multi-criteria empirical evaluation. Specifically, the primary objective is to identify visualization formats that maintain cognitive equity, defined as equivalent processing efficiency between ASRS positive and ASRS negative cohorts through rigorous statistical comparison of performance metrics. As far as the secondary Objectives are concerned, the first is to quantify the differences in format-specific performance, using the Inverse Efficiency Score to quantify the speed-accuracy tradeoff in eight complete visualization formats: Plain Text, Highlighted Text, Bar Charts, Bar Charts with Images, Pictographs, Simplified Infographics, Detailed Infographics, and AI-Modified Text. This metric allows a unified measure of processing efficiency, especially appropriate to research on the role of ADHD, in which fluctuations of attention generate variable response patterns. Second, to validate cognitive load as measured by physiological markers by using medical-grade pulse oximeters to obtain real-time heart rate and blood oxygen saturation (SpO_2). This gives us objective evidence for mental strain beyond self-reported ratings of difficulty as evidence of whether or not performance differences are due to real neurophysiological stress or motivational factors. Third, to investigate the preference- performance dissociation by using Pearson correlation analysis to quantify the relationship between subjective users' preference and objective processing efficiency. This helps to determine whether ASRS-positive people can correctly self-identify which formats are optimal for what they do best and fills a critical gap between what users prefer and what actually helps them. Fourth, to produce actionable design guidelines by synthesizing the findings using advanced statistical methods, namely Linear Mixed-Effects Models (LMM), Two-Way Mixed ANOVA, MANOVA, Bonferroni correction, and Bayes Factors. This rigorous statistical framework allows for the classification of formats as safe (cognitively equitable), equivocal (statistically unstable), or contraindicated (performance-impairing) for ASRS-positive inclusive design.

Ultimately, this research aims to move beyond the subjective feedback and is aimed at establishing empirically validated design principles that can allow students with ASRS-positive to process visual information with similar efficiency to their neurotypical peers, which will support the grand design of cognitive equity in digital learning environments.

Key Research Objectives:

- Identify visualization formats that can enable ASRS-positive university students to have processing efficiency comparable to neurotypical peers through multi-criteria empirical evaluation.
- Quantify the speed-accuracy tradeoff in eight visualization formats using the IES to account for the fluctuations of attention in ADHD persons.
- Validate cognitive strain, using heart rate and SpO_2 data from pulse oximeter to identify true neurophysiological stress from subjective or motivational factors.
- Measure the correlation between user preference and objective efficiency in order to see whether ASRS-positive people can accurately self-identify which designs actually optimize their performance.
- Synthesize statistical findings into actionable guidelines by classifying formats as safe, equivocal, or contraindicated with respect to inclusive data visualization design.

1.5 Scopes and Challenges

Scopes:

This research is solely focused on university students (age: 19 - 25) representing underrepresented perspectives from the Global South in the study of persons living with ADHD. Participants are tested with the WHO ASRS test [17] rather than clinical diagnosis, and the results are related to the likelihood of symptoms of ADHD, but not to medically diagnosed populations. Static visualizations are evaluated in an experimental protocol consisting of timed comprehension tasks in controlled laboratory conditions.

Challenges:

- **Age Restriction:** Findings may fail to generalize to children, adolescents, or older adults because of developmental differences in the symptoms of ADHD and the ability to compensate for cognitive deficits [18].

- **Screening Tool Specificity:** Although ASRS (v1.1) is highly sensitive (specificity 99%), it is not the same as clinical diagnostic gold standards [17], [18].

- **Environmental Control:** Testing in distraction-reduced laboratory settings may be out of context with the real-world academic situation involving ambient noise, multi-tasking demands, and time pressure.

- **Cultural Specificity:** Participant homogeneity (South Asian university students), which may limit generalizing to Western or other non-Western populations, but also a benefit in terms of addressing research gaps.

- **Static Visualizations:** This study focuses on non-interactive/static visualizations. The results may not apply to interactive dashboards and animated presentations of data.

- **Preference-Performance Gap:** The study found that ASRS-positive users tend to favor formats that are objectively detrimental to their performance, and this highlights that user feedback is not enough to evaluate accessibility.

1.6 Significance of the Study

This research contributes to three domains:

- **Theoretical Contribution:** Extends Cognitive Load Theory [30], [31] to the context of the specific symptoms of the disorder to show that extraneous visual elements impose a disproportionate mental strain on ASRS-positive cognition. Establishes phenomenon of preference-performance dissociation as a critical consideration in the neurodiverse user experience research to go beyond the aesthetic-usability effect [29].

- **Methodological Contribution:** Pioneers combining performance metrics integration (IES), physiological validation (biometric monitoring), and cutting-edge statistical rigor (Linear Mixed-Effects Models, ANOVA, MANOVA, Bonferroni correction, Bayes Factors) into a gold-standard protocol for accessibility research. Illustrates the need for multimodal forms of empirical validation in neurodiverse populations for subjective feedback to be adequate.

- **Practical Contribution:** Offers immediately actionable design guidelines for educators, learning management system developers, and information designers who are creating content in university environments. Identifies specific safe formats (Plain Text, Bar Charts, Bar Charts with Images) while identifying contraindicated formats (Detailed Infographics, AI-Modified Text) that can potentially enhance academic outcomes for a large number of ASRS-positive students around the world. Bringing critically needed Global South perspectives into an overwhelmingly Western research corpus [23].

1.7 Thesis Organization

To arrange this thesis, six chapters provide systemic considerations to the research about accessible data visualization to ASRS-positive university students.

- **Chapter 1:** Introduction provides the background of the research by stating the effects of ADHD on cognition, explaining the research gap of no empirical guidelines on neurodivergent populations, and stating the goals of identifying visualization forms that retain cognitive equality between neurodivergent populations and ASRS-negative groups.

- **Chapter 2:** Literature Review reviews the literature concerning ADHD cognitive processing, accessible visualization design, and Cognitive Load Theory, and finds some gaps that are vital parts of the lacking literature literature such as the lack of complete format comparison, the existence of preference-performance dissociation phenomenon, and the lack of physiological validation in previous studies.

- **Chapter 3:** Requirements, Impacts and Constraints outlines the technical specifications, ethical issues such as IRB approval and medical panel supervision, and the seven-step project management plan in assessing the eight format visualizations and full risk management and sustainability procedures.

- **Chapter 4:** Proposed Methodology gives a multi-criteria evaluation framework consisting of 70 participants (40 ASRS-negative, 30 ASRS-positive), the use of Inverse Efficiency Score (IES), cognitive load measures, and additional statistical analysis using Two-Way Mixed ANOVA, Linear Mixed-Effects Models, MANOVA, and Bayes Factors.

- **Chapter 5:** Result Analysis contains empirical results indicating the existence of significant effects of interaction ($p < 0.001$), safe formats (Plain Text, Bar Charts, Bar With Images), equivocal formats (Pictographs, Simplified Infographics), and contraindicated formats (Detailed Infographics, AI-Modified Text, Highlighted Text) with physiological support and full statistical evidence.

- **Chapter 6:** Conclusion provides a summary of the key finding, which is that simple, clean designs can be useful both in ADHD and neurotypical students, and also presents design guidelines based on empirical evidence. It also states how the study made contributions to available design knowledge and offers suggestions on future research, such as conducting experiments with different age groups, in real classroom conditions, as well as creating adaptive artificial intelligence systems capable of automatically adapting to the cognitive abilities of individual users.

Chapter 2

Literature Review

2.1 Preliminaries

There are existing research on the cognition involved in ADHD, available data visualization, and cognitive load to form the theoretical and empirical basis for this study. ADHD is a neurodevelopmental disorder characterized by persistently occurring patterns of inattention, hyperactivity, and impulsivity that cause impairment in day-to-day functioning [1]. Data visualization describes the act of visualizing information and data through the use of visual tools such as charts, graphs, and infographics [10]. Accessibility in visualization refers to ensuring that people from diverse populations, including people with disabilities, can perceive, understand, and interact with the visual data effectively [11]. The ASRS test is a standardised screening tool created by the World Health Organization WHO to assess the likelihood of having symptoms of ADHD in adult populations [17], [18]. This literature review discusses the intersection between these concepts and identifies key gaps in current research.

2.2 Review of Existing Research

2.2.1 ADHD and Cognitive Processing

Neurocognitive Characteristics of ADHD

The core features of an individual with ADHD are impulsivity and hyperactivity due to deficits in executive functioning, working memory capacity, and inhibitory control [19], [20]. Barkley's influential theory suggests that behavioral inhibition is the core deficit in the diagnosis of ADHD, which in turn causes problems in four key areas: working memory, self-regulation of emotions and motivation, internalization of speech, and the ability to break down and reconstruct behaviors [19]. Research supports this theory by indicating significant working memory deficits in populations with ADHD, where effect sizes are medium to large in both the spatial and verbal domains [20].

Brain imaging studies showed differences in the structure and function of areas of the brain that are important for regulating attention. There is research that indicates immature development of the cortex in those with an ADHD diagnosis, especially in the prefrontal areas involved in cognitive control and attention [32]. These neurobiological differences manifest behaviourally as heightened susceptibility to distraction when visual environments have high information density or competing stimuli [21].

A critical theoretical framework for understanding the role of the visual in ADHD is Perceptual Load Theory [24]. This theory suggests that attentional selection is dependent on the level and type of perceptual load in the current task. Under conditions of high perceptual load, when task relevant processing fully utilizes mental capacity, irrelevant distractors are not seen. In contrast, under low perceptual load, the irrelevant distraction is involuntarily processed [24] by the spare capacity.

Importantly, Forster and Lavie [25] showed that by increasing perceptual load, distraction can actually be decreased in ADHD individuals. Their study showed that the ADHD participants showed high levels of distraction under low load conditions, but under high perceptual load, this distraction was eliminated [25]. This implies that the critical design distinction is not simply between simple and complex visualizations. Instead, the important distinction is between task-relevant complexity (focuses attention) and extraneous visual clutter (competes for attention).

Speed-Accuracy Tradeoffs and Response Variability

A well-established finding in the study of the cognitive impairment of ADHD is increased variability in reaction times across a range of cognitive tasks [33], [34]. Kofler et al.'s meta-analysis of 319 studies showed that populations with ADHD have far higher variability in their response times that reflects moment-to-moment variability in attentional engagement [33]. This is not just random noise, but represents a basic neurocognitive characteristic with diagnostic utility [34].

Critically, this variability does not equally impair accuracy. Research on hyperfocus, a state of intense concentration on tasks of high intrinsic interest, shows that the performance of persons with ADHD. is comparable to that of neurotypical persons, frequently at a greater cognitive cost [35], [36]. Under conditions of high motivation or optimal task alignment, therefore, the processing speed in the case of people with ADHD may be even superior in comparison, but also accompanied by an increased mental effort [35].

This phenomenon makes it necessary to use evaluation metrics that count for measures of both speed and correctness at the same time. Simple measures of accuracy may overlook the high level of mental effort that is necessary to achieve the accuracy. In contrast, response time alone may indicate rushed and inaccurate processing. The Inverse Efficiency Score (IES) overcomes this limitation by computing the ratio of response time to accuracy, creating a common metric especially suited for use in studies of ADHD in which fluctuations of attentional functions result in variable response patterns [37], [38].

2.2.2 Accessible Data Visualization Research

Current State of Accessibility

The field of accessible visualization has mainly focused on accommodations for sensory impairments in the past. Substantial advances have been made in handling color vision problems through perceptually uniform color schemes [13], [14], to address the needs of blind and low vision users through alternative text and sonification [15], [16], and to prevent photosensitive seizures [39].

Recent work has started in the field of expanding to cognitive and developmental disabilities. Wu et al. [40], [41] have conducted fundamental research on the data experiences of people with intellectual and developmental disabilities (IDD). In their work, they showed that there are significant differences in both abilities and preferences in IDD subtypes. Their results showed that people with autism spectrum conditions preferred abstract representations, whereas the other groups of people with IDD favored more concrete, embellished visualizations [40].

A comprehensive evaluation framework called Chartability [12] is the current best practice in accessibility evaluation. It includes seven principles: perceivable, operable, understandable, robust, compromising, assistive, and flexible. While Chartability recognises attention related disabilities, only minimal empirical guidelines for the selection of a specific format for ADHD populations are provided [12].

Similarly, the Web Content Accessibility Guidelines (WCAG) [26] focus on the perceivability principle for the content, which means that the information must be presentable to users in ways they can perceive, and the interface components must be operable. However, in terms of neurodiverse populations, optimization for cognitive load is not covered in WCAG. This is a critical gap because it is the way information is processed, and not if it can be perceived.

Empirical ADHD-Visualization Research

The most comprehensive empirical investigation of specific visualization processing in the context of ADHD is the study by Tran et al. in 2024 [22]. Using crowdsourced methodology and 147 participants (70 people with ADHD and 77 without an ADHD), they systematically manipulated three elements of the charts to understand how ADHD people interact with visualizations.

For color hue, they experimented with using ColorBrewer palettes in red, blue, green, and gray. They found no significant differences in performance between the groups with and without ADHD [22]. This finding is in contradiction to previous hypotheses based on dopaminergic theory, suggesting blue-yellow discrimination deficits in ADHD [11]. The null finding indicates that color choice, while important for general accessibility, is not differentially important to populations with ADHD.

For text annotation density, for both groups, optimal performance was achieved with minimal textual annotation, consisting of axes labels only. Performance degraded significantly as annotation density increased from including some data labels to extensive data labels and descriptions. Critically, there was no differential impairment in the ability of the individuals with ADHD with respect to the controls, which indicates that visual clutter on the text also has a similar impact on the population of neurotypical individuals [22].

For visual embellishments, there were task-dependent effects for pictographic representations. Pictographs increased accuracy for ratio-type questions and min/max identification tasks and disrupted accuracy for search-based tasks involving the need to extract precise values [22]. This is in accordance with Perceptual Load Theory [24], [25]. When the pictographic icons are task-relevant, for example, indicating which category is the largest, they have a beneficial effect on perceptual load. When it is task-irrelevant, such as an exact numerical value, they are distractors.

The most significant result from Tran et al. was the preference-performance dissociation. They documented that the preferred format for the presentation of information for the subjects in the group of those with ADHD was visually rich formats, such as extensive annotations and pictographs that were not correlated with optimal response times or accuracy [22]. This dissociation indicates that for the populations with ADHD, subjective appeal and objective effectiveness are not parallel, and thus user centered design approaches based primarily on feedback of user preferences [27], [42].

While groundbreaking, Tran et al.'s study has important limitations. They focused on isolated elements of charts, e.g., color, text quantity, and embellishment, rather than on entire format comparisons. Real-world design consists of decisions between fundamentally different modes of presentation: Plain Text paragraphs, Bar Charts, Infographics, or AI generated/modified contents. Additionally, their large reliance on the self-reported diagnosis of an individual with ADHD without standardized screening and a lack of physiological validation restricts the conclusiveness of their findings [22].

General Visualization Design Principles

Principles of visualization were established and based on that the initial guidance is provided, but their application to the ADHD populations will need to be empirically tested. The principle of data-ink ratio proposed by Tufte is to use as much ink as possible when displaying real data and exclude the use of chartjunk, or superfluous graphic elements [43]. This theoretically coincides with the minimization of non-essential factors of extraneous cognitive load among ADHD users.

The argument on embellishing has contradictory data on visual embellishments. Borkin et al. [44] showed that visualizations that showed greater visual distinctiveness, such as embellishments, those formats showed better memorability in recognition. On the other hand, Gillan and Richman [45] discovered that decorative features did increase the time needed to respond, but they did not enhance the task understanding. Haroz et al. [46] have given subtle evidence in the form of pictographs or ISOTYPE visualizations, which enhanced proportional thinking but took more time to see and observe and had an increased error rate in precise extraction tasks [46].

Recent studies show that titles, captions and annotations play a major role in perceived message and user takeaways [11], [47]. Yet, Stokes et al. [48] discovered that readers have varying preferences of the text-chart integration levels and none of them were preferred universally [48]. In the case of ADHD populations in particular, the influence of the density of annotation has not been explored further than the element-level results of Tran et al.

2.2.3 Cognitive Load Theory and Measurement

Theoretical Framework

Sweller's Cognitive Load Theory (CLT) [30], [31] is the main theoretical framework for this study. CLT makes a distinction between three types of cognitive load. First, there is intrinsic load, which is the inherent complexity of the information itself and is determined by element interactivity. This is mostly unchangeable for a given learning objective. Second, extraneous load is unnecessary mental effort that is imposed by poor instructional design, unclear presentation, or visual clutter. This is where cognitive burden can be reduced through design interventions. Third, germane load is cognitive effort that is productive (i.e., schema construction and deep learning). Optimal designs reduce the amount of extraneous load in order to save capacity for germane processing.

For people with ADHD, an increase in baseline cognitive demands in executive functioning effectively reduces the capacity for working memory [19], [20]. This makes them extremely susceptible to extraneous load [21]. Visualization formats that neurotypical users can process easily may be a severe extraneous load on the ADHD cognition and can cause a depletion of resources needed for comprehension, or germane load.

Measurement Approaches

Subjective measures of cognitive load are usually taken by means of single-item clarifications or multi-dimensional tools such as the NASA Task Load Index (NASA-TLX) [49]. Research has shown high correlations greater than 0.8 between single-item ratings of workload and full scores on the NASA-TLX for brief and focused cognitive tasks [49], [50]. Given the brevity of the visualization comprehension tasks, usually 60 to 180 seconds, single-item measures offer efficient measures without the survey burden.

However, subjective measures have one major limitation in relation to people with ADHD. Individuals may normalize high levels of mental effort or be inaccurate in the knowledge of their cognitive strain. This makes objective validation a need.

Objective physiological measures give cognitive load assessment that is independent from self-report. There are some common methods, such as heart rate variability (HRV) where lower HRV is an indicator of higher cognitive load [51], pupillometry where dilation of the pupil is related to mental effort [52], and electroencephalography (EEG) where theta/beta indices are neurophysiological indicators of cognitive load [51].

However, short task durations and relatively low cognitive demands in normal visualization comprehension are likely to result in minor physiological variations [52]. Medical-grade pulse oximeter for taking measurements of heart rate and blood oxygen saturation (SpO_2) gives a viable alternative given its non-invasive nature, continuous measurement capability, and demonstrated reliability in the detection of cognitive stress.

Performance-based measures known as IES correctly address the speed-accuracy tradeoffs by calculating the ratio of mean response time to the proportion. This unified measure is especially amenable for study of the effects of ADHD, in which the levels of attention produce variable response patterns [33], [34]. By penalizing slow responses as well as incorrect responses, IES reflects genuine processing efficiency [37], [38].

2.3 Summary of Key Findings

Table 2.1 summarizes the most relevant literature informing this research.

Table 2.1: Summary of Key Findings.

Authors	Year	Method	Key Findings	Relevance to Current Study
Barkley [19]	1997	Theoretical framework	Behavioral inhibition is core ADHD deficit, causing cascading executive function impairments	Establishes theoretical basis for why ADHD populations experience heightened cognitive load
Willcutt et al. [20]	2005	Meta-analysis (83 studies)	Medium-to-large working memory deficits across ADHD populations	Justifies focus on minimizing extraneous cognitive load in visualization design
Forster and Lavie [25]	2014	Experimental (n = 40)	High perceptual load eliminates distraction in ADHD; low load increases distraction	Critical theoretical foundation: task-relevant complexity may help, clutter harms
Kofler et al. [33]	2013	Meta-analysis (319 studies)	ADHD exhibits elevated reaction time variability across tasks	Justifies use of IES metric that accounts for speed-accuracy tradeoffs
Ashinoff and Abu-Akel [35]	2021	Literature review	Hyperfocus enables ADHD individuals to achieve performance parity under optimal conditions	Explains why some formats may show equivalent performance despite higher effort

Authors	Year	Method	Data Source	Result/Findings
Tran et al. [22]	2024	Crowdsourced study (n = 147; 70 ADHD, 77 non - ADHD)	No color effect; text density affects both groups equally; pictographs are task-dependent; preference-performance dissociation in ADHD	Most directly relevant prior work; current study extends from elements to complete formats
Elavsky et al. [12]	2022	Heuristic evaluation framework	Chartability provides 7-principle accessibility assessment but lacks ADHD-specific empirical guidance	Highlights gap in format-level recommendations for neurodiversity
Wu et al. [40]	2021	Mixed methods (n = 18 IDD participants)	IDD populations show heterogeneous visualization preferences across subtypes	Demonstrates need for subgroup-specific accessibility research
Kim et al. [11]	2021	Design space analysis	Accessible visualization requires addressing perceivability, describability, and interpretability	Establishes broader accessibility framework this study contributes to
Sweller et al. [31]	2019	Theoretical review	Cognitive Load Theory updated: intrinsic, extraneous, germane load types	Primary theoretical lens for understanding why complex formats harm ADHD cognition
Bruyer and Brysbaert [37]	2011	Methodological review	IES provides superior metric for tasks with speed-accuracy tradeoffs compared to separate RT/accuracy analysis	Justifies primary performance metric selection
Hart and Staveland [49]	1988	Instrument development	NASA-TLX correlates highly ($r > 0.8$) with single-item ratings for brief tasks	Supports use of efficient single-item cognitive load measure

Authors	Year	Method	Data Source	Result/Findings
Chen et al. [51]	2016	Methodological review	Multimodal physiological measures (HRV, pupillometry, EEG) provide objective cognitive load assessment	Justifies physiological validation approach, though simpler pulse oximetry used for practicality

Chapter 3

Requirements, Impacts and Constraints

3.1 Final Specifications and Requirements

To conduct this research properly, a specific mix of people, equipment, and software was needed. The selection of the participants was the most significant methodological requirement. Recruitment of a good number of university students between the ages of 19 and 25 was done to conduct this study. It was necessary to utilise the ASRS test published by WHO [17]. This enabled us to divide the group into ASRS-negative participants and ASRS-positive participants. The study also needed to be conducted under conditions of a controlled and quiet environment to avoid the interference of external noise that has the ability to distract the participants or influence their heart rate measurements.

The technical requirements for the data visualization tasks involved creating eight different versions of the widely used visualization formats consisting almost same kind of information difficulty and density. Such formats were Plain text, Highlighted text, Bar charts, Bar With Images, Pictographs, Simplified infographics, Detailed infographics and AI-modified text. To develop the AI-Modified version, a text of the same nature of difficulty and data density as in the other formats was selected and then requested to ChatGPT-4 [53] to make visual edits in the text to make it ADHD friendly. It was done to see if an ASRS positive person had tried this method to make their work or text in hand simpler, what it would be like in comparison with the others. There was a need to have a certain testing plan such that the order of these formats was randomised for each student to ensure that they did not score better or worse on a given task simply because they were tired near the end of the session.

The session was conducted with the help of the LabJS study builder for each of the participants [54]. The platform recorded the participants' answers, individual duration and subjective preference. A medical-grade pulse oximeter was employed to monitor physical stress by recording heart rate and blood oxygen concentration in real-time when working on the visual format based MCQ questions. After collecting necessary data, the IES was calculated by dividing the time on task by the accuracy to obtain numerical value which demonstrates the performance of individuals. The cognitive load which is in fact an inverse of the preference which informs about the mental strain that the individual had to face based on his or her own judgment was calculated. Lastly, to determine whether the differences that were observed between ASRS-positive and ASRS-negative participants were scientifically sound, complex tests such as Linear Mixed-Effects Models, ANOVA, and MANOVA were conducted using statistical software.

3.2 Societal Impact

The findings of this research have a significant impact on several areas of daily life such as health, economy and designing technology to suit all.

Health and Well-being: ADHD is not a childhood issue only. It impacts a large number of adults and leaves them severely mentally distressed and well-being deprived [55]. This study contributes to mitigating the cognitive or mental fatigue experienced by individuals with ADHD and ADHD-likelihood by identifying ADHD-safe formats. By making the digital tools simpler to navigate less frustration, improvement in emotional health, and less stress will occur in individuals, as well as their families.

Social and Economic Impact: ADHD has an enormous economic impact on society. It has been found to cost billions of dollars in lost productivity, and untreated ADHD may result in a significant reduction in the annual earnings of an individual [56]. ADHD students tend to have problems in studying and, therefore, poor GPAs and increased dropout rates. This study can be used to develop superior educational and professional tools by offering evidence-based design principles. This will assist students to work better in their learning institution or learning facility, as well as assist adults increasing their productivity in the workplace, ultimately lowering the general economic cost to society.

Safety and Legal Aspects: In order to observe safety of all the involved participants, the work in this study was pre-screened and validated by the medical specialists. Heart rate and oxygen were monitored by medical-grade sensors to make sure that the mental load of the tasks was not dangerous to the participants. Legally, the Institutional Review Board of Brac University approves this study. This study upholds the right to accessibility in the ethical sense. It demonstrates that for the neurodiverse populations the designers have a role to play in ensuring that the information is presented in a manner that does not alienate individuals according to the manner in which their brains interpret information.

Cultural Aspects: This study focuses on university students in South East Asia, representing the Global South. The majority of the studies conducted on ASRS-positive people in the past have centred on Western countries [23]. Through undertaking this study in an alternative cultural environment, the work aids in ensuring that the support of positive individuals with ASRS is more accommodating to people across the globe. The study urges a shift to cognitive equity, where technology is developed so that it can accommodate the individual differences in neurological requirements of a person, instead of compelling everyone to utilize the complex and distracting technology.

3.3 Environmental Impact

This project is concerned with sustainability in its attempt to develop digital tools that are useful and have functional integrity in the long term. The research did not require large volumes of paper-based testing to run the tests and capture the data; therefore, saving both waste and natural resources by using digital platforms. Such as the LabJS study builder was used to host the tasks and capture the data. All the responses and feedback on tasks were noted digitally, and the study was practically paperless. Technically and in terms of energy, the minimalist designs as recommended by the studies also have a positive impact on the environment. Plain Text and Bar Charts are also simple formats that do not demand high computing powers and energy to load, store and represent in comparison to the high-density and complex infographics. This implies that in case such design guidelines are applied in the real world, the digital devices would consume less battery and electricity to display information. Also, the research involved medical quality sensors produced by recycled materials, such as pulse oximeters, to reduce electronic waste. All in all, the research promotes a more efficient and sustainable means of using technology that is more environment and people-friendly.

3.4 Ethical Issues

In doing research on individuals, particularly those with ADHD and ADHD-likelihood, concern on adhering to strict ethical guidelines and professionalism remains. The following are the key ethical concerns we have dealt with in this study:

Privacy and Data Security: Top priority was given on protecting the privacy of the participants. Since sensitive data (ADHD screening scores and physiological data - heart rate and oxygen levels) was gathered, high levels of security were adhered to. All data was kept confidential, and none of the names were used; the identification number was utilized ensuring that the identity of the participants remained unknown.

Informed Consent and Voluntary Participation: All the individuals were properly informed of what the study was beforehand and their consent was obtained. It was to ensure that all people knew it was all voluntary. They were also informed that they would be able to have breaks whenever they felt or even terminate the study anytime without the penalty.

Professional Responsibility in Design: This study was guided by a strict commitment to professional responsibility, starting with the ethical obligation to ensure participant safety through a medically sound methodology. Instead of the subjective assessment of the task difficulty, formal pre-screening and acceptance of the experimental protocol and task designs were done by a dedicated medical panel and it was confirmed that physiological data monitoring was medically suitable and would not cause physical injury or unjustified stress. This foundational ethical rigor transitions into a clear directive for future designers, who bear the responsibility of fostering cognitive equity by prioritizing minimalist, safe formats for ASRS positive (ADHD likelihood) that reduce the cognitive load on the user's brain. The findings demand that practitioners exercise extreme caution and avoid harmful and ineffective visualizations as these formats often act as contraindicated visual noise that triggers severe performance impairment. Furthermore, designers must ethically rely on objective data like the Inverse Efficiency Score (IES) and other suitable criterias rather than subjective feedback alone.

3.5 Standards

In conducting this research, a number of international and academic standards were adhered to to make the data collection and analysis accurate, safe, and professional. The Adult ADHD Self-Report Scale (ASRS v1.1) was the most significant criterion according to which the participants were selected. It is a consistent screening instrument that was created by the World Health Organisation (WHO) to address the detection of ASRS-positive symptoms in adults. This international criterion was useful in assuring that the clustering of ASRS-positive and ASRS-negative participants was done on an accepted and trusted medical framework utilised by researchers across the world. Moreover, the research was performed in accordance with the ethical and procedural standards of the IRB of Brac University, which reviewed it and approved the plan to comply with all the safety and academic standards.

IES was used to keep the standards of performance measurements high. This is a conventional measure of cognitive psychology that is applied to even the speed v/s accuracy ratio. Through IES, standard scientific procedures were utilised to avoid instances of speed-accuracy tradeoffs in which an individual may appear to be fast just because he or she is committing errors. In the case of the physiological data, the standard was observed with the help of medical grade pulse oximeters to record heart rate and oxygen saturation. They were accurate, constant readings and guaranteed that the profiles of physiological characteristics were based on the quality of medical data and not the irregular sensors.

Lastly, the research was done in strict adherence to the standards of statistical requirements so that research conclusions were not done on a whim. More sophisticated techniques were used such as ANOVA, LMM and MANOVA that are customary in Human-Computer Interaction studies to address multifaceted data. In order to be as precise as possible in conducting several comparisons, Bonferroni correction was used. This is a standard statistical adjustment that makes the testing more strict to avoid errors as to eliminate errors that occur when an outcome is randomly believed to be substantial when it is not. The adherence to the mathematical and medical standard meant that the design recommendations can be founded on strong, reproducible science.

3.6 Project Management Plan

The administration of this research project is spread in a linear planning of seven different phases, combined with a resource management strategy and a low-cost economy framework.

3.6.1 Project Workflow Phases

Figure 3.1 shows the summarized project workflow.

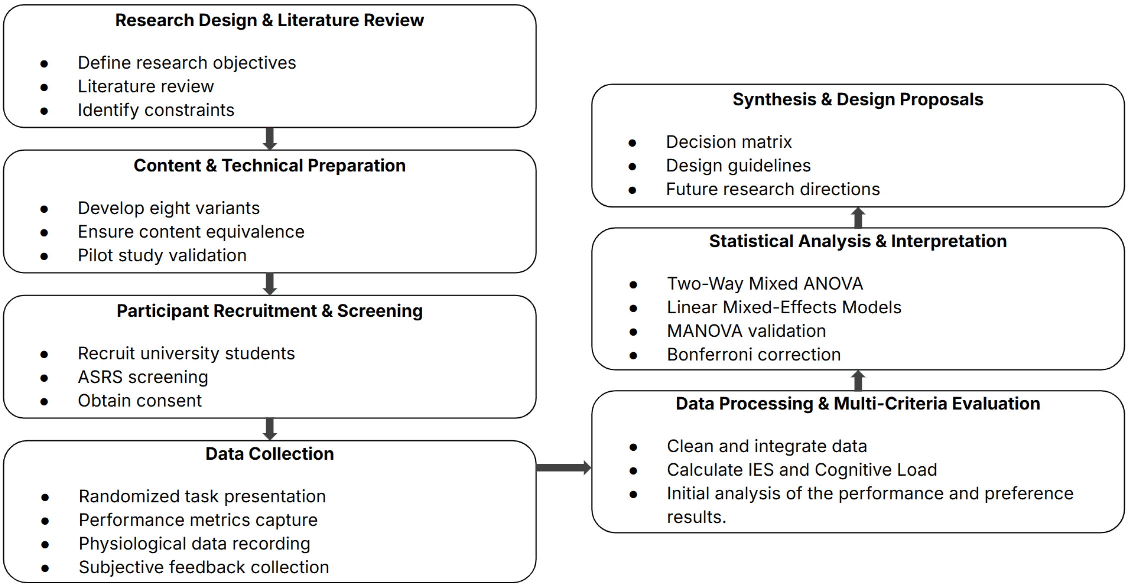

Figure 3.1: Work Plan

The research workflow starting with the inception through to design proposal in details is structured as follows:

- **Phase 1: Research Design & Literature Review:**
  - State fundamental research goals involving the optimization of visualization of special neurological conditions, predominantly with the ADHD or the ADHD likelihood.
  - Conduct a comprehensive literature review on ADHD and ASRS positive or ADHD-likelihood cognition, available visualization research, and design gaps.
  - Identify research constraints, including participant access and technical limitations.
- **Phase 2: Content & Technical Preparation:**
  - Develop eight visualization formats: Plain Text, Highlighted Text, Bar Charts, Bar Charts with Images, Pictographs, Simplified Infographics, Detailed Infographics, and AI-Modified Text.

  - Ensure content equivalence across all formats to isolate the effect of the visualization style itself.
  - Confirm the consistency of information and technical reliability through the use of a pilot study with 3 - 4 participants.

- **Phase 3: Participant Recruitment & Screening:**
  - Recruit university students (aged 19-25) from student communities.
  - Screen participants using the ASRS test to categorize them into ASRS-negative and ASRS-positive groups.
  - Get informed consent and adhere to ethical issues relating to IRB standards.

- **Phase 4: Data Collection:**
  - Host tasks on the LabJS study builder and randomize the presentation so as to avoid fatigue bias.
  - Capture objective performance measures, including task accuracy and response duration for comprehension MCQs.
  - Measuring the physiological parameters in real-time with medical grade pulse oximeters to check the heart rate and the blood oxygen.
  - Collect qualitative data, such as preference ratings (0 - 5 scale) and qualitative engagement response.

- **Phase 5: Data Processing & Multi-Criteria Evaluation:**
  - Process and integrate divergent data streams (LabJS logs and manual physiological readings) using matching participant IDs.
  - Compute composite measures, the main one being the Inverse Efficiency Score (IES) to trade-off between speed and accuracy.
  - Derive Cognitive Load scores by inverting user preference ratings.
  - Determine the best vs. the worst visualization type on a standard scale.

- **Phase 6: Statistical Analysis & Interpretation:**
  - Find out the main effects and the interaction effects between the user groups and the visualization types using Two-Way Mixed ANOVA.
  - Utilize LMM to account for participant-level variance and calculate time penalties relative to the Plain Text baseline.
  - Conduct MANOVA for physiological validation to ensure that the difference between performance is related to different physical stress profiles.
  - Implement Bonferroni correction in all the pairwise studies to avert. false-positive results.

- **Phase 7: Synthesis & Design Proposals:**
  - Develop a multi-criteria assessment in comparison of user preference to objective performance.

– Generate evidence-based design guidelines and task-specific recommendations for accessible visualizations for ASRS positive persons.

– Suggest future research issues that can be developed in this area.

3.6.2 Resource Management

The study successfully allocated the following critical resources to achieve the research objectives:

- **Human Resources:** A group of university students and a specialized medical panel for protocol approval and safety monitoring.
- **Hardware:** Pulse oximeters that will capture high-quality continuous physiological data.
- **Software:** LabJS study builder to host tasks and custom JavaScript to log performance in an automated manner.

3.6.3 Budget and Financial Analysis

The financial plan prioritized sustainability and high-engagement data collection: This study had a budget which was well managed to ensure that the results were of high quality and the budget was cheap. The LabJS online platform maintained operational costs to the minimal since it did not require the use of expensive paper-based testing and high-powered computing. The money saved on technology was allocated to incentives to the participants to ensure that the volunteers do not get bored throughout the face-to-face sessions. These costs included the purchase of chocolate for all the participants to keep them focused and the provision of soft drinks as the reward to the student who achieved high levels of accuracy. Such minor and focused expenses constituted the largest portion of the financial plan of the project to guarantee the reliability and accuracy of the data received.

3.7 Risk Management

In the research framework, there are a number of mitigation strategies that aim at dealing with the main project risks, including fatigue of the participants, technical breakdown, and breach of privacy. To ensure that the evidence of fatigue bias does not distort the outcomes, the arrangement of presentation of the eight visualisation variants was randomised to each of the participants. Technical risks were taken care of by pilot testing in a small group (n = 4) and using medical-grade pulse oximeters to guarantee physiological data of high quality. The threat of data security was addressed through utilization of anonymized participant IDs and by adhering to the ethical requirements of the IRB.

3.8 Economic Analysis

The economic form of this study can be described as low cost of operation and high potential value to society. Direct costs were reduced through the use of sustainable online programs which did not require the use of paper-based testing. To ensure high-quality data collection during the in-person surveys, small motivational incentives were utilized: chocolate was provided to all participants to encourage sustained attention, and a performance-based reward of soft drinks was offered to those who achieved a specific accuracy threshold in the comprehension tasks. The prospective economic returns of these humble expenses are explained by the high cost-benefit ratio of the study; the ADHD and ADHD-likelihood have cost society billions of dollars in missed productivity and lower annual incomes, so the evidence-based design principles generated here can positively influence the output of academic and professional performance, which will benefit the economy as a whole through the economic cost of neurodiverse impairment.

Chapter 4

Proposed Methodology

4.1 Methodology Overview

The research was designed in a systematic, adaptive way, to serve a single purpose, which is to streamline the visualisation methods for people who have ADHD or likely to have ADHD (ASRS-positive) by testing different visual forms and evaluating their impact on their cognitive and physiological responses. In Figure 4.1, the methodology is given in the flowchat. In this research, the data were obtained among ASRS positive and ASRS negative participants to observe the influence of various visual styles on their performance and stress levels. The total number of participants in this study was $n = 70$. The two major objectives were to determine what different visualization styles such as Plain Text, Highlighted Text, Bar Charts, Bar With Images, Pictographs, Simplified infographics, Detailed infographics and AI Modified text, have on accuracy and time to complete the task and also to estimate the effects of these types of visualizations on physiological responses. By including both groups, it was possible to compare how ADHD or ADHD likelihood people react differently to visual information compared to general people. It is to determine whether the design format causes mental stress.

To address these objectives, the design process was structured in a series of phases. In preparing the content, there were eight variants of visualisations that were developed by ensuring that they contained the same amount of information and density but displayed the information in a different format. This separated the impact of the visualisation style itself, not the content. In the data collection phase, both positive and negative ASRS participants were recruited to experiment with the various visualisation styles under controlled conditions. Performance based measures (accuracy, response time) and physiological measures (heart rate, oxygen saturation) were recorded. The subjective measures, such as preference ratings and feedback, were also taken to make sure that the data had both objective and subjective answers. The obtained information was organised into quantifiable measures, including efficiency allowing a combined measure of precision and preference and response time in the assessment stage. This step was needed to compare the variants on a similar scale and identify the visualisation forms that work better regarding effectiveness and the comfort of potential users.

This research design facilitated the process of carrying out complicated tests, such as LMM, ANOVA, and Bayesian analysis, to gain a real insight into the differences between the two groups. A combination of performance data, physiological data and user preferences allowed forming a clear image of the best and the worst designs that the ASRS-positive and the ASRS-negative individuals can use.

The evaluation framework is developed based on three separate yet complementary constructs, as is common in the study of Human-Computer Interaction and cognitive psychology research. To begin with, performance efficiency, which is how well the participants can process visual information as it balances between accuracy and time spent. It is one of the primary factors in case of ADHD populations that may have speed-accuracy tradeoffs [57]. Second, cognitive load quantifies the cognitive efforts required to interpret every visualisation by measuring subjective clarity ratings and behavioral measures [31], [58]. Third, user satisfaction is a subjective choice and qualitative feedback of the participants accepting the fact that the best design must be capable of weighing between objective performance on one side and user experience on the other side [27]. This type of structure assists in finding the visualisations that are working effectively across multiple dimensions and show noteworthy tradeoffs. A visualization can be very efficient but less satisfying or the opposite and such associations are important design considerations. This is because by analyzing the constructs separately and then integrating them, it can be ensured that the analysis is clear and even broad cross-comparisons can be made through visualization.

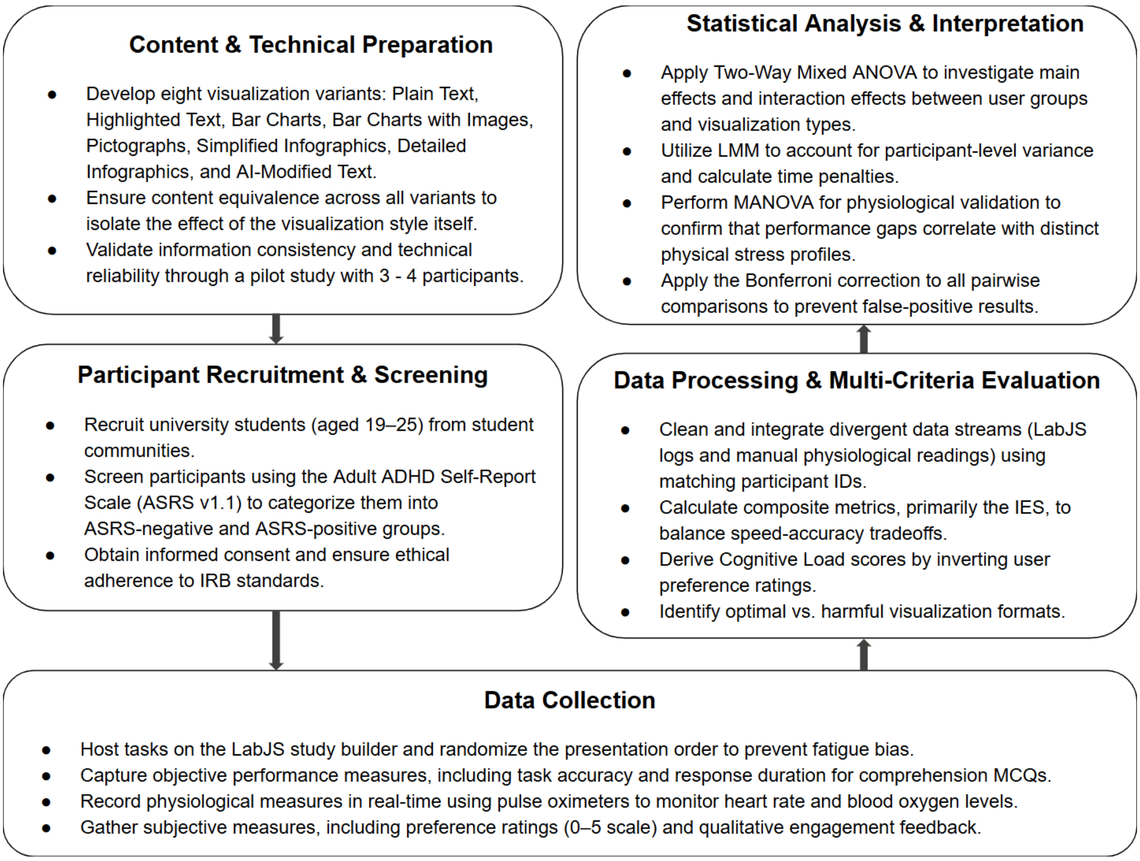

Figure 4.1: Methodology Flowchart

The focus on adult university students participants is a critical limitation of the current methodology. These study participants are adults who have positive and negative screening of the likelihood of ADHD based on the Adult ADHD Self-Report Scale test [17], [18] as compared to children or adolescents with ADHD. This is a serious restricting factor to the generalizability of the findings since ASRS positive symptoms, cognitive processing strategy and attention processes differ between children and adults. Thus, the results cannot be extended to the population of pediatric ADHD unless further investigations are done.

4.2 Design Specification

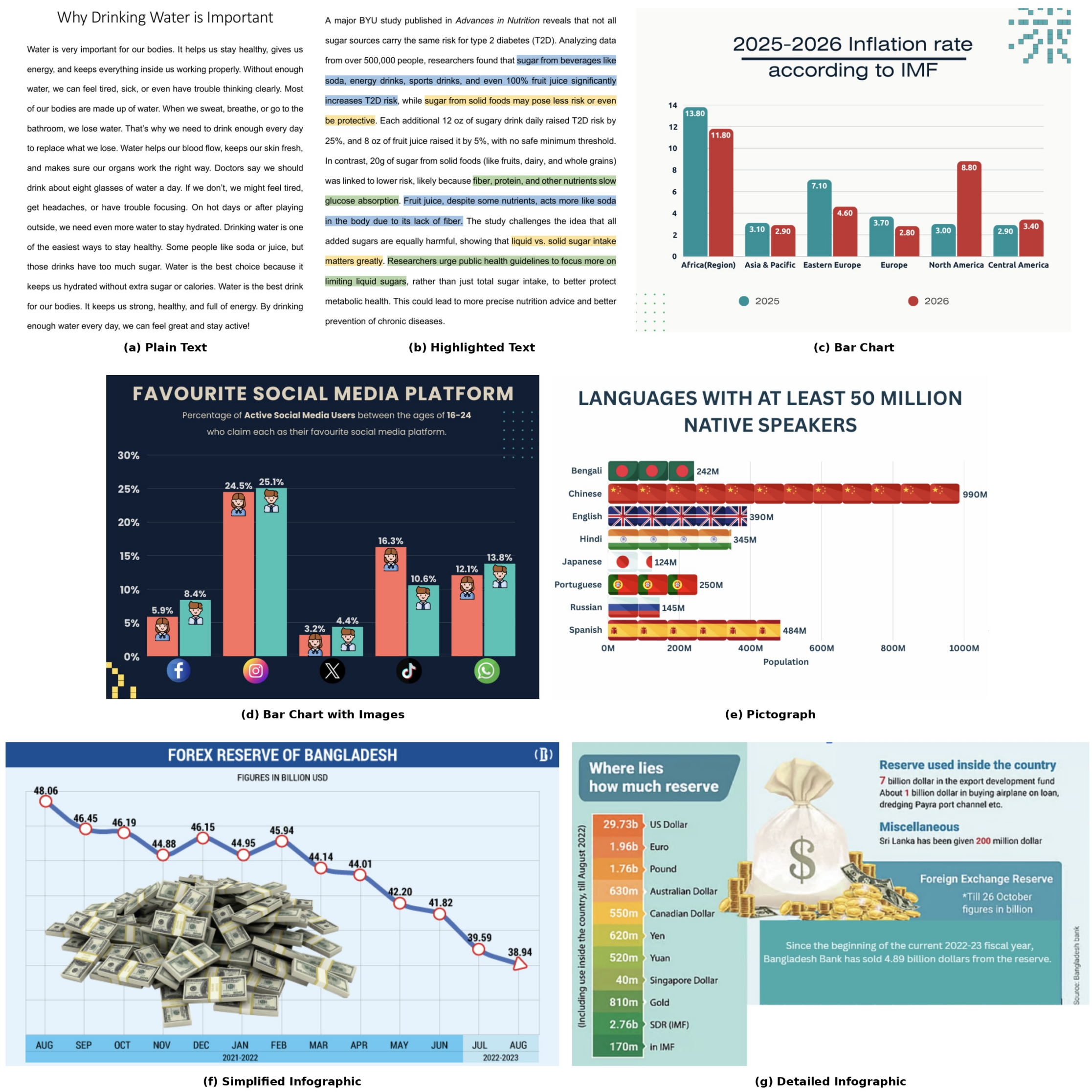

Figure 4.2: Examples of the visualization formats used to test effectiveness of ASRS and Neurotypical participants: (a) Plain Text; (b) Highlighted Text; (c) Bar Chart; (d) Bar with Images; (e) Pictograph; (f) Simple Infographic; (g) Detailed Infographic

At the beginning of the research, several alternative solutions were employed and designed to present similar information in different visual forms. Eight different common visual formats were used to learn about the impact of presentation style on user performance and physical response. It was ensured beforehand that all the visualisation formats must have almost the same level of difficulty. Because if each format had a different difficulty level, then one format may outperform the others just because it was easy, and one format may lag just because it was hard to understand the information in it. This would hamper the goal of the study. The medical panel was requested specifically to examine the difficulty level of all the design formats that were chosen according to the medical grade standards that they use to examine in their field. They gave feedback on them, and necessary adjustments were made. Thus, it was ensured that all the formats had almost the same kind of difficulty. This verification helped to ensure that only the design method of the data representation format itself would affect the participants in this study and not the information itself. Figure 4.2 shows the fist seven visualisation formats.

The first category consisted of text-based models. One version was a plain text format, while the other version had highlighted keywords to attract attention. This was a deliberate attempt to create contrast. The second category included chart-based models. Three kinds of charts were developed to determine whether these helped people understand numbers better. These were a normal bar chart, a pictograph, and a Bar Chart with Images. In the case of the Bar Chart with Images, task-related icons were used to label the categories (such as icons representing various products). These images served as scaffolding to enable users to understand what they were looking at without having to read as much text.

The third category was image-based models. Two types of infographics were tested depending on the amount of information they contained. The Simplified Infographic was sparse in information density, containing few visuals and minimal text to ensure clarity. The Detailed Infographic was rich in information density, meaning it was visually intense and contained numerous complicated visuals and pieces of information within a limited area. These designs tested the influence of visual density on understanding, accuracy, and user preference.

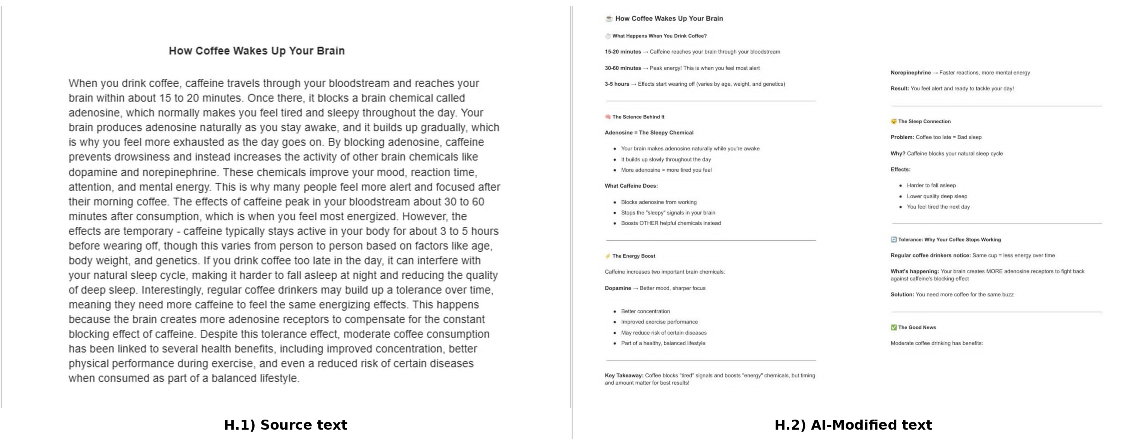

Figure 4.3: (H.1) Source Text (left), and (H.2) AI-Modified Text (right)

The final model used is an AI-modified text shown in Figure 4.3. This variant was adapted using the prompt - *"Suppose there is an adhd person. Now, represent this* *paragraph or the information in the paragraph in such a way that the adhd person can easily grab the information delivered in the paragraph. any format or way of representation is allowed, just make sure that the adhd people can understand and grab the information properly and efficiently"* in ChatGPT-4 [53], which processed the source text, simplified sentences, emphasised significant points, and increased visual scanability - features commonly proposed as making content ADHD friendly. This represents one of the newer approaches introduced because the generation of adaptive content through generative AI is becoming a reality. To ensure that no one would be influenced by tiredness or boredom from the presentation of these formats, the sequence of presentation was randomised for each participant.

4.3 Data Collection

The main portion of the study involved recruiting 70 participants: 40 ASRS negative and 30 ASRS positive participants. All the participants were recruited using online forms distributed in student communities. The study participants included students in the university who were aged between 19 and 25 years. The sample consisted of both male and female students (South-East Asia, specifically Bangladesh), and they represented the Global South. By targeting this particular age and level of education, a just level was established when it comes to the way students process digital information. All the participants were surveyed in person and the process of data collection began in July 2025 and concluded in December 2025. The study was conducted in stages; initially, the people were contacted, secondly, appointments were done, and the surveys were finally carried out. The surveys lasted approximately 15 to 20 minutes. Moreover, the special medical panel was occupied on certain occasions hence their screening and advice were also time consuming. Due to the face-to-face surveys, no massive amount of data was possible, which led to the ultimate sample of ASRS positive and ASRS negative respondents. To select participants who may have ADHD or a possibility of having it, the ASRS test by the WHO was applied. All respondents completed this screening. In the case they scored low, they were termed as ASRS negative. It is necessary to add that although the ASRS is a very precise screening instrument (specificity is approximately 99%), it is not a medical gold standard diagnosis; it is applied in a research environment to uncover symptoms. Eight visualisation models were utilised by all the participants. Regarding all the visualisations, the participants answered four multiple-choice comprehension questions, which were designed to examine how they perceived the display information. Data collection was conducted on both objective and subjective measures in order to get a comprehensive view of how the users interact and respond.

Objective measures included:

- Visualisation of the four MCQ questions' precision of responses for all formats.
- Time (in seconds) to do each visualisation task. No time constraint was provided. The participants were allowed to work at their own pace.
- The physiological measurements, such as the heart rate and blood oxygen levels, were monitored with the pulse oximeter in all the tasks.

Subjective measures included:

- Preference rating (0 - 5) of each visualisation (0 = very unclear, 5 = very clear), which is an inverse measure of perceived cognitive load.
- Determine Final preference and engagement qualitative feedback. The data collection was carried out in controlled conditions in order to minimise the influence of external distraction.

The research was focused on phases, and the participants were informed that the conditions of the experiment were the same during the testing of the separate versions of the design. The participants had an alternative of resting between tasks. Digital recordings of task responses, timing and physiological data were carried out so that these could be analysed in the future. The testing system was tested to confirm its validity by conducting a pilot study (4 participants) before the actual data collection, to check that the questions were narrow and that the technical reliability of measurement tools was good, which led to a complete collection of data. The given method not only gives numerical data but also qualitative data, which enhances the credibility and richness of the results.

4.3.1 Data Cleaning

Before analysis, the data was cleaned to guarantee the reliability and consistency of the data. These cleaning operations were quite straightforward since the data collection process was highly restrictive, and structural consistency was given preference over fixing a high number of errors. Before additional processing, the nomenclature of the eight types of visualization was standardized.

The values that have been omitted are selective in the dataset. As much as the Preference and Most Preferred columns were filled with cells, which are a sign that the respondents were interested in these subjective measures, there are some cells that are purposely blank in the Correct column. The omissions were correlated with rows linked to the visual content presentation as compared to the comprehension queries, i.e. no question was asked, which rules out the chance of creating a judgment of correctness. This peculiarity of the structure had to be approached very carefully when working on the data to make sure that it is not understood in a false manner.

In the case of physiological variables, there was no missing value of Heart Rate or Oxygen Level. All the readings were successfully recorded due to the constant monitoring and utilisation of high medical-quality pulse oximeter devices. Simultaneously, the presence of several measurements of each participant in each visualisation generated mean values, which gave a whole picture of the physiological profile of each task and exhibited universal trends rather than short-term alterations.

The data did not have any outliers. The method of data collection was rather directed and highly controlled. The subjects were observed throughout the study period, and physiological measurements were done using calibrated medical equipment, and the measurement accuracy was maintained. Consequently, extreme values in both period and physiological measures were deemed as true measures of variation in the subjects, not artificial and as such were retained as they are to protect the natural range of the human response and to ensure artificial manipulation of the data.

The cleaning process was purposely minimal, and this signified how high the initial data collection processes were. The data integrity was ensured by not over-processing the data, by paying close attention to the structural nuances e.g. intentionally missing the cells and non-homogeneous types of data. It also generates clean, analysis-ready data, which is a true and fair representation of the performance and physiological reactions of the subjects of all eight types of visualisation.

4.3.2 Data Transformation

Once the data cleaning stage was performed, the data was converted into a format suitable for undertaking comparative analyses. One of them was the categorical encoding processes and the accuracy scaling algorithm usage that was used to equalise performance measures among participants. The visual contents were described as NP (Plain text), HP (Highlighted text), N_Bar (Bar chart), Pic_Bar (Bar chart with images), Pictograph, Imgl (Simple infographic), Imgst (Detailed infographic), and AI (AI-modified text). It is important to note that this nature of categorical encoding facilitates easier accomplishment of coherent grouping and subsequent comparative evaluation across the identified classes of visualization.

Comprehension performance was also measured by the answers provided by the respondents to four multiple-choice questions to be used at the end of each visualisation. The number of correct responses (ranging between 0 and 4) was converted to a proportional index of accuracy using a special mapping: 0 correct = 0.0, 1 correct = 0.25, 2 correct = 0.5, 3 correct = 0.75 and 4 correct = 1.0. This scaling procedure scaled the performance variables within the 0.0 to 1.0 scale, hence convenient to conduct a strictly comparable measure of comprehension efficiency across the various types of visualisations.

4.3.3 Data Integration

This was required to integrate the data, as we had a hybrid system of data collection. The LabJS platform recorded and time-stamped performance metrics (accuracy and duration) automatically and in real-time. On the other hand, physiological parameters (heart rate and oxygen saturation) were manually observed on a pulse oximeter at any specific moment of time in each task. The LabJS feedback node received subjective responses (preference ratings and feedback) at the end of each of the visualisations. We transformed these divergent streams of data by using similar keys of the participants, ID, and type of visualisation. The results of LabJS were exported, automated and also made in a tabular format. Manual physiological readings were late additions. There were constant measurements in all interactions of the visualisation. At this stage, several readings were held at this point and averaged at a further aggregation stage. The outcome of this combination in the data was objective performance data, physiological data and the subjective appraisal in one format. The source multi-integration enabled the performance of a complete analysis of the effect of visualisation types of influence on cognitive performance, physiological response, and user satisfaction in parallel, which gave a strong foundation to pre-process and statistically analyse later.

4.3.4 Data Reduction

Data reduction helped to simplify our dataset. It was easier to analyse it, and key patterns were not lost. We applied a two-level aggregate scheme on feature selection to reduce the number of dimensions with insignificant loss of information.

Individual participant analysis Aggregation: Each participant-visualisation combination was then summed to various metrics in the creation of overall performance profiles:

- **Total Duration:** The cumulative amount of time on the information of the primary visualisation, and all the questions associated with understanding it, which represents the cumulative amount of time per type of visualisation.
- **Average heart rate and Oxygen Level:** The observed physiological values obtained during every activity were averaged, and peaks and valleys of the values were averaged to provide constant values of physiological response.
- **Preference and Final Feedback:** The first non-zero value in his/her participant part group was taken. The preference rating stated by the participant, and the feedback was not duplicated.

This summarisation led to the dataset being flattened to an individual question level to a participant-by-visualisation format, where each row summarises the experience of one participant in one type of visualisation.

Group-Level Aggregation for Cross-Visualization Comparison: A second level of aggregation was carried out to enable comparison of all 70 participants in terms of visualisation type. The following were the summary statistics:

- **Mean Accuracy:** The average accuracy score of all participants of each kind of visualization displaying overall usefulness in perception.
- **Mean Total Duration:** The Mean time that visualizations required to process and finish tasks.
- **Mean Heart Rate and Oxygen Level:** Median physiological responses by the participating individuals provide a clue to the cognitive load or stress of every visualisation.
- **Average Preference:** Mean preference rating, which is a rating of subjective user satisfaction.
- **Population Preference Percentage:** The number of participants whose feedback was positive (coded as 1) for all types of visualisations is a binary method of overall approval.

This group-level summary created a composite dataset where each line entry is one of the eight types of visualisation comparing performance measures of each type individually across the entire ASRS-negative and ASRS-positive group of participants. The measure was helpful in the dimension reduction between participant-level and visualization-level data that minimised the dataset size without depending on its underlying patterns.

These reduction methods were efficient and analytical. The two-level aggregation of individual summaries and group averages successfully supported within-participant analysis and between-visualization analysis to determine which types of visualization gave the best understanding, engagement, and satisfaction to users.. The created condensed data provided a clear foundation of statistical analysis and visualisation at the result stage, thus simplifying it to attain powerful comparisons and more understandable conclusions.

4.3.5 Summary of Preprocessed Data

The pre-processed data set is in two organized levels that are ready to be analyzed. In the individual-level dataset, each row represents each interaction of a participant with a type of visualisation. This form reflects the performance of the participants in each of the eight variants, i.e. accuracy, average time spent in the task, average physiological measures (heart rate and oxygen saturation), preference rating, and feedback. The group-level data were the mean performance indices of both types of visualisation among the 70 participants. It is based on this overall view that the visualization performance can be directly compared based on the accuracy of understanding, the duration of the interaction, the physiological response, and the satisfaction of the user. The names of the variables in the data are similar, and the records are complete in both datasets after imputation and other similar categoric encodings. This two-structure design is easy within-participant pattern analysis and between-visualisation comparative analysis to provide the background for the solid statistical analysis and interpretation in subsequent portions.

4.3.6 Evaluation Metrics and Efficiency Calculation

Three key measures were estimated after preprocessing the data, which are the three constructs of our evaluation framework, i.e. performance efficiency, cognitive load, and user preference.

Performance Efficiency: Inverse Efficiency Score (IES): To find such performance efficiency, taking the tradeoff of speed-accuracy, we took the Inverse Efficiency Score (IES,) which is a popular tool of cognitive psychology and Neurodiverse research [37], [38]. IES is calculated as:

$$\text{IES} = \frac{\text{Mean Duration (seconds)}}{\text{Mean Accuracy}}$$

Duration refers to the overall amount of time taken to answer visualisation and comprehension questions, and Accuracy refers to the choice of 0.0 to 1.0. A lower IES score is more appropriate since it indicates that the individual was efficient, meaning that he completed the task within a short period of time and made fewer mistakes. When the score is high, it is normally because they took a long time or made more mistakes. As a measure, the latter is especially appropriate in the case of the ADHD or ASRS positive study, as it has been well-tested in the research of attention and executive functioning [33], [34]. IES addresses a fundamental limitation of analyzing accuracy and duration separately: it prevents misleading conclusions from speed-accuracy tradeoffs. An visualization may get fast response with a limited accuracy, or may give high accuracy using overly long duration, either of these is inefficient. By computing the ratio of time to accuracy, IES provides a unified performance measure that rewards both speed and correctness [59].

Cognitive Load: Inverted Clarity Rating: Cognitive load was determined on the subjective preference ratings of participants. These were reversed to accommodate a conventional approach of cognitive load scales whereby the higher the rating, the greater the mental stress [31], [60]. The transformation is:

$$\text{Cognitive Load} = 5 - \text{Preference Rating}$$

This approach is in line with existing literature on educational psychology where subjective ratings of comprehensibility are valid indicators of cognitive demand [61]. Studies have revealed that subjective measures of preference show a strong correlation with objective measures of cognitive load, placing this measure in high regard in terms of validity of the parameters [49], [60]. There were three methodological reasons as to why we used a single-item cognitive load measure (inverted preference rating) instead of multi-dimensional measures such as NASA Task Load Index (NASA-TLX). To begin with, the short length of our comprehension tasks (60-180 seconds) is consistent with experiments that have found that single-item workload ratings have a high relationship ($r > 0.8$) with complete NASA-TLX scores in focused cognitive tasks [49]. Second, the six-dimensional NASA-TLX assessments that would be added following every one of the eight visualisations would be a major burden to the survey, and response fatigue would have a disproportionate impact on our ASRS positive participants. Third, our physiological confirmation through MANOVA ($p < 0.001$) presents convergent analysis that the rating of subjective cognitive loads is based on actual differences in mental load, lessening the necessity of using a broad subjective measurement scale [50].

Population Preference Percentage: The population preference percentage for all eight visual contents was obtained in the final part of participant feedback. The purpose was to determine the most preferred format among participants. This provides a subjective description of which format was easier for most people. In this section of the analysis, participant feelings regarding the designs were asked. They were questioned on whether they considered the formats appealing, user-friendly, and easy to understand. Such feelings are significant because they determine whether individuals will actually apply such tools in real life. When an individual finds the appearance and feel of a chart appealing, there is a high likelihood of continued use and sustained interest in the information [27], [62]. User satisfaction is an important design objective, though not the same as objective performance, particularly in the case of ASRS positive populations who might have no emotional connection with a format they find unappealing despite it being functionally objective.

4.3.7 Statistical Analysis

In order to make sure that the findings of this study were scientific, a multi-layered statistical analysis was used. This structure enabled the study to go further than mere averages and explore the complicated associations among the two user groups and visualisation forms.

Two-Way Mixed ANOVA and Interaction Effects: Analysis of Variance (ANOVA) is a statistical method that helps to determine if there are real, meaningful differences between the averages of several different groups [63]. In this study, Two-Way Mixed ANOVA, which is basically a specific version of the ANOVA itself, is used to look at two main factors. One is the type of student (those who are ASRS-positive and those who are not), and the type of visual design used to show data. While the test looked at whether the groups or the designs were different on their own, the most vital part was finding the Interaction Effect. This effect checked if a specific design affected one group of students differently from the other. The results showed a robust connection ($p < 0.001$). This proves that different visualisation styles do not have the same impact on ASRS-positive and ASRS-negative users. This was a necessary discovery because it proved that it is important to study each design style one by one to identify which ones were actually difficult or confusing for students with ADHD traits.

Linear Mixed-Effects Model (LMM): LMM is a type of statistical tool which is used when the data points are related [64]. In this study, the case was when the same person completed many different tasks. The average of a whole group is looked into by ANOVA. On the other hand, LMM is more precise because it looks at the individual differences. The unique ways that different people approach a test or react to a design are seen by LMM. In this research, Plain Text was used as the baseline, or the simple starting point for the analysis. By comparing every other design format to the Plain text, it was possible to calculate exactly how many extra seconds of time or mental effort each new feature (like a chart, a picture, or a highlight) cost a person with ADHD traits.

MANOVA for Physiological Validation: Multivariate Analysis of Variance or MANOVA is a statistical tool which is used to see if there are real differences between groups when several different results are looked into at the same time [65]. It is more powerful than other tests. The reason behind this is that it considers how these different results relate to each other. In this research, MANOVA was used to study the physiological data gathered from the participants, which are measurements of how their body reacts physically. Heart rate and blood oxygen level ($SpO2$) were looked into together to see if the participants were experiencing any sort of physical stress or not. This is done because one of the agendas of this study was that when ASRS-positive students struggled with a task, it was because their bodies were stressed, not only because they weren't trying hard enough to perform well. The test found a strong result ($p < 0.001$), which means there is less than a 0.1% chance that the differences that were found happened by accident. This is proof that a person with ADHD traits experiences a different level of physical stress than a neurotypical person when trying to understand a complicated design.

Evidence Strength (Bayes Factors and Hedges' g:) To ensure the results of the study were solid and reliable, two special statistical tools: Bayes Factors (BF_{10}) and Hedges' g were used. Bayes Factors are used to measure exactly how strong the evidence is for a scientific idea. Bayes Factors allow to directly compare different explanations to see which one the data supports more, instead of just saying something is significant or not significant [66]. In this research, it was found that there were differences between the groups. Bayes Factors were used to show how much evidence there was for the differences. If the score of the Bayes Factor is above 10, this means the proof is strong, and if the score is in the range of thousands or millions, this shows that the evidence was overwhelming and there is a very high chance that the results were true. Hedges' g is a tool for measuring the effect size. This describes, in a real-life situation, how large the difference between two groups actually is. It is more accurate than other similar tools like Cohen's d because it uses a correction factor to reduce mistakes, especially when a study has a smaller number of participants [67]. Hedges' g was chosen specifically because it is more precise when comparing groups of different sizes, which was necessary for this study since there were 40 ASRS-negative participants and 30 ASRS-positive participants.

Post-hoc Adjustments and Pearson Correlation Analysis: Post-hoc adjustment is a follow-up test used right after an initial ANOVA. This is done to identify exactly which groups are different from each other [68]. To make these results reliable and significant, a rule known as the Bonferroni correction was applied. Some results may appear significant simply by examining the data. But when different results are combined, then it tells a different story. Then those significant results actually appear to be just lucky guesses or coincidences. These are false positive results. The Bonferroni correction heavily filters them out [69]. A false positive can be spotted by comparing two numbers: the initial p-value and the corrected p-value. Generally, a result looks important if the first p-value is less than 0.05. However, if the corrected p-value rises above 0.05 after the filter is applied, that gives proof that the original finding was likely a false positive [69]. This ensures that only the most robust and real results are used in the final analysis. By using this correction, it is ensured that only the most significant and real differences are labelled as such. Pearson Correlation Analysis is a statistical tool which is used to determine if two different things are related or not. It provides a score in the range of -1 and +1, and shows how closely two variables move [70]. In this study, it is used to compare the objective performance (which means how well the students actually performed in the tasks) with the subjective preference (which means how much the students preferred a specific visualisation format).

4.4 Implementation of Selected Design

The implementation - the participants would be shown the eight variants of visualisations in a distraction-reduced environment. Each of the variants was implemented in the LabJS platform one by one, and the responses on the task and time were automatically recorded by using custom JavaScript. Their physiological data was measured using pulse oximeters to determine the oxygen saturation and heart rate. Right after each visualisation, preference rating and qualitative feedback were received using an inbuilt feedback node, which captured the thoughts of the participants then. Automated performance logs and physiological records were put together in one CSV format. This was done by cross-checking to ensure that the automated and manual streams of data were consistent. The real-time issues were resolved, such as sensor misreads, in order not to undermine the integrity of data in the process of data collection. This was done to the ASRS-positive and ASRS-negative participants so that cross-group comparability is achieved. Since the same steps were employed on each individual, it would be quite justifiable to compare the reactions of the various groups to each of the visual styles. Medical experts examined the plan to ensure that the study was safe for all the individuals involved. Their review guaranteed the tasks would be medically correct and safe for each participant.

Chapter 5

Result Analysis

5.1 Performance Evaluation

To measure the effectiveness of the eight proposed visualization formats as to the level of performance, a multi-dimensional model consisting of three key constructs, including performance effectiveness, cognitive load and user satisfaction was applied. This analysis captures a rather critical aspect in how the participants interacted with the visualization formats, as well as provide some insight into whether the system is effective in general.

5.1.1 Performance Efficiency: IES

The IES was used to measure performance efficiency and this captures the speed-accuracy tradeoff as it offers a single measure representing better performance efficiency. This measure especially works in the ASRS positive research settings since it not only demonstrates the difference in performance with regard to executive function and attentional control, but also avoids misleading interpretations of analyzing performance based on speed and accuracy alone [33], [34]. Computing the ratio of processing time and accuracy, IES calculates both speed and accuracy simultaneously and therefore can make sure that inefficient situations like fast and inaccurate responses or slow and accurate responses are adequately represented.

As shown in Figure 5.1, Plain text performed the best in terms of IES (98.24) with the ASRS-negative subjects, which revealed the best efficiency in terms of speed and accuracy. Bar With Images proved to be quite effective (IES = 149.51), whereas the standard Bar Charts were the least efficient (IES = 204.06). Such results lead to the conclusion that in the case of neuro-typical university students, textual presentations with minimal content make the extraction of information efficient.

The performance was different among the ASRS-positive participants. The largest IES (226.76, 229.64, and 244.02 respectively) was created using Bar graphs, Pictographs, and AI-modified text, which is a significant difference when compared to ASRS-negative participants. This significant impairment is in agreement with theoretical models that indicate that the absence of appropriate representation of information overloads working memory systems already afflicted with symptoms of ADHD. On the other hand, Plain text (IES = 123.66) and Highlighted text (IES

= 102.77) did not show significant changes in performance and yet, ASRS-positive participants always needed more processing time in all formats.

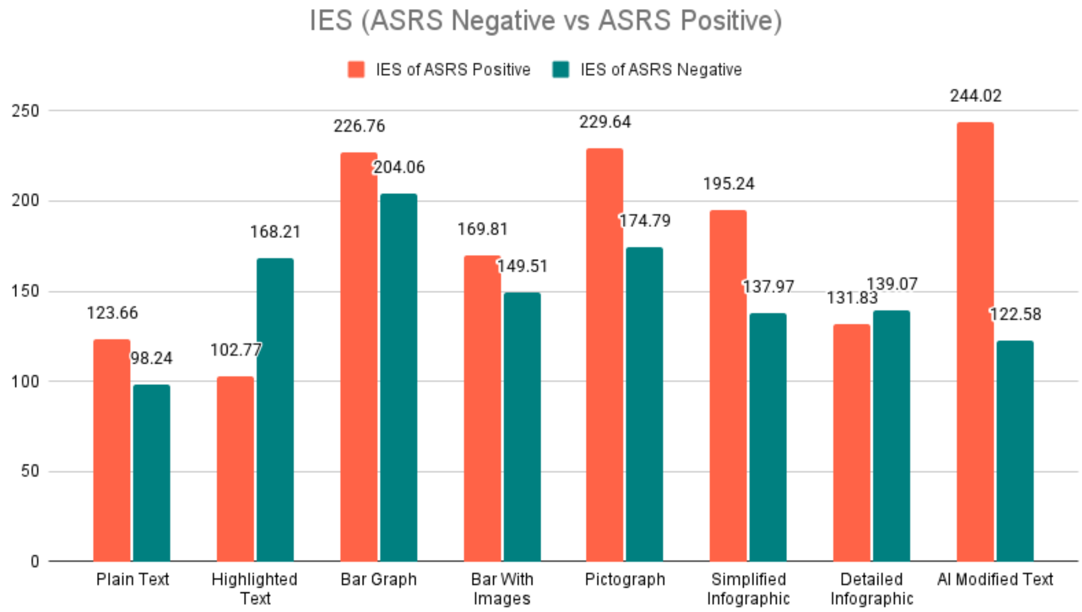

Figure 5.1: IES (ASRS Positive vs ASRS Negative)

5.1.2 User Satisfaction and Preference Patterns

User preference ratings, collected on a 0 - 5 scale (0 = very unclear, 5 = very clear), captured participants' subjective assessments of each visualization's clarity, usability, and overall appeal.

Figure 5.2 demonstrates that in the ASRS-negative group, the AI-modified text was rated highest (3.88) followed by Highlighted text (3.83) and Bar with images (3.81). These types of formats were both functional and aesthetically simple, which validated the fact that in the case of neurotypical users simplicity of information presentation was much more important than excessive visual decoration. Detailed Infographics showed the lowest ratings (2.69), which indicates that complexity is not the only tool that could ensure user satisfaction.

Participants with ASRS-positive showed preference patterns which were different. Bar charts and Highlighted text had the best ratings (3.45 and 3.52), which is good evidence that they are well-approved formats that lack visual clutter and still allow clear semantics. Notably, Detailed infographics received the lowest preference scores (1.5), representing a 0.79 point decline relative to ASRS-negative participants. This substantial dissatisfaction aligns with the format's elevated cognitive load (3.1) and moderately poor efficiency (IES = 131.83), confirming that ASRS-positive participants possess accurate metacognitive awareness of visualization difficulty.

This result aligns with the established findings on studies on Human-Computer

Interaction where aesthetic attractiveness and functional usefulness are usually inconsistent [62], [71].

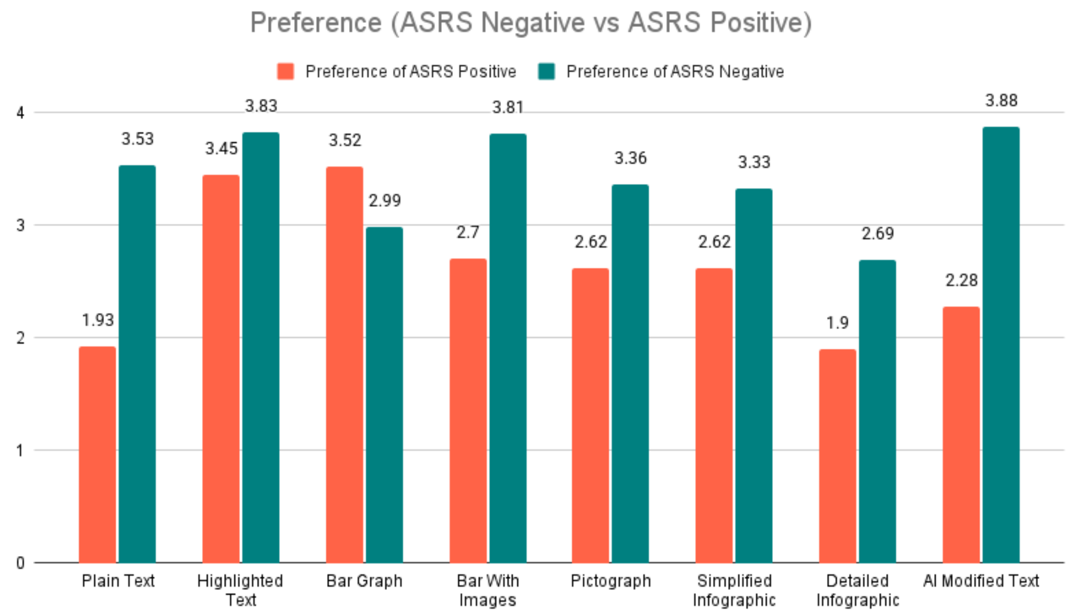

Figure 5.2: Preference (ASRS Positive vs ASRS Negative)

5.1.3 Cognitive Load Assessment

Cognitive load was calculated through inverted preference ratings, following established protocols in educational psychology and multimedia learning research [72]. Immediately after the completion of the task, the participants rated the clarity of each of the visualizations on a scale of 0 - 5 points. These scores were reversed to conform to the traditional cognitive load measurement norms, in which a higher score corresponds to an increased mental load:

$$\text{Cognitive Load} = 5 - \text{Preference Rating}$$

Research has indicated that the subjective clarity scores are closely connected with objective cognitive load tests, which proves that they are valid predictors of mental effort [49], [60].

Figure 5.3 revealed that the scores of cognitive loads in the ASRS-negative respondents were between 1.12 (AI modified text) to 2.31 (Detailed infographics), indicating relatively modest mental effort requirements across all tested formats. Such a small distribution provides an indication that neurotypical university students have enough cognitive resources that they can handle different types of visualizations without feeling significantly burdened.

The patterns of ASRS positive participants were significantly different. Cognitive load scores ranged from 1.48 (Bar graphs) to 3.1 (Detailed infographics), representing an almost 150% increase in perceived mental effort for the most demanding format. Detailed infographics were always the most cognitively challenging visualization, and ASRS-positive participants reported that they faced difficulty processing the volume of visual data, to stay focused on the original information and to be able to filter out the extraneous information.

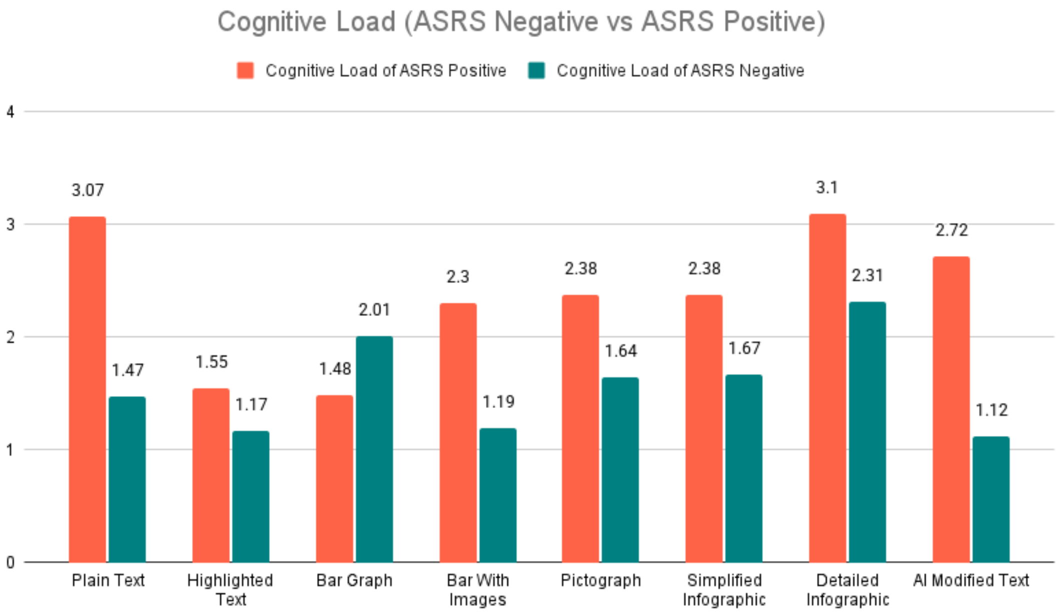

Figure 5.3: Cognitive Load (ASRS Positive vs ASRS Negative)

The separation of cognitive load and objective performance measures was highly eye-opening. As an example, Bar With Images and Pictographs resulted in moderate cognitive load (1.48 and 2.3 among ASRS-positive participants) and high performance advantage (lower IES value), indicating that ASRS-positive participants might use compensatory processing strategies, which allow them to perform efficiently despite the perceived difficulty.

Subjective preference ratings were chosen instead of physiological measures (heart rate, blood oxygen saturation) because of various methodological reasons. To begin with, preference ratings showed a significant amount of variability between types of visualizations (range: 1.9 - 3.52), which indicated that they had enough discriminative sensitivity to capture format specific differences. Moreover, there was low conditional difference in the measured physiological readings (80 - 85 bpm; SpO_2: 96 - 98), which is probably due to the low duration of the task (60 - 120 seconds per visualization) and the relatively modest cognitive load required to complete the tasks for healthy university students.

5.2 Analysis of Design Solutions

5.2.1 Text-Based Visualizations

Plain Text Performance: Figure 5.4 shows that, in the case of the Plain Text visualization, the ASRS-Negative group attained an accuracy score of 89% at a duration of 87.43 seconds, heart rate of 86.64 and a blood oxygen level of 98.58. This group reported a preference score of 3.53, a population preference of 15%, the IES of 98.24 and a cognitive load of 1.47.

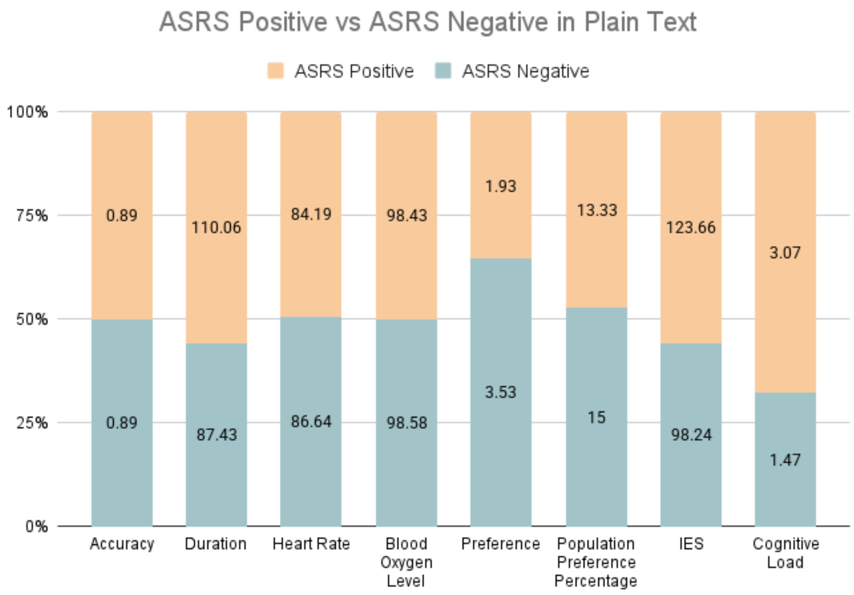

Figure 5.4: Plain Text (ASRS Positive vs ASRS Negative)

The ASRS Positive group using Plain Text recorded an identical accuracy of 89%, but required a longer duration of 110.06 seconds, with a heart rate of 84.19 and a blood oxygen level of 98.43. Their preference was much lower at 1.93, with a population preference of 13.33%, an IES of 123.66, and a significantly higher cognitive load of 3.07.

However, examining the Plain Text results, the most obvious conclusion to be drawn is that though the overall understanding level corresponded to an identical final result in both groups, the price of acquiring it was considerably greater in the ASRS-positive group. The two groups also scored 89% accuracy, which proves that the two are equally able to learn through this format. Nevertheless, the ASRS-positive group had to struggle much harder and longer in order to achieve such an objective. The ASRS-positive group took a bit over 23 seconds more to complete and declared a cognitive load (mental effort) that was greater than the ASRS-negative effort. This additional effort could have been the cause of their much lower rating of their preference of Plain Text, as they scored it much lower at 1.93 compared to the negative group at 3.53. They also had a higher inverted efficiency score (IES), which establishes the fact that although accurate, they were less efficient in general due to the time and effort which they needed to employ. Simply spoken, Plain Text suits all people but to those with the characteristics of ADHD, it seems a bit hard.

Highlighted Text Performance: Figure 5.5 shows that, the ASRS Negative group with Highlighted Text based performance scored 63% after 105.97 seconds, heart rate of 87.76, and blood oxygen level of 98.58. Their preference was 3.83 in favor, a population preference of 5%, IES of 168.21 and a cognitive load of 1.17.

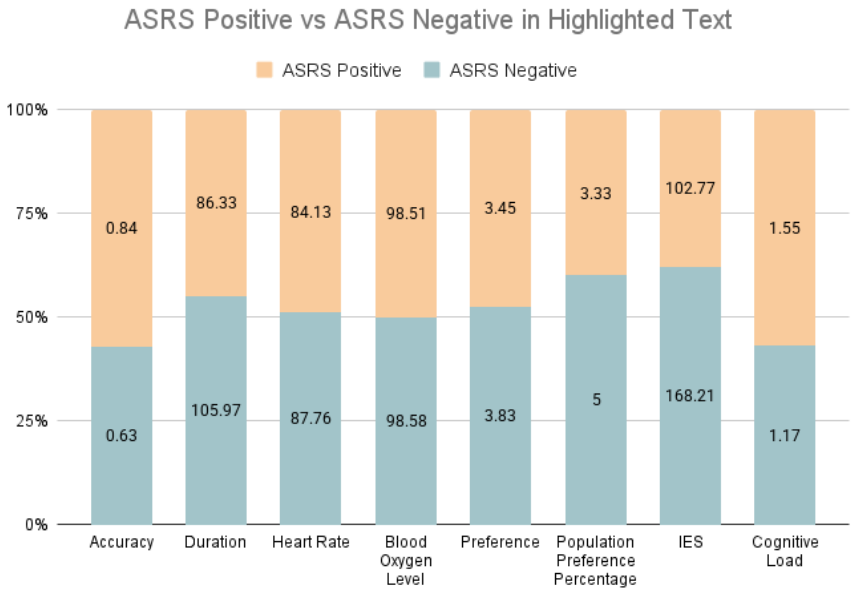

Figure 5.5: Highlighted Text (ASRS Positive vs ASRS Negative)

In the case of ASRS Positive group, the Highlighted Text had higher accuracy of 84% and shorter duration of 86.33 seconds with a heart rate of 84.13 and a blood oxygen level of 98.51. This group depicted a preference of 3.45, population preference of 3.33%, IES of 102.77 with a cognitive load of 1.55.

Comparing the two groups on the use of Highlighted Text, there is a very interesting change of the performance in the two. Although the same format was used in both groups, in actual the ASRS-positive group scored significantly better as compared to the ASRS-negative group. They were even more accurate and completed the task earlier which is also reflected by their very high efficiency score (IES). However this increased performance was received at a cost. Although the ASRS-positive group was more effective, they indicated a greater cognitive load, which amounted to more cognitive effort being used to make the results. Both groups remained fairly stable physically, having almost equal heart rates and oxygen content. Interestingly, even though they were high-performing, the ASRS-positive group, however, slightly disliked the format as compared to the ASRS-negative group. To summarize, the highlighting appears to be a strong vehicle to the ASRS-positive group since it has assisted them to concentrate and prosper, although it is apparently more mentally demanding to use.

5.2.2 Chart-Based Visualizations

Standard Bar Chart Performance: Figure 5.6 shows that, the ASRS-negative group acting with a Bar Graph showed low accuracy of 35% only, duration is 71.42 seconds, heart rate of 88.38 and an oxygen level in blood is 98.67. They indicated a preference of 2.99, population choice of 2.5% being the lowest, an IES of 204.06 and population cognitive load of 2.01.

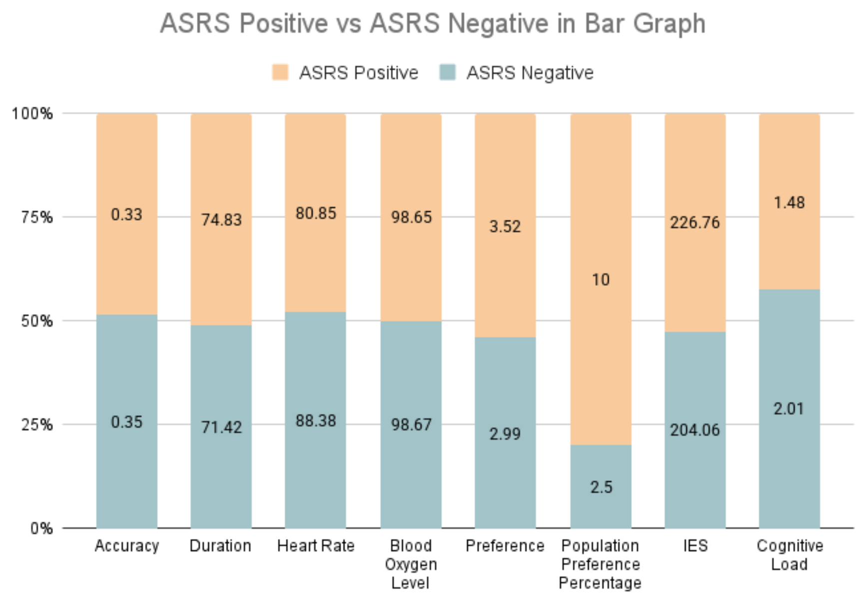

Figure 5.6: Bar Graph (ASRS Positive vs ASRS Negative)

At the ASRS-positive group, there was also a similar accuracy rate of 33%, duration of 74.83 seconds, heart rate of 80.85, and a blood oxygen reading of 98.65 using the Bar Graph. They preferred 3.52, their population preference of 10%, IES of 226.76 and a cognitive load of 1.48.

Analyzing the data provided in the Bar Graph, it is evident that this form was rather challenging to both groups. They performed dismally at accuracy with an overall score around 33% to 35% which is a far worse score than results using text-based formats. The time they took on the task was also highly comparable and there was only a few seconds gap between them. Surprisingly, although the performance of the two were almost the same, the subjective experiences were not the same. The ADHD-likelihood group (ASRS-positive) in fact favored the bar graph over the neurotypical participants and also registered a reduced cognitive load (subtraction of mental effort). Conversely, the graphs were more psychologically straining to the ASRS-negative group. Nevertheless, the Inverse Efficiency Scores (IES) of both groups were large, and this fact confirms that the Bar Graph was not an effective manner of helping either party in terms of accuracy and duration. In essence, the bar graphs were equally challenging to both groups. However, the ASRS-positive group was not as mentally drained when attempting to figure it out.

Bar With Images Performance: Figure 5.7 shows that, in the Bar With Images format, the ASRS-negative group achieved an accuracy of 41%, a duration of 61.3 seconds, a heart rate of 88.59, and a blood oxygen level of 98.51. The population preference of this group was high (25%), the preference of 3.81 was good, the IES was 149.51 and the cognitive load was low (1.19).

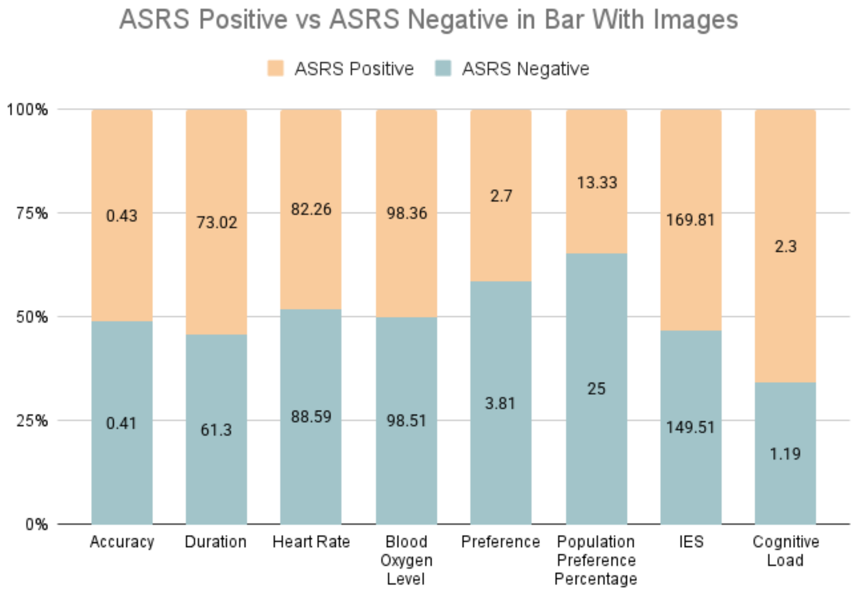

Figure 5.7: Bar With Images (ASRS Positive vs ASRS Negative)

The ASRS-positive group using Bar With Images had an accuracy of 43%, a duration of 73.02 seconds, a heart rate of 82.26, and a blood oxygen level of 98.36. They cited the preference of 2.7, population preference of 13.33%, IES 169.81 and cognitive load 2.3.

When looking at the Bar With Images format, both groups performed at a similar level of accuracy, scoring in the low 40%. While this is a slight improvement over the standard bar graphs, it still resulted in relatively low comprehension for everyone. Cognitive response to this visual style however was vastly different in the two groups. This format appeared to be working legitimately to the neurotypical group. They completed the work entirely at a lesser time and had a very low cognitive load, indicating that they felt it comfortable and easy to use. As a matter of fact, a huge percentage of this group (25%) adopted this as their most favorite format. On the other hand, the ADHD-likelihood (ASRS-positive) group took longer to process the information and felt a higher level of mental strain. Although they made the same kind of accuracy, they disliked the format and they rated it almost twice as stressful as the neurotypical group.

Pictograph Performance: Figure 5.8 shows that, the ASRS-negative group using the Pictograph format had an accuracy of 39%, a duration of 68.17 seconds, a heart rate of 89.28, and a blood oxygen level of 98.46. Their preference was 3.36, population preference was 17.5%, the IES was 174.79 and the cognitive load was 1.64.

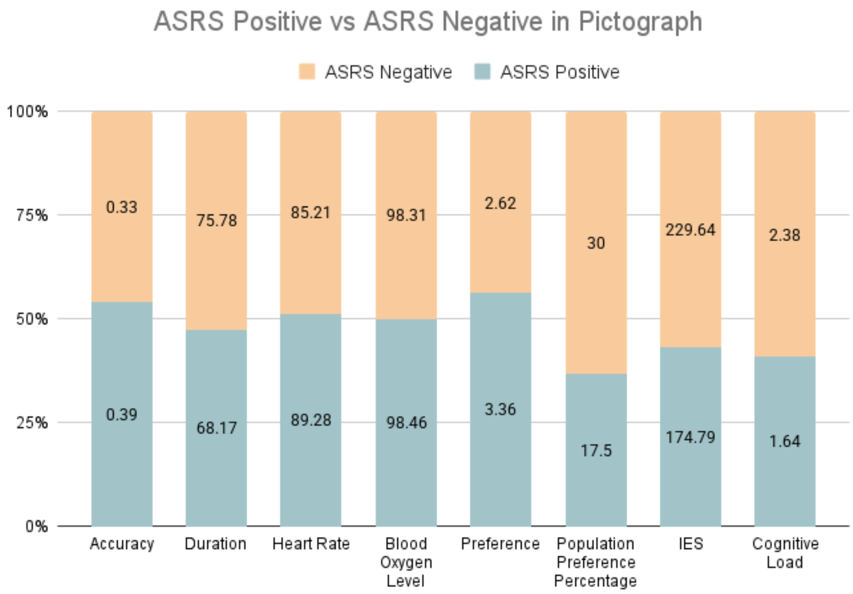

Figure 5.8: Pictograph (ASRS Positive vs ASRS Negative)

For the ASRS-positive group, the Pictograph resulted in an accuracy of 33%, a duration of 75.78 seconds, a heart rate of 85.21, and a blood oxygen level of 98.31. They indicated a preference of 2.62, high population preference of 30% and the IES of 229.64 and cognitive load of 2.38.

When looking at the Pictograph format, we see that both groups struggled to get the right answers, but their feelings about the format were quite surprising. The normal group(ASRS-negative) felt more precise and completed the task at a faster rate using a lesser amount of mental effort. It appears that they were okay with the format, but it was by no means a favorite among them. The ASRS-positive group, on the other hand, had a much harder time. They were also less precise and required more time to process the images hence, a considerably bigger cognitive load. This means they found the pictographs mentally tiring to use. However, despite the struggle and the low efficiency, a huge 30% of the ASRS-positive group chose this as their preferred format. This creates a strange contrast: the pictograph was objectively difficult and stressful for those with ADHD traits, yet it was their most popular choice. Apparently, they liked the visual appeal despite this being a visual style that complicated the completion of the actual task.

5.2.3 Infographic Visualizations

Simplified Infographic Performance: Figure 5.9 shows that, the ASRS-negative group with the Simplified Infographic achieved an accuracy of 63%, a duration of 86.92 seconds, a heart rate of 90.63, and a blood oxygen level of 98.45. Their preference was 3.33 and only 2.5% of the total population preferred it as their favourite. IES score of 137.97 and cognitive load of 1.67.

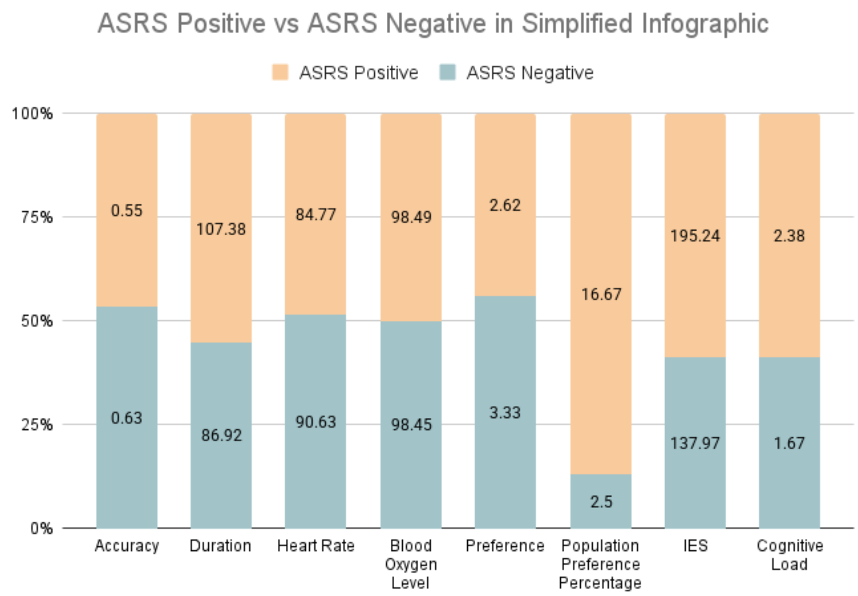

Figure 5.9: Simplified Infographic (ASRS Positive vs ASRS Negative)

The ASRS-positive group using the Simplified Infographic showed an accuracy of 55%, a duration of 107.38 seconds, a heart rate of 84.77, and a blood oxygen level of 98.49. Their preference is reported as 2.62, population preference of 16.67%, IES of 195.24 and a cognitive load of 2.38.

When looking at the Simplified Infographic, the ASRS-negative group clearly had a smoother experience. They were more precise and took the task much quicker than the other group. This format was at least reasonably effective and did not demand excessive mental effort in them as indicated by their reduced cognitive load. The ADHD-likelihood group, however, found this format much more challenging. They were less precise and they also needed approximately 20 seconds extra to complete. More than that, they experienced a much greater cognitive load. Although it was slightly harder for them, they in fact preferred this format the most of any format with almost 17% of them preferring this format as their favorite unlike the Negative group who almost none of them liked this format. Namely, although the ASRS-positive group appeared to value the visual approach disregarding the extra time and effort that it required, the Negative group apparently experienced a greater impact of the infographic.

Detailed Infographic Performance: Figure 5.10 shows that, the ASRS Negative group using the Detailed Infographic had an accuracy of 58%, a duration of 80.66 seconds, a heart rate of 89.7, and a blood oxygen level of 98.5. They showed a preference of 2.69, a population preference of 2.5%, an IES of 139.07, and a cognitive load of 2.31.

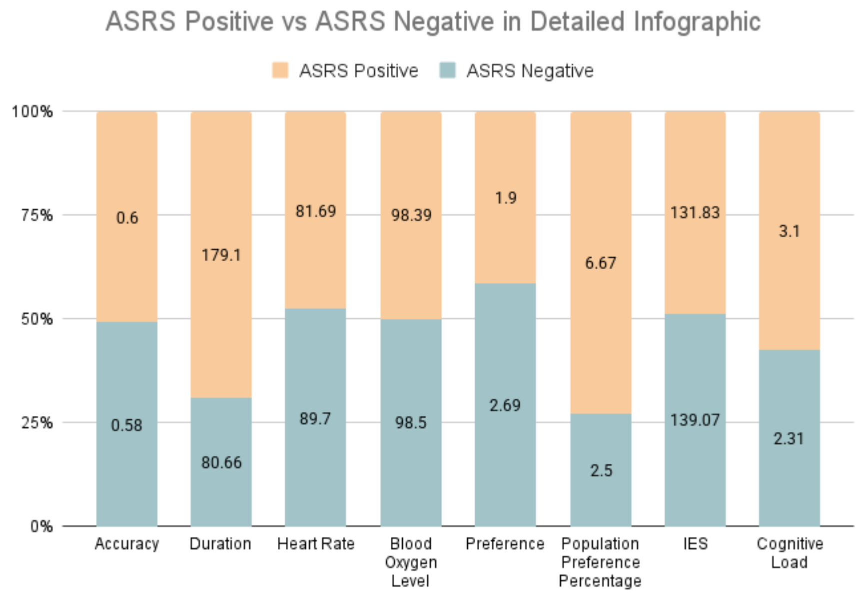

Figure 5.10: Detailed Infographic (ASRS Positive vs ASRS Negative)

The ADHD-likelihood group (ASRS-positive) with the Detailed Infographic achieved an accuracy of 60%, but with an extremely high duration of 179.1 seconds, a heart rate of 81.69, and a blood oxygen level of 98.39. Their preference was 1.9, with a population preference of 6.67%, an IES of 131.83, and a very high cognitive load of 3.1.

When comparing the Detailed Infographic results, we see a massive difference in the time and effort required by each group. Both groups ended up with a similar accuracy score (around 58% to 60%), but the ASRS-positive group took an incredibly long time to get there, nearly 180 seconds, which is more than double the time the Negative group needed. For the ASRS-negative group, this format was somewhat challenging but manageable. However, for the ASRS-positive group, the detailed nature of the infographic seemed to be overwhelming. They reported a very high cognitive load, indicating that processing all that detailed visual information was mentally exhausting. This struggle is clearly reflected in their preference score, which was a very low 1.9. While they were technically just as accurate as the other group, the price they paid in time and mental energy was much higher. Essentially, while the extra detail didn't hurt their final score, it made the task much slower and much more draining for those with ADHD likelihood.

5.2.4 AI Modified Text Visualization

Figure 5.11 shows that, In the case of the AI Modified Text, the ASRS Negative group scored 76% in accuracy, 93.16, 88.75 and 98.27, in duration, heart rate and blood oxygen, respectively. Their preference was 3.88 being the highest, along with 30% of the total participants claiming it as their favourite, IES was 122.58, and cognitive load was low (1.12).

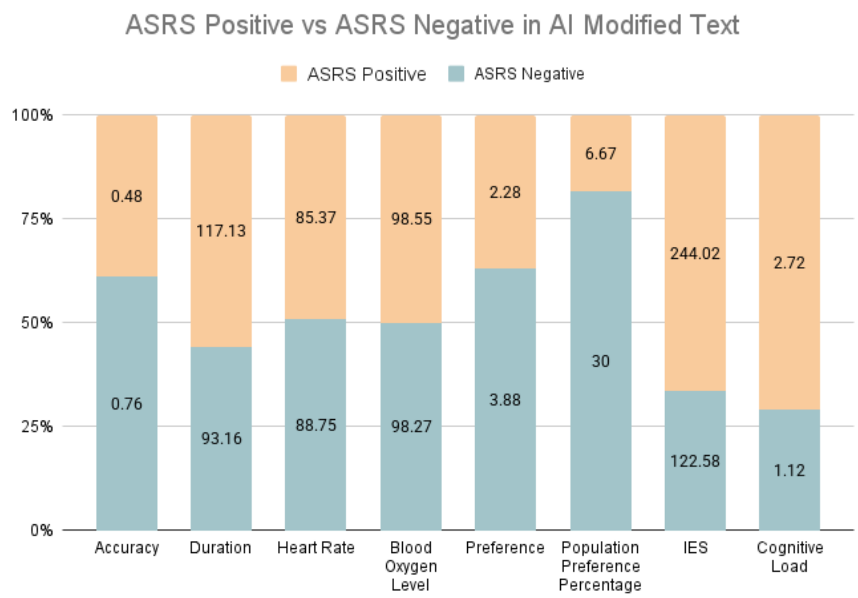

Figure 5.11: AI Modified Text (ASRS Positive vs ASRS Negative)

The ADHD-likelihood group(ASRS-positive) using AI Modified Text saw a lower accuracy of 48%, a duration of 117.13 seconds, a heart rate of 85.37, and a blood oxygen level of 98.55. Their preference was 2.28, with a population preference of 6.67%, a very high IES of 244.02, and a cognitive load of 2.72.

Upon examining the AI Modified Text, a very broad division between the two groups is visible. This format was a massive success with the ASRS-negative (neurotypical) group. They obtained a high precision of 76% and considered the task extremely easy to deal with, which resulted in the lowest mental effort (cognitive load) in nearly all forms. Nevertheless, the ADHD-likelihood group worked significantly worse with the AI text. They became very inaccurate at 48 percent and also took a long time to complete the task. They also experienced much more mental load, and the cognitive load was more than twice as much as in the Negative group. They also had a very low efficiency score (IES being higher), which revealed that this format did not suit them. As the Negative group perceived the AI modified text as clear and easy to enjoy, the Positive one perceived it as confusing and hard to process, which resulted in significantly lower scores and low preference of the format choice.

5.3 Statistical Analysis

5.3.1 ANOVA and Interaction Effects

The foundational analysis of this study utilized a Two-Way Mixed ANOVA to determine the global influence of participant grouping (ASRS positive vs. ASRS negative) and visualization type on the IES. As shown in Table 5.1, the results revealed a highly significant Main Effect for Group ($F(1, 68) = 13.04, p < 0.001$), accounting for a substantial portion of the variance with an effect size of $\eta_p^2 = 0.161$. The overall Cohen's d of 0.87 demonstrates a great standardized change between the two populations in each of the tasks. Furthermore, a significant Main Effect for Visualization Type was observed ($F(7, 476) = 9.15, p < 0.001, \eta_p^2 = 0.119$), confirming that the format of data presentation inherently alters processing efficiency regardless of the user group. Most importantly, the statistical model found a significant Interaction Effect between Group and Visualization Type ($F(7, 476) = 7.90, p < 0.001, \eta_p^2 = 0.104$).

Source of Variation	**df1**	**df2**	**F**	**p-value**	η_p^2
Group (Main Effect)	1	68	13.04	< 0.001	0.161
Visualization (Main Effect)	7	476	9.15	< 0.001	0.119
Interaction Effect	7	476	7.90	< 0.001	0.104

Table 5.1: Two-Way Mixed ANOVA Results for Inverse Efficiency Score (IES)

The significant interaction effect ($p < 0.001$, $\eta_p^2 = 0.104$) confirms that visualization type impacts ASRS positive and ASRS negative groups differently, justifying individual format analysis.

5.3.2 Linear Mixed-Effects Model

Visualization Format	**p-value**	**Hedges' g**	BF_{10}	**Status**
Plain Text	0.419	-0.226	0.331	Safe
Highlighted Text	0.002	0.775	20.01	Moderate
Bar Graph	0.372	0.205	0.35	Safe
Bar With Images	0.246	0.26	0.444	Safe
Pictograph	0.049	-0.527	1.403	Unclear
Simplified Infographic	0.02	-0.613	2.781	Unclear
Detailed Infographic	<0.001	-1.775	2.29×10^6	Critical
AI Modified Text	<0.001	-1.162	750.82	Severe

Table 5.2: Summary of Statistical Performance and Safety Classifications

To account for participant-level variance and nested data structures, a LMM was employed, establishing Plain Text as the primary baseline reference category. The format is the neutral base point of the model giving a clean and distraction free environment where all other types of visualization are compared. With this format serving as an anchor, the model is able to measure in mathematical terms or tangible seconds of the particular cognitive load or time penalties incurred in more complex design features. Table 5.2 shows the summary of statistical performance and safety classifications. Analysis of this baseline showed no significant ASRS positive group coefficient (+6.89s, $p = 0.240$), a result further corroborated by a pairwise comparison showing a non-significant p-value of 0.419 as shown in Figure 5.12 and a negligible Hedges' g of -0.226 as shown in Figure 5.13. This suggests that Plain Text provides an equitable, low-distraction environment for both groups, supported by a Bayes Factor (BF_{10}) of 0.331, which provides evidence in favor of the null hypothesis of group equality. Similarly, Bar Charts and Bar With Images were identified as ASRS positive safe formats. Although the Bar Chart also made the task duration increase universally (LMM coefficient: +30.46s, $p < 0.001$), the difference in the groups was found to be statistically insignificant ($p = 0.372, g = 0.205$). The Bar With Images format showed a marginal baseline increase (+9.79s, $p = 0.060$) but maintained group equity ($p = 0.246, g = 0.260, BF_{10} = 0.444$), indicating that moderate visual enhancements do not disproportionately burden ASRS positive cognition.

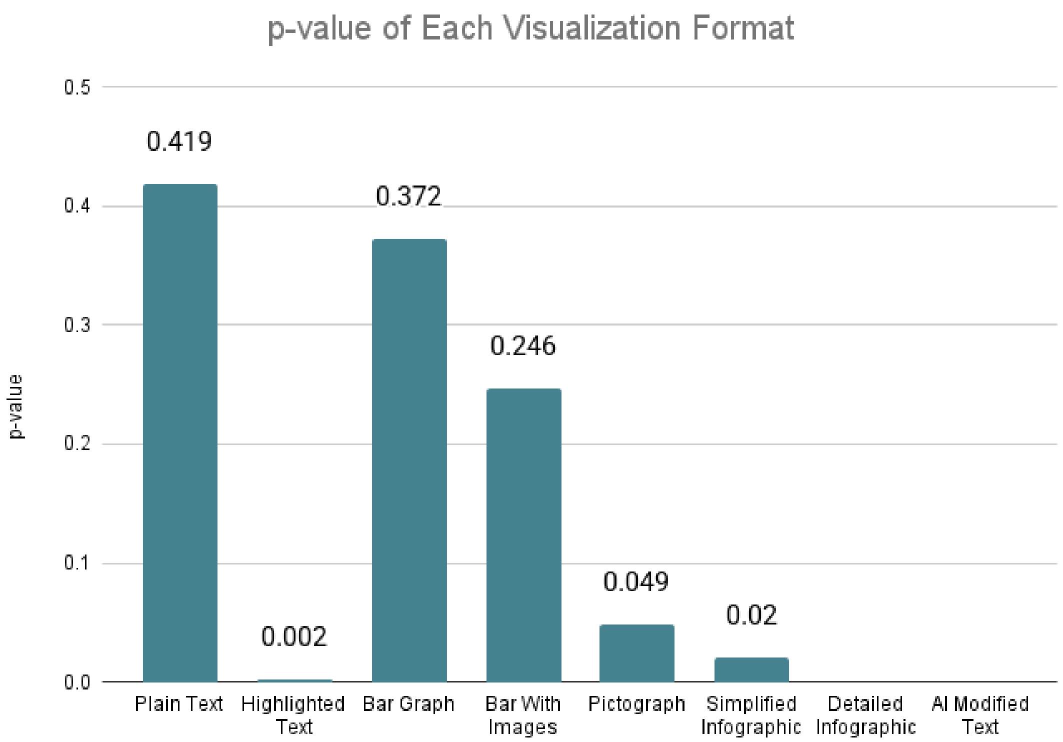

Figure 5.12: p_value of Each Visualization Format

5.3.3 Analysis of Equivocal and Correction-Sensitive Formats

The study identified several formats where initial significance was undermined by more rigorous post-hoc adjustments. Pictographs and Simplified Infographics both demonstrated increased baseline complexity in the LMM (+16.11s and +13.91s respectively, $p < 0.01$). While both formats initially appeared to offer a marginal ASRS positive advantage in uncorrected pairwise comparisons ($p = 0.049$ for Pictographs and $p = 0.020$ for Simplified Infographics), neither result survived Bonferroni correction ($p_{corr} = 0.393$ and $p_{corr} = 0.163$ respectively as shown in Table 5.3). The medium effect sizes (Pictograph $g = -0.527$; Simplified Infographic $g = -0.613$)

were not supported by significant interaction terms in the LMM ($p = 0.345$ and $p = 0.317$), and the Bayes Factors remained weak to moderate ($BF_{10} = 1.403$ and 2.781). Consequently, these formats are classified as equivocal, suggesting that any potential benefit to ASRS positive persons is statistically unstable and requires further replication before being considered a reliable design recommendation.

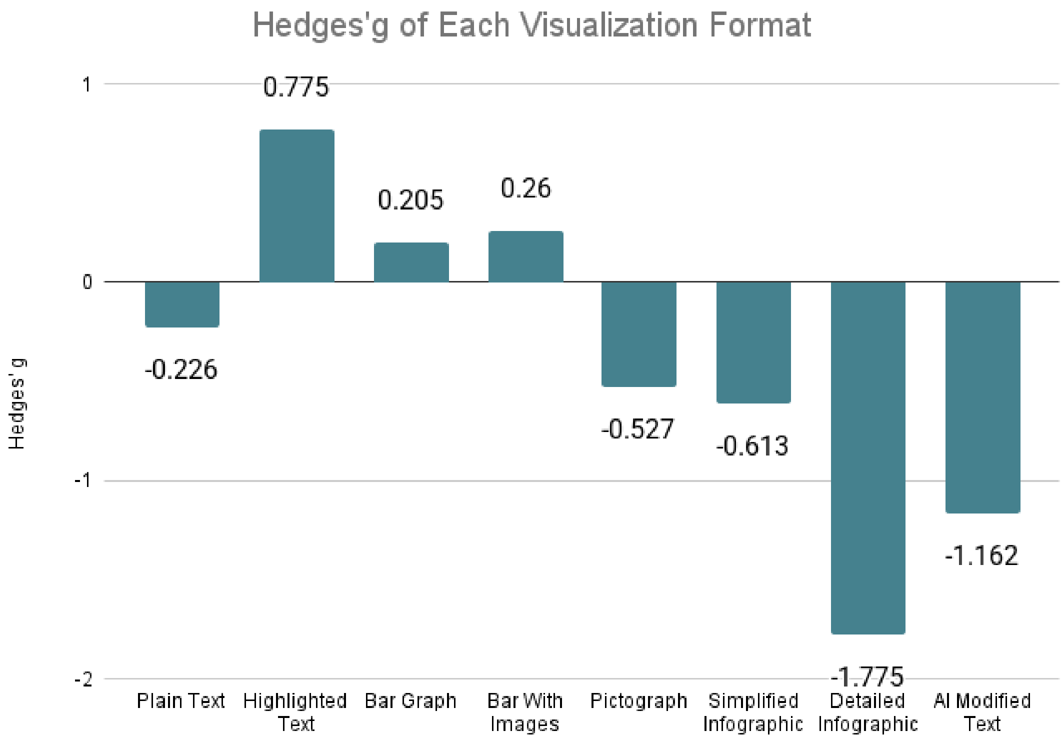

Figure 5.13: Hedges' g of Each Visualization Format

Format	Uncorrected p	Corrected p	Hedges' g	BF_{10}
Pictograph	0.049	0.393	-0.527	1.403
Simplified Infographic	0.020	0.163	-0.613	2.781

Table 5.3: Comparison of Uncorrected and Bonferroni-Adjusted Significance for Equivocal Formats

5.3.4 Statistical Evidence of ADHD-Impairing Formats

The most striking findings of the study involve formats that caused significant performance decrements for ASRS positive participants. Highlighted Text, despite its intended use as an attentional aid, resulted in a significant ASRS positive interaction penalty of -16.92 seconds ($p = 0.034$) beyond the baseline increase as shown in Table 5.4. Pairwise comparisons confirmed this impairment remained significant after Bonferroni correction ($p = 0.013$) with a strong Bayes Factor of 20.01. Even more severe results were found for AI Modified Text, which imposed an ASRS positive specific penalty of +17.20 seconds ($p = 0.031$), leading to a large effect size

($g = -1.162$) and highly significant group differences ($p < 0.001, BF_{10} = 750.82$). The most "catastrophic" impairment was observed in the Detailed Infographic format. This format produced a massive LMM interaction penalty of +28.13 seconds ($p < 0.001$), the largest in the study. The resulting pairwise comparison yielded a Hedges' g of -1.775, a very large effect size that characterizes extreme performance disparity. The Bayes Factor of 2.29 million provides overwhelming statistical evidence that this high-complexity format is critically detrimental to ASRS positive processing efficiency.

Visualization Format	**Interaction Penalty (s)**	**Std. Error**	***p*-value**
Highlighted Text	-16.92	7.96	0.034
AI Modified Text	+17.20	7.96	0.031
Detailed Infographic	+28.13	7.96	< 0.001

Table 5.4: LMM Interaction Coefficients: Quantifying ASRS Positive Specific Performance Penalties

5.3.5 Physiological Validation and Correlation Analysis

To ensure observed performance gaps were rooted in genuine cognitive and physiological processes rather than motivational differences, a MANOVA was conducted on physiological stress markers. The results were highly significant across all multivariate test statistics, including Wilks' Lambda (0.9541, $p < 0.001$), Pillai's Trace (0.0459, $p < 0.001$), and Hotelling-Lawley Trace (0.0481, $p < 0.001$) as shown in Table 5.5. This confirms that the ASRS positive and ASRS negative groups exhibited distinct physiological profiles during the tasks, validating the IES findings. Finally, Pearson correlation analysis was used to explore the relationship between objective performance and subjective preference (Figure 5.14). A weak negative correlation was found between IES and Preference ($r = -0.152, p < 0.001$), while no significant correlation was found between Accuracy and Preference ($r = 0.046, p > 0.05$). This statistical dissociation is significant for researchers as it indicates that users, particularly those of ASRS positive group, cannot accurately self-report or predict which visualization formats actually optimize their objective performance, underscoring the necessity for empirical testing over subjective feedback.

Test Statistic	**Value**	**F (2, 557)**	***p*-value**
Wilks' Lambda	0.9541	13.40	< 0.001
Pillai's Trace	0.0459	13.40	< 0.001
Hotelling-Lawley Trace	0.0481	13.40	< 0.001

Table 5.5: MANOVA Results for Physiological Stress Markers (Heart Rate and SpO_2)

5.4 Comparisons and Relationships

The development of the objective performance metrics and the statistical framework as a whole indicate a clear difference between the visualization formats with the ca-

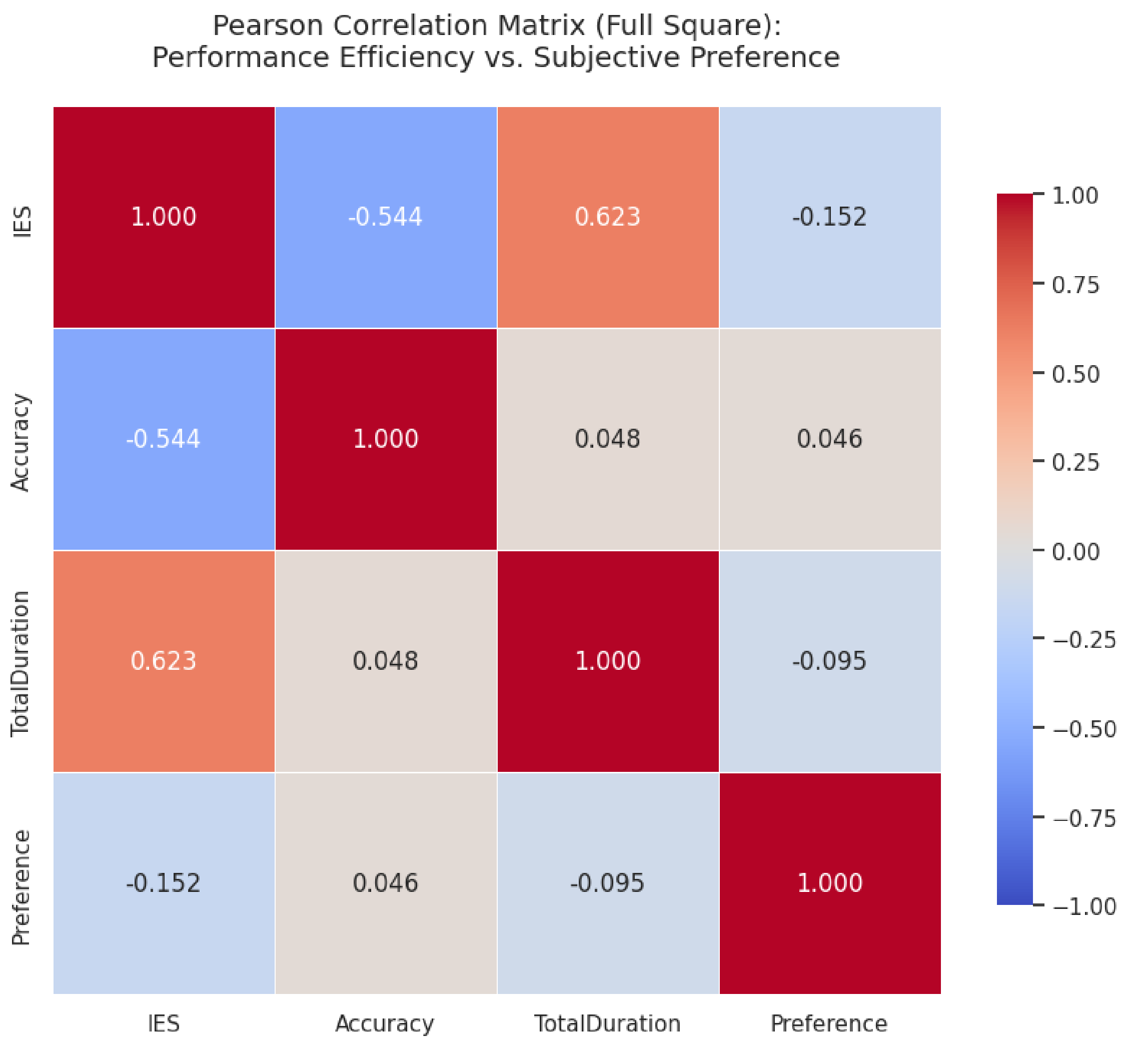

Figure 5.14: Pearson Correlation Matrix Heatmap

pacity to support cognitive equity and those with high barriers to ASRS positive persons. The general statistical model proved the existence of a significant interaction between the type of group and visualization ($p < 0.001, \eta_p^2 = 0.104$), which confirms the fact that the cognitive load and efficiency of the data interpretation process are fundamentally modified by the mode of presentation.

The Most Effective Formats: Based on the analysis, Plain Text, Bar Chart, and Bar With Images are the most possible format of ASRS-positive persons, but they suggest varying cognitive profiles. The most statistically optimal new baseline is identified to be the Plain Text, which appears to have no significant difference in efficiency (IES) in the case of ASRS-positive group and ASRS negative group ($p = 0.419, g = -0.226$). Although descriptive statistics show that the ASRS positive individuals had a greater cognitive load (3.07) and lower preference (1.93) than the ASRS negative ones, they still had a high accuracy (0.89). Likewise, the Bar Charts (both standard and with images) are considered as ADHD-safe as they can preserve the equity of performance ($p > 0.24$), although they take more absolute time to process among the groups. The Bar with Images format in particular demonstrated low-cognitive load (2.3) and accuracy (43%) comparable to the ASRS-negative group which would indicate that the Bar with Pictures do not excessively penalise the cognitive awareness of the likelihood of ADHD.

The Least Effective Formats: The findings and statistics specifically define Detailed Infographics and AI-Modified Text as the most harmful formats to ASRS-positive persons. The Detailed Infographic led to a so-called catastrophic impairment creating the biggest performance penalty in the experiment with an extra 28.13 second load ($p < 0.001$) and a very big effect size ($g = -1.775$). This is confirmed by descriptive data that indicated that, though the ASRS positive persons were able to make 60% accuracy, it took an incredible amount of time of 179.1 seconds and a cognitive load of 3.1 maximum. AI Modified Text is also contraindicated; although it gave the best results to ASRS-negative persons (low cognitive load of 1.12), it gave a high penalty of 17.20 seconds on ASRS positive persons, creating the greatest efficiency deficit (IES of 244.02) and a noticeable reduction in accuracy to 48%.

Paradoxical and Equivocal Formats: Highlighted Text presents a unique case, although it is meant to help with attention, it has a statistically contraindicated effect on ASRS-positive persons. It has an extra 16.92 second punishment of ASRS-positive persons ($p = 0.034$), which forms a medium-large performance difference (g = 0.755). On the other hand, Pictographs and Simplified Infographics are considered equivocal. Though they demonstrated slightly positive uncorrected benefits of ASRS-positive people, the results were not able to pass Bonferroni correction ($p_{corr} > 0.16$) which shows that they are not effective statistically.

Statistical and Physiological Validation: These results are supported by a significant MANOVA ($p < 0.001$) that proves that the observed gaps in performances are related to the different profiles of physiological stress in the two groups. Additionally, the sources point to the fact that there is a severe dissociation in the correlation analysis: the weak negative correlation between performance efficiency and user preference is observed ($r = -0.152, p < 0.001$). This demonstrates that in case of ASRS-positive people, when they like a design or think it is pretty, it does not imply that the design is mentally less draining to handle. Due to this reason, designers cannot simply do what users claim to like. They are better to employ formats which prove to be the most efficient, like Plain Text, Bar Charts, and Bar with Images. Applying these styles that have been tested is more significant than design decisions that are based on personal views alone.

5.5 Discussions

The highly significant interaction effect ($p < 0.001, \eta_p^2 = 0.104$) demonstrates that visualization formats impact ASRS-positive and ASRS-negative individuals fundamentally differently. This observation contradicts the fact that universal design principles sufficiently apply to neurodivergent groups and necessitates format-specific accessibility guidelines.

5.5.1 Significant Findings

Performance Patterns in Different Formats: In Plain Text format, no difference was found in the cognitive equity between groups as both got 89% accuracy, even though the ASRS-positive participants needed additional 23 seconds and reported higher cognitive load (3.07 vs. 1.47). This pattern exemplifies what research on hyperfocus suggests: ASRS-positive individuals can match neurotypical performance under optimal conditions, but at substantially higher cognitive cost. The format acts as low scaffolding that hardly addresses executive functioning problems.

Bar Charts were able to perform at the same level, although poor comprehension was universal (33 - 35% accuracy). Surprisingly, ASRS-positive participants favored this format (3.52 vs. 2.99) and indicated lower cognitive load (1.48 vs. 2.01). The structured spatial organization may reduce subjective mental effort even when it doesn't improve whole understanding, functioning as external organizational support that reduces executive control demands.

Bar Charts with Images maintained the cognitive equity and demonstrated different processing costs. The two groups had similar results with moderate accuracy (41 - 43%), however, neurotypical participants processed information 12 seconds faster with half the cognitive load. This represents a critical threshold where complexity slows ASRS-positive processing without causing catastrophic impairment, which implies the effective implementation of compensatory mechanisms, potentially with the help of the benefits of dual-coding.

The Highlighting Paradox: The most counterintuitive result was the Highlighted Text, instead of aiding attention, it imposed a 16.92-second penalty on ASRS-positive users ($p = 0.034, g = 0.755$). It has been shown that the attention of ADHD persons is more involuntary and directed to salient visual stimuli. Every emphasized part turns into a competing attention magnet disrupting the natural rhythm of reading and making one reorient continuously. It is indicative of impaired inhibitory control in frontal-striatal loops: whilst typical readers selectively deploy attention guided by highlighting, ADHD/ADHD-likelihood readers cannot filter the salience of highlighting from semantic importance, creating visual noise rather than navigational support. This object to the popular belief that visual emphasis can assist the attention of ADHD.

Catastrophic Failure of Visual Complexity: Detailed Infographics caused severe impairment, the ASRS-positive subjects took 179.1 seconds against 80.66 seconds (60 vs. 58). The effect size was very high ($g = -1.775$) and the Bayesian evidence ($BF_{10} = 2.29$ million) was overwhelming. This disintegration is an indicator of fundamental executive control impairment in ADHD. In the presence of several rival visual hierarchies (colours, shapes, icons, annotations, spatial relations), the executive functions of neurotypical people coordinate the processing and select out irrelevant information. In users with ASRS this causes the executive control system to be overwhelmed, resulting in cognitive disintegration. Perceptual Load Theory explains this as the worst-case design: high cognitive load requiring integration of disconnected streams, combined with low perceptual load from scattered elements that don't demand sustained focal processing. This is confirmed by the neurophysiological validation ($MANOVAp < 0.001$) that this is actual neurophysiological stress rather than motivational factors.

AI-Modified Content Failure: Automated accessibility proved a very important limitation in AI-Modified Text. Although this was very effective with neurotypical users (cognitive load 1.12, accuracy 76%), it had a crippling effect on ASRS-positive users (cognitive load 2.72, accuracy 48%), generating a 28% point difference in accuracy. Language models that are trained on general populations are optimized towards average users and can encode biases that are against neurodivergent populations. The AI changes were probably a breach of compensatory linguistic patterns that the ASRS-positive readers are dependent on and it created indeterminate structures that drain the already scarce executive resources. This brings up deep questions of how AI-enabled personalization on a large scale may in fact increase rather than decrease accessibility gaps.

Preference-Performance Dissociation: The weak negative correlation between IES and preference ($r = -0.152, p < 0.001$) and absent correlation between accuracy and preference ($r = 0.046$) reveal that ASRS-positive users cannot reliably identify which formats optimize their performance. Thirty percent of the respondents chose Pictographs as the most preferred, although it got one of the lowest effectiveness scores (IES = 229.64). This dissociation indicates the key ADHD features: objective performance is impaired by formats, and subjective satisfaction circuits are triggered by novelty-seeking and sensitivity to rewards. The aesthetic-usability effect plays off with ADHD neurobiology in that the visually stimulating formats innervate positive, but with functional impairment.

This finding has critical implications for user-centered design. Standard UX methods relying on preference rankings and satisfaction ratings systematically mislead when applied to neurodivergent populations. Designers must triangulate subjective preferences with objective performance metrics as well as physiological measures if possible to identify truly effective designs.

Design implications of Cognitive equity: The way to cognitive equity is to remove extraneous visual complexity not to provide stimulation. The main common features of safe formats (Plain Text, Bar Charts, Bar Charts with Images) are as follows: single coherent organizational structure, minimal decorative elements, and use of space rather than color for guidance. This aligns with Cognitive Load Theory predictions that ASRS-positive users benefit most from designs reducing extraneous load by simplifying visual environments, even sacrificing aesthetic appeal.

Contraindicated formats (Detailed Infographics, AI-Modified Text, Highlighted Text) all introduce complexity neurotypical users can filter but ASRS-positive users struggle with. Be it spatial density, unpredictable restructuring, or salient marking, the cognitive outcome is the same, that is, poor processing efficiency despite the same or better preference ratings.

Key Design Principles:

- **Structured visual scaffolding:** Task-relevant images in Bar Charts with

Images reduce physiological stress and maintain performance parity. This aligns with Dual Coding Theory [73] showing enhanced learning when pictures and words work together without overwhelming cognitive capacity.

- **Avoid highlighting paradox:** Bold and highlighted text acts as visual noise for ASRS-positive readers by triggering attentional capture. Better organization through spacing and clear headings outperforms color emphasis.
- **Mitigate catastrophic density:** Detailed infographics and AI text cause severe impairment. Any complex format must ensure consistent, predictable information flow for ASRS-positive users.
- **Empirical metrics over preference:** Preference-performance gap necessitates relying on IES and physiological monitoring rather than subjective feedback when evaluating accessibility.
- **Physiological parity:** Accessibility standards should ensure tasks remain effortless, not just accurate, maintaining low physiological stress levels.

5.5.2 Comparative Analysis with Published Research

This study of the formats is an immediate continuation of the groundbreaking element-level study by Tran et al. [22], where the authors studied 147 participants (70 ADHD, 77 non-ADHD). Integrated visualization formats had to be thought of as they thought of single objects of the charts (color, text density, embellishments) as they can be seen in real-life applications. It is a very important methodological distinction that the designers do not choose individual elements but rather whole presentation modes.

In both studies, preference-performance dissociation was discovered independently. As Tran et al. [22] note, the visually rich format was preferred by the ADHD subjects but was not correlated with the optimal response time and accuracy. The statistical size of our quantified correlation analysis ($r = -0.152$) provides a more statistical justification of this phenomenon in two different samples that the fact is an actual phenomenon and must be taken into account in the context of research associated with accessibility.

The results of the Highlighted Text show that the Tran et al. [22] methodology was incapable of discussing the issue of ADHD-specific impairments. They found that the text annotation density affected both groups in the same manner and there existed an optimal level of annotation that produced optimal performance. However, in investigating the theme of deliberate highlighting, it was discovered in this study that not all issues with textual highlighting proceed in a similar vein: since highlighting has relevant and attracts attention, there are special problems with highlighting that is not generalized by annotation density.

They also found an accuracy difference across tasks with pictographs: where ratio estimation had better results than precision of exact value extraction. Consistently low performing Pictograph scores (IES 229.64, cognitive load 2.38) were received in this study that would reasonably be the outcome of the comprehension activities that entailed the extraction of accurate information, which would be comparable to their exact value condition when pictographs were counterproductive. It is a confirmation that pictographic visualization can be used to mediate gist knowledge and not fine analytic studies that involve ADHD groups.

Alignment with Cognitive Load Research in Neurodiversity: Newer studies by Le Cunff and others are essential background. Their 2024 study of neurodivergent students as focus groups revealed that reading long form text where there were no visual aids was especially difficult, and that it required a lot of effort to remain on task [74]. Although this may appear to be a contradiction of the positive Plain Text results of this study, the most important difference is content length and duration of the tasks. They did their study based on the extensive reading sessions where fatigue prevails and in the case of this study, Plain Text sessions were focused on short time (60 - 180 seconds) tasks. It implies a critical point: minimalistic formats can maximise the amount of information extracted and need to be supplemented in order to maintain engagement.

A systematic review led by Le Cunff et al. [75] found that 92% of cognitive load studies on online learning did not take into account the issue of neurodiversity. Of the 8% who did, they discovered that ADHD students were less cognitively loaded with redundant visual information than their neurotypical counterparts were with the same effect. This contradicted classic redundancy effect predictions. It is also consistent with the Bar Chart with Images results of this study, in which task-relevant visual additions did not cause performance differences, implying that not all visual complexity is clutter to ADHD populations.

In a quantitative investigation of 231 students, it was discovered that neurodivergent students, particularly ADHD ones, experienced much greater extraneous cognitive load during online learning [76]. This is a direct confirmation of the Detailed Infographic results: the fragmented visual items created the extraneous load that could not be filtered by the ASRS-positive students, but could be handled by the neurotypical participants due to the intact executive functions.

Convergence with Perceptual Load Theory: A seminal publication by Forster and Lavie [25] proved that the concept of high perceptual load kills attention in ADHD as it completely fills the perceptual capacity. This same principle was applied to full-fledged visualization formats: Plain Text and Bar Charts impose narrow constraints of perception (sequential processing, spatial comparison) that achieves success at engaging ADHD attention without excessive executive load. Detailed Infographics are failed due to the diffuse and scattered perceptual requirements as opposed to concentrated perceptual requirements.

More recent studies by Akerman et al. [77] indicates that people with ADHD do not have global processing bias in either visual or auditory format, which also implies a more extensive and generic processing format with equal vulnerability to both local and global distractions. This is the reason why Detailed Infographics did not work: the format presented both global structure (overall layout) and local details (individual elements) without hierarchy distracting ASRS-positive users on both levels.

Divergence from Traditional Accessibility Guidelines: The study revealed some fundamental flaws in existing systems. WCAG [26] focuses on perceivability (ensuring content can be seen) but provides minimal guidance on cognitive processing optimization. Chartability [12], despite comprehensive accessibility coverage, offers limited empirical guidance for ADHD-specific format selection. Both acknowledge attention related shortcomings but do not specify what sorts of visualization to favor and what to avoid.

It is common in popular industry recommendations that visual interest and embellishment should be applied to keep ADHD users engaged [78]. This is directly disproved by our data: the formats which ASRS-positive users have found most favoring (Pictographs, 30% preference) were the least efficient in comprehension. The design space described by Kim et al. [11] in their study formulated the principles of perceivability, describability, and interpretability but did not consider neurocognitive specificity needed by the ADHD population. According to our findings, we propose the inclusion of a fourth dimension, cognitive load optimization specific to executive function profiles.

Methodological Advances: This research advances the field through multi-modal validation. While Tran et al. [22] relied on self-reported ADHD diagnosis and behavioral metrics, we combined standardized ASRS screening, objective performance measures (IES), subjective ratings, and medical-grade physiological monitoring. This triangulation addresses limitations in single-measure studies.

The use of pulse oximeter represents a practical middle ground between invasive neuro-imaging and purely behavioral measures, appropriate for short visualization tasks. Though not as advanced as EEG or fMRI applied in the pilot study by Le Cunff et al. [79], our methodology gave good consistent measurements to show that the differences in performance are actual physiological stress and not motivation difference.

Our rigorous statistical framework (ANOVA, LMM, MANOVA, Bonferroni correction, Bayes Factors) exceeds most prior work's analytical sophistication. Many existing studies relied on simple t-tests without multiple comparison correction, potentially inflating Type I errors. Our multi-layered approach provides confidence in effective robustness and replicability.

AI-Generated Accessibility: This study is the first to attempt empirically investigate the hypothesis of whether AI-generated ADHD-friendly formatting proves beneficial or not to ADHD users. As generative AI is fast becoming used in the educational field, the highly negative results (28% point gap in accuracy) are a very important warning signal. Language models trained on general populations may systematically disadvantage neurodivergent users, requiring specialized training data and evaluation frameworks explicitly including neurodiverse populations.

Synthesis and Future Directions: There is convergence between several independent studies on central results (preference-performance dissociation, benefits of minimalist design, problems of visual complexity) which gives the confidence that real phenomena is determined, and not methodological artifacts. However, substantial gaps remain:

- **Heterogeneity within ADHD:** The different inattentive, hyperactive-impulsive, and combined subtypes probably need varied visualization techniques. Future studies should examine whether the results can be extrapolated between different ADHD subtypes.

- **Comorbidity effects:** Since clinical ADHD has 50% comorbidity rates [23], it is essential to understand how the comorbid conditions (dyslexia, anxiety, autism) can regulate visualization processing.

- **Developmental trajectories:** The university sample is a sample of persons who managed to survive educational systems in spite of the symptoms of ADHD indicating that they have compensatory strategies that younger children or elderly persons may not have.

- **Dynamic visualizations:** Static formats are only a tiny portion of the visualization world. And that is regardless of whether the values (minimize visual complexity, offer clear structure) apply to animated charts, interactive dashboards, and augmented reality displays or not.

- **Participatory design:** The discipline needs to shift past describing the problems to designing solutions, and the neurodivergent individuals should be made co-creators not just research participants [74].

The final objective is actually adaptive systems that should present individual cognitive profiles. The findings empirically support this work and determine which dimensions are the most important and give quantitative standards of cognitive equity. The future of available technology should be based on this to accomplish the creation of really inclusive digital spaces.

5.5.3 Limitations of the Study

Although this study has strong empirical support for the use of ASRS-positive inclusive data visualization design, several methodological limitations could not be ignored:

Participant Demographics:

- **Age Restriction:** The research has only enrolled participants who were university students aged between 19 and 25 years. The presentation of ADHD symptoms and cognitive compensation mechanisms differ greatly among developmental stages of the disorder [80], which do not permit generalization to children, adolescents, and older adults.

- **Screening Methodology:** ASRS test was used to categorize the participants instead of clinical diagnostic gold standards. With a high level of specificity (99% specificity) [17], [18] of this test, the data is used to determine the probability of ADHD symptoms, but not a definite diagnosis and does not distinguish the subtypes of ADHD [81].

- **Geographic Specificity:** The participants were all members of South Asian university communities (from Bangladesh to be specific). Although the study also intends to fill the crucial knowledge gaps [23] in the Global South literature, cultural variations in education systems, exposure to technology, and visual literacy can potentially restrict immediate extrapolation to Western or other non-Western groups of people, as well as vice versa [82].
- **Sample Size:** n = 70 (40 ASRS-negative, 30 ASRS-positive) was not large enough to detect big effects (Cohen's d = 0.87), but larger samples would increase the likelihood of equivocal results (Pictographs, Simplified Infographics) to pass Bonferroni correction [83].

Methodological Constraints:

- **Controlled Environment:** The data collection was in distraction-reduced settings, which does not reflect the academic setting in real-world, with surrounding noise, social distractions, and competing task demands. This could have been an artificial advantage of ASRS-positive participants whose main difficulty is the ability to manage distractions [21].
- **Static Visualizations:** The study exclusively evaluated static, non-interactive formats. Interactive dashboards with user-controlled filtering and dynamic updates may present different cognitive demands for ASRS-positive users [84].
- **Task Duration:** Comprehension tasks were short (60 - 180 seconds) which were characterized by focused information extraction rather than sustained engagement. Symptomatology of ADHD is more evident in the case of extended tasks [33] and making a difference in format may enhance in the case of a longer interaction.

Measurement Limitations:

- **Single-Item Cognitive Load:** Cognitive load was measured with inverted preference ratings as opposed to multi-dimensional measures such as NASA-TLX. While justified by strong correlations ($r > 0.8$) for brief tasks [49], [50] and validated through physiological data (MANOVA $p < 0.001$), this could have overlooked subtle workload dimensions.
- **Physiological Monitoring:** Pulse oximeter provides non-invasive monitoring but represents a coarse measure compared to heart rate variability (HRV), electrodermal activity (EDA), or pupillometry [51], [52]. Brief task duration may have limited observable physiological changes.

Generalization:

- **Format Selection:** The 8 visualization formats, while representative of common presentations, are not a limit on the design space.
- **Content Domain:** The comprehension questions were based on the interpretation of quantitative data, which can not necessarily be generalized to the interpretation of qualitative visualization, process diagram, or narrative infographics [85].

Despite these limitations, the study's medical oversight, multi-method statistical validation (ANOVA, LMM, MANOVA, Bayesian analysis), substantial effect sizes (Hedges' g:-1.775 to 0.775), and focus on under-served Global South populations provide confidence in the findings and establish a foundation for ADHD inclusive design principles.

Chapter 6

Conclusion

6.1 Summary of Findings

The research results prove that the interaction effect between the participant groups and the visualization type is highly significant, and it becomes the basis of the statistics of the research. This interaction proves that there is an inconsistent impact of data presentation format on ASRS negative and ASRS positive students. It is, therefore, crucial that the specific cognitive problems and supports that it needs should be carefully researched. The MANOVA results further prove the validity of such performance-based results as ASRS positive and ASRS negative groups displayed different physiological patterns during the tasks and, therefore, the existing observed differences in performance can be attributed to real cognitive and physiological processes rather than to the differences that are based solely on motivation.

One of the fundamental study findings is the recognition that some formats offer cognitive equity, that is, they allow processing inclusivity, without unfairly punishing ASRS positive students. Plain Text, Bar Charts and Bar Charts with Images are chosen as the best basis since they create almost distraction-free and task focused backgrounds of which both groups are statistically equivalent. These are specially accessible for ASRS positive students as these are easy to make available across all study materials. Although these spatial visualizations at all times take longer times to process compared to simple text based on the complexity in translating numbers, they are characterized by group equity and in the ability of ASRS positive participants to compensate by means of concentrative visual processing.

On the other hand, complex formats such as the Detailed Infographic have been known to cause what is termed as extreme impairment to the ASRS positive individuals. The format yielded a great performance penalty in the whole experiment which consisted of an enormous interaction effect and astronomical Bayes Factor which overwhelmingly demonstrates high cognitive load. The gross visual clutter and excessive information of Detailed Infographics do not comply with the principles of ASRS positive friendly design, which results in a failure in processing efficiency. It was also determined that AI Modified Text was also severely impairing to ASRS positive students. Although, the format was the most efficient format for ASRS negative participants. The chaotic format or abnormal linguistic patterns seemed to be a great challenge in performance, effectiveness and choice among ASRS positive people.

One of the most counter-intuitive results is associated with Highlighted Text, which is conventionally used as an attention-directing resource. This study concluded that emphasizing or highlighting the facts actually decreased ASRS positive performance and it is detrimental that this serves as a visual noise, not an aid. Although the typographic emphasis was advantageous to the ASRS negative users, the visual stimulus of highlighting incurred a major performance penalty on the ASRS positive users, implying that highlighting is maybe using the same limited attentional resources that were available to process the text and gather information from it. This renders the format contraindicated to ASRS positive-inclusive design although it finds a large amount of preference as an educational resource.

Lastly, the study demonstrates a very important difference between preference and objective performance, which cannot be neglected. There was also a small negative correlation between efficiency and preference, which implies that especially the ASRS positive ones are not accurate enough to predict or report themselves what formats actually maximize their performance. As an example, the participants of the ASRS positive group tended to state that they preferred visually stimulating charts the most when they were the least efficient on the latter. This observation highlights the importance of using the empirical measures, including the IES and other methods, and not the subjective feedback during the creation of accessible data visualization.

Finally, the study comes to a conclusion that the best and most accessible ASRS positive-safe formats of inclusive data representations are: Plain Text, Bar Charts and Bar With Images. These particular visualizations help create cognitive equity because there is better performance equivalence between ASRS positive and ASRS negative groups. In order to apply these findings in practice, designers ought to focus on a minimalist approach which excludes unnecessary visual clutters, additional decorations, and high-density information displays, which prove to impose severe defects in processing efficiency for ASRS positive students. Particularly, the presentation of information must be simple text or spatial bar based and organized in a way that will cause minimal cognitive load to the user, without using traditional tools such as heavy highlighting or elaborate infographics, which will actually cause more distraction and cognitive load to the ASRS positive students.

6.2 Contributions to the Field

The study provides a groundbreaking contribution to the study of Human-Computer Interaction and accessible technology as it creates a strict, evidence-based model of ASRS positive-inclusive data visualization. In the heart of this study, a key phenomenon of cognitive equity was found out, showing that whilst it is true that the ASRS positive persons might experience general difficulties in the area of concentration, minimalist and structured formats such as plain text, normal bar charts and bar with images enable them to perform at the same level as that of their counterparts, the ASRS negative ones. This work serves as a guide to the developers and designers to get beyond the decorative or stimulating visuals which in most cases are a cognitive burden on the ASRS positive brain and concentrate on format which allows information to be extracted with minimum mental effort.

One of the most significant aspects that can bring some changes to existing teaching and design concepts is the finding that attention-grabbers are not necessarily useful for productivity and effectiveness to all. The study also shows an alarming paradox of the characteristics such as text highlighting, that is supposed to focus attention turned to being distracting and noise making to ASRS positive students. This research refutes some of the many assumptions in the history of educational technology and provides a clue that less is more in cases of neurodiverse populations. Moreover, the research also recognizes a serious impairment linked with high-density infographics, which is empirically verified that too much visual complexity can essentially be severe to the processing efficiency of an ASRS positive student, irrespective of motivation levels.

Even the methodology of this study is a major contribution in the research on accessibility as it revealed an important dissociation between user preference and objective performance. It is demonstrated in the course of the research that, due to their ASRS positive status, many students cannot accurately classify which formats they personally find the most efficient since they can be influenced by subjectively appealing visuals and find them objectively inefficient and slow in accuracy. Having created the IES as a better measurement tool than plain accuracy or time, the study has established a new benchmark in the way accessibility and actual productivity is to be measured, and that is through the importance placed on speed and accuracy in balance. This demonstrates the need to ensure that the development of tools for such neurodivergent students must be guided by empirical and multi-criteria data, but not only subjective feedback in the development of tools.

Lastly, the study is also an addition to the rapidly expanding field of bio-behavioral validation by addressing real-time physiological indicators, including heart rate and blood oxygen levels, to statistical models of performance. This multi-modal method validates the fact that the challenges that ASRS positive users face are based on real physiological stress and cognitive overload, which creates a scientific justification of neurodiverse inclusion. With this study providing the actionable and evidence-based recommendations on safe and accessible ASRS positive designs, the field can be empowered to proceed to the more inclusive digital future in which technology is informed by the individual physiological and cognitive realities of the individual.

6.3 Recommendations for Future Work

One of the key areas of concern of the future studies will be expansion of the range of participants beyond the current age that is limited to university-going students, to a wider group of people especially children, teenagers and the elderly people. Because there are notable age-to-age changes in the ASRS positive symptoms and cognitive processing strategies, the research question needs to be whether such safe and accessible ASRS positive formats found in this study will continue to be effective among pediatric populations or whether alternative age developmental stages require completely different visualization patterns. Moreover, a broader geographic and cultural scope of the study will assist in finding out whether the results can be generalized or whether educational backgrounds and familiarity to digital interfaces have an impact on the way neurodiverse people process visual data.

The next generation of research ought to also move beyond the controlled condition to real life conditions with its distractions, including ambient noise, social disruptions and the multitasking requirements of the contemporary work and study environment for the students. Although the existing study provided a normative level of research in a silent setting, the experimentation of these visualization formats under regular pressure will give a more realistic idea of the usefulness of these mediums in real life. This involves researching the effects of environmental sensitivities like light levels and frequency of noise and how they influence various data presentation styles to increase or reduce cognitive overload in ASRS positive individuals.

A critical area of focus remains which is technological development, namely, the enhanced inter-connection between real-time biofeedback and adaptive machine learning algorithms. The systems that will come in the future ought to provide an upgrade to the current state by categorizing the user by using wearable devices like smartwatches or a better, more comfortable EEG headset to track the current state of physiological stress and attention of a person in real-time. It will be then possible to train machine learning algorithms to dynamically change the visual complexity, information density and formatting of a display according to the current cognitive state of the person. A system could, as an example, switch to a minimalist Plain text or Bar chart interface when it notices an increase in heart rate or indications of mental exhaustion and thus offer a really customized and reactive accessibility device to those who happen to be ASRS positive.

A few long term studies are also required to determine how these visualizations actually stand and continue to make a difference over the time. Most studies on performance have tended to assess instant performance yet it is not clear that measures such as fatigue during many hours or the effect of learning to be conversant with a format would modify the processing efficiency over time. Also, the gap between subjective taste and objective performance in future studies should be reduced by exploring design aspects that may make safe and accessible formats such as bar charts more interesting without reducing their cognitive equity or to find out some completely new formats if possible, that will balance all aspects. This will demand participatory design, in which ASRS positive individuals will be used in the initial phases of the creative development so that the developed tools will empower the user as opposed to controlling the disruptive behaviors.

Lastly, this field of research would be enhanced by applying official medical diagnoses and not simply quick screening surveys in order to classify individuals. Although surveys are effective in general research, the evaluation based on official clinical records and full time involvement of medical specialists in this field would assist in clarifying how various ASRS positive persons, those who primarily have issues with focus and those who are very active respondents react to various visuals. One can also take a closer look at picture-based charts and simple infographics to understand whether they can be enhanced so that they could benefit a greater number of people.

With the emphasis on these various spheres, one can develop technology which will be able to be truly inclusive and respectful of the way of thinking and processing of each person.

Bibliography

[1] L. L. Weyandt and G. DuPaul, "Adhd in college students," *Journal of attention disorders*, vol. 10, no. 1, pp. 9–19, 2006.

[2] P. Song, M. Zha, Q. Yang, Y. Zhang, X. Li, and I. Rudan, "The prevalence of adult attention-deficit hyperactivity disorder: A global systematic review and meta-analysis," *Journal of global health*, vol. 11, 2021.

[3] G. Ayano, S. Demelash, Y. Gizachew, L. Tsegay, and R. Alati, "The global prevalence of attention deficit hyperactivity disorder in children and adolescents: An umbrella review of meta-analyses," *Journal of affective disorders*, vol. 339, pp. 860–866, 2023.

[4] J. Lagacé-Leblanc, L. Massé, and N. Rousseau, "Academic impairments faced by college students with attention-deficit hyperactivity disorder: A qualitative study.," *Journal of Postsecondary Education and Disability*, vol. 35, no. 2, pp. 131–144, 2022.

[5] C. M. M. Hasan, M. M. Islam, M. M. R. Mahib, and M. A. C. Arju, "Prevalence and assessment of biochemical parameters of attention-deficit hyperactivity disorder children in bangladesh," *Journal of basic and clinical pharmacy*, vol. 7, no. 3, p. 70, 2016.

[6] S. V. Faraone et al., "Attention-deficit/hyperactivity disorder in adults: An overview," *Biological psychiatry*, vol. 48, no. 1, pp. 9–20, 2000.

[7] E. Sciberras et al., "Social and economic costs of attention-deficit/hyperactivity disorder across the lifespan," *Journal of attention disorders*, vol. 26, no. 1, pp. 72–87, 2022.

[8] L. E. Arnold, P. Hodgkins, J. Kahle, M. Madhoo, and G. Kewley, "Long-term outcomes of adhd: Academic achievement and performance," *Journal of attention disorders*, vol. 24, no. 1, pp. 73–85, 2020.

[9] A. Jangmo et al., "Attention-deficit/hyperactivity disorder, school performance, and effect of medication," *Journal of the American Academy of Child & Adolescent Psychiatry*, vol. 58, no. 4, pp. 423–432, 2019.

[10] J. Kim, A. Srinivasan, N. W. Kim, and Y.-S. Kim, "Exploring chart question answering for blind and low vision users," in *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, 2023, pp. 1–15.

[11] N. W. Kim, S. C. Joyner, A. Riegelhuth, and Y. Kim, "Accessible visualization: Design space, opportunities, and challenges," in *Computer graphics forum*, Wiley Online Library, vol. 40, 2021, pp. 173–188.

[12] F. Elavsky, C. Bennett, and D. Moritz, "How accessible is my visualization? evaluating visualization accessibility with chartability," in *Computer graphics fórum*, Wiley Online Library, vol. 41, 2022, pp. 57–70.

[13] D. A. Szafir, "Modeling color difference for visualization design," *IEEE transactions on visualization and computer graphics*, vol. 24, no. 1, pp. 392–401, 2017.

[14] K. B. Schloss, C. C. Gramazio, A. T. Silverman, M. L. Parker, and A. S. Wang, "Mapping color to meaning in colormap data visualizations," *IEEE transactions on visualization and computer graphics*, vol. 25, no. 1, pp. 810–819, 2018.

[15] A. Sharif, O. H. Wang, A. T. Muongchan, K. Reinecke, and J. O. Wobbrock, "Voxlens: Making online data visualizations accessible with an interactive javascript plug-in," in *Proceedings of the 2022 CHI conference on human factors in computing systems*, 2022, pp. 1–19.

[16] M. Z. I. Alam, S. Islam, and E. Hoque, "Seechart: Enabling accessible visualizations through interactive natural language interface for people with visual impairments," in *Proceedings of the 28th International Conference on Intelligent User Interfaces*, 2023, pp. 46–64.

[17] R. C. Kessler et al., "The world health organization adult adhd self-report scale (asrs): A short screening scale for use in the general population," *Psychological medicine*, vol. 35, no. 2, pp. 245–256, 2005.

[18] C. Daigre et al., "Adult adhd self-report scale (asrs-v1. 1) symptom checklist in patients with substance use disorders," *Actas españolas de psiquiatría*, vol. 37, no. 6, pp. 299–305, 2009.

[19] R. A. Barkley, "Behavioral inhibition, sustained attention, and executive functions: Constructing a unifying theory of adhd.," *Psychological bulletin*, vol. 121, no. 1, p. 65, 1997.

[20] E. G. Willcutt, A. E. Doyle, J. T. Nigg, S. V. Faraone, and B. F. Pennington, "Validity of the executive function theory of attention-deficit/hyperactivity disorder: A meta-analytic review," *Biological psychiatry*, vol. 57, no. 11, pp. 1336–1346, 2005.

[21] S. Forster and N. Lavie, "Establishing the attention-distractibility trait," *Psychological science*, vol. 27, no. 2, pp. 203–212, 2016.

[22] T. Tran, H.-N. Lee, and J. H. Park, "Discovering accessible data visualizations for people with adhd," in *Proceedings of the CHI Conference on Human Factors in Computing Systems*, 2024, pp. 1–19.

[23] S. Cortese and D. Coghill, "Twenty years of research on attention-deficit/hyperactivity disorder (adhd): Looking back, looking forward," *Evidence-Based Mental Health*, vol. 21, no. 4, pp. 173–176, 2018. DOI: 10.1136/ebmental-2018-300050.

[24] N. Lavie, A. Hirst, J. W. de Fockert, and E. Viding, "Load theory of selective attention and cognitive control.," *Journal of Experimental Psychology: General*, vol. 133, no. 3, pp. 339–354, 2004. DOI: 10.1037/0096-3445.133.3.339.

[25] S. Forster, D. J. Robertson, A. Jennings, P. Asherson, and N. Lavie, "Plugging the attention deficit: Perceptual load counters increased distraction in adhd.," *Neuropsychology*, vol. 28, no. 1, pp. 91–97, 2014. DOI: 10.1037/neu0000020.

[26] T. Chatziemmanouil and C. Katsanos, "Accessibility academy: Interactive learning of the wcag 2.1 web accessibility guidelines," in *2024 IEEE Global Engineering Education Conference (EDUCON)*, 2024, pp. 1–7. DOI: 10.1109/EDUCON60312.2024.10578915.

[27] M. Hassenzahl and N. Tractinsky, "User experience-a research agenda," *Behaviour & information technology*, vol. 25, no. 2, pp. 91–97, 2006.

[28] D. A. Norman, *Emotional Design: Why We Love (or Hate) Everyday Things*. New York: Basic Books, 2004, ISBN: 978-0465051366.

[29] W. Lidwell, K. Holden, and J. Butler, *Universal principles of design, revised and updated: 125 ways to enhance usability, influence perception, increase appeal, make better design decisions, and teach through design*. Rockport Pub, 2010.

[30] J. Sweller, "Cognitive load during problem solving: Effects on learning," *Cognitive science*, vol. 12, no. 2, pp. 257–285, 1988.

[31] J. Sweller, J. J. Van Merriënboer, and F. Paas, "Cognitive architecture and instructional design: 20 years later," *Educational psychology review*, vol. 31, no. 2, pp. 261–292, 2019.

[32] L. A. Friedman and J. L. Rapoport, "Brain development in adhd," *Current Opinion in Neurobiology*, vol. 30, pp. 106–111, 2015. DOI: 10.1016/j.conb.2014.11.007.

[33] M. J. Kofler et al., "Reaction time variability in adhd: A meta-analytic review of 319 studies," *Clinical psychology review*, vol. 33, no. 6, pp. 795–811, 2013.

[34] L. Tamm, M. E. Narad, T. N. Antonini, K. M. O'brien, L. W. Hawk Jr, and J. N. Epstein, "Reaction time variability in adhd: A review," *Neurotherapeutics*, vol. 9, no. 3, pp. 500–508, 2012.

[35] B. K. Ashinoff and A. Abu-Akel, "Hyperfocus: The forgotten frontier of attention," *Psychological Research*, vol. 85, no. 1, pp. 1–19, 2021. DOI: 10.1007/s00426-019-01245-8.

[36] K. E. Hupfeld, T. R. Abagis, and P. Shah, "Living 'in the zone': Hyperfocus in adult adhd," *ADHD Attention Deficit and Hyperactivity Disorders*, vol. 11, no. 2, pp. 191–208, 2019. DOI: 10.1007/s12402-018-0272-y.

[37] R. Bruyer and M. Brysbaert, "Combining speed and accuracy in cognitive psychology: Is the inverse efficiency score (ies) a better dependent variable than the mean reaction time (rt) and the percentage of errors (pe)?" *Psychologica Belgica*, vol. 51, no. 1, 2011.

[38] J. T. Townsend and F. G. Ashby, *Stochastic modeling of elementary psychological processes*. CUP Archive, 1983.

[39] T. South, K. Marriott, and M. Wybrow, "Photosensitivity in computer applications," in *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, ACM, 2023, pp. 1–14. DOI: 10.1145/3544548.3580718.

[40] K. Wu, S. S. Petersen, T. Ahmad, D. Burlinson, E. S. Tanis, and D. A. Szafir, "Understanding data accessibility for people with intellectual and developmental disabilities," in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, ACM, 2021, pp. 1–16. DOI: 10.1145/3411764.3445743.

[41] K. Wu et al., "Data experiences: Investigating and designing for data accessibility and disability justice," in *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*, ACM, 2023, pp. 1–8. DOI: 10.1145/3544549.3573796.

[42] K. Hornbæk and M. Hertzum, "Technology acceptance and user experience: A review of the experiential component in hci," *ACM Transactions on Computer-Human Interaction (TOCHI)*, vol. 24, no. 5, pp. 1–30, 2017. DOI: 10.1145/3127358.

[43] E. R. Tufte, *The Visual Display of Quantitative Information*, 2nd. Cheshire, CT: Graphics Press, 2001, ISBN: 978-0961392147.

[44] M. A. Borkin et al., "What makes a visualization memorable?" *IEEE Transactions on Visualization and Computer Graphics*, vol. 19, no. 12, pp. 2306–2315, 2013. DOI: 10.1109/TVCG.2013.234.

[45] D. J. Gillan and S. B. Richman, "Minimalism and the syntax of graphs," *Human Factors*, vol. 36, no. 4, pp. 619–644, 1994. DOI: 10.1177/001872089403600405.

[46] S. Haroz, R. Kosara, and S. L. Franconeri, "Isotype visualization: Working memory, performance, and engagement with pictographs," in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15)*, ACM, 2015, pp. 1191–1200. DOI: 10.1145/2702123.2702508.

[47] H.-K. Kong, Z. Liu, and J. Heer, "Frames and slants in titles of visualizations on controversial topics," in *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*, ACM, 2018, pp. 1–12. DOI: 10.1145/3173574.3174012.

[48] C. Stokes, V. Setlur, B. Cogley, A. Satyanarayan, and M. Hearst, "Striking a balance: Reader takeaways and preferences when integrating text and charts," *IEEE Transactions on Visualization and Computer Graphics*, vol. 28, no. 1, pp. 1233–1243, 2022. DOI: 10.1109/TVCG.2021.3114811.

[49] S. G. Hart and L. E. Staveland, "Development of nasa-tlx (task load index): Results of empirical and theoretical research," in *Advances in psychology*, vol. 52, Elsevier, 1988, pp. 139–183.

[50] S. Rubio, E. Díaz, J. Martín, and J. M. Puente, "Evaluation of subjective mental workload: A comparison of swat, nasa-tlx, and workload profile methods," *Applied psychology*, vol. 53, no. 1, pp. 61–86, 2004.

[51] F. Chen et al., "Robust multimodal cognitive load measurement," in *Robust Multimodal Cognitive Load Measurement*, ser. Human–Computer Interaction Series, Cham: Springer, 2016, pp. 1–13. DOI: 10.1007/978-3-319-31700-7_1.

[52] J. Klingner, R. Kumar, and P. Hanrahan, "Measuring the task-evoked pupillary response with a remote eye tracker," in *Proceedings of the 2008 Symposium on Eye Tracking Research & Applications*, 2008, pp. 69–72. DOI: 10.1145/1344471.1344489.

[53] J. Achiam et al., "Gpt-4 technical report," *arXiv preprint arXiv:2303.08774*, 2023.

[54] F. Henninger, Y. Shevchenko, U. K. Mertens, P. J. Kieslich, and B. E. Hilbig, "Lab.js: A free, open, online study builder," *Behavior Research Methods*, vol. 54, no. 2, pp. 556–573, 2022. DOI: 10.3758/s13428-019-01283-5.

[55] S. J. Kooij et al., "European consensus statement on diagnosis and treatment of adult adhd: The european network adult adhd," *BMC Psychiatry*, vol. 10, no. 1, p. 67, 2010. DOI: 10.1186/1471-244X-10-67.

[56] L. S. Matza, L. C. Paramore, and S. Prasad, "A review of the economic burden of adhd," *Cost Effectiveness and Resource Allocation*, vol. 3, no. 1, p. 5, 2005. DOI: 10.1186/1478-7547-3-5.

[57] B. Metin, H. Roeyers, J. R. Wiersema, J. van der Meere, and E. Sonuga-Barke, "A meta-analytic study of event rate effects on go/no-go performance in attention-deficit/hyperactivity disorder," *Biological psychiatry*, vol. 72, no. 12, pp. 990–996, 2012.

[58] J. Klingner, B. Tversky, and P. Hanrahan, "Effects of visual and verbal presentation on cognitive load in vigilance, memory, and arithmetic tasks," *Psychophysiology*, vol. 48, no. 3, pp. 323–332, 2011.

[59] A. Vandierendonck, "A comparison of methods to combine speed and accuracy measures of performance: A rejoinder on the binning procedure," *Behavior research methods*, vol. 49, no. 2, pp. 653–673, 2017.

[60] F. Paas, J. E. Tuovinen, H. Tabbers, and P. W. Van Gerven, "Cognitive load measurement as a means to advance cognitive load theory," in *Cognitive load theory*, Routledge, 2016, pp. 63–71.

[61] J. L. Plass, R. Moreno, and R. Brünken, "Cognitive load theory," 2010.

[62] D. Norman, *Emotional design: Why we love (or hate) everyday things*. Basic books, 2007.

[63] L. St, S. Wold, et al., "Analysis of variance (anova)," *Chemometrics and intelligent laboratory systems*, vol. 6, no. 4, pp. 259–272, 1989.

[64] A. Gałecki and T. Burzykowski, "Linear mixed-effects model," in *Linear mixed-effects models using R: a step-by-step approach*, Springer, 2012, pp. 245–273.

[65] A. French, M. Macedo, J. Poulsen, T. Waterson, and A. Yu, "Multivariate analysis of variance (manova)," *San Francisco State University*, 2008.

[66] R. E. Kass and A. E. Raftery, "Bayes factors," *Journal of the american statistical association*, vol. 90, no. 430, pp. 773–795, 1995.

[67] D. Enzmann, "Notes on effect size measures for the difference of means from two independent groups: The case of cohen'sd and hedges'g," *January*, vol. 12, no. 2015, 2015.

[68] L. J. Williams and H. Abdi, "Post-hoc comparisons," *Encyclopedia of research design*, pp. 1060–1067, 2010.

[69] Q. Shi, E. S. Pavey, and R. E. Carter, "Bonferroni-based correction factor for multiple, correlated endpoints," *Pharmaceutical statistics*, vol. 11, no. 4, pp. 300–309, 2012.

[70] J. Benesty, J. Chen, Y. Huang, and I. Cohen, "Pearson correlation coefficient," in *Noise reduction in speech processing*, Springer, 2009, pp. 1–4.

[71] K. Hornbæk, "Current practice in measuring usability: Challenges to usability studies and research," *International journal of human-computer studies*, vol. 64, no. 2, pp. 79–102, 2006.

[72] F. G. Paas, “Training strategies for attaining transfer of problem-solving skill in statistics: A cognitive-load approach.,” *Journal of educational psychology*, vol. 84, no. 4, p. 429, 1992.

[73] J. M. Clark and A. Paivio, “Dual coding theory and education,” *Educational psychology review*, vol. 3, no. 3, pp. 149–210, 1991.

[74] A.-L. L. Cunff, V. Giampietro, and E. Dommett, “Neurodiversity and cognitive load in online learning: A focus group study,” *PLoS ONE*, vol. 19, no. 4, e0301932, 2024. DOI: 10.1371/journal.pone.0301932.

[75] A.-L. L. Cunff, V. Giampietro, and E. Dommett, “Neurodiversity and cognitive load in online learning: A systematic review with narrative synthesis,” *Educational Research Review*, vol. 51, p. 100 604, 2024. DOI: 10.1016/j.edurev.2024.100604.

[76] A.-L. L. Cunff, R. Ford, V. Giampietro, and E. Dommett, “Neurodiversity positively predicts perceived extraneous load in online learning: A quantitative research study,” *Education Sciences*, vol. 14, no. 5, p. 516, 2024. DOI: 10.3390/educsci14050516.

[77] A. Akerman, A. Etkovitch, and E. Kalanthroff, “Global-local processing in ADHD is not limited to the visuospatial domain: Novel evidence from the auditory domain,” *Journal of Attention Disorders*, vol. 27, no. 8, pp. 906–914, 2023. DOI: 10.1177/10870547231153952.

[78] A.-L. L. Cunff and E. Dommett, “Cognitive load and neurodiversity in online education: A preliminary framework for educational research and policy,” *Frontiers in Education*, vol. 9, p. 1 437 673, 2024. DOI: 10.3389/feduc.2024.1437673.

[79] A.-L. L. Cunff, V. Giampietro, and E. Dommett, “Neurodiversity and cognitive load in online learning: A pilot EEG and eye-tracking study,” *Journal of Cognitive Enhancement*, 2025. DOI: 10.1177/27546330251400677.

[80] R. A. Barkley and M. Fischer, “Predicting impairment in major life activities and occupational functioning in hyperactive children as adults: Self-reported executive function (EF) deficits versus EF tests,” *Developmental Neuropsychology*, vol. 36, no. 2, pp. 137–161, 2011. DOI: 10.1080/87565641.2010.549877.

[81] B. B. Lahey and E. G. Willcutt, “Predictive validity of a continuous alternative to nominal subtypes of attention-deficit/hyperactivity disorder for DSM–V,” *Journal of Clinical Child & Adolescent Psychology*, vol. 39, no. 6, pp. 761–775, 2010. DOI: 10.1080/15374416.2010.517161.

[82] J. Henrich, S. J. Heine, and A. Norenzayan, “The weirdest people in the world?” *Behavioral and Brain Sciences*, vol. 33, no. 2-3, pp. 61–83, 2011. DOI: 10.1017/S0140525X0999152X.

[83] K. Mack, E. McDonnell, D. Jain, L. L. Wang, J. E. Froehlich, and L. Findlater, “What do we mean by ”accessibility research”? a literature survey of accessibility papers in CHI and ASSETS from 1994 to 2019,” in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, New York, NY, USA: Association for Computing Machinery, 2021, pp. 1–18, ISBN: 9781450380966. DOI: 10.1145/3411764.3445401.

[84] B. Shneiderman, "The eyes have it: A task by data type taxonomy for information visualizations," in *Proceedings 1996 IEEE Symposium on Visual Languages*, IEEE, 1996, pp. 336–343. DOI: 10.1109/VL.1996.545307.

[85] E. Segel and J. Heer, "Narrative visualization: Telling stories with data," *IEEE Transactions on Visualization and Computer Graphics*, vol. 16, no. 6, pp. 1139–1148, 2010. DOI: 10.1109/TVCG.2010.179.