The implications of information load on usability and performance in dashboards

Emily O'Hear

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THE IMPLICATIONS OF INFORMATION LOAD ON USABILITY AND PERFORMANCE IN DASHBOARDS

Emily O’Hear

A THESIS

Submitted in partial fulfillment of the requirements for the degree of Master of Arts in Psychology in The Department of Psychology to The Graduate School of The University of Alabama in Huntsville May 2023

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Abstract

THE IMPLICATIONS OF INFORMATION LOAD ON USABILITY AND PERFORMANCE IN DASHBOARDS

Emily O’Hear

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Arts in Psychology

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As learning analytics dashboards become ubiquitous in various industries, understanding how users process data and information is crucial to their design. Previous literature has brought valuable knowledge to dashboard design and cognitive load, but it is unclear how individuals perform with and digest a high or low information load. Tradeoffs are present as a dashboard with a lower information load requires more clicks and a dashboard with a higher information load could lead to information overload. This study presented a data-rich and minimalistic dashboard to active-duty airmen at Fairchild Air Force Base. Results indicated that participants largely preferred the data-rich dashboard but rated the minimalistic dashboard higher in satisfaction. There were no significant differences between the dashboards regarding usefulness, ease of use, ease of learning, and response time. The current study provided further research into how dashboard design and cognitive load impact performance and usability.
Acknowledgements

During my time as a master’s student at the University of Alabama in Huntsville, I faced both rewarding and challenging experiences. Without the invaluable support and guidance from those around me, I would not have been able to persevere through my studies. I would like to extend my heartfelt appreciation to the people who helped me along the way.

First and foremost, I would like to express my immense gratitude to my faculty advisor and committee chair, Dr. Nathan L. Tenhundfeld, for his unwavering support and guidance throughout the planning, writing, and data collection process of my thesis. Dr. Tenhundfeld always made himself available to address any concerns or obstacles I faced, no matter how many meetings or projects he had on his plate. Joining the Advanced Teaming, Technology, Automation, and Cognition (ATTAC) Human Factors Lab in 2019 under his mentorship provided me with a solid foundation for this paper’s work through learning about data collection, data analysis, and collaboration, among other topics. I am also privileged for having Dr. Lisa Vangsness and Dr. Kristin Weger on my thesis committee, who provided constructive criticism and valuable feedback. The difficult questions I was asked both in this document and in my presentations allowed me to think critically about my decisions and explore avenues I would not have initially.

I would also like to acknowledge the inestimable encouragement I received from my peers in the ATTAC Lab. Being surrounded by well-rounded researchers with diversity of thought and experiences contributed to ideas and conversations I would not have come upon had I not joined the ATTAC Lab.
This endeavor would not have been possible without RippleWorx, who sponsored this research and provided me with the opportunity to conduct user evaluations at Fairchild Air Force Base. Thank you to Brian Hadley, Larry Lowe, and Carolyn Sanders for fostering a positive and professional environment where I could provide my feedback and design recommendations where necessary.

Lastly, I am deeply indebted to my friends and family. Without the tremendous understanding and unconditional support my parents have given me this past year, this study would not have been possible. I am also grateful for my fiancé, who offered his continuous encouragement throughout this entire process and offered reassurance on those late nights where I found myself confused and unsure about my work. I would not be where I am today without the sacrifices these people made for my education.
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Chapter 1. Introduction

1.1 Data Visualization in Dashboards

A product interface serves as a channel for conveying and transmitting information between users and a product (Jacob, 2001). Business Intelligence and Analytics dashboards have become a widespread and robust interface for presenting information and large data to users through graphics and data visualization (Toreini & Morana, 2017). By synthesizing multiple data sources into a central location, they enable users to access high-level information at a glimpse (Few, 2006). Users can then conduct further analysis by clicking through the dashboard to uncover information about their organization or product (Yigitbasioglu & Velcu, 2012). By providing insight into performance, competitive analyses, and progress tracking, dashboards can help with attaining higher levels of situational awareness by the user through data visualizations (Baysal et al., 2014; Few, 2006; Lechner & Fruhling, 2014; Sedrakyan et al., 2019; Yilmaz et al., 2021). Data visualization involves converting quantitative or qualitative data into a visual format, allowing for easier exploration, examination, and communication of the data (Azzam et al., 2013). For example, data visualizations have been used in the US Army to display the readiness of War Reserve equipment (Schafer et al., 1998). As logistical planning for an Army requires quick decision-making from a host of data sources, these data visualizations aggregate the data across several dimensions.
into one source and as such, increase efficiency. Data visualization allows decision-makers to view analytics in a visual form where they can more easily understand and discover patterns in data (Sadiku et al., 2016).

In an era wherein massive amounts of big data are being produced and dispersed, it is critical to examine how users comprehend and digest the information presented by visualizations. Data visualization involves more than the displaying of visual and quantitative information; it is a large form of communication that demands designers to carefully evaluate their use of visual design techniques and the amount of information presented (Engebretsen & Kennedy, 2020). Poorly designed dashboards with too little or too much information, for example, can be challenging to use, leading to disuse if users must excessively click or are overwhelmed with information (Chen, 2018; Costa & Aparício, 2019; Glassey, 2005). In addition, design choices regarding composition and spatial organization can significantly influence users’ perception and comprehension of the data presented. Although dashboards can be a powerful tool of displaying data and information, their success relies on careful consideration of theoretical foundations such as human cognition, information load, and design principles (Park & Jo, 2019).

1.2 Interface Usability

A large objective for designers is to create interfaces that users find satisfying and useful. A well-designed dashboard should clearly present data and be user-friendly (Bhutani, 2019). Usability encompasses ‘ease of use’ and the acceptability of a system or product. ‘Ease of use’ affects user performance and satisfaction, and the acceptability of a system affects whether or not the product is used (Bevana et al., 1991). Usability is often
measured through performance measures and the evaluation of a user’s subjective experience through questionnaires. The USE Questionnaire has gained traction in usability literature and has demonstrated strong psychometric properties (Gao et al., 2018). This specific questionnaire measures dimensions of usefulness, satisfaction, and ease of use in an interface or system (Lund, 2001). The USE Questionnaire along with other usability questionnaires/testing is often administered to test performance, identify usability problems, compare a product to another product, or compare it to a target measurement (Lewis, 2006).

Emotional experiences with data visualizations and interfaces are closely linked to their aspects of usability (Mõttus et al., 2013; Silvennoinen & Jokinen, 2016). Arrangements of data visualization including visual components of a balanced composition, spatial organization, centeredness, and colors provoke individuals’ senses and emotions in a distinct fashion (Kennedy & Engebretsen, 2020). Users’ engagement with data is energized by emotions such as frustration, anxiety, calmness, and boredom (Saifer & Dacin, 2021; Silvennoinen & Jokinen, 2016). For example, a user may experience boredom while interacting with a dashboard if it has poor spatial organization resulting in extra clicks while another user may feel calm if a dashboard has grouping, adequate negative space, color, and spatial organization. A user may also feel anxiety when interacting with a cluttered dashboard with a large load of information presented. In the USE Questionnaire, responses regarding satisfaction can be indicative of positive, neutral, or negative emotions stemming from the interface (Lund, 2001). The application of previously mentioned visual components can increase positive emotions and aid in the
acceptability, learnability, comprehensibility, and productivity of an interface (Ngo et al., 2003).

Displaying excessive detail or cluttering a screen with unactionable decoration are some common pitfalls in dashboard design (Costa & Aparício, 2019). As such, presenting only the essential information to the user is crucial for their experience (Gao et al., 2006). Usability heuristic analysis is commonly used to assess usability and guide design and can be valuable for evaluating information visualization systems to ensure that they are of high quality (Dowding & Merrill, 2018). A list of heuristic evaluators includes visibility of system status, spatial organization, flexibility and efficiency of use, aesthetic and minimalist design, etc. (Convertini et al., 2004, Fakun & Greenough, 2002; Nielson, 1994). The heuristic of aesthetic and minimalist design, in particular, suggests that user interfaces should be simple in design and must be as easy to use as possible. In keeping a minimal and simple dashboard design, unnecessary functionality should be hidden, non-redundant information should be provided, and user workload should be relieved (Gao et al., 2006). Dashboard content can be divided into three categories: incorporating what users need to know, including information that would be nice to know as an option, and excluding what users do not need to know (Schwier & Misanchuk, 1993). The information that would be nice to know, such as a student’s grade compared to the average grade, can be presented through a filter or an option box. Presenting this as an option rather than another load can help reduce the load of presented information while still providing data users may want access to. Effectively selecting information to include on a dashboard can keep the load of information minimal, increasing usability and
helping mitigate users becoming overwhelmed. The tradeoff here, with a more minimalistic dashboard, is an increase in clicks to access information.

The literature notes that the number of clicks necessary to reach information is a cost to users (Chen, 2018; Edwards & Kelly, 2017). However, findings are inconsistent regarding the specific number of clicks that impact usability the most. Oftentimes, designers attempt to adhere to the “Three-click rule” of web design and organization (Glassey, 2005). This rule posits that users should ideally reach the desired information or destination within three mouse clicks (Zeldman, 2001). While this is not an official rule, some literature suggests that websites and interfaces that adhere to this rule receive more positive responses than those that require more clicks or are based on a free structure (Dilen, 2022). Other research shows that there is no such relationship (Porter, 2003). There is no systematic identification of a specific number of clicks as results vary from author to author, but an increase in the number of clicks appears to negatively impact usability (Glassey, 2005). As such, the possibility stands that a sparse and minimalistic dashboard page requiring more clicks may lead to the disuse of the interface and a more negative user experience. The inconsistent literature highlights the need to further investigate how information load plays into clicking and usability in a dashboard.

1.3 Information Load

A challenge for designers has been effectively managing information load, or the amount of information and data displayed on a single page. Poorly designed dashboards with too little or too much information presented can lead to the disuse of the interface. With an increase in data presented, perceptual clutter can confuse or increase the amount
of time it takes to complete a task or obtain information (Zhou et al., 2013). Presenting greater amounts of information on one page can also increase the possibility of information overload. Information overload occurs when the amount of relevant and potentially useful information presented hinders a user’s efficiency in using the information (Bawden & Robinson, 2009). It can lead to stress, confusion, distraction, and misinterpretation (Edmunds & Morris, 2000). These negative effects can impact decision-making and increase the possibility of user errors, hindering the success of a dashboard (Schick et al., 1990). Perceptual clutter can be handled by reducing information load or changing the layout of an interface (Van den Berg et al., 2009). Other downsides arise with reducing information load as a minimal and uncluttered display can become sparse and inefficiently use the available space for display (Rosenholtz et al., 2005). In a minimalistic dashboard, users may be forced to click through multiple pages to access the information needed. This results in performance costs and can generate feelings of frustration or boredom. With the tradeoffs existing between minimalistic and visually cluttered or data-rich dashboards, providing a balance between the two is a difficult task.

When designing a dashboard, it is important to also consider that humans have cognitive limitations such as working memory and limited capacity for attention (Haroz and Whitney, 2012). Cognitive load refers to any demands on the processing of information and working memory storage (Schnotz & Kürschner, 2007). An adult’s central working memory is limited to 3 to 5 chunks of information, which underlie decision-making and abstract thought (Baddeley & Logie, 1999; Cowan, 2010; Yigitbasioglu & Velcu, 2012). A high information load occupies working memory
capacity, which is used to hold and process present information (Rose et al., 2004). Cognitive tasks, such as completing a task on a dashboard to obtain information, can only be done well with a sufficient ability to hold the information as it is processed (Cowan, 2010). Dashboards typically implement graphics or data visualizations rather than presenting individual numbers, increasing memory retention and enhancing perception (Park & Jo, 2019). Although the utilization of graphs and visual displays aids in reducing the number of chunks of information on a page, information overload is still a challenge, as any task that demands a large number of items or data to be stored in short-term memory can support an excessive cognitive load (Sweller, 1988).

An interface that is visually cluttered or promotes large loads of information can also generate performance costs (Van den Berg et al., 2009). Perceptual clutter refers to the state wherein the presentation or organization of excess items leads to a decline in performance at some task (Rosenholtz et al., 2005). The literature notes that performance (accurate decision-making) and information load are positively correlated, but only up to a certain point. Characterized by an inverted U-curve (see Figure 1.1), a “sweet spot” exists between information usage and information load wherein adding additional information beyond the sweet spot will result in the information no longer being integrated into decision-making (Chewning & Harrell, 1990; Eppler & Mengis, 2008; Schroder et al., 1967). Surpassing this point in turn leads to information overload in which a user begins to utilize the available information less, reflected by their decisions. Likewise, presenting too little information can lead to decreased decision accuracy. Designers should identify the most important information that users need to make informed decisions and ensure that this information is presented in a clear and concise
manner. They should also avoid cluttering the interface with irrelevant or unnecessary information that could distract users from the most important data. By finding the right balance between information load and decision accuracy, designers can create a dashboard that effectively supports decision-making and improves user experience.

![Information Load Inverted U-curve](image)

**Figure 1.1** Information Load Inverted U-curve (Eppler & Mengis, 2008). The amount of information presented and a user’s decision accuracy have an inverted U-curve relationship. High and low information load can yield low decision accuracy. The middle line represents the “sweet spot”.

Oftentimes users must obtain the information they need from data visualizations in a short period of time. In healthcare, for instance, data visualizations have been used to present patient progression where healthcare workers must be able to glance at a large number of patients and quickly identify salient groups (Widanagamaachchi, 2017). The amount of information options presented to users directly impacts how quickly they access the needed data. Formulated back in the 1950s, the Hick-Hyman law assesses the amount of time it takes individuals to process a certain amount of information to act on or choose a command (Hick, 1952; Hyman, 1953). Specifically, the law indicates the relationship between information entropy and reaction time (Rosati, 2013). With a cluttered or data-rich page incorporating too much functionality and too many available choices, users are likely to spend more time making decisions as they must visually
attend to more stimuli (see Figure 1.2). This law implies that designers can lessen the number of stimuli on one page to reduce decision-making time, but other obstacles may be introduced. Reducing the number of stimuli then runs the risk of inefficiently using the available space to present information on a landing page (Rosenholtz et al., 2005). With the direct effects of information load and entropy on usability, decision accuracy, and decision response time, designers must carefully consider the amount of functionality offered on any given page of a dashboard.

![Figure 1.2](image)

**Figure 1.2** Hick-Hyman Law (Rosati, 2013). The logarithmic function between information entropy and reaction time. As the number of options available increases, the amount of time taken to make a decision increases.

### 1.4 The Present Study

Though there has been much focus on dashboard design, design principles, and user-interface design, there is limited research on optimizing information load on a dashboard. This study analyzes and applies dashboard-specific design guidelines and practices to a minimalistic dashboard and a data-rich dashboard. The current study seeks to evaluate the tradeoffs of high and low information loads in usability, accuracy, response time, and preference of users through the presentation of a minimalistic and data-rich dashboard.
Participants navigated through a data-rich and minimalistic dashboard to find responses to performance task questions and rated each dashboard on various factors of usability. Given the current literature, the following is expected:

**Hypothesis One:** Users will prefer the minimalistic dashboard condition more than the data-rich dashboard.

**Hypothesis Two:** Users will provide more accurate responses to task performance questions in the minimalistic dashboard condition than in the data-rich dashboard.

**Hypothesis Three:** Users will respond faster to task performance questions in the minimalistic dashboard condition than in the data-rich dashboard.

**Hypothesis Four:** Users will rate the minimalistic dashboard higher in usefulness, ease of use, ease of learning, and satisfaction than the data-rich dashboard.
Chapter 2. Method

2.1 Participants

A convenience sample of participants \((N = 30)\) was selected from active-duty enlisted U.S. Air Force aircraft maintenance unit personnel at Fairchild Air Force Base. Although not analyzed for this study, half of the participants were leaders \((n = 15)\), and half of the participants were subordinates \((n = 15)\). The average age of participants was 25 years old, where 10% reported female as their sex assigned at birth and 90% reported male. In regard to ethnicity, the sample was 13.3% Black/African American, 13.3% Hispanic/Latino, 56.7% White, and 10% Multi-Ethnic. One participant preferred not to share their age and ethnicity. Approval was obtained from the Institutional Review Board at the University of Alabama in Huntsville before collecting data for this study.

An a priori G*Power analysis (see Figure 2.1) calculated an appropriate sample size of \(N = 34\) to detect a medium-sized effect with desired power set at \(1-\beta = .80\) (Faul et al., 2007). The number of participants in this sample was slightly below this number. As such, effect sizes were reported for analyses.
Figure 2.1 Power Analysis Output Using G*Power Version 3.1.9.6. A G*Power analysis calculated a minimum sample size of 34 to detect a medium-sized effect.

2.2 Design

This study implemented a two-group within-subjects design. The dashboards included two levels: the minimalistic dashboard and the data-rich dashboard. All participants were presented with the data-rich dashboard first, followed by the minimalistic dashboard. This present study was part of a larger examination of user experience with dashboards, including a concurrent study investigating framing and role effects (Gray, 2023). The Framing Effects study presented a gain-framed and a loss-framed dashboard and was counterbalanced and randomly assigned in presentation with this study. Participants were measured on performance (accuracy and response time) and provided their preference between the dashboards along with their perceived usefulness,
ease of use, ease of learning, and satisfaction with each dashboard. The ratings of these four factors of usability were collected in this fixed order.

2.3 Materials

2.3.1 Task Environment

The current study took place in a computer lab at Fairchild Air Force Base. Six dual-monitor computer stations were set up by UAH researchers in the lab to present the survey and interactive dashboards. The right-hand monitor at each station displayed a web-based survey presented through Qualtrics, an online tool used to distribute surveys and analyze responses (Qualtrics, 2022). This screen was recorded with no audio to cloud storage using the Zoom video conferencing platform (Zoom Video Communications, Inc., 2022) to later analyze response times. The left-hand monitor displayed the data-rich, minimalist, gain-framed, and loss-framed dashboards with respect to the randomization of the survey. The dashboards were developed by RippleWorx employees through Tableau, an interactive data visualization software (“Tableau Dashboard Showcase”, 2022). The dashboards displayed a series of training requirements for airmen ranked below a 5 Level, where participants were familiar with the information.

2.3.2 Dashboard

For the current study, a data-rich and minimalistic dashboard was developed. A view of the minimalistic dashboard is shown in a wireframe in Figure 2.2. A screenshot of the data-rich dashboard is shown in a wireframe in Figure 2.3. The visualizations on the dashboard presented training data for a fabricated airman under the name “Tyler
Cash.” All participants viewed the same training data on each dashboard. The minimalistic dashboard displays only the categories of tasks as pie charts on its landing page, where users had to click on the pie charts to view any specific task information or details (see Figure 2.2). Users had to click one to two times to navigate to the information they needed to access. The data-rich dashboard presents categories of tasks as pie charts, airman information, and task information for the selected task category in the pie chart (see Figure 2.3). Users were able to view the airmen’s information, task categories, and task information on the same page and could navigate to the information they needed with one click.

**Figure 2.2** Minimalistic Dashboard View. The minimalistic dashboard that will be used for tracking airmen’s training. This dashboard was presented after the data-rich dashboard for all participants.
Figure 2.3 Data-rich Dashboard View. The data-rich dashboard that will be used for tracking airmen’s training. This dashboard was presented first and before the minimalistic dashboard for all participants.

2.3.3 Qualtrics

The survey questionnaire was presented through Qualtrics. As this study was part of a larger investigation and administered in conjunction with the Framing Effects study (Gray, 2023), the questionnaire instruments were delivered through one Qualtrics survey that incorporated randomization to counterbalance the presentation of the order in which study was presented first. Participants reported their position (leader or subordinate) at the beginning of the survey, which then prompted the appropriate counterbalanced study questions. All participants completed a set of task performance questions for each condition analyzing information load (the present study), as seen in Table A.1. The presentation of these task conditions was randomized such that some participants viewed the Condition A tasks first ($n = 16$) and others viewed the Condition B tasks first ($n = 14$). Usability was measured through a 30-item Usefulness, Satisfaction, and Ease of Use...
(USE) Questionnaire (Lund, 2001), as shown in Table A.2. Ad hoc questions were presented regarding user preference for the dashboard and user demographics.

2.3.4 Description of Task

Two sets of task performance questions were created to evaluate how quickly participants were able to find information on each dashboard in addition to the percentage of responses they answered correctly. These performance questions prompted participants to navigate to the dashboard on the left-hand screen to find specific information or answers to the prompts. For example, participants were tasked with entering the due date for the “Cyber Awareness Challenge 2021” in month/day/year format. They were also asked to enter the number of qualified or overdue tasks for specific task knowledge. A full list of task performance questions is listed in Table A.1. The task performance questions along with their correct answers were developed with RippleWorx employees and subject matter experts familiar with the dashboard and training information.

2.3.5 Measures

Accuracy scores were calculated as the percentage of correct responses to the task performance questions. For example, if a participant answered three out of the four task performance questions correctly, they were given an accuracy score of 75% for that condition.

Response times were calculated following data collection through Zoom recordings of participants’ survey screens (Zoom Video Communications Inc., 2022). Timestamps were recorded when a question would load onto the screen and when
participants would finish typing out their final responses to a question. The beginning
timestamp for each question was subtracted from the end timestamp to give a total
number of seconds per question. These seconds were then added together to give a total
response time per dashboard condition per participant.

Usability ratings were collected through the USE Questionnaire. The USE
Questionnaire provides statements wherein the user rates their level of agreement on a 7-
pt Likert scale ranging from strongly disagree to strongly agree. This instrument has been
used frequently in usability literature and has been psychometrically evaluated for
reliability and validity with overall Cronbach’s α = .98 (Gao et al., 2018). The 30-item
questionnaire is divided into four factors of usability including usefulness, ease of use,
ease of learning, and satisfaction. USE rating scores were calculated by averaging each
participant’s ratings across the four factors. The USE questionnaire was presented after
the completion of each set of task performance questions.

2.4 Procedure

Eight one-hour experimental sessions were held with an average of five
participants per session. Four sessions occurred on each day over two consecutive days.
Each participant’s survey randomly assigned whether the present study or the concurrent
framing effects study (Gray, 2023) was presented first. A flow chart of the experimental
session is shown in Figure 2.4. Before beginning the experiment, IDs were checked to
ensure that each participant was at least 18 years of age. As participants arrived,
researchers obtained their written informed consent. Employees from RippleWorx began
by introducing the dashboard product to participants and explaining its purpose.
Participants did not receive training on the dashboard as the training is an exploratory process conducted by the user. The appropriate dashboard was presented based on the counterbalancing and randomization of the studies in Qualtrics. Participants simultaneously completed the experimental trials on separate computers. Participants were first presented with either the data-rich dashboard from this study or the gain dashboard from the concurrent Framing Effects study. Researchers had the appropriate dashboard in the background and began the Qualtrics survey, wherein performance task questions were presented. Participants navigated through the dashboard to find the answers to the task questions about specific information. Following these task questions, participants answered a survey on the USE scale where items were presented in a fixed order. Next, they were presented with the opposite dashboard in the respective study. Participants navigated through the dashboard to find the information they are tasked with answering, followed by the USE survey. If the randomization began with the Framing Effects study, participants were then presented with risk tendency verbal and visual questions. They then selected their preferred dashboard, whether that was the data-rich/minimalistic dashboard or the loss/gain frame dashboard depending on which set of dashboards was presented first. Following this, the dashboard for the opposite study was presented. Once again, participants completed task performance questions followed by questions from the USE scale for each dashboard condition. They then selected their preferred dashboard for that study. Finally, participants answered basic demographic questions (i.e., age, gender, and ethnicity) at the end of the survey. Researchers and employees from RippleWorx waited for all participants to complete the survey before beginning an open-ended feedback session. Participants were asked to provide any
positive or negative feedback from their experience with the dashboards. Lastly, participants were thanked for their time and dismissed by RippleWorx employees.

**Figure 2.4** Experimental Procedure. Walkthrough of the experiment’s procedure where participants interacted with and responded to task performance questions in a data-rich, minimalistic, gain-framed, and loss-framed dashboard and provided ratings of usability for each.
Chapter 3. Results

This study analyzed the effects of high and low information load in dashboards. Measurements of dashboard preference, accuracy, response time, and various factors of usability were taken from a data-rich and minimalistic dashboard. The minimalistic dashboard was expected to be preferred over the data-rich dashboard and generate higher accuracy scores, faster response times, and show higher usability ratings. A Chi-square goodness of fit test, reliability analyses, paired samples t-tests, mixed methods analysis of variance (ANOVAs), and descriptive statistics were conducted through SPSS 28, a statistical software suite (IBM Corp., 2021). All Bayesian analyses were performed through JASP, an open-source statistical program (JASP Team, 2023). All post-hoc Bayes Factors were calculated using uniform priors.

3.1 Dashboard Preference

Subjective self-report measures of preference between the data-rich and minimalistic dashboards were collected. It was expected that participants would prefer the minimalistic dashboard over the data-rich dashboard. A chi-square test of goodness-of-fit was performed to determine whether there was a significant association between information load and dashboard preference. Preference for the two dashboards was not equally distributed in the population as participants largely preferred the data-rich dashboard, $\chi^2 (1) = 19.2, p < .001$ (see Figure 3.1).
Figure 3.1 User Dashboard Preference. The data-rich dashboard was overwhelmingly preferred over the minimalistic dashboard. Error bars represent the standard error of the mean.

3.2 Response Time

Response time was recorded as a function of how many seconds elapsed between each question loading onto a screen and when participants typed out their response. It was expected that participants would respond more quickly (yielding a lower response time) when interacting with the minimalistic dashboard than with the data-rich dashboard. To examine whether participants responded quicker in the data-rich or minimalistic dashboard, a paired-samples t-test was performed. Results indicated that the mean difference of the response times in the data-rich dashboard ($M = 192.04; SD = 77.27$) and the minimalistic dashboard ($M = 210.92; SD = 88.56$) was not statistically significant at the .05 level of significance, $t(24) = -.975, p = .339, d = -.195, BF_{10} = 0.323$ (see Figure 3.2). The 95% confidence interval of the difference between each mean
ranged from [-58.86 to 21.10]. There was no significant difference between the means of the samples.

**Figure 3.2** Response Time by Dashboard. Mean total task time in seconds that participants took to complete set of performance task questions in the data-rich and minimalistic dashboard. Error bars represent the standard error of the mean.

### 3.3 Usability: Usefulness

Usefulness ratings were obtained for each dashboard as a portion of the USE Questionnaire. We evaluated this questionnaire for reliability and validity with overall Cronbach’s $\alpha = 0.94$, with individual alpha values per usability factor and administration of the questionnaire listed in Table B. These usefulness ratings over eight items per condition were averaged across dashboards and participants. It was expected that participants would find the minimalistic dashboard to be higher in usefulness than the data-rich dashboard. A paired samples t-test was conducted to determine whether the data-rich or minimalistic dashboard was associated with higher usefulness ratings. Results indicated that the mean difference between the usefulness scores in the data-rich
dashboard \((M = 5.60; SD = 1.44)\) and the minimalistic dashboard \((M = 5.99; SD = 0.78)\) was not statistically significant at the .05 level of significance, \(t(29) = -1.849, p = .075, d = -.338, BF_{10} = 0.873\) (see Figure 3.3). The 95% confidence interval of the difference between each mean ranged from [-0.81 to 0.04] and did not indicate a difference between the means of the samples.

![Figure 3.3 Usefulness Ratings by Dashboard](image)

**Figure 3.3** Usefulness Ratings by Dashboard. Mean usefulness ratings given by participants in the data-rich and minimalistic dashboard on a 7-pt Likert scale. Error bars represent the standard error of the mean.

### 3.4 Usability: Ease of Use

Ease of use ratings were obtained for each dashboard as a portion of the USE Questionnaire. These ratings over 11 items per condition were averaged across dashboards per participant. It was expected that the minimalistic dashboard would be associated with higher ease of use ratings than the data-rich dashboard. A paired-sample t-test was conducted to determine whether participants rated the data-rich or minimalistic
dashboard higher in regard to ease of use. Results indicated that the mean difference between the ease of use ratings in the data-rich dashboard ($M = 5.55; SD = 1.55$) and the minimalistic dashboard ($M = 5.69; SD = 1.12$) was not statistically significant at the .05 level of significance, $t(29) = -0.520$, $p = .607$, $d = -0.095$, $BF_{10} = 0.220$ (see Figure 3.4). The 95% confidence interval of the difference between each mean ranged from [-0.69 to 0.41] and did not indicate a difference between the means of the samples.

![Figure 3.4 Ease of Use Ratings by Dashboard. Mean ease of use ratings given by participants in the data-rich and minimalistic dashboard on a 7-pt Likert scale. Error bars represent the standard error of the mean.](image)

3.5 Usability: Ease of Learning

Ease of learning ratings were collected for each dashboard as a portion of the USE Questionnaire. These ratings covering four items per condition were averaged across dashboards per participant. It was expected that the minimalistic dashboard would be associated with higher ease of learning ratings than the data-rich dashboard. A paired-sample $t$-test was performed to examine if participants rated the data-rich or minimalistic
dashboard higher in ease of learning. Results revealed that the mean difference between
the ease of learning ratings in the data-rich dashboard ($M = 5.42; SD = 1.47$) and the
minimalistic dashboard ($M = 5.71; SD = 1.03$) was not statistically significant at the .05
level of significance, $t(29) = -1.080, p = .289, d = -.197, BF_{10} = 0.330$ (see Figure 3.5).
The 95% confidence interval of the difference between each mean ranged from [-0.84 to
0.26]. There was no significant difference between the means of the samples.

![Figure 3.5](image)

Figure 3.5 Ease of Learning Ratings by Dashboard. Mean ease of learning ratings given by participants in
the data-rich and minimalistic dashboard on a 7-pt Likert scale. Error bars represent the standard error of
the mean.

3.6 Usability: Satisfaction

Ratings of satisfaction were received for each dashboard as a portion of the USE
Questionnaire. These ratings for seven items per condition were averaged across
dashboards per participant. The minimalistic dashboard was expected to yield higher
satisfaction ratings than the data-rich dashboard. To analyze whether participants rated
the data-rich or minimalistic dashboard higher in satisfaction, a paired-samples t-test was conducted. Results signified that the mean difference between the ease of learning ratings in the data-rich dashboard ($M = 4.88; SD = .43$) and the minimalistic dashboard ($M = 5.65; SD = 1.05$) was statistically significant at the .05 level of significance, $t(29) = -4.02$, $p < .001$, $d = -.733$, $BF_{10} = 78.997$ (see Figure 3.6). The 95% confidence interval of the difference between each mean ranged from [-1.15 to -0.37], indicating a significant effect of information load on satisfaction ratings.
Figure 3.6 Satisfaction Ratings by Dashboard. Mean satisfaction ratings given by participants in the data-rich and minimalistic dashboard on a 7-pt Likert scale. Error bars represent the standard error of the mean.

3.7 Order Effects

As the current study was counterbalanced with a concurrent study analyzing framing and user roles, potential order effects were investigated. These order effects were teased out by evaluating whether the current study (information load) or the framing study was presented first as a variable and the effects and interactions with the amount of information presented. Mixed methods ANOVAs were conducted along with Bayesian mixed ANOVAs for response time, accuracy, usefulness, ease of use, ease of learning, and satisfaction ratings.

A mixed methods ANOVA was conducted to evaluate how information load and order affect response time. There was no main effect of information load on response time, $F(1, 25) = 0.23, p = .638, \eta^2 = .009$. A Bayesian mixed methods ANOVA indicated
moderate evidence in favor of the null hypothesis, BF\textsubscript{10} = 0.319. Results indicated that there was no main effect of the order on response time, \(F(1, 25) = .91, p = .350, \eta^2 = .035\). A Bayesian mixed methods ANOVA revealed that there was anecdotal evidence for the null hypothesis, BF\textsubscript{10} = 0.505. Additionally, there was no significant interaction between information load and order, \(F(1, 25) = 2.48, p = .128, \eta^2 = .090\). Bayesian mixed methods ANOVA results suggested that there was moderate evidence for the null hypothesis, BF\textsubscript{10} = 0.155.

A mixed ANOVA was performed to evaluate the effects of information load and order on accuracy. Results revealed that there was a main effect of information load on the accuracy, \(F(1, 25) = 12.01, p < .05, \eta^2 = .324\), such that the minimalistic dashboard yielded higher accuracy scores. A Bayesian mixed methods ANOVA suggested very strong evidence in favor of the research hypothesis, BF\textsubscript{10} = 63.453. The main effect of the order on accuracy was not statistically significant, \(F(1, 25) = .14, p = .714, \eta^2 = .005\). Results from a Bayesian mixed methods ANOVA indicated that there was anecdotal evidence in favor of the null hypothesis, BF\textsubscript{10} = 0.342. No significant interaction was found between information load and order, \(F(1, 25) = 1.06, p = .313, \eta^2 = .041\). Bayesian mixed methods ANOVA results revealed that there was strong evidence in favor of the research hypothesis, BF\textsubscript{10} = 21.672.

A mixed methods ANOVA was performed to examine the impact of order and information load on usefulness ratings. Results showed that there was no main effect of information load on usefulness ratings, \(F(1, 25) = 1.81, p = .191, \eta^2 = .068\). A Bayesian mixed methods ANOVA indicated that there was anecdotal evidence in favor of the null hypothesis, BF\textsubscript{10} = 0.583. There was no main effect for order on usefulness, \(F(1, 25) =\)
2.65, \( p = .116, \eta^2 = .096 \). A Bayesian mixed methods ANOVA suggested anecdotal evidence for the null hypothesis, \( BF_{10} = 0.945 \). The interaction between information load and order failed to reach statistical significance as well, \( F(1, 25) = .10, p = .754, \eta^2 = .004 \). A Bayesian mixed methods ANOVA indicated anecdotal evidence in favor of the null hypothesis, \( BF_{10} = 0.541 \).

A mixed methods ANOVA was conducted to analyze the effects of order and information load on ease of use ratings. Results indicated no main effect of information load on ease of use ratings, \( F(1, 25) = .30, p = .589, \eta^2 = .012 \). A Bayesian mixed methods ANOVA indicated moderate evidence in favor of the null hypothesis, \( BF_{10} = 0.299 \). The main effect of the order was not statistically significant, \( F(1, 25) = 1.47, p = .237, \eta^2 = .055 \). A Bayesian mixed methods ANOVA suggested that there was anecdotal evidence for the null hypothesis, \( BF_{10} = 0.630 \). There was no significant information load by order interaction, \( F(1, 25) = 1.47, p = .237, \eta^2 = .055 \). A Bayesian mixed methods ANOVA revealed moderate evidence in favor of the null hypothesis, \( BF_{10} = 0.193 \).

A mixed methods ANOVA was performed to investigate the impact of information load and order on ease of learning ratings. Results revealed no significant main effect of information load on ease of learning ratings, \( F(1, 25) = 1.40, p = .248, \eta^2 = .053 \). A Bayesian mixed methods ANOVA suggested that there was anecdotal evidence for the null hypothesis, \( BF_{10} = 0.495 \). There was also no main effect of the order on ease of learning ratings, \( F(1, 25) = 3.38, p = .078, \eta^2 = .119 \). A Bayesian mixed methods ANOVA indicated anecdotal evidence in favor of the research hypothesis, \( BF_{10} = 1.139 \). No significant interaction was found between information load and order, \( F(1, 25) = .34, \).
$p = .539, \eta^2 = .015$. A Bayesian mixed methods ANOVA signified that there was anecdotal evidence in favor of the null hypothesis, $\text{BF}_{10} = 0.558$.

A mixed methods ANOVA was conducted in order to examine the effects of information load and order on satisfaction ratings. The results indicated that there was no main effect of information load on satisfaction ratings, $F(1, 25) = 1.45, p = .239, \eta^2 = .055$. A Bayesian mixed methods ANOVA suggested anecdotal evidence for the null hypothesis, $\text{BF}_{10} = 0.380$. A significant main effect of order was found, $F(1, 25) = 4.92, p < .05, \eta^2 = .165$. Bayesian mixed methods ANOVA results indicated anecdotal evidence in favor of the research hypothesis, $\text{BF}_{10} = 1.936$. There was no interaction between information load and order, $F(1, 25) = 1.12, p = .300, \eta^2 = .043$. A Bayesian mixed methods ANOVA suggested anecdotal evidence for the null hypothesis, $\text{BF}_{10} = 0.925$. 
Chapter 4. Discussion

Although there is a growing body of literature on dashboard design, the existing research has not clearly established how high and low information loads impact a user’s interaction with a dashboard. Overloading or underloading a dashboard with information can have negative effects on cognitive processing, decision-making, and usability (Chen, 2018; Costa & Aparício, 2019; Glassey, 2005; Hick, 1952; Hyman, 1953). Understanding how users perceive and perform with varying levels of information load can allow designers to create more usable and successful dashboards. The current study investigated whether the design of a dashboard, precisely the amount of information presented on a page, influenced the performance and usability of the dashboard. It was expected that there would be differences between the dashboards such that the minimalistic dashboard would be preferred and result in higher usability ratings, accuracy scores, and faster response times. Most of these hypotheses were not supported by the results, however. There are several possible explanations for these disparate outcomes.

4.1 Dashboard Preference

It was expected that users would prefer the minimalistic dashboard over the data-rich dashboard due to cognitive limitations and the potential benefits of managing information overload, such as reducing stress, confusion, distraction, and misinterpretation (Edmunds & Morris, 2000). However, the finding that 90% of participants preferred the data-rich dashboard over the minimalistic dashboard was
intriguing. The most considerable trade-off between high and low information load is the possibility of information overload or additional clicking. Yet, based on these results, it appears that participants vastly preferred to interact with a dashboard displaying more information at once than to interact with a dashboard that requires more clicks to access information. The sample consisted of airmen that currently interact with the same information on the dashboards but through a host of different sources. The current system requires much time and effort from airmen to access these large amounts of data, while these dashboards offer a convenient solution that synthesizes those sources into one location. It is perhaps the case that participants did not find the data-rich dashboard to be overwhelming or overloaded with information in comparison to their current system. Priming effects may also be at play. The concurrent Framing Effects study adopted the information load presented in the original dashboard prototype, which was very similar to the information load and organization of the data-rich dashboard. The data-rich dashboard was also always presented before the minimalistic dashboard. It is possible that participants learned how to navigate through the data-rich or loss/gain-framed dashboards first and then found the minimalistic dashboard to have unnecessary clicks (Nisbett & Wilson, 1977). These results may help provide insight into the tradeoffs between information load and clicking (Chen, 2018; Rosenholtz et al., 2005).

4.2 Accuracy

Accurate decision-making has a quadratic relationship with the number of options presented at a time. Too few options on a dashboard are associated with poor decision-making just as too many options are correlated with poor decision-making. The peak of
this inverted U-curve relationship maximizes both the number of options and accurate decision-making (Eppler & Mengis, 2008). Results from this study did not support my hypothesis that the minimalistic dashboard would yield more accurate responses than the data-rich dashboard. Because the outcome indicated no difference between the two dashboards in accuracy, it is possible that the minimalistic dashboard presented too few options at once and that the data-rich dashboard surpassed this optimal peak point where decision accuracy/performance begins to decline as information overload begins to occur (Chewning & Harrell, 1990; Schroder et al., 1967). As high and low information loads sit at opposite ends of the inverted U-curve, their implications on accurate decision-making may be similar. The consistency of accuracy in responses to task performance questions also helps to confirm that the Condition A and Condition B questions were of equal difficulty. Another potential explanation may be the absence of a time constraint for task questions. Participants were unaware of time tracking and were not given a set amount of time to complete the tasks. Available processing time impacts information overload (Eppler & Mengis, 2004). Having a short amount of time to find information or having time pressure can increase information overload, and in turn negatively influence performance (Schick et al., 1990). Without this added pressure of time, participants could take the time they need to find the correct answers to task questions. If this were the case, it could be an indication of a ceiling effect occurring.

### 4.3 Response Time

A heavy information load can negatively impact the speed of a user (Eppler & Mengis, 2004). With more data/information provided on a page, a user may have a more
difficult time trying to find or identify the relevant information needed. As such, it was hypothesized that participants would respond more quickly to performance task questions in the minimalistic dashboard than in the data-rich dashboard. Results indicated that there were no significant differences in response times between the two dashboards. One potential explanation for this could be that the amount of time participants spent exploring the data-rich dashboard to find a task response and the time spent clicking through to find answers in the minimalistic dashboard balanced each other out. Although clicking through the minimalistic dashboard was not expected to take a substantial amount of time, it is an added time cost that the data-rich dashboard did not present. A mixed methods ANOVA analyzing order effects for response time revealed no main effects of order or information load and no interaction between the two variables. These results align with the outcomes from the paired samples t-test.

4.4 Usability

A minimalistic platform or dashboard presents less information on one page, providing a more simplified layout for users. As such, it was anticipated that participants would rate the ease of use and ease of learning higher than the data-rich dashboard. As simplicity has been used as a measure of interface aesthetic and usability, it was also expected that usefulness and satisfaction ratings would be rated higher in the minimalistic dashboard (Gao et al., 2006; Mõttus et al., 2013). Results from paired samples t-tests revealed no significant differences between the data rich and minimalistic dashboards regarding their usefulness, ease of use, and ease of learning. There was, however, a significant difference between the two dashboards in satisfaction ratings, such that the
minimalistic dashboard was associated with higher satisfaction ratings than the data-rich dashboard. This was an unexpected outcome given that the majority of participants selected that they preferred the data-rich dashboard over the minimalistic dashboard. The mixed methods ANOVAs examining order effects revealed no main effects of order or information load for usefulness, ease of use, and ease of learning. Results from the mixed methods ANOVA analyzing order effects for satisfaction indicated a main effect of order such that there were significant differences in satisfaction ratings based on whether the current study was presented first or the Framing Effects study was presented first. No main effect of information load or interaction between information load and order was found, however. These analyses support that the counterbalanced order of this study with the concurrent study did not influence participants’ usability ratings, aside from satisfaction ratings. A potential explanation for null results for usefulness, ease of use, and ease of learning ratings could be that participants found the dashboard platforms in general to be much higher in usability as compared to their current system of information from multiple sources, leading them to rate highly across both dashboards.
Chapter 5. Conclusions and Future Work

The main purpose of this study was to examine whether the information load on a dashboard page impacts performance and usability. Dashboards are becoming more prevalent in a variety of industries such as in the medical field, education, military, government, and corporate companies, among others. As they synthesize large amounts of data into one source, it is important to evaluate how the amount of information presented affects how users interact with them. The current study presented a minimalistic dashboard and a data-rich dashboard where measures of accuracy, response time, usability, and preference were collected. The expectation that the minimalistic dashboard would be preferred and associated with higher accuracy scores, faster response times, and higher usability ratings was only partially supported. Participants largely preferred the data-rich dashboard and rated the minimalistic dashboard higher in satisfaction. Null results were present for all other dependent variables.

Several limitations were present in this study that should be expanded upon in future research. While the current study was counterbalanced with the Framing Effects study in presentation, this study was unable to counterbalance the presentation of the data-rich and minimalistic dashboards. This resulted in every participant interacting with the data-rich dashboard before the minimalistic dashboard. Future studies should seek to counterbalance the presentation of stimuli to reduce uncontrolled error or the possibility of order effects. Secondly, the sample consisted of airman at Fairchild Air Force Base.
While this was a unique opportunity for airmen to interact with a specific dashboard prototype they may use in the future, these airmen may have different values or cultures than the general population. As such, results may not prove to be very generalizable. The initial G*Power analysis indicated that a minimum sample size of 34 was required to achieve a statistical power of .80, but this study only gathered data from a total of 30 participants. Additionally, it is possible that the data-rich dashboard and the minimalistic dashboard did not contrast each other enough. The minimalistic dashboard only required one more click compared to the data-rich dashboard. Future research should further investigate thresholds for what is considered a high or low information load and their implications for performance and usability. Future work analyzing information load in dashboards should incorporate additional measures of cognitive load, a larger sample size, and counterbalanced conditions. These limitations make it difficult to conclusively state the impacts of high and low information load in dashboards. While this study was not able to provide conclusive statements on the impact of high and low information load in dashboards, the investigation of information load with clicking, performance, and usability must continue as dashboards become omnipresent. Results from this study will help to expand the existing theory and will provide insight into how designers can manage the tradeoffs of information load on a dashboard.
References

https://www.afpc.af.mil/About/Air-Force-Demographics/


JASP Team (2023). JASP (Version 0.17)[Computer software].


Table A.1 Task Performance Questions. Condition A and Condition B were counterbalanced with the presentation of the data-rich or minimalistic dashboard. Accuracy scores were calculated as the percentage of correct answers. If a participant correctly answered 3 questions in one condition, they received a score of 75% for that dashboard condition.

<table>
<thead>
<tr>
<th>Dashboard</th>
<th>Items</th>
</tr>
</thead>
<tbody>
<tr>
<td>Condition A</td>
<td>Did Airman Cash complete the Air Force manuals and instructions task? Enter the due date for RT FTAC (mm/dd/yyyy). Enter the number of qualified tasks in GO-81. Is Airman Cash a high performer, an average performer, or a low performer?</td>
</tr>
<tr>
<td>Condition B</td>
<td>Did Airman Cash complete the Wheel &amp; Tire Assemblies task? Enter the due date for Cyber Awareness Challenge 2021 (mm/dd/yyyy). Enter the number of overdue tasks in GO-81. Enter Airman Cash’s rate of progression (%)</td>
</tr>
</tbody>
</table>
Appendix A. List of Questionnaire Items

Table A.2 USE Questionnaire Items. The USE Questionnaire encompasses four factors of usability including usefulness, ease of use, ease of learning, and satisfaction. All 30 items are measured on a 7-pt Likert scale with 1 = Strongly disagree, 7 = Strongly agree.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Item</th>
</tr>
</thead>
<tbody>
<tr>
<td>Usefulness</td>
<td>It helps me be more effective.</td>
</tr>
<tr>
<td></td>
<td>It helps me be more productive.</td>
</tr>
<tr>
<td></td>
<td>It is useful.</td>
</tr>
<tr>
<td></td>
<td>It gives me more control over the activities in my life.</td>
</tr>
<tr>
<td></td>
<td>It makes the things I want to accomplish easier to get done.</td>
</tr>
<tr>
<td></td>
<td>It saves me time when I use it.</td>
</tr>
<tr>
<td></td>
<td>It meets my needs.</td>
</tr>
<tr>
<td></td>
<td>It does everything I would expect it to do.</td>
</tr>
<tr>
<td>Ease of Use</td>
<td>It is easy to use.</td>
</tr>
<tr>
<td></td>
<td>It is simple to use.</td>
</tr>
<tr>
<td></td>
<td>It is user-friendly.</td>
</tr>
<tr>
<td></td>
<td>It requires the fewest steps possible to accomplish what I want to do with it.</td>
</tr>
<tr>
<td></td>
<td>It is flexible.</td>
</tr>
<tr>
<td></td>
<td>Using it is effortless.</td>
</tr>
<tr>
<td></td>
<td>I can use it without written instructions.</td>
</tr>
<tr>
<td></td>
<td>I don't notice any inconsistencies as I use it.</td>
</tr>
<tr>
<td></td>
<td>Both occasional and regular users would like it.</td>
</tr>
<tr>
<td></td>
<td>I can recover from mistakes quickly and easily.</td>
</tr>
<tr>
<td></td>
<td>I can use it successfully every time.</td>
</tr>
<tr>
<td>Ease of Learning</td>
<td>I learned to use it quickly.</td>
</tr>
<tr>
<td></td>
<td>I easily remember how to use it.</td>
</tr>
<tr>
<td></td>
<td>It is easy to learn to use it.</td>
</tr>
<tr>
<td></td>
<td>I quickly became skillful with it.</td>
</tr>
<tr>
<td>Satisfaction</td>
<td>I am satisfied with it.</td>
</tr>
<tr>
<td></td>
<td>I would recommend it to a friend.</td>
</tr>
<tr>
<td></td>
<td>It is fun to use.</td>
</tr>
<tr>
<td></td>
<td>It works the way I want it to work.</td>
</tr>
<tr>
<td></td>
<td>It is wonderful.</td>
</tr>
<tr>
<td></td>
<td>I feel I need to have it.</td>
</tr>
<tr>
<td></td>
<td>It is pleasant to use.</td>
</tr>
</tbody>
</table>
Appendix B. USE Questionnaire Reliability Analysis

Table B USE Questionnaire Reliability Analysis. Cronbach’s alpha values are shown for each usability factor of usefulness, ease of use, ease of learning, and satisfaction. This table displays those alpha values for the administration of the data-rich and minimalistic dashboard questionnaire.

<table>
<thead>
<tr>
<th>Dashboard</th>
<th>Usability Factor</th>
<th>Number of Items</th>
<th>Cronbach’s α</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data-rich</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Usefulness</td>
<td>8</td>
<td>0.97</td>
</tr>
<tr>
<td></td>
<td>Ease of Use</td>
<td>11</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td>Ease of Learning</td>
<td>4</td>
<td>0.94</td>
</tr>
<tr>
<td></td>
<td>Satisfaction</td>
<td>7</td>
<td>0.97</td>
</tr>
<tr>
<td>Minimalistic</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Usefulness</td>
<td>8</td>
<td>0.89</td>
</tr>
<tr>
<td></td>
<td>Ease of Use</td>
<td>11</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td>Ease of Learning</td>
<td>4</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td>Satisfaction</td>
<td>7</td>
<td>0.94</td>
</tr>
</tbody>
</table>
### Appendix C. Demographic Questionnaire

Table C Demographic Questionnaire. Participants entered their demographic responses or selected if they preferred not to answer.

<table>
<thead>
<tr>
<th>Item</th>
<th>Response</th>
</tr>
</thead>
<tbody>
<tr>
<td>What is your age?</td>
<td>_____ years</td>
</tr>
<tr>
<td>What was your sex assigned at birth?</td>
<td>□ Prefer Not To Answer</td>
</tr>
<tr>
<td></td>
<td>□ Male</td>
</tr>
<tr>
<td></td>
<td>□ Female</td>
</tr>
<tr>
<td></td>
<td>□ Intersex</td>
</tr>
<tr>
<td>What is your ethnicity?</td>
<td>□ Prefer Not To Answer</td>
</tr>
<tr>
<td></td>
<td>□ American Indian/Alaskan Native</td>
</tr>
<tr>
<td></td>
<td>□ Asian</td>
</tr>
<tr>
<td></td>
<td>□ Black/African American</td>
</tr>
<tr>
<td></td>
<td>□ Hispanic/Latino</td>
</tr>
<tr>
<td></td>
<td>□ Multiple</td>
</tr>
<tr>
<td></td>
<td>□ Native Hawaiian/Other Pacific Islander</td>
</tr>
<tr>
<td></td>
<td>□ White</td>
</tr>
<tr>
<td></td>
<td>□ Unknown</td>
</tr>
</tbody>
</table>
Appendix D. UAH IRB Approval

Table D UAH IRB Approval. The UAH Institutional Review Board of Human Subjects Committee granted permission to conduct this research on September 28, 2022.

Date: 28 September 2022

PI: Nate Tenhundfeld
PI Department: Psychology
The University of Alabama in Huntsville

Dear Nate,

The UAH Institutional Review Board of Human Subjects Committee has reviewed your proposal titled: Dashboard Design and found it meets the necessary criteria for approval. Your proposal seems to be in compliance with these institutions Federal Wide Assurance (FWA) 00019998 and the DHHS Regulations for the Protection of Human Subjects (45 CFR 46). Please note that this approval is good for one year from the date on this letter. If data collection continues past this period, you are responsible for processing a renewal application a minimum of 60 days prior to the expiration date.

No changes are to be made to the approved protocol without prior review and approval from the UAH IRB. All changes (e.g. a change in procedure, number of subjects, personnel, study locations, new recruitment materials, study instruments, etc) must be prospectively reviewed and approved by the IRB before they are implemented. You should report any unanticipated problems involving risks to the participants or others to the IRB Chair.

If you have any questions regarding the IRB’s decision, please contact me.

Sincerely,

Ann L. Bianchi
IRB Chair
Associate Professor, College of Nursing